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Review

Application of Digital Twin in Electric Vehicle Powertrain: A Review

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Abstract: Digital Twin (DT) is widely regarded as a highly promising technology with the potential to revolutionize various industries, making it a key trend in the Industry 4.0 era. In a cost-effective and risk-free setting, digital twins facilitate the interaction and merging of the physical and informational realms. The application of digital twins spans across different sectors, including aerospace, healthcare, smart manufacturing, and smart cities. As electric vehicles have experienced rapid growth, there is a growing demand for the development of innovative technologies. One potential area for digital twins application is within the automotive sector. The powertrain system of electric vehicles (EVs) consists of three parts, power source, power electronic system, and electric motor, which are considered as the core components of electric vehicles. The focus of this paper is to conduct a methodical review regarding the use of digital twins in the powertrain of electric vehicles (EVs). While reviewing the development of digital twin technology, its main application scenarios and its use in electric vehicle powertrains are analysed. Finally, the digital twins currently encounter several challenges that need to be addressed, and so the future development of their application to electric vehicles are summarized.

Keywords: digital twin; electric vehicle; powertrain; proton exchange membrane fuel cell

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1. Introduction

In the past few years, the growing economy and population mobility have led to an increased demand for automobiles. However, the automotive industry is encountering significant obstacles in its development. This is attributed to the rising environmental pollution and the anticipated depletion of fossil fuels, posing considerable challenges, there is an urgent need for new strategies in the development of automobiles in order to obtain more efficient, cleaner and safer vehicles. Electric vehicles, as well as clean energy vehicles, have gained widespread attention and development in recent years due to their environmental and efficiency benefits. The powertrain of an electric vehicle is seen as the fundamental element of the vehicle, requiring efficiency, reliability, and cost-effectiveness to ensure satisfactory operational performance [1]. Digital twins may provide a new way of thinking to address these issues. Digital twins were first created in aerospace and then gradually applied to other fields [2]. Advancements in sensor technology and the Internet of Things (IoT) have propelled the expansion of smart manufacturing. The integration of sensor technology and the Internet of Things has resulted in vehicles becoming the third most connected device, following mobile phones and computers. This has led to the involvement of substantial amounts of data throughout the entire process of designing, manufacturing, maintaining, and utilizing automobiles for transportation [3], in turn, this data is the basis for vehicle design, manufacturing, maintenance and applications. Big data have enormous economic potential if it is fully utilized in the right way [4]. Using big data analytics enables the data generated to be accessed via intelligent analytical tools, facilitating the efficient and informed decision-making process. This allows for the quick and accurate selection of the most suitable course of action [5]. To maximize the utilization of data, utilizing an appropriate data model is crucial [6], like virtual high-fidelity models that are digitally generated to replicate the actions of physical entities. This enables the simulation of real-world scenarios with accuracy and precision [7]. By utilizing these technologies, real-time monitoring of real-life scenarios can be synchronized with virtual environments. This allows for swift analysis and calculations to be conducted, enabling prompt decision-making and response, which provides for the emergence of digital twins [8]. The automotive sector is demonstrating significant potential in the exploration and utilization of digital twin technology. Currently, digital twin technology is increasingly becoming essential in various areas of the automotive industry, and its application scope will be further expanded in the future. The advancement of automotive powertrain is notably prominent as a key area of application for digital twins. In Section 2 of this paper, the development of Industry 4.0 is outlined, while Section 3 delves into the various applications of digital twin technology across different fields. In particular, Section 4 focuses on how digital twin technology is applied in the context of electric vehicles. The powertrain configuration of electric vehicles is presented, with a focus on the implementation of digital twin technology across diverse electric vehicle types. Additionally, an overview of potential challenges and future developments in digital twin technology is provided.

2. Definition and Evolution of Industry 4.0

The concept of Industry 4.0, also known as the fourth industrial revolution, embodies a significant transformation [9]. It is the application of information-physical systems to all aspects of industrial production and manufacturing, and is a comprehensive enhancement of industrial production and manufacturing technology. The amalgamation of different technologies, including the Internet of Things (IoT), Artificial Intelligence (AI), Cloud Computing, big data analytics, and digital twins is essential in Industry 4.0. One important component in this combination is the digital twin, a virtual model that simulates the functionality of tangible systems in an actual environment. By utilizing data from sensors and information systems in real time, the model effectively depicts the present condition of the system and predicts as well as improves its performance. Coined in 2011 as part of the German government's High Tech Strategy initiative, the term "Industry 4.0" describes the continuous evolution in manufacturing, marked by the fusion of digital, physical, and biological systems [10]. The evolution of Industry 4.0 has been influenced by several factors. The swift advancement and development of manufacturing technologies have played a crucial role in driving the progression of Industry 4.0. Furthermore, the swift expansion of interconnected devices and sensors, along with enhanced computing capabilities, has significantly eased the real-time collection and analysis of data. This, in turn, is crucial for predictive maintenance, optimizing production processes, and improving manufacturing decision-making [11]. Industry 1.0 to 4.0 represent four stages of industrial development. In the 1.0 era, mechanical production methods, represented by the steam engine, replaced manual work. In the 2.0 era electrified production methods gradually dominated, further increasing productivity. From the 1970s through the early 21st century, a period referred to as the era of Industry 3.0, witnessed the fast-paced advancement of electronic and computer technologies, the production method is gradually moving towards information technology. Automated production and digital management have greatly improved production efficiency and product quality. In the present day, the most recent iteration of information technology encompasses a wide range of advancements, including the Internet of Things, artificial intelligence, cloud computing, big data analysis, and digital twins, as the representative of the intelligent mode of production, which is a disruptive shift in the manufacturing landscape. It emphasizes the development of digitalization, intelligence, automation and informatization, and promotes the rapid development and improvement in intelligent manufacturing systems, leading a new round of industrial revolution [12]. Table 1 shows the evolution from Industry 1.0 to 4.0.

Table 1. History of industrial development.

Industry X	Year	Evolution
Industry 1.0	1784	automated weaving looms powered by steam technology
Industry 2.0	1870	large-scale manufacturing, assembly line production and the utilization of electrical energy
Industry 3.0	1969	the automation of tasks using computers and electronic systems
Industry 4.0	present	a system that integrates cyber-physical components with an Internet of Things (IoT) framework

3. The Evolution of Digital Twins and Application Scenarios

3.1. The Development of Digital Twins

As early as the 2000s, the formal introduction of the concept of the digital twin occurred; then, in 2003, Professor Grieves presented the idea of the digital twin during a course on Total Product Lifecycle Management at the University of Michigan in the USA [13]. He suggested tangible items, intangible items, and their interrelation. Nevertheless, the theory did not attract much attention and there was scarce research related to it, mainly because of the constraints imposed by time and technology. In 2011, the initial publication on digital twins discussed their ability to predict the remaining operational lifespan of an aircraft [13]. In the beginning of 2012, the first paper that defined the digital twin model was published by the National Aeronautics and Space Administration (NASA). The digital twin was defined as a comprehensive simulation of a system that includes various physical fields, scales, and probabilities. Employing the most accurate physical models, sensors, historical data, and other variables, this simulation replicates the physical behaviour, current state, and developmental patterns of its corresponding physical counterpart in real time [7]. Chen [14] defines a digital twin as a computerized model that responds to the functional characteristics of a physical system. Zheng et al. [15] consider digital twins as virtual information sets describing actual physical assets. According to Mandi [16], a digital twin is a virtual model of a physical system that consistently refreshes data on the performance, maintenance, and overall condition of the physical system throughout its entire lifespan. As stated by Rios et al. [17], the digital twin consists of a comprehensive "product", combing various aspects of the physical system enabling its application to domains beyond just aircraft. In 2017, Michael Grieves [18] provided a new definition of the digital twin, describing it as "a comprehensive set of virtual information constructs that depict a potential or existing physical manufactured product." Digital twins are highly praised by Gartner, which includes them in the list of promising technology trends for 2019 [19]. In 2021, a modelling approach called ECoM4DT for digital twins was introduced by Zhang et al. [20]; in addition to embracing the principles of the conventional M&S (Modelling and Simulation) method, it also emphasizes the distinguishing features of digital twins in comparison to traditional models. This systematic approach guides the modelling process of digital twins. In 2022, the virtual model composition was expanded by Tao et al. [21]. Following this, in 2023, an updated methodology for multidimensional digital twin models was suggested by Zhang et al. [22]. Table 2 shows the evolution of digital twins. Due to technological limitations in the early stages, the history of digital twins is relatively short [19]. The research and application of digital twins have expanded significantly in recent years. This indicates that digital twins are currently experiencing a period of rapid growth and development.

Table 2. History of digital twin technology.

Ref.	Year	Evolution [1]
[13]	2003	Formation stage, Professor Grieves first proposed the concept of digital twins
[23]	2004–2010	The rapid development of communication technology promotes the formation of digital twins
[13]	2011	The first paper on digital twins was published
[7]	2012	NASA published a paper defining digital twins model

Table 2. *Cont.*

Ref.	Year	Evolution [1]
[13]	2014	Whitepaper of digital twins was published
[19]	2016	Siemens applied digital twin technology in the context of Industry 4.0
[24]	2017	Digital twins was proposed by Beihang University
[25]	2019	Professor Tao Fei of Beihang University proposed the five-dimensional digital twin model
[26]	2021	Ehab analyses the potential of city digital twin
[27]	2023	Tran discussed the role of BIM in the integration of digital twins in building construction

[1] Data were obtained from Scopus and Web of Science.

3.2. Digital Twins and Digital Shadows

The idea of a digital shadow is rooted in the concept of a digital twin, which is essentially a virtual representation that accurately reflects the physical system. The digital shadow is essential for monitoring, analysing, and improving the performance of the physical system. It serves a critical role in ensuring the efficient operation and maintenance of the system [28]. The definitions of digital twins and digital shadows are closely connected, and they have overlapping roles [29]. The proposal by AboElHassan et al. [30] suggests a role-based separation of digital shadow and digital twin. According to their proposal, a digital shadow is a digital replica of a physical system that matches the real-time state of the physical system. On the other hand, a digital twin is described as a real-time decision support sandbox. The digital twin relies on the digital shadow as its central component, as it offers a live depiction of the physical system to the digital twin. In real-time, the digital twin uses a digital copy of the digital shadow to optimize the performance of the physical system. This process enhances the efficiency and effectiveness of the system by leveraging the digital replica [31]. A digital shadow is a representation in the digital realm of an object, with information flowing unidirectionally between the physical and digital entities. This indicates that the digital shadow precisely mirrors the up-to-date state or data of the physical object in real-time, but any modifications made to the digital representation do not impact the physical object. The digital shadow essentially acts as a reflection or snapshot of the physical object's status, enabling monitoring, analysis, and decision-making based on the information it provides [32].

By incorporating information from physical models, sensor updates, and operational history, the digital twin concept brings together a range of disciplines, physical parameters, sizes, and likelihoods in a simulation process. This process creates a complete mapping in virtual space to accurately mirror the full life cycle of corresponding physical equipment. The digital twin transcends reality by acting as a digital mapping system for crucial and interdependent equipment systems. Figure 1 shows how digital shadows differ from digital twins.

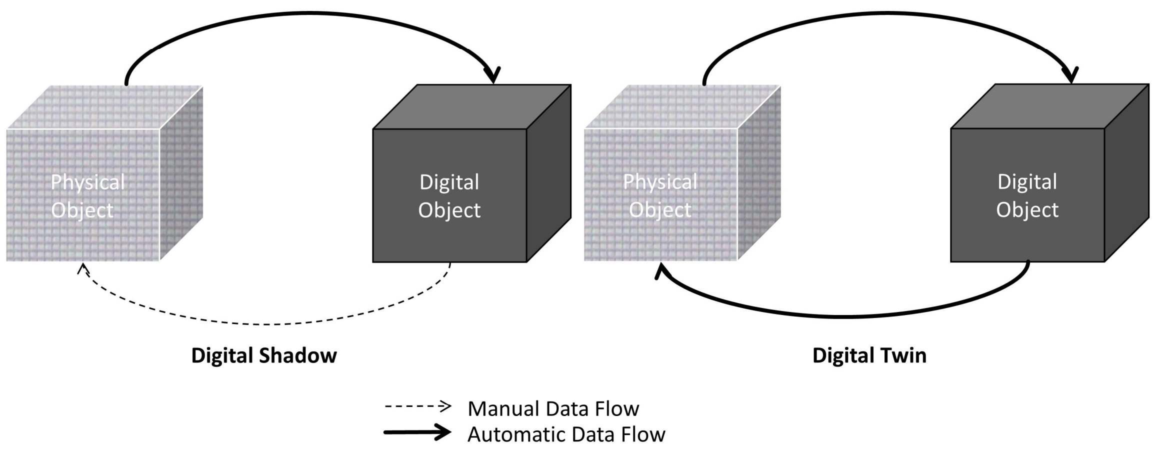

Figure 1. The difference between digital shadows and digital twins.

3.3. The Application of Digital Twins in Smart Cities

Leveraging digital twins is advantageous for both the design of new intelligent urban centre and the continuous improvement in established smart city infrastructure [33]. Smart city refers to the improvement in urban governance and service quality through information technology and intelligent equipment to achieve sustainable urban development. Digital twin technology can provide important technical support for smart city construction. Digital twin technology enables the creation of a comprehensive digital model of a city, facilitating the integration of digitalization and intelligence throughout all stages of urban planning, construction, management, and operation [34]. Through digital twin technology, it can simulate and predict the spatial layout, traffic planning, environmental protection and other aspects of the city, and improve the scientific and forward-looking urban planning. Digital twin technology can improve the intelligence level of public services and enhance the quality of citizens.

3.4. Digital Twins in Healthcare

Healthcare professionals, hospitals, and researchers have the ability to utilize digital twin technology to create customized environments that can be used in real time or to prepare for future advancements and applications. This technology allows for tailored simulations to meet specific needs in the healthcare industry [35]. Doctors can be built with digital twin technology to simulate and plan surgeries on the 3D models of patients' bodies. This can help doctors better understand the patient's body structure and condition, develop more accurate surgical plans, and improve the accuracy and success rate of surgery while reducing surgical risks and errors [36]. Digital twin technology can be applied in the creation and assessment of medical devices. This technology is useful for developing and evaluating medical equipment, such as artificial joints and prosthetics. Through the simulation in a digital twin model, it is possible to enhance the assessment of the device's performance and effectiveness. This, in turn, can lead to improved efficiency in the design and manufacturing of medical equipment. The application of digital twin technology extends to the development and testing of medical equipment, including artificial joints, prosthetics, and other devices. This technology allows for virtual simulations and analysis, contributing to the enhancement of medical device design and performance. Digital twins in medical environments, like artificial intelligence (AI), have the ability to make life-saving decisions based on real-time and historical data [37].

3.5. Digital Twins in the Ocean

The advancement of ocean observation through the implementation of a digital twin is significant. This involves the integration of diverse data sources, along with modelling, simulation, and specialized tools, including artificial intelligence algorithms and best practices. This innovation represents a major step forward in understanding and monitoring the ocean. It serves as an approach to ocean management that leverages digital twin technology to create interactive and dynamic virtual representations of the ocean, subsurface, and marine assets. This is achieved by integrating and analysing large volumes of historical and real-time marine scientific data [38]. Ocean digital twins can simulate and replicate marine ecosystems, providing knowledge and insights to enhance our understanding of the ocean, future risks and how to mitigate them. Furthermore, digital twin technology can predict and analyse ocean scenarios by simulating the operational parameters of wind turbine equipment in various ocean environments and operating conditions. This predictive analysis enables the technology to anticipate and assess the impact of different ocean scenarios on the performance of the wind turbines, providing valuable insights for optimizing their operation and maintenance. The European Union (EU) is the first organization to take this action [39].

3.6. Digital Twin Technology in Smart Buildings

With the advancement of science and technology, the evolution of smart buildings is rapidly progressing. Property companies are leveraging their intelligence to anticipate the needs of customers and emerging technologies. Digitization plays a key role in achieving this goal by reducing time and costs. This technology-driven approach offers significant strategic value to the real estate sector. By utilizing digital twins, operations can be optimized, resulting in enhanced customer experiences and overall benefits throughout the entire lifespan of a building. This is achieved by simulating complex scenarios [40]. The digital twin for smart buildings is a technology based on a digital model that enables digital copies of real-world physical systems through virtual simulation and real-time data monitoring. It provides support for managing the complete life cycle of building design, construction, operation, and maintenance. This enables buildings to be digitally simulated from the design phase, offering data and information for subsequent operational management and maintenance [41].

The application of digital twin technology in the automotive industry is also pertinent to the aforementioned areas. For instance, the integration of digital twins in the automotive industry with intelligent transport systems in smart cities can facilitate real-time communication between vehicles and city infrastructure. This integration can enhance traffic efficiency and safety. Similarly, the use of remote diagnostics in healthcare can also be applied in the automotive industry. It allows for real-time monitoring of vehicle health and early detection of potential issues through digital twins.

Digital twins are being employed in a growing range of industries. This trend is becoming more prevalent with time, but digital twins are still new to many fields and have yet to be fully utilized. The future potential of digital twins is virtually unlimited, with the ability to continually acquire and assimilate new skills and capabilities that can continue to make application objects better and processes more efficient [5].

4. Digital Twins in Electric Vehicles

The number of electric vehicles (EVs), encompassing both all-electric and hybrid vehicles, is on the rise. According to Markit, a company specializing in information processing services, EVs are projected to represent 45% of new car sales in 2040 and nearly 80% by 2050. This growth can be attributed to significant technological advancements, reduced manufacturing costs, and global initiatives promoting the adoption of EVs [42]. Figure 2 shows the comparison between power battery (BEV), plug-in hybrid (HEV), fuel cell (FCV), and conventional internal combustion engine (ICE) vehicles.

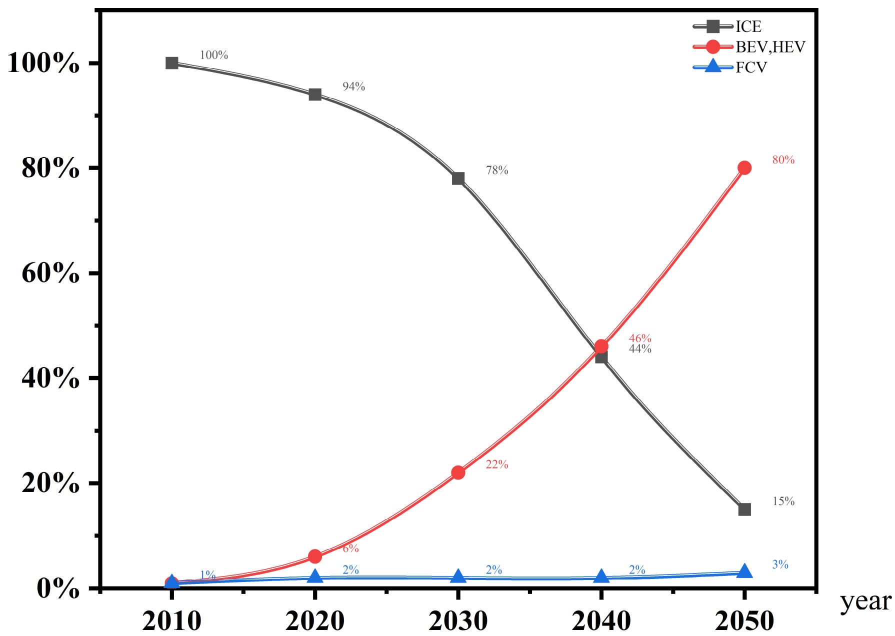

Figure 2. Global trends of EV, ICE, and FCV markets.

4.1. Electric Vehicle Powertrain Architecture

The powertrain of an electric vehicle comprises three main components: the power source, the power electronics system, and the motor drive system.

Many studies consider power cells and fuel cells as power sources for electric vehicle drive systems, including their additional hydrothermal and energy management systems [43]. The driving range of an electric vehicle depends primarily on the power cell's capacity, with greater capacity resulting in longer driving distances. In the EV battery industry, lithium-ion batteries (LIBs), nickel–manganese–cobalt (NMC) lithium oxide, and nickel–cobalt–aluminium (NCA) lithium oxide are the dominant technologies [44]. Inverters design and operation are directly impacted by EV batteries. The utilization of digital twin technology is being explored for monitoring the health, detecting faults, and predicting the lifespan of EV batteries.

Within the powertrain, the inverter and converter serve as the power electronic components. These components are comprised of three main subcomponents: the DC-DC converter, the inverter, and the motor control unit (MCU). The primary function of the DC-DC converter is to convert high-voltage DC from the power cell into low-voltage DC. The low-voltage DC is used to operate a variety of systems, including headlights, interior lighting, wiper and window motors, fans, and water pumps [45].

Electric vehicles use electric motors instead of engines, which make less noise and vibration and is smaller, providing extra space and making the vehicle design more efficient. Electric motors also convert kinetic energy into electrical energy, which is stored in batteries. Manufacturers of electric vehicles utilize a variety of motors, including permanent magnet synchronous motors, brushless DC motors, three-phase induction motors, permanent magnet-assisted synchronous resistance motors, and switched reluctance motors, each with unique strengths [42]. Figure 3 shows the powertrain components of a battery electric vehicle (BEV).

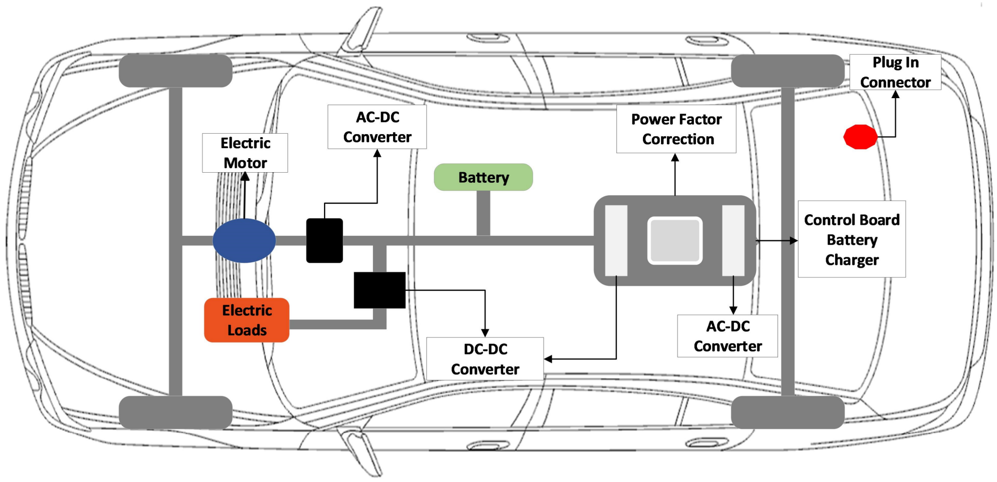

Figure 3. Battery Electric Vehicle Powertrain Components.

The plug-in hybrid electric vehicle falls between battery electric vehicles and traditional fuel vehicles, serving as a new energy vehicle option. It has the traditional vehicle engine, transmission system, etc., but also the battery, electric motor, control circuit and so on [46]. This hybrid electric vehicle greatly increases the driving range of the vehicle, and can also have the advantages of environmental protection and pollution-free pure electric vehicles. Figure 4 shows the powertrain composition of a plug-in hybrid electric vehicle. Dižo [47] introduced the composition and charging methods of BEVs and PHEVs, and listed the charging infrastructure of BEVs and PHEVs in a particular European region. The increasing number of charging stations being built and the growing utilization of electric vehicles indicate that the advancement of electric vehicles is essential and inevitable. In addition to traditional charging post charging, using solar charging shed charging is also an extremely environmentally friendly charging method. Małek [48] implemented a shed equipped with a photovoltaic system on the roof to generate power and provide shading. He utilized the Metalog probability distribution family to assess the power supply options for electric vehicles at the shed.

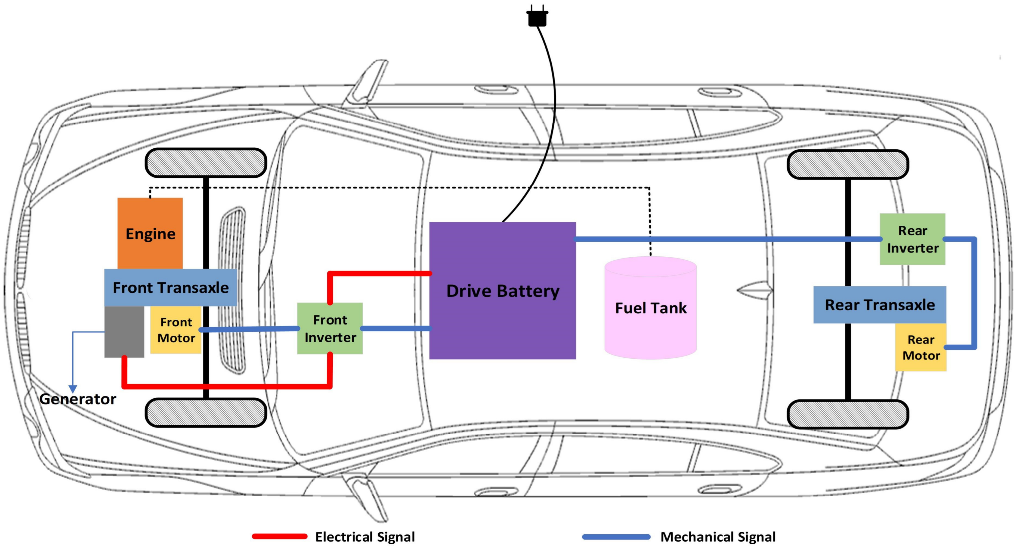

Figure 4. Plug-in hybrid electric vehicle powertrain components.

The fuel cell is an effective power generation device that transforms the chemical energy of fuel into electrical energy through an electrochemical reaction, and the vehicle equipped with electricity generated by the fuel cell device as a power source is called a fuel cell vehicle [49]. The fuel used by the fuel cell is high-purity hydrogen, which goes through a REDOX reaction with oxygen in the atmosphere to generate water and a small amount of nitrogen oxides, so the fuel cell is also known as a green new environmentally friendly car. Fuel cell vehicles offer numerous advantages over traditional internal combustion engine vehicles, including zero emissions, superior fuel efficiency, high combustion efficiency, and stable, and noise-free operation. Figure 5 shows the composition of the powertrain of a fuel cell vehicle.

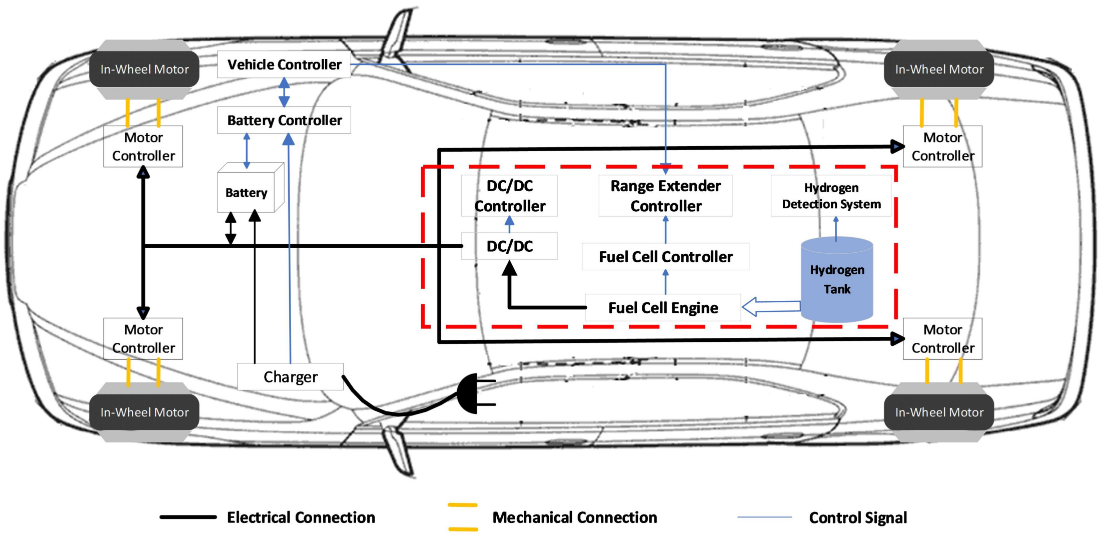

Figure 5. Fuel cell vehicle powertrain components (The red frame is the powertrain of the fuel cell vehicle).

BEVs, PHEVs and FCVs are three different types of electric vehicles, but they have all been developed to reduce reliance on conventional fuels and reduce tailpipe emissions.

While they differ in their power composition, all three types of vehicles require advanced battery technology to store and deliver electricity.

4.2. Digital Twins for EV Powertrains

Digital twins are frequently employed for electric vehicle powertrain applications to conduct system health monitoring, diagnosis, prediction, optimization, as well as scenario and risk assessment [32]. Digital twins can be developed for a range of assets, including the system level, subsystem level, individual component level, and various other levels within the electric vehicle powertrain [50].

Wunderlich and Santi [51] proposed a real-time digital twin modelling approach for power electronic converters at the subsystem level. This approach utilized a dynamic NARX-ANN (nonlinear autoregressive exogenous artificial neural network) to combine time-domain, switch-averaged, large-signal, real-time, and embedded models. Their physical model is based on a boost converter with a current source. The proposed digital twin model of the converter can be implemented on various platforms, including being executed locally on the converter's digital controller. These models are primarily utilized for detecting faults, making predictions, managing health, as well as assessing scenarios and risks.

In their work [52] Rjabtsikov et al. introduced a digital twin model designed for detecting faults in AC three-phase induction machines. This digital twin of the motor is specifically used to identify short circuit faults. The simulation is created using historical data and the motor's mathematical model. Integrated with ROS services, the motor employs Unity 3D for real-time condition monitoring. Furthermore, the virtual sensor in the digital twin model functions as a representation of the physical motor model.

In their study [53], Venkatesan and colleagues presented a digital twin system designed for monitoring and predicting the health of the EV-PMSM power system. This system focuses on monitoring variables such as housing temperature, winding temperature, bearing oil fill time, and flux deterioration to estimate the remaining useful life (RUL) of the permanent magnet (PM). Two different methods are suggested by the authors for the implementation of health monitoring. The first approach involves developing internal health monitoring and prognostics to assess the performance of internal motors. The second approach, known as remote monitoring, allows electric vehicle service providers to remotely monitor motor performance through cloud-based communication channels.

The application of digital twin technology in battery storage systems (BESS) is a crucial area of research that plays a significant role in promoting sustainable development and mitigating climate change. This technology not only helps in reducing CO_2 emissions but also facilitates the implementation of eco-friendly strategies for clean energy production. At the heart of a battery, the battery management system (BMS) is responsible for monitoring, protecting, and ensuring the reliability, safety, and efficiency of the battery. Numerous scientific studies have been conducted to explore the various important applications of digital twins in battery systems. In the year 2020, Wu and colleagues [54] utilized Python Battery Mathematical Modelling (PyBaMM) and MATLAB to present a combined model that incorporates a physics-based model along with a data-driven approach. The aim is to address the increasing availability of substantial data resulting from the widespread deployment of low-cost sensing and IoT devices in numerous applications. These applications are focused on developing cyber-physical systems by combining remote sensing of operational physical devices with cloud-based models. These models are responsible for monitoring and optimizing devices within a networked system, thereby generating a virtual representation of the physical system. This concept is further illustrated in Figure 6. The potential of this approach is based on the close interaction between a physical object, its digital counterparts, and a collection of proxy data operating under diverse conditions. Although the data collected by these agents alone may not be sufficient to provide statistical significance for a data-driven RUL model, when aggregated, the underlying ML (machine learning) model can be enhanced and then integrated with a closed-loop optimizer to continually update vehicle control. Battery electric vehicles (BEVs) already have a Battery Management System (BMS) capable of recording sensor data and performing onboard processing. Within the digital twin framework, researchers have also been investigating the utilization of low-order models and a degree of offline processing to fully leverage the robust pseudo-2D (P2D) framework [55]. Typically, BMS data are saved on local systems, but there is a growing trend among researchers to suggest cloud-based systems as a way to reduce on-site computing needs. This approach also allows for the consolidation of extensive datasets to enhance the effectiveness of machine learning algorithms [56]. Furthermore, the researchers suggest implementing a holistic approach that monitors essential information throughout the entire process, starting from material synthesis and continuing through to vehicle utilization. For example, Yang et al. [57] introduced the CHAIN framework, which establishes a network hierarchy and interactive system for the management of battery systems. They proposed that critical physical and electrochemical parameters of the battery should be transmitted to a cloud server during the manufacturing stage, enabling closed-loop optimization and facilitating comprehensive life cycle management. The CHAIN framework is designed to dissect complex systems into interconnected layers, each with distinct functions.

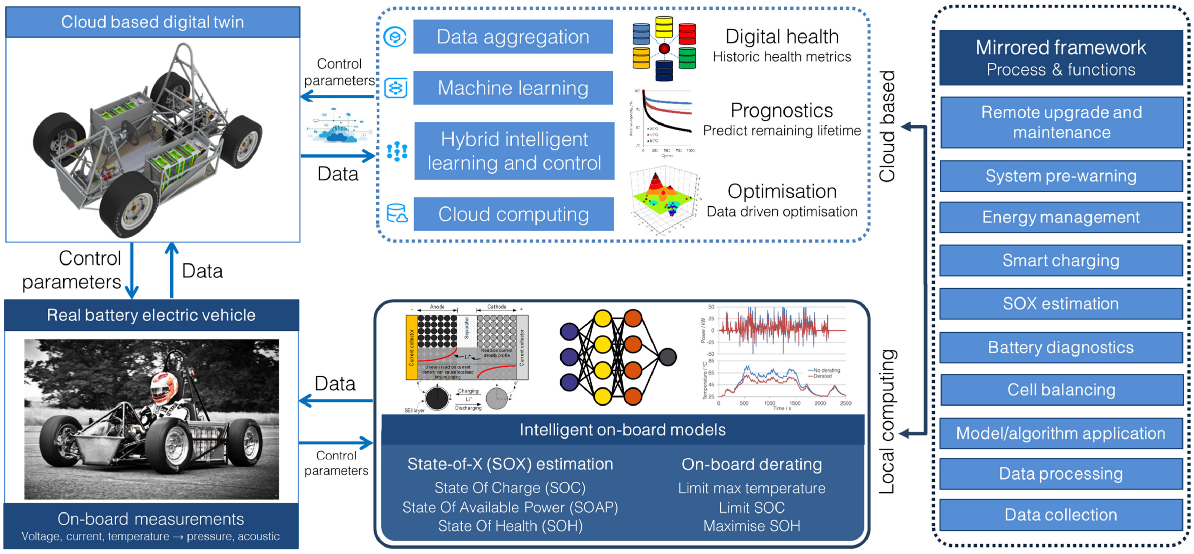

Figure 6. Cyber-physical elements of a battery digital twin. Reprinted from Ref. [54].

Over time, the approach to battery control and lifetime estimation has transitioned from predominantly empirical methods to a greater emphasis on model-driven techniques. As computational processing power continues to grow, there is a resurgence in the use of data-driven and machine learning (ML) methods. However, their practical applicability in real-world scenarios remains a challenge. Figure 7 highlights this evolution and hints at a proposed hybrid model/data approach that leverages real-time data collection from IoT systems to enable battery digital twinning.

Special DT platforms have also been implemented to evaluate performance degradation of lithium-ion batteries. Peng et al. [58] developed a low-cost digital twin based on LabView 2018 using an equivalent circuit model (ECM) to achieve battery pack degradation assessment for lithium-ion battery packs. One of their major contributions was the development of a digital twin platform for testing different battery types and load algorithms to estimate state of charge (SOC). The findings demonstrate that their platform presents a precise novel approach for monitoring real-time battery degradation. However, further enhancements are required for compatibility with various algorithms and the integration of additional features like virtual reality and augmented reality.

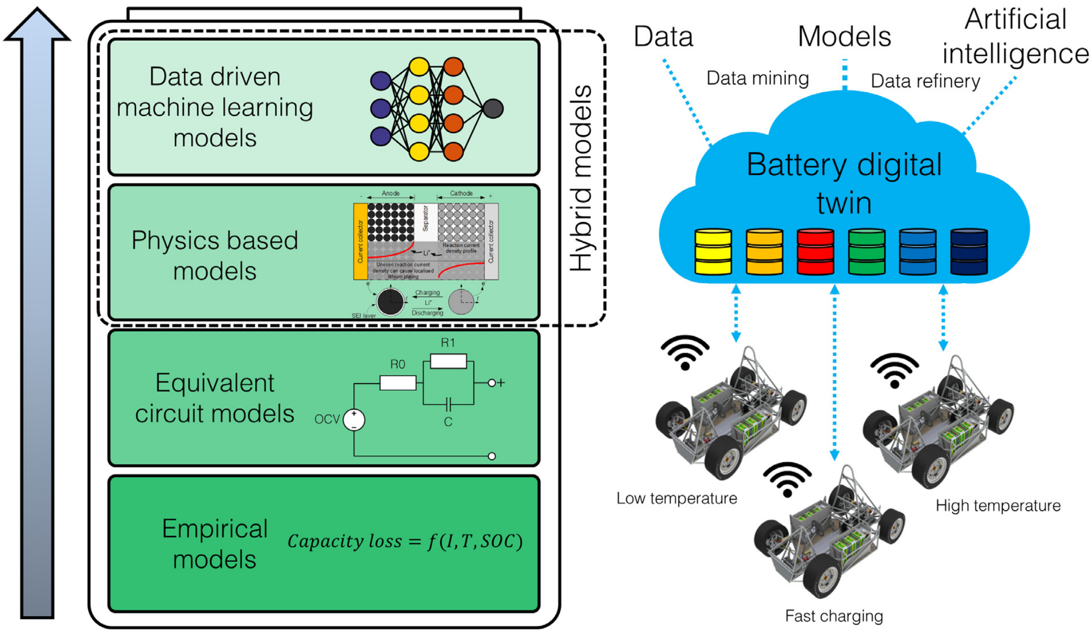

Figure 7. Evolution of approaches for battery modelling and the potential eco-system for battery digital twin data aggregation. Reprinted from Ref. [54].

Wang et al. [59] conducted a study in which they gathered field data from 60 electric vehicles that had been in operation for over four years. They have created a strong statistical method using data analysis to forecast the ageing of lithium-ion batteries. Their proposed method includes data preprocessing, which involves integrating data cleaning, transformation, and reconstruction. The researchers used multilevel screening techniques to extract statistical characteristics from past usage behaviour. Furthermore, they employed machine learning to forecast ageing trajectories accurately and identify batteries with the lowest lifespan, all while quantifying prediction uncertainties. Figure 8 shows the framework of this model.

The use of proton exchange membrane fuel cell (PEMFC) in automotive powertrain systems is well-known for its environmental friendliness, as well as its high efficiency and significant commercial prospects [60,61]. Just like lithium-ion batteries, proton exchange membrane fuel cells also face challenging concerns regarding their cost, performance, and longevity [62]. The issue could potentially be reversed by the rapid emergence of digital twins. Creating a digital twin model for PEMFC holds great importance in the realm of battery design and operational control [63]. Nevertheless, the establishment of a digital twin model for PEMFC still faces several challenges. One major obstacle lies in the complexity of obtaining the necessary data, which poses a significant challenge in the development of digital twins [64]. The performance of a PEMFC, a system with multiple physical fields, is influenced by various parameters including gas reactant concentration, water content, and temperature. However, accurately measuring the spatial distribution of these parameters is challenging, especially in real-time on a PEMFC vehicle, due to limitations of field methods [65]. Figure 9 shows the structure of a proton exchange membrane fuel cell.

An innovative and clever method, known as the data-driven proxy model, can be employed to create digital replicas of PEMFCs. By integrating physical system modelling with common machine learning methods, this approach offers a promising solution to the challenges mentioned above [66]. The agent model framework, proposed by Wang et al. [67] integrates the precision of PEMFC and physical models with the efficiency of data-driven models to establish a digital twin model of PEMFC. The utilization of advanced 3D modelling has significantly advanced PEMFC technology, allowing for the simulation of various scenarios for PEMFC stacks, including complex flow field designs for vehicles. The simulation results of PEMFC model are in good agreement with the experimental results. However, this process requires a lot of time and computing costs, which seriously limits its application in PEMFC. Wang et al. [67] obtained the simulation result of PEMFC through the simulation of PEMFC. By utilizing the generated data as a dataset, the state-of-the-art and validated PEMFC 3D multi-physics model was simulated under 100 randomly varying working conditions. Subsequently, the dataset was randomly split into training and test sets, and machine learning algorithms were employed to create the model. Concurrently, the numerical model predicted the parameter distribution of PEMFC. This approach to developing digital twins has proven highly successful, leading to significant reductions in computational costs and time. Figure 10 simulates the principle of PEMFC.

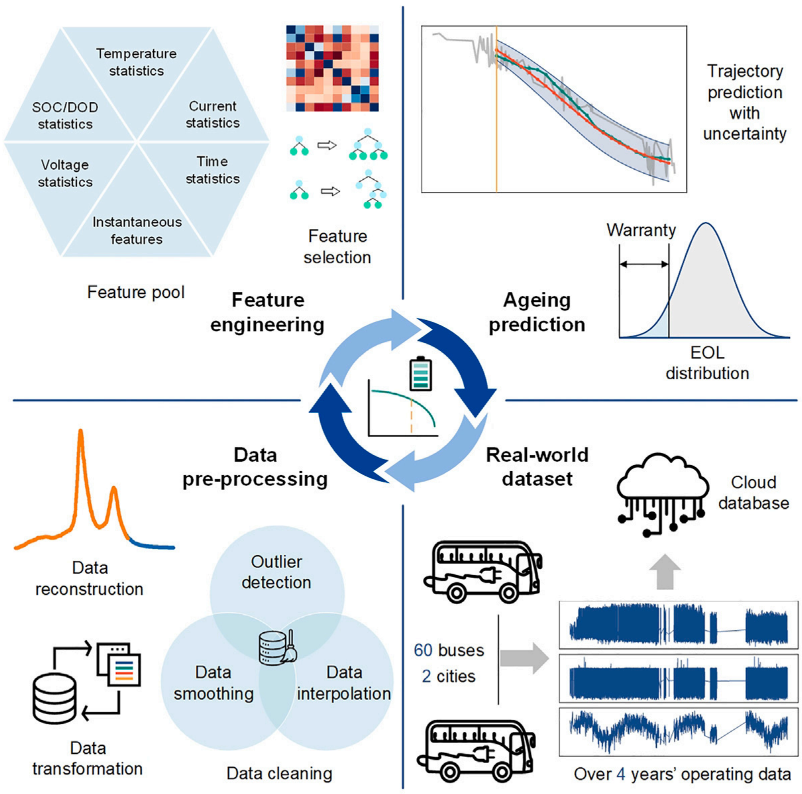

Figure 8. Large-scale field data battery ageing prediction mode. Reprinted from Ref. [59].

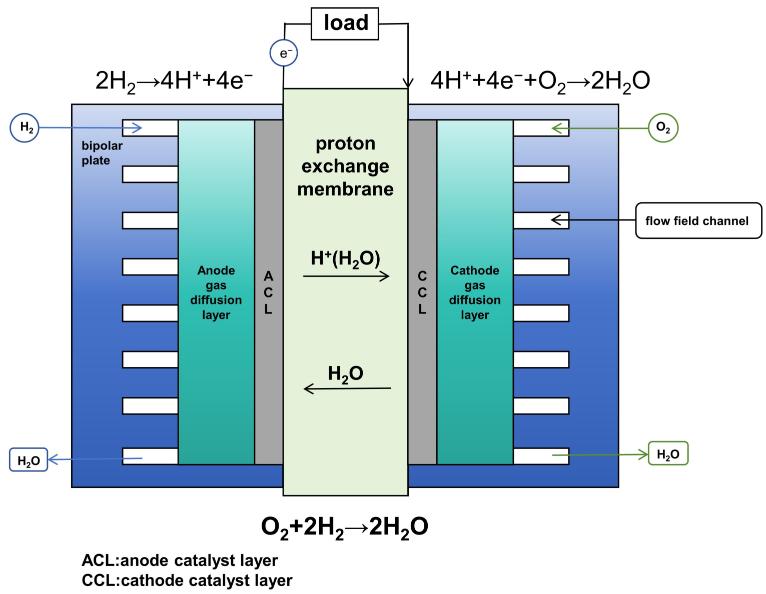

Figure 9. Schematic diagram of proton exchange membrane fuel cell.

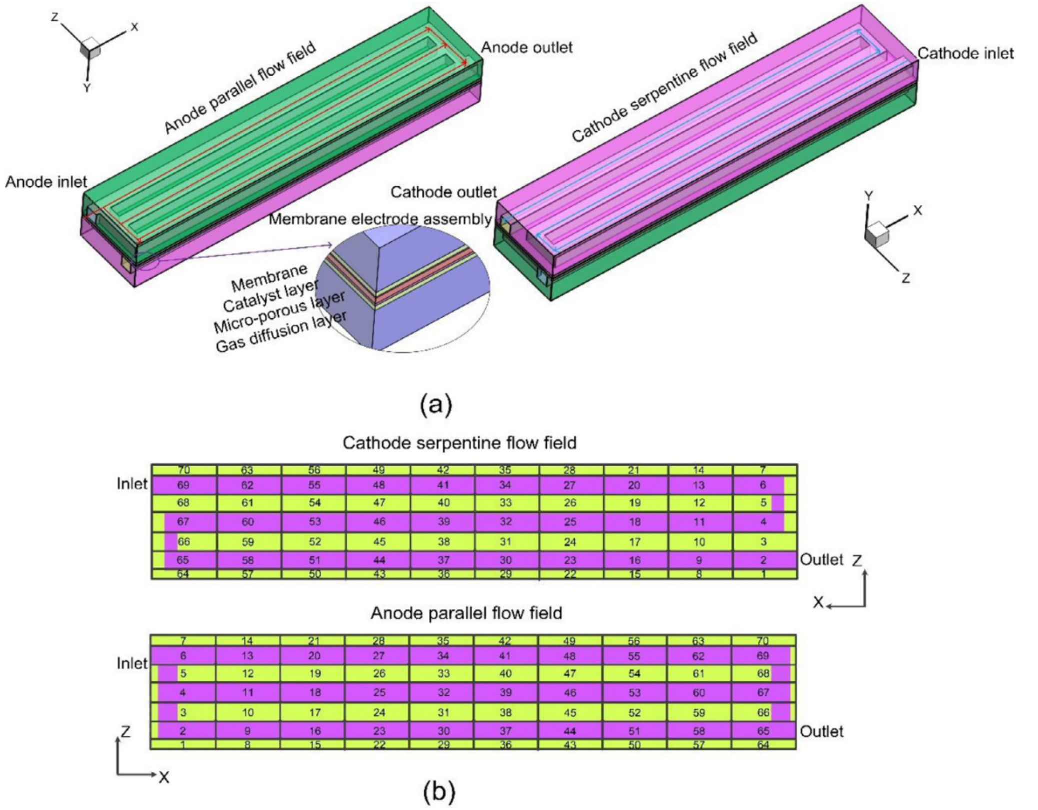

Figure 10. (**a**) Schematic diagram simulating PEMFC. (**b**) Schematic diagram of the cathode serpentine flow field and the anode parallel flow field, as well as node division for generating multi-physical field data. Reprinted from Ref. [67]. Purple shows the serpentine flow field of the cathode and the parallel flow field of the anode, respectively.

Utilizing high-precision physical models in simulations can compensate for data limitations. Conversely, when data are more abundant, digital twins can be created directly through machine learning techniques. In the context of fuel cells, an experimental-based digital twin model can be constructed to forecast and identify issues with battery performance [68]. Safa et al. [69] introduced a digital twin approach for studying PEMFC degradation, demonstrating that accurate prediction of Remaining Useful Life (RUL) is possible even when using a limited amount of measurement data. The digital twin model is established by utilizing a stacked denoising autoencoder (SDA) to model stack voltage, which is a readily measurable parameter. The operational results indicate an error within an acceptable range, thus enabling effective and accurate analysis of PEMFC RUL. Unlike static models, the digital twin is adaptable and can self-update based on new measurement data. Following data preprocessing, the measured superimposed voltage is employed to train the SDA model, and the pre-processed SDA model is used to analyse the RUL of PEMFC. Online acquired data are utilized for model updating, thus making the digital twin more closely aligned with real PEMFC and enhancing the accuracy of decisions.

The applications of digital twin technology in electric vehicle powertrains are extensive, encompassing the design of all aspects of the system, including the system level, subsystem level, and individual component level. This technology can be utilized throughout the entire spectrum of the powertrain system.

5. The Challenge of Digital Twins

Although digital twins have many advantages, such as improving decision-making efficiency, optimizing processes, product innovation, reducing risks, and intelligent management. But the development of the system is equally challenging due to its rich prerequisites in engineering, marketing, technology, and data [70]. Here are some of the challenges of digital twin technology.

5.1. Accurate Model Building

It is easy to build accurate models for simple objects. However, in many cases, the structure, process flow and operating environment of the processing equipment can be very complex, which presents a modelling challenge [71]. The model construction of digital twins depends on complete and accurate data input. However, in practical applications, the data may be incomplete due to various reason, which will make model construction difficult. In addition, in a digital twin system, it is often necessary to integrate data from multiple sources. These data may come from different sensors, systems, or human input, so their accuracy needs to be verified to ensure the reliability of the model construction. On the other hand, in order to make the digital twin model accurately predict and simulate the dynamic changes in the real world, it is necessary to fine-tune the model parameters. This process can be very complex, especially for highly nonlinear and complex systems.

5.2. Data

All tasks related to data, such as collecting, transmitting, storing, and processing it, pose significant challenges. While there are diverse methods for data acquisition, challenges are often encountered in the actual collection process. These challenges may include the lack of open data acquisition interfaces in some devices, the inability to install sensors, and high functional requirements for sensors in complex conditions. As data continue to exponentially grow, the speed of data transmission is also increasing. However, this rapid transmission brings with it the risk of data leakage and tampering. Thus, enhancing data security has become a crucial challenge in today's context. The increasing volume of data has intensified the strain on data storage systems. Conventional hardware-based storage methods are encountering limitations. Consequently, software-defined storage, which involves the control of storage resources through software, and innovative optical storage are emerging as potential alternatives for data storage [72]. Efficient and sophisticated algorithms are crucial for data processing. It is important to enhance the interpretability, resilience, and equity of the algorithms.

5.3. Privacy and Security

Protecting the privacy and security of digital twins presents a significant challenge. The complexity of building models and processing data in digital twins makes digital assets a crucial element of the technology's value. This is particularly evident in the case of smart cars, where the integration of the Internet of Things has introduced numerous issues related to data and system security. Given the close connection between smart cars and human users, data security risks can have severe consequences. Without effective resolutions to these security challenges, effective collaboration across industrial chains becomes difficult.

5.4. Sensors

Sensors are crucial elements in linking the real world to the virtual realm. The data collected by sensors form the foundation for creating digital twins, and any inaccuracies or omissions in the data will impact the accuracy of the digital twin. Furthermore, the real-time changes in the state and behaviour of the physical entity being monitored may necessitate the use of various types of sensors, such as those for temperature, humidity, pressure, and light, among others. Different sensors can produce inconsistent data, which also poses challenges for data integration and processing. Finally, the cost and power consumption of sensors directly affect the sustainability and affordability of digital twin systems, and how to achieve low-cost, high-efficiency sensor applications is also one of the challenges that needs to be addressed today.

5.5. Agile Development

Iterative and incremental, agile development is an approach to software development that involves multiple stages. This method aims to deliver high-quality software by breaking the project into smaller, manageable segments [73]. Digital twin prototypes can be built quickly through agile development methods. The iterative approach to development can also be utilized in creating digital twins, where the system's functionality and performance are enhanced through continuous refinement. A well-crafted digital twin empowers users not only to contribute input and feedback for agile development but also to take the lead in decision-making processes [74]. Agile development includes a variety of methods, such as Scrum, Kanban, Extreme Programming (XP), and Dynamic Systems Development Methods (DSDM). Table 3 lists the differences between these development methods and the possible ways in which digital twins can be combined with them. The automotive industry has been challenged by dynamic market growth, shorter product lifecycles and increased customer individualization. Agile development is a promising solution to the current challenges [75]. Whilst the agile development methodology is an effective guide to the digital twin development process, many people in many development teams will be designed in large scale agile development. How to address the lack of consistency between teams and customer collaboration among the many stakeholders in a team becomes a challenge that needs to be solved nowadays [76].

Table 3. Possible applications of digital twin technology in different agile development methods.

Ref.	Methods	Features	Applications of Digital Twins
[74]	Scrum	Iterative, teamwork, self-organization and rapid response.	Create a virtual Scrum board to track the status of tasks in real time.
[77]	Kanban	Visualization, limiting WIP (work in progress) quantities, process transparency, continuous improvement.	Create a virtual Kanban board for visual management of work tasks.
[78]	XP	Test-driven development, continuous integration, small-scale feedback and simple design.	Real-time code integration and rapid delivery through automated build, automated test and continuous integration tools.
[79]	DSDM	Iterative and incremental, accelerate software delivery and reduce risk	Modelling the behaviour, interaction and performance of software systems.

6. The Future of The Electric Vehicles Digital Twin

In the future, digital twins may have a broader role, extending beyond automotive technology innovation to become a tool for promoting smart electric vehicle sales. Through interactive VR or AR technology, digital twin simulations of smart cars could be visualized to engage potential users with customized utilities and virtual driving experiences. Once the initial architecture is set up, the digital twin framework can be customized for any model and optimized for future development. It has the ability to simulate hundreds of EV models within seconds. Additionally, digital twin technology can streamline research and testing for self-driving cars and other forms of autonomous mobility, acting as a catalyst for the mainstream realization of self-driving car technology [80]. Real-time monitoring and fault diagnosis are key aspects of digital twin technology. This enables electric vehicles to be continuously monitored and potential issues to be identified and flagged, ultimately enhancing vehicle safety and reliability. The advancement of digital twin technology may also lead to the creation of innovative business models, such as pay-as-you-go energy services and personalized vehicle customization, which can bring about new business opportunities and drive innovation. Achieving the longevity of digital twin technology requires collaborative efforts from all stakeholders. These potential opportunities are summarized in Table 4.

Table 4. Future opportunities for digital twins in electric vehicles.

Opportunity	Implementation Method
Vehicle sales tool	Visualization of the digital twin model for electric vehicles and virtual driving experience.
Customized vehicle	Utilize the advanced digital twin platform to customize the vehicle according to user preferences.
Automatic drive	Optimize the development and testing of autonomous driving algorithms and driving tools.
Improve security and reliability	Real-time Monitoring and fault diagnosis continuously monitor the vehicle to determine risks.

7. Conclusions

The comprehensive overview in this article examines the digital twin technology in detail, which is already widely utilized in various industries such as aerospace, healthcare, buildings, smart cities, and automotive. Digital twins have the capability to process extensive and diverse datasets, enabling their application in creating models for components, assets, or entire drive systems. Depending on the foundational model and the nature of data exchanged with the physical counterpart, digital twins can serve multiple purposes including predictive maintenance, fault detection, health monitoring, and lifetime prediction [50].

While digital twins have been widely used in the traditional automotive industry, there are still areas within the field that have not been fully explored. Research in traditional automotive applications has predominantly focused on the design and production of vehicle bodies and electronic systems. Furthermore, enhancing simulation methods is essential for improving real-time performance and accuracy.

Challenges related to data present a significant obstacle in the advancement of digital twins. Future efforts are expected to concentrate on the development of a comprehensive digital twin for vehicles, incorporating enhanced sensor and subsystem support. The automotive industry is in dire need of digital twins to propel its progress. Therefore, innovative research is essential to address these challenges and refine digital twin technology for wider application across various aspects of vehicle design and development.

The advancement of relevant technologies will provide more systematic solutions for the development of digital twins, expanding their application in the automotive industry, particularly in transportation and battery technology. The increased utilization of digital twin technology in the automotive sector is poised to lower vehicle costs, enhance longevity, optimize traffic flow, and promote environmental sustainability. Research on digital twins for automotive powertrains is still in its nascent stages, requiring significant time and resources for further exploration and development.

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