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Application of Digital Twin in Smart Battery Electric Vehicle: Industry 4.0

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Abstract—It is believed that using electric vehicles (EVs) for transportation is essential for addressing environmental and sustainable development challenges. Current ecofriendly concerns, such as the fast depletion of fossil fuels, rising air pollution, rising energy demand, global warming, and climate change, have made it possible to electrify the transportation industry. EVs can address all of the aforementioned issues. For electric vehicles (EVs), and particularly those powered by lithium-ion (Li-ion) batteries, portable power supplies have become indispensable. Although Li-ion batteries have been the focus of EV research for a long time, issues like battery aging and safety have yet to be fully understood. According to our current understanding of smart technology, we have the ability to use the digital twin (DT) to overcome a problem that has been holding back battery development, as well as the preliminary DT applications in complicated systems such as industry 4.0. This research focuses on the characteristics of batteries and how they relate to their modeling, state estimation, remaining usable life prediction, safety, and control. We put together an analysis of some of the most current achievements in battery prognostics and health monitoring. Finally, we provide prospects for the development of DTs in the field of EV batteries.

Index Terms—Electric vehicles, li-ion battery, digital twin technology, health monitoring, industry 4.0

I. Introduction

Automobiles are one of the primary sources of emissions of carbon dioxide and other chemicals that contribute to global warming. A major first step toward achieving carbon peaking and carbon neutralization [1] is to encourage the usage of electric vehicles (EVs). It could also help the energy revolution and the energy transformation move forward. EV use will continue to rise exponentially in the future, putting greater pressure on the existing grid's power supply capacity as new charging stations are built on a huge scale [2]. In the creation and administration of new energy vehicles, batteries are the most important technology [3]. High energy density, an extended life cycle, and low self-discharge rates make lithium-ion batteries an attractive option [4]. There are a large number of complex micro-electrochemical reactions in the battery, which are seriously harmful to the long-term stable operation of the battery. The external sensors of the battery, such as current, voltage, and temperature, are weak and have hysteresis. Often, the battery management system (BMS) cannot detect abnormal signals until the internals of the battery have caused combustion and explosion due to violent reactions [5] [6]. Smart batteries with multiple intelligent sensors can monitor various signals such as battery internal temperature, electrode potential, pressure, and gas, so that charge state estimation and active control can be carried out more accurately. It is the development direction of the next generation of batteries [7]. There is still a lack of systematic research on the processing and analysis of sensor signals and their role in BMS. In addition, at present, most sensors are still parasitic outside the battery. On the one hand, the implantation technology is immature; on the other hand, the battery's hidden dangers caused by implantation are difficult to eliminate. At present, regulating the pore structure of the electrode is one of the main methods to improve the mass transfer efficiency of lithium battery electrodes [8] [9]. However, it is still a challenge to determine the practical role of electrode optimization in the process of battery charging and discharging. The mainstream research method is still to analyze the changes of internal parameters in the process of battery discharge through battery performance tests and numerical simulation. Li et al. made a model of a lithium-air battery with an ultra-thin electrode and studied how oxygen moves through it, how fast reactions happen, and how products are left behind [10]. Wang et al. built an electrode pore model through SEM and analyzed the effect of electrode saturation on battery performance [11]. Pan et al. summarized an optimization method for the porous electrode of a lithium battery through the analysis of pore size distribution, porosity, specific surface area, and other parameters of the electrode [12]. Li et al. proposed a linear gradient pore structure and proved that this structure can improve the performance of organic lithium batteries [13]. The traditional continuous pore lithium battery model can indeed describe the trend of various parameters when the battery works in principle. However, it is necessary to further clarify the mass transfer process in porous media and introduce the discrete pore structure into the model analysis. With the progress of technology, digital twin (DT) can be used to deal with more complicated systems and create a DT framework for battery systems in particular [14]. Joonam et al. used a DT model to reveal parameters such as dead particles and three-dimensional charge distribution of contact specific surface area in solid-state batteries, which are difficult to achieve by experiments and traditional simulation [15]. Ngandjong et al. used the DT method to build the electrode model of the lithium-ion battery, providing an optimization method for the production process of li-ion batteries [16]. Wang et al. built a fuel cell model based on a DT model, showing the development potential of numerical twinning technology in the field of fuel cells [17]. However, in the 3D simulation analysis, the influence of some complex factors on numerical calculation needs to be ignored to ensure the operational feasibility and efficiency of the model. Therefore, the model assumptions are set as follows:

- The main product of the model is lithium peroxide, and the by-products lithium oxide and lithium carbonate are not considered in the model.
- There is an adequate supply of reactants in the reaction process.
- The influence of temperature change caused by battery reaction is not considered.
- The mass transfer in the model is only carried out by diffusion, without considering the convection effect.

II. INDUSTRY 4.0 AND DT

The concept "Industry 4.0" refers to the following characteristic pillars that are applied in smart batteries manufacturing industries for electric automobiles that are in their fourth generation. A description of how the elements of Industry 4.0 can be used in automation, as shown in Table I.

The automobile industry 4.0, manufacturing an EV that gets its power from an independent system that changes fuel into electricity. This system could consist of a battery, solar panels, fuel cells, or an electric generator, among other things. The layout of a battery-powered EV is shown in Figure 1. In this section, the application and key technologies of DT in the battery EV manufacturing industry 4.0 will be discussed.

TABLE I. SMART APPLICATION OF INDUSTRY 4.0 IN AUTONOMY

Applications	Literature	Details
Transport	[18] 2019	Connectivity between items is facilitated by the Industrial Internet of Things (IIoT).
Monitoring	[19] 2016	The use of DTs and SMA materials facilitates simple maintenance.
Scheduling	[20] 2019	IIoT assists in the scheduling of all essential parts during the assembly line process.
Big data	[21] 2017	When there are so many things to choose from, big data will keep building up and needs a proper assortment of products.
Process control	[22] 2016	IIoT plays a critical role here, since it tracks and monitors the current processes and uses big data and analytics to do so.
Layout	[23] 2018	Design software contributes to the expansion of the layout necessary for a certain industry.
Manufacturing	[24] 2019	Each industrial process requires a unique set of robots that can handle it.

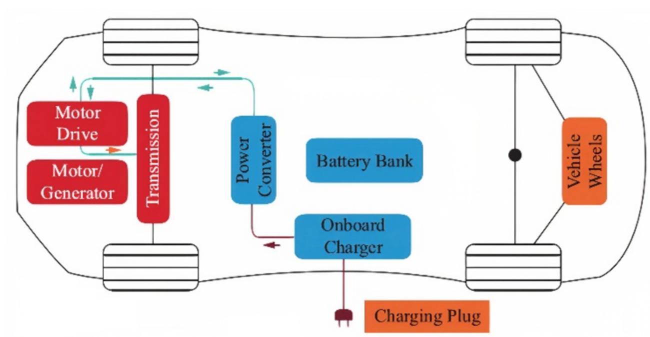

Fig. 1. A model of a battery-powered electric vehicle (BEV)

A. DT technology

It makes full use of physical models and sensors to collect information and operational data; integrates multi-disciplinary, multi-physical quantities, and multi-scale simulation processes; completes the mapping of the whole life cycle process of solid lithium-ion batteries in the virtual space [26]; and constructs a high-precision digital simulation model for vehicle BMS, also known as the virtual battery model [27]. According to the historical data of the cloud, building a battery twin model based on the powerful computing power and storage space of the platform can greatly improve the accuracy of state estimation, the ability of safety early warning and the efficiency of active safety protection mechanisms. Compared to traditional BMS technology, it can reduce the number of experiments needed in the early stages of development and shorten the time it takes to develop something [28].

B. Big Data

sensor, model, and virtual-to-real fusion data are only a few of the many types of information that can be incorporated into twin data [29]. Big data can help explain and estimate the outcomes and processes of real-world events by assembling important information from the huge amounts of data generated by the DT. According to the DT model, large data sets have a consistent data type. The DT can be seen as a bridge between the digital world and the physical world in several ways. Wang et al. introduced the DT technology and cloud-side-end collaboration for BMS. They also introduced the DT model and important technologies like state estimation, big data, and cloud-assisted battery adjustment [30]. The proposed model can help manage the battery, and big data can be used to plan the upgrade path of the battery.

C. Augmented Reality (AR)

Augmented reality connects the virtual world with the natural world. This technology hasn't been used in factories yet, but it will soon have a big effect on the automobile industry.

D. Machine learning

It is one of the most important algorithms in the field of batteries [31], which is one of the many fields that can benefit from AI's wide applications. The DT is able to accomplish functions such as simulation, diagnosis, prediction, and optimization control by utilizing its high-fidelity virtual model, enormous twin data, and real-time two-way dynamic interaction. DT is able to make data far more usable with the assistance of AI, as well as enhance the speed and accuracy of various processes.

E. Additive manufacturing and 3D printing

With the advent of the additive (layer-by-layer) manufacture of goods with varying shapes, sizes, and materials, the industry has changed quite a bit. Additive manufacturing is also known as "additive" manufacturing. The advent of 3D printing has made it possible to manufacture a wide variety of items on a variety of scales, including commercial, industrial, and even personal. This includes making everything from small items to huge printing houses and even rockets [32] [33].

F. Cybersecurity

This is an important foundational component of the fourth industrial revolution (Industry 4.0). Cybersecurity keeps networks, servers, devices, and data from being used in the wrong way or by people who shouldn't. This is important because everything in the 21st century is accessed and used through digital systems.

G. IoT

Internet of Things: devices and services that gather, process, analyze, and transport digital data from the physical world to the virtual world operate as "ladders." Twin data frequently have the properties of big data, and battery DT uses these data to predict the future state of the battery using machine learning technology in situations where the physical mechanism and the input data are both inadequate. Saad et al. addressed modeling the deployment of energy-efficient cyber-physical systems (ECPSs) for diverse applications. The results of the experiments show that IoT and cloud computing can be used to make the DT for the ECPS work in real time [34].

H. Cloud

At the present time, academics are focusing their efforts on the investigation of cloud-based business management systems (BMS), and they feel that cloud-based BMS is an unavoidable trend of future development [35]. The use of the cloud computing platform will be required by DT because of the extensive amount of data and the intricate nature of the algorithm.

I. Blockchain

Each data block in the blockchain contains a string of data that may be used to verify whether or not the transaction information is valid. The integration and analysis of data is at the heart of DT. However, certain aspects of data management can be fraught with danger, including the loss of data or its unauthorized modification. The primary benefits of combining distributed ledger technology (DT) and blockchain technology are evident in the fact that the combination protects data from being altered while it is being stored or transmitted and makes it possible for DTs to communicate with one another.

III. METHODOLOGY

High-precision digital simulation model for vehicle BMS as shown in Figure 2, also known as the virtual battery model, which is the result of DT technology's use of physical models and sensors to collect information and operational data; integration of multi-disciplinary, multi-physical quantities, and multi-scale simulation processes; and completion of the mapping of the entire life cycle process of solid lithium-ion batteries in the virtual space. When the organic electrolyte lithium battery works, the lithium metal of the cathode loses electrons to form Li+, which is transferred to the electrolyte through the diaphragm and forms lithium peroxide with the oxygen that obtains electrons. Because lithium peroxide is a decomposable product, the stable cycle of a lithium battery is realized. The chemical equation in the reaction process is as follows;

$$Li = Li^{+}e^{-} \tag{1}$$

$$2Li^{+} + O_2 + 2e^{-} = Li_2O_2 \tag{2}$$

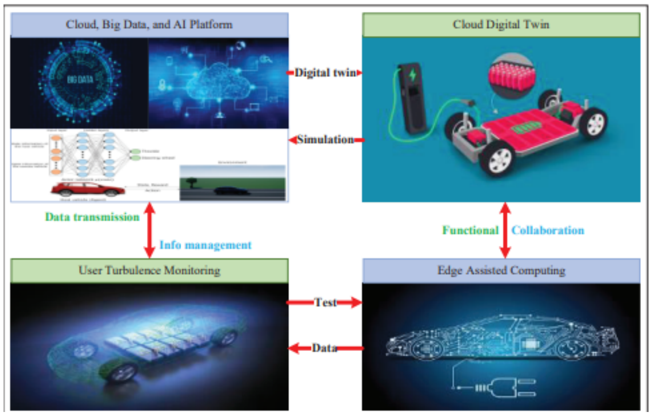

Fig. 2. Digital simulation model for vehicle BMS

It is possible to recreate the changes that occur in the electrode during the discharge process by building a model of a lithium battery based on the actual pore structure and simulating the process. The model uses Unity3D software to build the numerical twin structure of the electrode, imports the numerical twin model into COMSOL software to build the transient discharge model of a three-dimensional lithium battery, and then uses COMSOL software to output the model results after it has been calculated. This information is made available to users in real time by the BMS, which measures the capacity of the battery, the degradation of the battery as it is being charged or discharged, and the optimal performance of the battery [36]. Condition-Based Maintenance (CBM) of the batteries can now be carried out thanks to battery health monitoring, which eliminates the need to rely on fault-based or time-based maintenance. The BMS verifies that the subsystem is operating in its normal state and that there has been no unexpected breakdown. DTs give automobile producers with an expanded capacity to identify abnormal states and estimate the remaining usable life of a vehicle's ablative components within the context of this paradigm. This is accomplished without the requirement for any form of field testing. This leads to an increase not only in the level of happiness experienced by the owner, but also in the level of safety experienced by the user [14]. Figure 3 demonstrates how incorporating DT technology into the management of a vehicle's overall health can make the process more efficient overall.

IV. DIGITAL TWIN OF BATTERY ELECTRIC VEHICLE

Battery management systems and smart charging architectures are directly related to one another and both contribute to the overall efficiency of smart EV systems. The model uses Unity3D software to build the numerical twin structure of the BMS, imports the numerical twin model into COMSOL software to build the transient discharge model of a 3D li-lion battery, and then uses COMSOL software to output the model results after it has been calculated. Electronic Control Units, also known as ECUs, along with EV power trains, are the fundamental components of this smart technology. As a consequence of this, the optimization of these components through the application of DT technology plays a major role in the creation of an efficient charging architecture and is a significant area of academic research. A DT-based electrical and mechanical co-simulation (virtual automobile) is realized in the cited literature [37], which also depicts the behavior of the automobile while it is charging. The development of an EV automated charging system was made possible by the development tool for virtual vehicles, in which simulation-based verification was used to make adjustments to the algorithm even before the real system was deployed. A microprocessor electronic control unit (ECU) with intelligent data acquisition is used to get the battery state of health (SoH) and battery state of charge (SoC) through the collaboration of conventional monitoring parameters (CMPs) and a new-age battery monitoring model. Additionally, virtual ECU, hardware-in-the-loop, and virtual microprocessor are used to train the battery electrochemical model for the 3D rendering engine in order to get the unified interconnection among DT model and BMS of EVs, as shown in Figure 4.

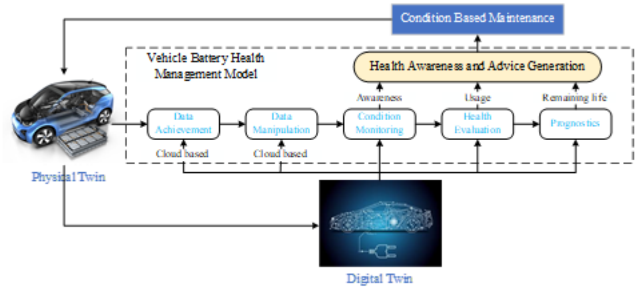

Fig. 3. Integrated vehicle battery health management model with DT technology

The figure shows how the combination of DT technology and BMS can help the battery EV industry 4.0 and allow consumers to know the health and charging status of their vehicles before any danger. Because of the high load requirements, charging EVs can frequently have a negative impact on the public grid. In order to create a realistic model of a smart grid, the authors in [38] use a genetic algorithm to optimize a distribution tree (DT) of electric vehicle (EV) charging infrastructure. This is done in order to lessen the impact of the effect that was discussed earlier. This topic is investigated by Park et al. [39], who do so by developing a DT-driven model for an all-solid-state battery that makes use of voxel-microstructures. This article outlines the exceptional procedures and applications of DT technology for BMS and smart charging systems. These are helpful for the

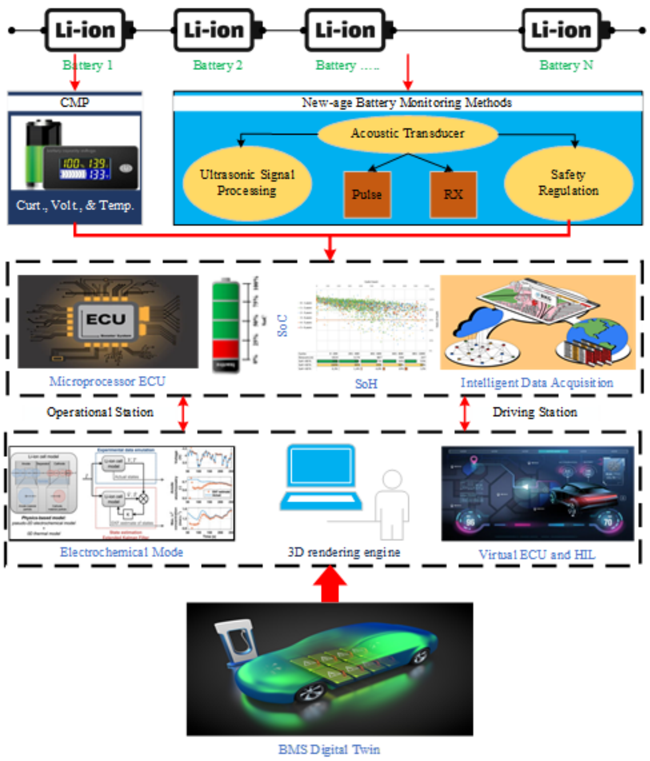

Fig. 4. Fusion of DT technology with BMS

manufacturing industry 4.0. From refueling to charging, the energy supply mode of vehicles has undergone great changes, and vehicles can also become mobile energy storage stations. These are technical problems that need to be solved urgently.

A. Fast charging and fast changing

The safety of lithium-ion battery fast charging is insufficient, the heat generation problem in the fast-charging process is serious, the design of the thermal management system is difficult, and the infrastructure construction and operation costs are too high [40]. However, it is the biggest difficulty to realize the compatible exchange of multi-station and multi-vehicle types through power exchange supply.

B. Station interaction

Charging and changing facilities, roof photovoltaics, building energy, etc. form an energy supply microgrid. In-depth research is needed to optimize the energy scheduling between the superior power grid, renewable energy power generation, EV charging, and changing loads; promote the consumption of renewable energy within the microgrid; and reduce the impact on the power grid.

C. Vehicle network coordination

At present, the real-time performance of large-scale EV scheduling technology needs to be verified, the cost of infrastructure transformation is high, and there is a lack of an effective market mechanism and business model.

V. CONCLUSION

Vehicle electrification is a positive trend of vehicles in all even the world. EVs will be the primary means of transportation in the future. The power battery system is the key core component that needs to be promoted from multiple levels. The fastest growing areas, such as AI, big data, cloud computing, IoT, and blockchain, are essential in the advancement of DT and the battery research process. This article contains a detailed DT model for EVs and lithium-ion battery systems, as well as some future works that are discussed in detail: In terms of intelligent battery and active control, considering the influence of the barrier effect, the design of flexible distributed multi-signal integrated sensors and corresponding feedback control systems for implantable wireless transmission will be the crucial to the lightweight design and disruptive development of the next generation of BMS with the help of flexible electronic technology and advanced communication technology. In terms of battery defect and safety monitoring, it is necessary to further analyze the failure boundaries corresponding to different types and degrees of defects in combination with the actual manufacturing process; study the evolution mechanism and modeling of the whole life cycle of defects; explore production line detection technologies such as ultrasound, DT, and vision; and combine advanced sensing technology with big data and artificial intelligence algorithms to form a reliable whole process battery safety monitoring method. In terms of battery degradation and intelligent management, it is important to: face the multi-stage application of the whole life cycle of the battery; create a top-down management system from the cloud to the vehicle based on mechanism research and the combination of cloud-side technology and intelligent algorithms; put an emphasis on closed-loop management in the context of the whole life cycle; and improve aging management, echelon utilization, and battery recycling. In terms of battery energy storage and smart energy, it is currently in the early stages of exploration. With the rapid development of new energy vehicles and the increase in renewable energy, it is necessary to develop advanced power electronics technology and hierarchical control optimization algorithms at all levels of source network load storage, consider charge and exchange coordination, wind and light consumption, multi energy complementarity, and multi-vehicle combination, and explore and take into account robustness. The real-time and optimal vehicle station network multi-level and multi-space-time scale optimization strategy will build an energy intelligent dispatching system with multi-microgrid coordination and dynamic interaction with the large power grid. This will allow for the intelligent connection of power, energy, and transportation.

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