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Digital Twin Technology Based Lithium-Ion Battery Management System for Smart Use

[1] Misbah Noreen, [2] Abid Hussain, [3] Muhammad Waqas Akbar, [4] Shakeel Ahmed, [5] Khurram Rasheed, [6] Muhammad Usama Raza, [7] Muhammad Imtiaz, [8] Ikram Ul Haq

[1] Department of Zoology, The Govt. Sadiq College Women University Bahawalpur, Punjab Pakistan
[2, 3, 5] School of Engineering, Bohai University, Jinzhou 121013, China
[4] School of Materials Science and Engineering, Hainan University, Haikou 570228, China
[6] School of Materials Science and Engineering, Wuhan University of Technology, Wuhan 30070, China
[7] Institute of Computer and Software Engineering, Khawaja Fareed Uni. of Engr. and Information Technology, Rahim Yar Khan, Pakistan
[8] Computer Science Faculty of Sciences, University of Agriculture Faisalabad, Punjab Pakistan

Corresponding Author: **Muhammad Imtiaz**

Abstract
Scientific and reliable battery management systems (BMS) are the key to the safe and efficient application of lithium-ion battery energy storage systems. The traditional BMS has problems such as low computing resources and weak data processing ability, which makes the application of intelligent control algorithms and high simulation models limited. The digital twin (DT) technology characterized by the integration of information and physics has brought new opportunities for the development of BMSs. The creation of an intelligent BMS is accomplished through the creation of a DT that corresponds to the physical entities of the battery, virtual and real interactive feedback mechanisms, and data fusion. Systematically introduce the technical system and functions of the DT, including the data assurance layer, the modeling and calculation layer, the functional application layer, and the human-machine interaction layer. The key technologies, such as model modeling, data fusion, and mechanism model fusion, in the construction of battery DTs are analyzed. On this basis, the design framework of a lithium-ion BMS based on DT is clarified, with the goal of providing guidance and a reference for research into building an intelligent management system.

Keywords: Digital Twin, Lithium-Ion Battery, BMS, Artificial Intelligent, IoT, Electrochemical Energy Storage

1. Introduction

Under the background of "carbon peak, carbon neutral" green energy, energy storage systems have become a key link in building a new type of power system with new energy as the main body. The energy storage technologies can be divided into electrochemical energy storage, mechanical energy storage, and electromagnetic energy storage. Compared with other energy storage methods, electrochemical energy storage has the advantages of fast response, high conversion efficiency, a short construction period, and so on, making its application scale continue to expand [1]. Lithium-ion batteries have become the main technical route for electrochemical energy storage with the advantages of high energy density, long service life, and no memory effect [2]. Scientific and effective management of lithium-ion batteries is the premise for ensuring the safe and efficient use of the battery energy storage system and is also an important link to achieving low carbon. Because the traditional embedded lithium-ion battery management system has limited data processing capacity and computing resources and the complex management strategy and algorithm model cannot run on the BMS, it is still challenging to carry out scientific and effective management, operation, and maintenance of lithium batteries.

The DT technology, characterized by the integration of information and physics, has attracted the attention of academic and industrial circles at home and abroad [3]. On the DT platform, the virtual model corresponding to the physical entity can be established, and the data such as the characteristics and performance of the physical entity can be described through the virtual model. The virtual model can also be used to predict the future development trend of the physical entity [4], allowing for status monitoring, health diagnosis, future prediction, and performance optimization of the physical entity.

NASA created the twin of the spacecraft in the Apollo program in 1969 [5]. The earth twin was placed to simulate and reflect the spacecraft's on-orbit working state in space, as well as the prediction and resolution of emergencies. With the continuous development of modeling and simulation technology, the concept of DT was proposed by Professor Michael Grieves of the University of Michigan [6] in his product life cycle course in 2003, and the main framework of DT was described in the white paper on DT. However, the concept of DT was not mature at that time and only pointed out the need to use virtual models to simulate physical entities and operate and test on virtual models. Professor Grieves then conducted additional research and exploration on this concept, naming it "DT". In 2012, NASA proposed an example of the combination of future aircraft and DT technology, defining the DT model as a simulation process that fully utilizes data and integrates multi-physics, multi-scale, and multi-probabilistic simulation [7]. As a result, the use of DT has become widespread, gradually infiltrating from the aircraft field to the industrial field, and the functions that can be realized are also moving towards the development trend that can predict the future of physical entities. In order to promote the digital revolution and accelerate the integration of the virtual world and the physical world [8], DT technology has been incorporated into the general direction of enterprise strategy by many technology companies. ANSYS, a giant simulation and modeling company, uses DT technology to model the whole life cycle of complex physical product objects and analyzes them in combination with simulation. Siemens applies its products and systems to the DT solution system based on the industrial internet platform; and Dassault has created a 3D product experience platform through DT technology, through which users and managers can interact with products more intuitively.

Wu *et al*. [9] applied DT technology to the condition monitoring of a power battery pack and introduced the data-driven modeling method to further integrate DT and model data into a framework to create a complete DT. Merkle *et al*. [10] put the DT model in the cloud computing environment for operation and combined the twin model with the corresponding data generated by physical entities in the cloud computing environment, improving the computing capacity and data storage capacity of the battery system. He *et al*. [11] achieved rapid prediction of the life of lithium-ion batteries by establishing DT of lithium-ion batteries to generate battery aging tracks under different working conditions.

At present, research on the application of DT technology in BMSs is still lacking. This paper systematically describes the various parts involved in the BMS based on DT, providing guidance and assistance for the research on building a lithium BMS based on DT. The content of this paper is arranged as follows: Section 2 introduces the four main levels of the DT technology system; Section 3 introduces the modeling method of lithium-ion batteries; Section 4 describes the dual-driven method of data and model fusion of DT; In Section 5, a DT framework for lithium BMSs is proposed; Section 6 summarizes the full text.

2. Digital twin technology

The digital representation of physical entities is known as twinning [12]. The virtual process in DT is completely matched with the operation of a real-time physical process. During the whole life cycle of the physical entity, the corresponding virtual model will continuously update the same performance and state data as the physical entity. In order to build a complete DT system, it is necessary to integrate multiple platform-based frameworks into a closed loop of information interaction from the physical world to the digital space. A complete DT technology system includes the following four main layers [13]: data assurance layer, modeling and computing layer, functional application layer, and human-machine interaction layer. Each layer is an indispensable part of the DT system, which involves the utilization of the resources of the upper layer and provides the necessary conditions for the formation of the next layer. A complete DT technology system is shown in Fig 1.

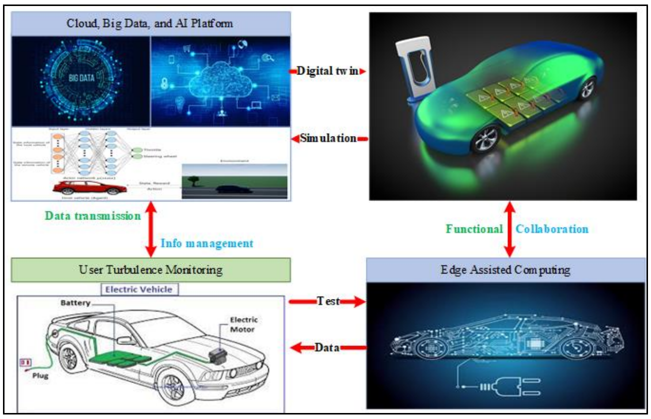

Fig 1: Schematic diagram of digital twin technology [14]

The data assurance layer is used to realize the functions of collection, transmission, and storage of physical entity operation data. Data is the basis of the entire DT technology system [26]. All functions in the model and the interaction between virtual and real models will be performed around data. Before modeling, it is necessary to clean, normalize, and sort the collected relevant data for calibration and detection by the model. The operation data of the physical entity is collected by the high-performance sensor installed on the entity, and the corresponding data is transferred to the data management system for storage through the high-speed data transmission tool.

The modeling and computing layer is the backbone of the DT technology system. Before modeling the virtual model, it is necessary to understand the working principle of the physical entity and the relevant internal reactions. By establishing a multi-physical, multi-scale, multi-probabilistic simulation model, the virtual modeling of the physical entity is realized, the collected data is analyzed and calculated at multiple levels, the virtual model is iteratively optimized, and the fidelity of the virtual model is evaluated to judge whether the model is reliable. High-precision models can allow DT to operate and control physical entities from more perspectives in their applications.

The functional application layer is oriented toward the design and maintenance management of the actual system, including the task risk assessment, the whole life cycle management of the system, the monitoring of the system production process, the intelligent decision-making of the system, and other functions to achieve all-round and multi-angle management. In some complex situations, simulation operations can be performed through the functional application layer [15] to guarantee system maintenance and save human and material resources generated by system maintenance and operation.

The human-computer interaction layer provides users with a good operation platform to manage and use the DT system, including data visualization, optimization control, diagnosis, and prediction functions, which is convenient for users to operate the DT system [16]. Various information sensing, such as a multi-function 3D sensor, can be added to this layer to improve the user experience and allow users to understand the entire system more intuitively and deeply. The existence of a human-computer interaction layer makes the DT system more closely connected with users, and the ease of interaction with the system is an important indicator of the practicality of this layer.

3. Lithium Battery Models

3.1 Electrochemical mechanism model

The electrochemical mechanism model of the battery is a model that describes the characteristics of the battery based on the electrochemical reaction mechanism inside the lithium-ion battery, and its parameters have clear physical significance. The positive and negative electrodes in the electrochemical mechanism model are composed of porous electrode structures, which are divided into homogeneous and heterogeneous models according to the size of the active particles. Because the calculation cost of the heterogeneous model is high and the optimization of the homogeneous model can obtain high-precision prediction results similar to the heterogeneous model [17], the homogeneous model is used in this paper for research. Newman *et al.* [18] simplified the electrochemical mechanism model of the battery to a pseudo-two-dimensional (P2D) model, as shown in Fig 2. The model includes six parts: a positive electrode, a positive current collector, a negative electrode, a negative current collector, electrolyte, and a separator, which can provide internal information about the battery reaction, such as lithium-ion concentration in the electrode and electrolyte. The P2D model has a high calculation accuracy when calculating the electrode state, but it involves a large number of partial differential equations and parameters, which makes it very time-consuming to directly use the P2D model for calculation and is difficult to directly apply in the embedded BMS [19]. Based on the homogeneous porous electrode theory and concentrated solution theory of the P2D model, researchers have simplified the P2D model. Romero-Becerril *et al.* [20], based on the SPM model, simplified the diffusion and concentration polarization effects in the electrolyte and further improved the calculation efficiency of the model. Goel *et al.* [21] reduced the P2D model to a 1D model by simplifying the control equation and testing the method's feasibility.

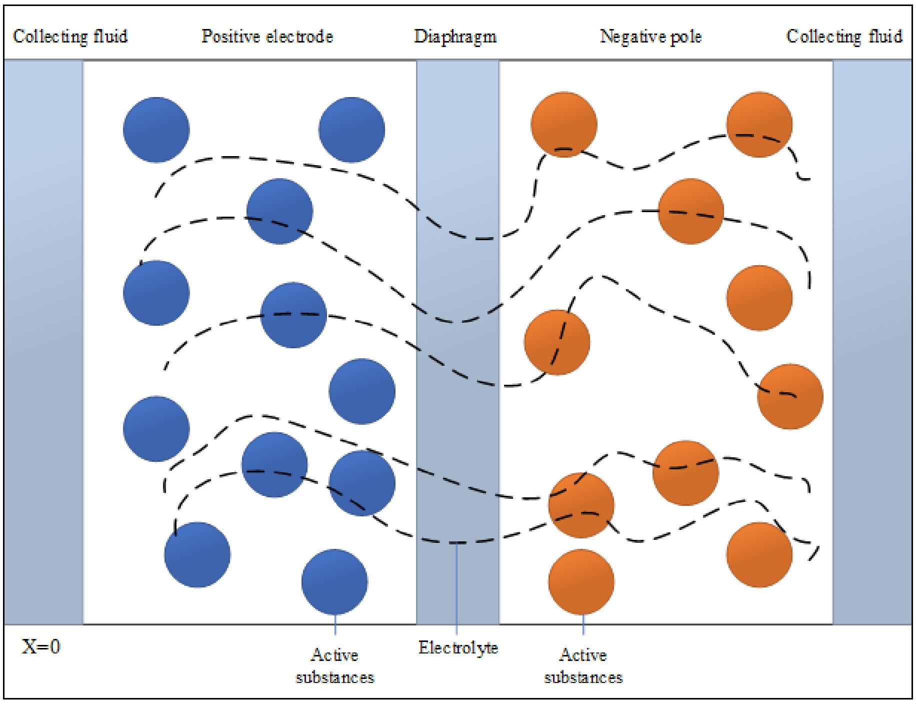

Fig 2: P2D electrochemical model

3.2 Thermal model

The operating temperature of the battery is an important parameter that reflects the battery's safe state. The accurate establishment of the battery thermal model plays an important role in battery management. The thermal model expression of a battery generally includes an energy balance equation, a heat generation equation, and a boundary condition equation [22]. At present, the commonly used thermal models of batteries include the concentrated parameter thermal model and the distributed parameter thermal model. Among them, the lumped parameter model regards the heat source of the entire lithium-ion battery as a uniform heating entity, and the heat production rate of each area in the battery is consistent. The change in battery temperature during the battery charging and discharging process is the result of electrochemical reactions, mixing effects, and joule heat reactions [23]. The thermal characteristics of the battery can be estimated by using the general energy balance equation describing the thermal characteristics of the battery. However, the lumped parameter model cannot describe the spatial distribution of the internal temperature of the battery. The distributed parameter thermal model takes into account the non-uniformity of the spatial distribution of the internal temperature of the battery. Based on the study of the rate at which the battery produces heat, research on the local current distribution heat generation and the finite element method is added to solve the fact that the battery's internal temperature is not spread out evenly in space [24].

3.3 Electrochemical-thermal coupling model

Due to the complex reaction of the heat generation mechanism inside the battery, it is impossible to accurately simulate the battery based on a single thermal model, and the coupling of a thermal model with an electrochemical mechanism model has become a trend. The heat generation rate of the battery is calculated by the electrochemical model and mapped to the thermal model as the heat source, and then the internal temperature field of the battery is calculated by the thermal model. The relevant parameters in the electrochemical model are adjusted according to the temperature of the internal temperature field of the battery to realize the coupling between the electrochemical model and the thermal model. Mastali *et al.* [25] established the electrochemical-thermal coupling model of a large lithium-ion battery to simulate the three-dimensional distribution of electrochemical and thermal variables in the battery and verified the accuracy of the model through experiments. Tang *et al.* [26] established an electrochemistry-thermal coupling model for battery discharge. After studying the distribution of cathodic reaction current density and the evolution of reaction current density with discharge time, it was found that the electrochemistry-thermal coupling model has higher accuracy than the single electrochemical model, especially at high discharge rates. Compared with other coupling models, the electrochemistry-thermal coupling model can simulate the working state of the battery from multiple perspectives, such as the heat generation of the chemical reaction inside the battery, laying the foundation for the research on the DT model of the lithium battery.

4. Design of DT Model for lithium BMS

The BMS plays an important role in ensuring the safety and efficiency of lithium-ion batteries. The application of DT technology in the lithium-ion BMS can improve the reliability of the system [27]. This technology transmits the collected real-time data to the cloud for calculation to update the status of the battery twinning model in real time. Users can view the operation status of the battery in real time through the visual interface [28]. The DT system can be used to simulate a battery that is not easy to operate or that is operated under extreme conditions, so as to obtain the corresponding results, and then predict, judge, or control the battery according to the results.

The lithium-ion BMS framework based on DT technology includes four parts [29], including a virtual model, a physical entity, the DT cloud platform, and a BMS, as shown in Fig 3.

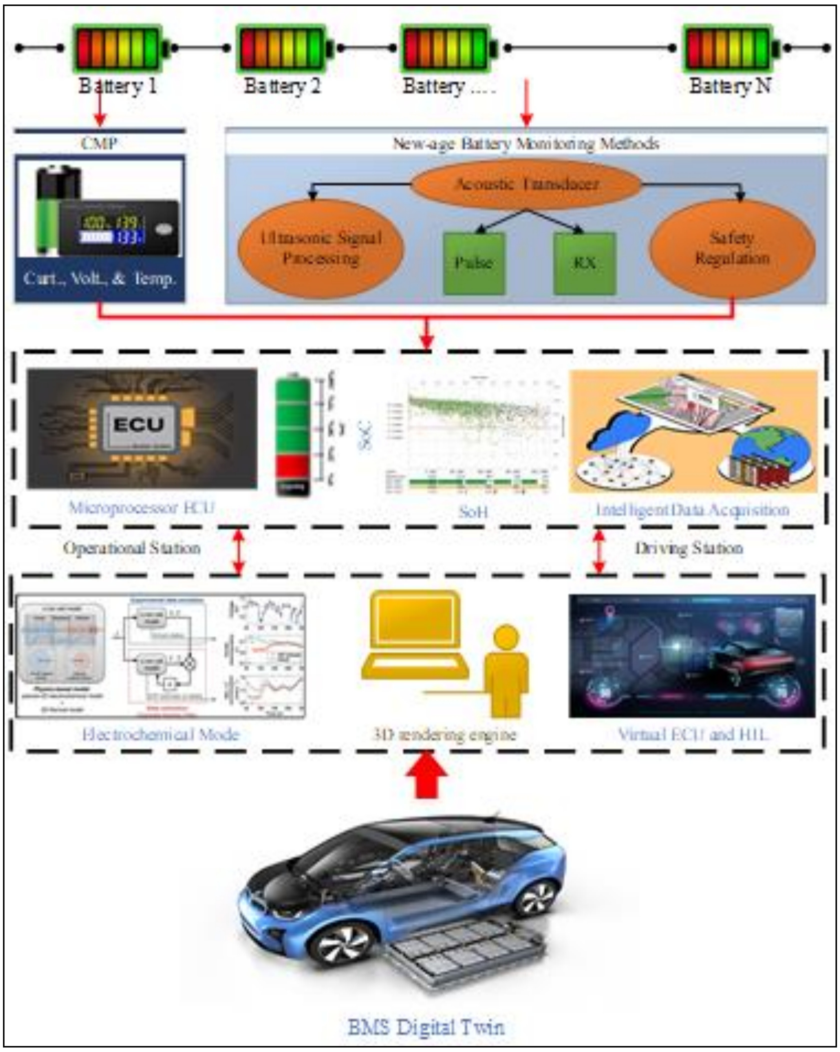

Fig 3: Shell of lithium-ion battery management system based on digital twin

In the process of establishing the system, the battery is first regarded as a physical entity, and the real-time operation data of the physical entity is collected through high-performance sensors. The simulation modeling tool is used to establish a multi-dimensional, multi-scale, multi-physical field coupling virtual model corresponding to the physical entity according to the internal principles of the battery (electrochemical reaction principle, heat generation principle, etc.) and the physical field (electrochemical, thermal, mechanical, etc.). Then, deploy the virtual model to the DT cloud platform, use 3D rendering software to draw the 3D visualization model of the battery, and import the model into the 3D scene software (such as Unity3D) to establish the corresponding 3D visualization interface. Through data interaction between the Twin Cloud data system and 3D visualization interface, further intelligent management and optimization of models are carried out on the DT cloud platform. In this process, common modeling tools include COMSOL Multiphysics, MATLAB, and ANSYS Twin Builder. The twin cloud data system will pre-process and store the data generated by the operation of physical entities and virtual models, update the status information of virtual models, integrate the status information of physical entities (physical element attribute data, real-time collected battery data, etc.) and virtual model status information (simulation data, virtual model parameter information), and then transmit them to the cloud computing system [30]. The cloud computing system calculates the received data to obtain the real-time model parameters, status information, etc., of the battery, and after optimizing the control strategy for the whole life cycle of the battery, it transmits the control strategy and parameter information to the BMS through the data transmission interface. After receiving the data, the BMS updates the status information and control strategy of the battery accordingly to realize the rolling optimization management of the whole life cycle of the battery.

5. Conclusion

Digital twin technology plays an important role in promoting intelligent manufacturing and digitalization. The introduction of DT technology into the field of battery energy storage provides new opportunities for the development of intelligent battery management system and battery energy storage system, especially promoting the development and application of intelligent control algorithms and high simulation models. This paper focuses on the application of DT technology in BMS, analyzes the DT technology system hierarchically, expounds the modeling method of battery electrochemical model and thermal model, introduces the method of data and model dual-driven, and further clarifies the technical framework design of BMS based on DT, and introduces the DT BMS into multiple modules, The corresponding design scheme is given. The DT technology plays an important role in battery management and other fields in the future, but it still faces many challenges: for example, there are many parameters to build a high simulation virtual model, and the accuracy of parameters needs to be improved; Utilize technologies such as high-performance computing and artificial intelligence to meet the needs of long-term large-scale data analysis; Advanced communication technology is used to reduce the transmission delay of data information and realize accurate real-time mapping of virtual and real systems.

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