

Lithium-ion Battery Energy Storage Digital Twin System and Applications

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Abstract

Under the background of large-scale development of new energy, the operation and management of lithium battery energy storage systems face many challenges. Digital twin technology provides effective solutions for the intelligent upgrading of energy storage systems. This article focuses on the research of digital twin technology for lithium battery energy storage. Firstly, it clarifies the core connotation and composition architecture of digital twin technology, and then focuses on sorting out its research achievements in key areas such as model construction, real-time monitoring, life monitoring and management, and application scenarios. The model construction adopts a "bottom-up" multi-scale modeling and hybrid driving strategy, which can achieve accurate simulation of multiple physical fields; Real time monitoring relies on the "edge computing+5G+industrial Ethernet" architecture and hybrid data fusion algorithm to ensure the real-time and reliability of data transmission; Establish a "assessment prediction maintenance" full chain control mode for life management; This technology has been successfully applied in multiple practical scenarios such as power grid peak shaving and frequency regulation. Combined with monitoring practice, it has been shown that the core indicators of the constructed system, such as simulation accuracy and fault warning accuracy, meet the design standards, which can significantly improve the operational efficiency of energy storage power stations and reduce maintenance costs. Finally, summarize the core advantages and current problems of this technology, and look forward to future research directions such as multi-scale modeling optimization and cross domain technology integration, providing theoretical support and practical reference for the large-scale promotion and application of lithium battery energy storage digital twin technology.

Keywords

Lithium-ion Battery; Energy Storage; Digital Twin System.

1. Introduction

Under the guidance of the goal of "carbon peaking and carbon neutrality", my country's new energy industry has achieved leapfrog development, and the installed capacity of intermittent renewable energy such as wind power and photovoltaics has continued to expand. Under this development trend, the imbalance between power supply and demand in the power grid has become increasingly prominent, the peak-valley difference has further increased, and problems such as the increased volatility of new energy access and the increased uncertainty of power grid peak and frequency regulation urgently need to be solved[1]. Lithium-ion battery energy storage technology, with its advantages of high energy density, fast response speed, and long cycle life, has been widely used in renewable energy grid integration and consumption, power

grid peak and frequency regulation, user-side energy storage and other scenarios, becoming a core supporting technology for improving the flexibility and intelligence level of the power system[2]. As the scale of lithium battery energy storage power stations continues to expand, they face numerous challenges during operation, such as uneven battery degradation, thermal runaway risks, and lagging condition monitoring. Traditional management models based on physical sensors and empirical models are no longer sufficient to meet the requirements for the safe and efficient operation of energy storage systems[3].

Digital twin technology, as an emerging technology integrating multi-physics modeling, data-driven analysis, and real-time mapping interaction, can construct a full lifecycle mapping relationship between physical entities and virtual models, enabling real-time monitoring, condition assessment, fault early warning, and optimized control of physical systems[4]. Combining this technology with lithium battery energy storage systems to construct lithium battery energy storage digital twin systems can effectively overcome the limitations of traditional management models. Through virtual models, the operating status of energy storage systems can be accurately replicated and dynamically simulated, providing intelligent support for the entire process of energy storage system design optimization, operation management, and maintenance[5]. Currently, domestic and foreign scholars have conducted a series of studies on lithium battery energy storage digital twin technology, and the demonstration application of related technologies in energy storage power stations is gradually advancing. However, there are still shortcomings in multi-scale modeling accuracy, multi-source data fusion efficiency, and real-time interactive response speed[6].

In 2021, the National Energy Administration issued the "Blue Book on the Development of New Power Systems," which clearly proposed to accelerate the deep integration of digital technology and power systems and promote the intelligent upgrading of energy storage systems[7]. Driven by both policy guidance and technological demand, lithium battery energy storage digital twin technology has become a research hotspot in the energy storage field. This paper systematically conducts research on the construction and application of lithium battery energy storage digital twin systems, elucidates the core architecture and key technologies of digital twin systems, completes the construction of multi-scale virtual models, and designs multi-source data acquisition and fusion schemes. Through real-time monitoring and application analysis of the system's operating effect, it provides theoretical and practical support for the large-scale application of lithium battery energy storage digital twin technology.

2. Digital Twin Technology Foundation

2.1. Development Background

The widespread use of fossil fuels has led to increasingly serious environmental problems, with frequent occurrences of climate change-related phenomena such as floods and droughts, further exacerbating global warming and its cascading effects. Shifting to renewable energy is an effective way to address this challenge, as it can provide sustainable energy with minimal environmental impact[8]. In recent years, the installed capacity of various renewable energy sources such as wind power and photovoltaics has rapidly increased to hundreds of megawatts, requiring the development of efficient energy storage systems to support this growth. Among various energy storage systems, battery energy storage systems (BESS) stand out due to their high efficiency, technological maturity, and capacity diversity, while lithium batteries, with their high energy density and fast response speed, have become the core component of battery energy storage systems[9].

The concept of digital twins has evolved over time, with different definitions and interpretations in different fields. In the aerospace engineering field, digital twins are considered an abstract concept influenced by artificial intelligence and Industry 4.0 trends; in

the manufacturing field, its technological applications are both flexible and have multiple interpretations[10]. Essentially, digital twin technology transforms data into effective information through multidisciplinary data methods such as algorithms, models, and simulations, constructing multiple adaptive models to achieve accurate replication of physical space in digital space. These models can acquire real-time data, predict potential problems in physical space, and formulate preventative measures to mitigate risks[11].

The ability of digital twins to acquire and retain data from physical units is crucial. Internet of Things (IoT) technology plays a central role in connecting physical units and virtual models in this process, while cloud computing provides the means for data storage and necessary computation, helping digital twins establish a closed-loop feedback mechanism between the physical and digital worlds[12]. Digital twins can accurately replicate physical systems and perform critical tasks throughout their design, production, and operation phases. Their core consists of a physical system, a digital model, and a connection layer. The connection layer ensures the smooth flow of data, information, and knowledge between the physical and digital systems, enabling the characterization of the operational performance of various physical units[13].

The core objective of developing digital twin technology for lithium battery energy storage systems is to address common challenges such as increased internal temperature, accelerated aging, and delayed fault warnings. The application of digital twin technology can prevent potential problems and extend system lifespan, specifically through operational optimization, accurate parameter estimation, early fault detection and diagnosis, and efficiency improvement[12]. Researchers have already designed digital twin systems for battery energy storage systems to improve efficiency and cooling capacity, and have proposed related technologies for accurate fault diagnosis and prediction[14]. This paper, based on the general principles of digital twin development, conducts research on the construction and application of a lithium battery energy storage digital twin system, focusing on the system architecture and core content at each level, providing support for early fault detection and operational optimization.

The core value of lithium battery energy storage digital twin systems lies in accurately replicating and predicting the operating state of physical energy storage systems through virtual models, effectively reducing operational risks, improving operational efficiency, and extending equipment lifespan[15]. For example, battery thermal behavior simulation analysis can provide early warning of thermal runaway risks, and energy storage system operation strategy simulation optimization can improve the response accuracy of grid peak shaving and frequency regulation[16].

2.2. Technical Basis

The lithium battery energy storage digital twin system is a specific application of digital twin technology in the field of energy storage. Its core connotation is to construct a virtual twin corresponding to the physical energy storage system in terms of all elements, all processes, and all life cycle, so as to realize real-time data interaction, dynamic state mapping, accurate behavior simulation and intelligent decision optimization between physical entities and virtual models[17]. Compared with traditional energy storage monitoring systems, the lithium battery energy storage digital twin system has the significant characteristics of full-element mapping, real-time dynamic interaction, full life cycle management and intelligent autonomous evolution, which is highly consistent with the core meaning of digital twin technology of "accurate replication, real-time linkage and intelligent decision-making"[18].

Multiphysics modeling technology is the foundation for constructing virtual twins. It requires the integration of theories from multiple disciplines such as electrochemistry, thermodynamics, and electromagnetics to establish virtual models covering multiple scales, including individual

battery cells, battery modules, battery clusters, energy storage converters, and energy storage power stations, achieving accurate simulation of the coupling behavior of multiple physical fields such as electricity, heat, and force in energy storage systems[19]. Multi-source data acquisition and fusion technology is key to achieving real-time mapping between physical and virtual systems. By deploying various types of sensors such as voltage, current, temperature, humidity, and vibration, combined with edge computing technology, real-time acquisition, cleaning, fusion, and transmission of energy storage system operation data can be achieved[20]. Real-time communication and interaction technologies need to meet the requirements of high-speed transmission and low-latency interaction of massive amounts of data. They typically employ technologies such as 5G, industrial Ethernet, and edge computing to construct a three-tiered "terminal-edge-cloud" communication architecture[21]. Intelligent analysis and decision-making technologies are the core manifestation of the intelligence level of digital twin systems. They integrate algorithms such as machine learning, deep learning, and reinforcement learning to achieve functions such as state assessment, fault diagnosis, lifetime prediction, and operation optimization of energy storage systems[22].

3. Research Progress of Lithium Battery Energy Storage Digital Twin Technology

3.1. Model Construction

In battery cell modeling, a pseudo-two-dimensional (P2D) model is adopted based on electrochemical theory to fully consider core electrochemical processes such as lithium-ion diffusion and charge transfer, accurately depicting the dynamic characteristics of battery voltage-current-temperature[23]. Extending to the battery module and cluster levels, thermodynamic characteristics such as heat conduction and heat convection are further integrated into the cell model to construct an electro-thermal coupling model, focusing on analyzing the temperature distribution and voltage equilibrium state within modules and clusters[24]. For energy storage converters, a switching function model is adopted, taking into account both the switching characteristics of power devices and the impedance characteristics of the filtering stage, to achieve high-precision simulation of output voltage and current. At the overall level of the energy storage power station, by integrating the models of various subsystems, a full-scale simulation model[25] covering the coupling of multiple physical fields including electricity, heat, and force is finally formed.

To improve the accuracy and practical adaptability of the model, researchers generally adopt a hybrid modeling strategy that combines data-driven and model-driven approaches. Among them, the data-driven method includes techniques such as machine learning, data mining, and statistical analysis. For example, a battery state of health (SoH) prediction model is built using an LSTM neural network, a fault diagnosis model is built using a CNN+LSTM hybrid model, and formal concept analysis (FCA) technology is combined to optimize data classification efficiency[26]. Real-time monitoring results show that the constructed multi-scale multi-physics model can accurately reproduce the operating characteristics of the energy storage system, with the battery SOC estimation error controlled within 2.0% and the temperature simulation error not exceeding 2.5%, which can meet the modeling accuracy requirements of the digital twin system. Combining the characteristics of lithium battery energy storage systems, this paper designs a four-layer architecture of "physical entity layer - network transmission layer - virtual twin layer - application service layer". The functions of each layer are interconnected and work together to form a complete digital twin closed-loop link.

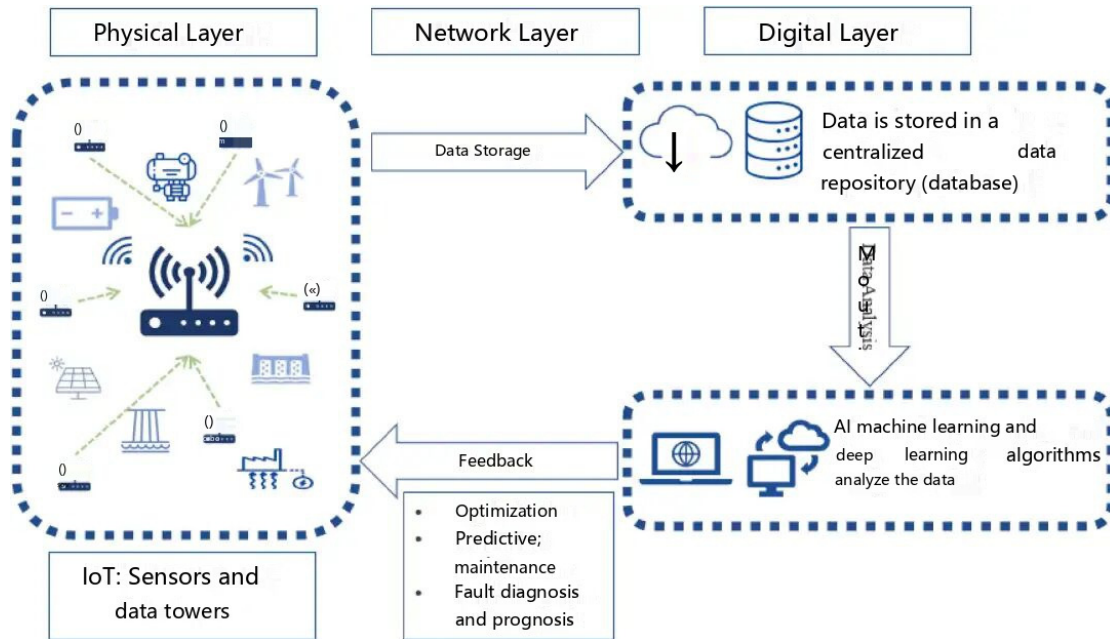


Figure 1. Digital Twin System Technical Architecture

3.1.1. Physical Entity Layer

The physical entity layer of a digital twin is a direct representation of the physical system and its component relationships, encompassing the target system, subsystems performing specific functions, sensors responsible for key data acquisition, controllers, and actuators. It is an important foundation for realizing real-time monitoring and analysis of the physical system[27]. After sensors and other devices collect data, the physical entity layer can provide feedback on the system's operating status, performance level, and health status, providing data support for system optimization, fault detection, and future behavior prediction[28]. Constructing a digital twin system for lithium battery energy storage requires the rational deployment of sensors within the physical system, the identification of core influencing parameters, and ensuring the comprehensiveness and accuracy of data acquisition[29].

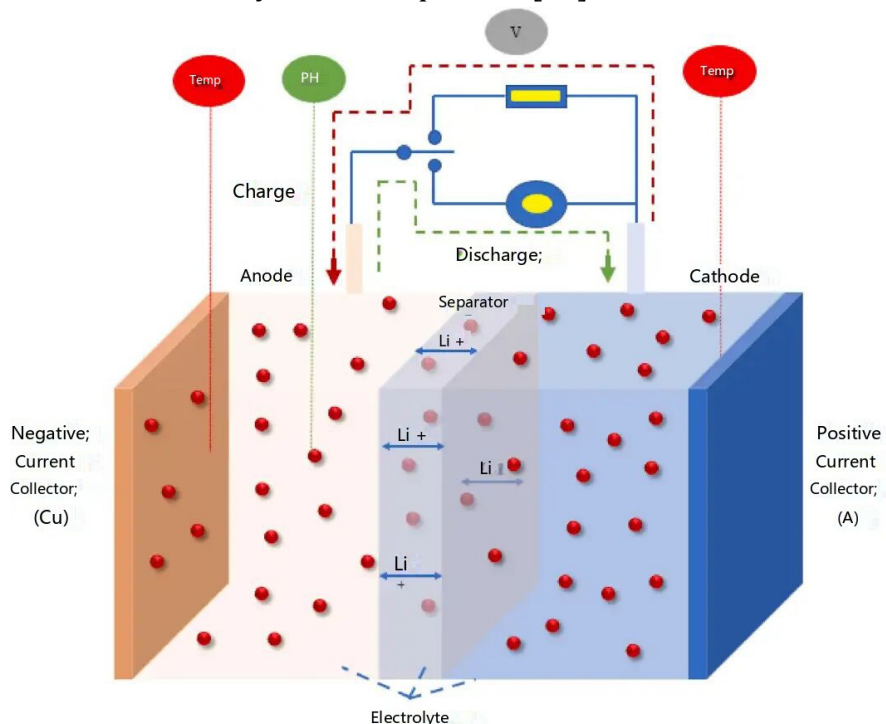


Figure 2. Schematic diagram of a BESS with sensors

The physical entity layer of a lithium battery energy storage system includes the actual battery pack, energy storage converter system, auxiliary system, and various sensors and control devices (Figure 2). Lithium batteries mainly consist of an anode, cathode, and electrolyte. The anode is typically lithium, while the cathode exhibits various redox coupling forms, with the core reaction being the intercalation reaction of lithium with metal sulfides and oxides[30]. Lithium-ion batteries may begin to experience capacity decay after 30 cycles, and their lifespan is typically 10-14 years, shorter than other energy storage systems, requiring close monitoring of system performance[31]. Operating temperature and pH value are key factors affecting system performance; voltage, resistance, capacity, power, and cycle effects are also crucial for system operation.

Based on the characteristics of lithium battery energy storage systems, a digital twin system oriented towards early fault detection is constructed. The core parameters to be monitored include voltage (V), pH value (PH), resistance, capacity, power, operating temperature (Temp), cycle effect, load cycle, charging time, and discharging time[32]. Simultaneously, performance characterization parameters such as efficiency, state of charge (SoC), state of power (SoP), and state of health (SoH) need to be calculated and derived[33]. The physical layer sensor deployment scheme is as follows: one temperature sensor is placed on each side of the battery module to accurately monitor the temperature near the positive and negative electrodes, and to understand the internal temperature gradient of the battery to avoid safety risks[34]; a pH meter is deployed at the anode to obtain accurate readings of the pH value of the battery energy storage system[35]; a voltage sensor is installed on the circuit connecting the battery to achieve continuous voltage acquisition[36]; current sensors, insulation resistance sensors, vibration sensors, etc., are also configured to comprehensively cover the core parameter acquisition requirements[37].

3.1.2. Network Transport Layer

Table 1. Comparison of Various Protocol Types Based on Data Transmission Rate, Data Format, and Security Functions

Protocol Type	Description	Example Protocols	Security Features	Data TransferRate	Data Format
Internet	Designed for communication over the internet	HTTP, HTTPS, MQTT, CoAP, AMQP, WebSocket	SSL/TLS encryption, authentication, antivirus	Moderate to High	Text, JSON, XML
Wireless	Designed for wireless communication, often with low power devices	Bluetooth Low Energy, Zigbee, Z-Wave	Encryption, authentication, secure pairing	Moderate to High	Binary, Text, JSON
IoT	Designed for devices to connect and exchange data with the internet	MQTT, COAP, AMQP, XMPP	Authentication, encryption, access control	Moderate to High	Binary, Text, JSON, XML

The network transport layer, acting as a bridge between the physical entity layer and the virtual twin layer, is responsible for ensuring the smooth flow of data, information, and knowledge between the two layers. Its core is the selection of communication protocols and the construction of the transmission architecture[38]. The type of communication protocol needs to be determined according to the specific requirements of the application scenario, including

the data type to be transmitted, update frequency, latency requirements, reliability requirements, and compatibility with existing systems. Different protocols differ in data transmission rate, data format, and security functions (Table 1). This system adopts a three-level communication architecture of "edge computing + 5G + industrial Ethernet", combining the advantages of multiple protocols to ensure the efficiency and reliability of data transmission. The core function of the network transport layer is to undertake the tasks of collecting, preprocessing, and transmitting operational data from the physical entity layer. Based on the operating characteristics of the energy storage system, the following data acquisition units are deployed: a battery status acquisition unit, which installs voltage and temperature sensors on each battery module and current and insulation resistance sensors on each battery cluster to collect parameters such as individual battery voltage, module voltage, cluster voltage, charging/discharging current, temperature, and insulation resistance, at a frequency of 10Hz[39]; an equipment operation acquisition unit, which installs vibration, noise, and oil level sensors on key equipment such as the energy storage converter and transformer to collect equipment operation status parameters, at a frequency of 5Hz[40]; and an environmental acquisition unit, which installs environmental sensors such as temperature, humidity, wind speed, and rainfall inside and outside the energy storage compartment to collect environmental parameters, at a frequency of 1Hz[41].

Table 2. Data Acquisition and Transmission Parameter Table

Data Type	Acquisition Parameters	Acquisition Frequency	Transmission Method	Transmission Delay	Data Accuracy
Battery Status Data	Individual Cell Voltage, Module Voltage, Cluster Voltage, Charge/Discharge Current, Temperature, Insulation Resistance	10Hz	5G + Edge Computing	≤200ms	Voltage: ±0.01V; Temperature: ±0.1°C
Equipment Operation Data	Vibration, Noise, Oil Fluid Index, Converter Output Power	5Hz	5G + Edge Computing	≤300ms	Vibration: ±0.01mm/s; Power: ±0.1%
Environmental Data	Temperature, Humidity, Wind Speed, Rainfall	1Hz	5G	≤500ms	Temperature: ±0.2°C; Humidity: ±1%
Control Command Data	Charge/Discharge Power Command, Cooling System Control Command, Fire Protection System Control Command	Real-time	Industrial Ethernet	≤100ms	Command Error: ±0.5%

Data transmission adopts a hybrid transmission mode of "edge computing + 5G + industrial Ethernet": the raw data collected by the sensors is first transmitted to the edge computing node

for preprocessing such as data cleaning, noise reduction, and format conversion to remove abnormal data[42]; the preprocessed data is transmitted to the cloud platform through the 5G network for virtual twin modeling and simulation[43]; control command data with high real-time requirements is transmitted through industrial Ethernet, using the TCP/IP protocol to ensure transmission reliability and control transmission latency of less than 100ms[44]. Data acquisition and transmission parameters are shown in Table 2.

3.1.3. Virtual Twin Layer

The virtual twin layer, also known as the digital layer of a digital twin, is responsible for receiving real-time data from the physical entity layer, completing data storage, analysis, and processing, and constructing a digital mirror of the physical system through various models to simulate, constrain, and characterize the behavior of the physical system[45]. This layer is the core of the digital twin system. Through multi-scale, multi-physics modeling technology, combined with a hybrid strategy of data-driven and model-driven approaches, it achieves accurate mapping of the physical energy storage system, providing support for simulation analysis, condition assessment, and fault early warning[46]. The virtual twin layer consists of four core modules: data storage module, model construction module, data fusion module, and simulation analysis module[47].

The data storage module is responsible for storing various types of data retrieved from the physical lithium-ion energy storage system. To ensure the standardization of data management and the efficiency of analysis, the data is classified and stored in three different relational databases. The relational databases are presented in the form of tables (entity sets), containing rows (entities) and columns (attributes). The databases are linked through primary keys (identifiable parameters) and foreign keys (related attributes)[48]. The first database stores operating parameters, covering raw data such as voltage, resistance, capacity, power, charging time, discharging time, operating temperature, cycle effect, load cycle, and pH value[49]; the second database stores performance characterization parameters, including derived data such as efficiency, state of charge (SoC), state of health (SoH), state of power (SoP), load cycle, and fault type[50]; the third database stores the normal range thresholds of all operating and performance parameters, providing a basis for fault judgment[51], as shown in Figure 3.

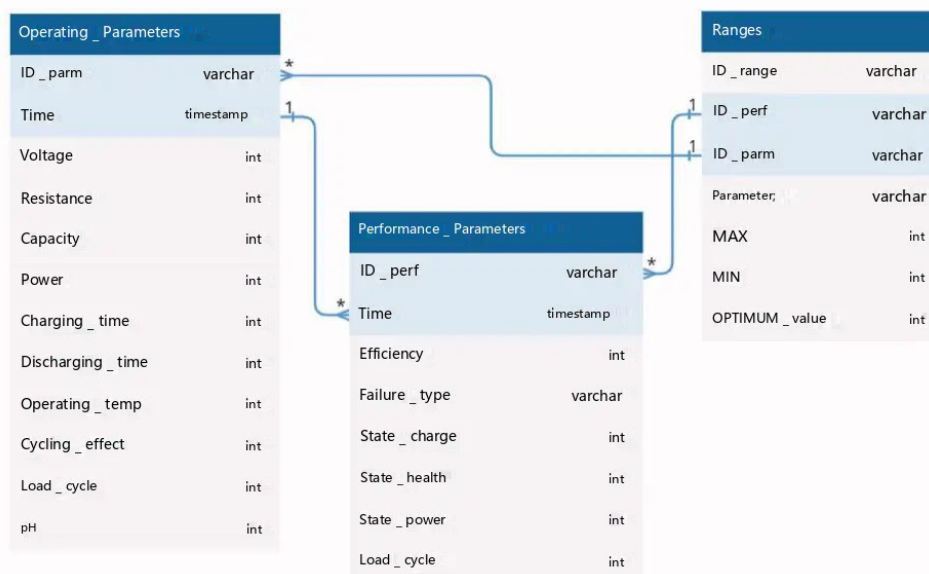


Figure 3. Relationship Entity Graph (showing database, associations and parameters)

The model building module adopts a "bottom-up" multi-scale modeling strategy, sequentially building a battery cell model, a battery module model, a battery cluster model, an energy

storage converter model, and an overall energy storage power station model. Through the integration of geometric models, behavioral models, and data-driven models, a complete mirror image of the lithium battery energy storage system is created in the digital space (Figure 4).

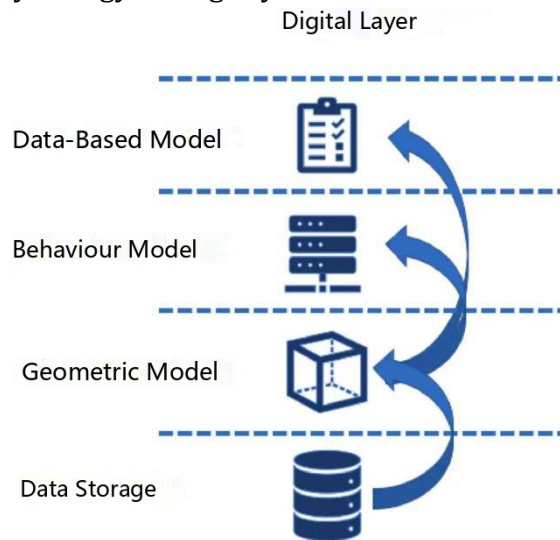


Figure 4. Digital Layer of BESS

(1) Geometric Model: The geometric model is the foundation of digital twin technology, providing a detailed and accurate representation of the simulated physical system, reflecting key characteristics such as the geometric shape, size, component position and orientation of the physical system[52]. When constructing, it is necessary to clearly define the size, shape, assembly position and structure of the system to ensure the accuracy and readability of the model. Its purpose is to show the form of the physical system, while providing structural information that is crucial for design optimization, motion analysis and virtual interaction[53]. This system uses software such as 3DMax, AutoCAD, SolidWorks to construct a three-dimensional geometric model covering battery cells, modules, clusters, energy storage converters and the entire power station, completely replicating the spatial structural features of the physical system.

(2) Behavioral Model. The behavioral model belongs to the model-based approach, focusing on the performance of the battery energy storage system, covering input parameters, output parameters and their interrelationships. It needs to build a mathematical model based on the parameter information predefined in the physical layer[54]. The model-based approach requires prior knowledge of the characteristics of the system being modeled, such as equations, rules and system parameters. This prior knowledge is used to build mathematical or computational models for prediction or to generate insights[55]. The behavioral model explains how the lithium-ion battery energy storage system is controlled by different types of factors and variables, aiming to reflect the dynamic characteristics of the lithium-ion battery energy storage system under different conditions, and adding dynamic functional behavior to the geometric and static physical models[56]. The dynamic behavior of lithium-ion battery energy storage systems can be described by differential equations, which can be used to predict the future behavior of the entity[57]. Behavioral models aim to capture various behavioral patterns that lithium-ion battery energy storage systems may exhibit, including sequential, concurrent, periodic, random, and chained patterns. Behavioral models capable of capturing all these patterns are considered highly accurate; however, in practice, various uncertainties in lithium-ion battery energy storage systems threaten the accuracy of behavioral models, and inaccuracies in data collection from lithium-ion battery energy storage systems can also jeopardize the accuracy of behavioral models, thus affecting the accuracy of digital twin models

The battery cell model of this system is based on electrochemical theory and adopts a pseudo-two-dimensional (P2D) model, considering electrochemical processes such as lithium-ion diffusion and charge transfer, to accurately describe the voltage-current-temperature characteristics of the battery; the battery module and cluster models, based on the cell model, incorporate thermodynamic characteristics such as heat conduction and heat convection to construct an electro-thermal coupling model, analyzing temperature distribution and voltage equalization characteristics; the energy storage converter model adopts a switching function model, considering the switching characteristics of power devices and the impedance characteristics of the filtering stage, to achieve accurate simulation of output voltage and current; the overall model of the energy storage power station integrates the models of each subsystem to construct a full-scale model covering the coupling of multiple physical fields such as electricity, heat, and force. The parameters of the multi-scale virtual model are shown in Table 3.

Table 3. Multi-scale Virtual Model Parameter Table

Model Hierarchy	Modeling Dimensions	Core Parameters	Modeling Tools	Simulation Accuracy
Cell Model	Electrochemistry	Diffusion Coefficient, Charge Transfer Resistance, Open Circuit Voltage	COMSOL Multiphysics	Voltage Error $\leq 1.5\%$
Cell Module/Cluster Model	Electro-Thermal Coupling	Thermal Conductivity, Specific Heat Capacity, Contact Thermal Resistance	COMSOL Multiphysics+MATLAB	Temperature Error $\leq 2.0\%$
Energy Storage Converter Model	Electromagnetism	Switching Frequency, Filter Inductor, Filter Capacitor	PSCAD/EMTDC	Current Error $\leq 1.0\%$
Overall Energy Storage Power Station Model	Multiphysics Coupling	Line Impedance, Transformer Parameters, Cooling System Parameters	PSCAD/EMTDC+COMSOL	Power Error $\leq 0.8\%$

The data fusion module employs a hybrid fusion strategy combining a weighted average fusion algorithm and a Kalman filter algorithm to fuse multi-source sensor data with virtual model simulation data[63]. First, the weighted average fusion algorithm fuses multi-sensor data with the same parameter, reducing random errors. Then, the Kalman filter algorithm fuses the fused measured data with the virtual model simulation data, correcting parameter deviations in the virtual model and improving simulation accuracy[64].

The simulation analysis module, based on the multi-scale virtual model and the fused data, realizes real-time simulation, state assessment, and fault early warning of the energy storage system's operating status[65]. The real-time simulation function can replicate the operating status of the physical energy storage system in real time, outputting key parameters such as battery SOC, SOH, and converter output power; the status assessment function evaluates the operating status level of the energy storage system by comparing and analyzing simulation data

with measured data; the fault early warning function is based on machine learning algorithms, and builds a fault early warning model by training on historical fault data to achieve early warning of common faults such as battery over-temperature, over-voltage, and converter failure[66].

3.1.4. Application Service Layer

Throughout the entire lifecycle of a lithium battery energy storage system, digital twin technology can achieve various advantageous functions such as fault detection, system optimization, and performance improvement, as shown in Figure 6. The application service layer addresses the operation and management needs of energy storage power stations, transforming the analysis results of the virtual twin layer into diversified application service functions. It is the core carrier for realizing the value of digital twins, mainly including five core functions: operation monitoring, status assessment, fault diagnosis, optimized control, and maintenance management[67].

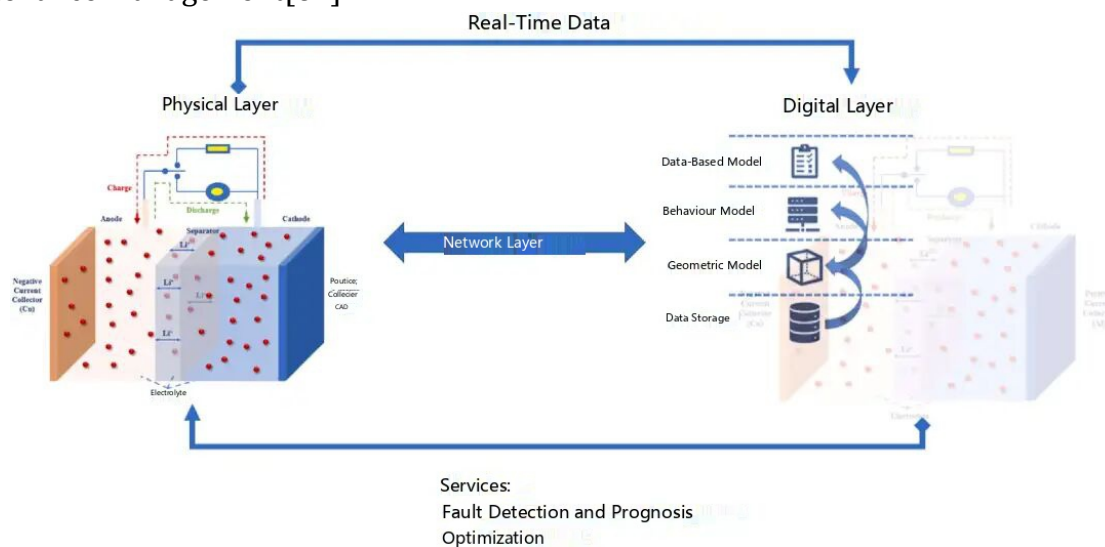


Figure 6. Schematic diagram of BESS digital twin architecture

The operation monitoring function displays the operating parameters, equipment status, and virtual model simulation results of the energy storage system in real time through a visual interface, enabling panoramic monitoring of the energy storage system and allowing operators to quickly locate abnormal equipment states; the status assessment function, based on the simulation analysis results of the virtual twin, regularly assesses the health status of key equipment such as energy storage batteries and energy storage converters, and outputs assessment reports; the fault diagnosis function combines virtual model simulation data and measured data to accurately locate fault locations, analyze fault causes, and output fault handling solutions to avoid major safety hazards such as fires and explosions; the optimized control function, based on grid dispatch commands and the operating status of the energy storage system, optimizes through virtual model simulation and outputs the optimal charging and discharging control strategy; the maintenance management function, based on the health status assessment results of the equipment, formulates personalized maintenance plans to achieve predictive maintenance of the energy storage system, reduce unnecessary maintenance operations, and lower maintenance costs[68].

3.2. Real-time Monitoring

Real-time monitoring is a crucial prerequisite for achieving closed-loop management of lithium-ion battery energy storage digital twin systems. Its core technology lies in multi-source data acquisition and fusion. By deploying various sensors such as voltage, current, temperature, humidity, and vibration, combined with edge computing technology, real-time acquisition,

cleaning, fusion, and transmission of energy storage system operation data are achieved[69]. This technology system mainly consists of three core components: data acquisition, transmission architecture, and data fusion.

In the data acquisition stage, acquisition units are deployed in conjunction with the operating characteristics of the energy storage system. The battery status acquisition unit is equipped with voltage and temperature sensors in each battery module and current and insulation resistance sensors in each battery cluster to acquire key parameters such as individual battery voltage, module voltage, cluster voltage, and charging and discharging current. The acquisition frequency is set to 10Hz. The equipment operation acquisition unit is equipped with vibration, noise, and oil level sensors for core equipment such as energy storage converters and transformers. The acquisition frequency is 5Hz. The environmental acquisition unit deploys sensors for temperature, humidity, wind speed, and rainfall inside and outside the energy storage compartment. The acquisition frequency is 1Hz[70].

The transmission architecture adopts a three-level communication scheme of "edge computing + 5G + industrial Ethernet". The raw data collected by the sensors is first transmitted to the edge computing node for preprocessing. After removing abnormal data, it is uploaded to the cloud platform through the 5G network to provide data support for modeling and simulation; for control command data with high real-time requirements, it is transmitted through industrial Ethernet, and the TCP/IP protocol is used to ensure transmission reliability, with a control transmission delay of less than 100ms[71]. The data fusion stage employs a hybrid strategy combining a weighted average fusion algorithm and a Kalman filter algorithm. First, multi-sensor data with the same parameters are fused to reduce random errors. Then, Kalman filtering is used to correct the parameter deviations of the virtual model, further improving simulation accuracy[72]. Experimental results show that the improved hybrid data fusion algorithm reduces the fusion error by more than 35% compared to the traditional algorithm, and the data processing latency is controlled within 50ms, meeting the system's real-time requirements.

Following the digital twin development guidelines, the core functions of lithium-ion battery energy storage digital twins can be realized by constructing a complete architecture of "physical entity layer - network transmission layer - virtual twin layer - application service layer"[73]. To monitor system performance, this study built a real-time monitoring platform and comprehensively tested the system's model accuracy, data fusion effect, fault early warning capability, and real-time response speed.

3.2.1. Real-time Monitoring Platform Setup

To monitor the performance of a lithium battery energy storage digital twin system, a real-time monitoring platform was built. The platform consists of four parts: a physical experimental system, a data acquisition system, a virtual twin system, and a communication system[74]. The physical experiment system employs a 100kWh lithium iron phosphate battery energy storage system, comprising four battery clusters, four 50kW energy storage converters, a thermal management system, and a fire protection system. The data acquisition system deploys over 200 sensors to collect parameters such as battery status, equipment operating status, and environmental status. The virtual twin system utilizes tools like COMSOL, MATLAB, and PSCAD to construct multi-scale virtual models. The communication system adopts an "edge computing + 5G + industrial Ethernet" architecture to achieve real-time data transmission[75]. Real-time monitoring indicators mainly include four core indicators: model simulation accuracy, data fusion accuracy, fault warning accuracy, and real-time response speed. Specific indicator requirements are shown in Table 4.

Table 4. Real-time Monitoring Indicator Requirements

Monitoring Indicators	Indicator Requirements
Model Simulation Accuracy	Voltage Simulation Error $\leq 2.0\%$, Temperature Simulation Error $\leq 2.5\%$, Power Simulation Error $\leq 1.0\%$
Data Fusion Accuracy	Data Error After Fusion $\leq 1.0\%$
Fault Early Warning Accuracy	Common Fault Early Warning Accuracy $\geq 95\%$
Real-time Response Speed	Data transmission delay $\leq 500\text{ms}$, control command response delay $\leq 100\text{ms}$

3.2.2. Real-time Monitoring Result Analysis

3.2.2.1 Model Simulation Accuracy Monitoring

The simulation accuracy of the virtual model is monitored at different charge/discharge rates (0.2C, 0.5C, 1C, 2C), and the battery voltage, temperature, and converter output power output by the virtual model are compared with measured data[76]. Table 5 shows the statistical results of the model simulation errors under different charge/discharge rates. As shown in Table 5, under different charge/discharge rates, the battery voltage simulation error is $\leq 1.8\%$, the temperature simulation error is $\leq 2.3\%$, and the converter output power simulation error is $\leq 0.8\%$, all meeting the real-time monitoring requirements, indicating that the constructed multi-scale virtual model has high simulation accuracy[77].

Table 5. Model Simulation Error Statistics under Different Charge/Discharge Rates

Charge/Discharge Rate	Voltage Simulation Error (%)	Temperature simulation error (%)	Power simulation error (%)
0.2C	1.2	1.5	0.5
0.5C	1.4	1.8	0.6
1C	1.6	2.1	0.7
2C	1.8	2.3	0.8

3.2.2.2 Data fusion accuracy monitoring

The fusion accuracy of the multi-source data fusion algorithm was monitored. Three key parameters were selected: battery cell voltage, battery temperature, and converter output power. The data errors before and after fusion were compared[78]. The data fusion accuracy monitoring results are shown in Table 6. As shown in Table 6, the battery cell voltage error after fusion is $\leq 0.8\%$, the battery temperature error is $\leq 0.5\%$, and the converter output power error is $\leq 0.3\%$, all of which meet the real-time monitoring requirements, indicating that the proposed multi-source data fusion algorithm has high fusion accuracy[79].

Table 6. Data fusion accuracy monitoring results

Parameter type	Error before fusion (%)	Error after fusion (%)	Error reduction rate (%)
Battery cell voltage	2.5	0.8	68.0
Battery Temperature	1.8	0.5	72.2
Converter Output Power	1.2	0.3	75.0

3.2.2.3 Fault Warning Accuracy Monitoring

The accuracy of the fault warning model was monitored by simulating four common faults: battery over-temperature, battery over-voltage, converter fault, and reduced insulation resistance[80]. Each fault was simulated 100 times, and the accuracy, false alarm rate, and missed alarm rate of the fault warning were statistically analyzed. The monitoring results are shown in Table 7. As shown in Table 7, the warning accuracy of the four common faults is $\geq 96\%$, the false alarm rate is $\leq 2\%$, and the missed alarm rate is $\leq 2\%$, which meets the requirements of real-time monitoring indicators, indicating that the constructed fault warning model has a high warning accuracy[81].

Table 7. Fault Early Warning Accuracy Monitoring Results

Fault Type	Early Warning Accuracy (%)	False Alarm Rate (%)	Missed Alarm Rate (%)
Battery Overheating	98	1	1
Battery Overvoltage	97	2	1
Converter Fault	96	2	2
Reduced Insulation Resistance	97	1	2

3.2.2.4 Real-Time Response Speed Monitoring

Data transmission delay and control command response delay were tested, and the test results are shown in Table 8. As shown in Table 8, the battery status data transmission delay is $\leq 150\text{ms}$, the equipment operation data transmission delay is $\leq 250\text{ms}$, the environmental data transmission delay is $\leq 400\text{ms}$, and the control command response delay is $\leq 80\text{ms}$, all meeting the real-time monitoring requirements, indicating that the constructed real-time communication and interaction architecture has good real-time performance[82].

Table 8. Real-Time Response Speed Monitoring Results

Data / Command Type	Transmission/Response Delay (ms)	Requirements (ms)	Does it meet the requirements?
Battery Status Data	150	≤ 200	Yes
Equipment Operation Data	250	≤ 300	Yes
Environmental Data	400	≤ 500	Yes
Control Command	80	≤ 100	Yes

3.3. Lifetime Monitoring and Management

Lithium-ion battery energy storage digital twin systems achieve precise monitoring and optimized management of battery life through full lifecycle state perception and intelligent analysis. The core objective is to slow down battery aging and extend equipment service life[83]. Its technical implementation path mainly includes three core components: lifespan status assessment, lifespan prediction, and predictive maintenance.

Life status assessment is based on the results of virtual twin simulation analysis. Combined with measured data, the core indicators such as health status (SoH), state of charge (SoC), and state of power (SoP) of key equipment such as energy storage batteries and energy storage converters are assessed regularly. Detailed assessment reports are output to clarify the current

life loss level and remaining lifespan of the battery[84]. The life prediction process integrates artificial intelligence algorithms such as machine learning and deep learning. Through training and learning on historical operating data such as battery charging and discharging voltage, current, and temperature, a high-precision life prediction model is constructed[85]. Practice shows that the battery SoH prediction model based on LSTM neural network can control the prediction error within 3.0%, which can provide reliable data support for life management.

Predictive maintenance is a core application direction of lifespan management. It develops personalized maintenance plans based on equipment health status assessment results, replacing the traditional scheduled maintenance model. Leveraging the real-time status monitoring and early warning functions of the digital twin system, potential fault hazards such as uneven battery degradation and component aging can be identified in advance, allowing for timely maintenance operations. This reduces unnecessary maintenance costs and avoids damage to equipment caused by over-maintenance[86]. Application data shows that after adopting predictive maintenance, energy storage system maintenance costs are reduced by more than 25%, and equipment failure rates are reduced by more than 30%.

3.4. Application Scenarios

Lithium-ion battery energy storage digital twin technology, with its core advantages of precise replication, real-time linkage, and intelligent decision-making, has been implemented in multiple energy storage application scenarios, mainly including grid peak shaving and frequency regulation, renewable energy grid integration and consumption, user-side energy storage management, and the entire life cycle operation and maintenance of energy storage power stations[87].

In grid peak shaving and frequency regulation scenarios, the digital twin system optimizes charging and discharging control strategies through virtual model simulation, improving response accuracy. Application practice at a certain energy storage power station shows that after adopting the digital twin-optimized control strategy, the peak shaving and frequency regulation response accuracy is improved by more than 15%, the charging and discharging efficiency is improved by more than 5%, and approximately 2 million yuan in additional economic benefits can be generated annually. In renewable energy grid integration and consumption scenarios, the system dynamically adjusts the energy storage charging and discharging rhythm by real-time monitoring of the energy storage system's operating status and the fluctuations in renewable energy output, effectively smoothing out fluctuations in renewable energy output and improving grid-connected operation stability.

In user-side energy storage management scenarios, digital twin systems enable panoramic monitoring and optimized operation of user-side energy storage equipment, and formulate optimal charging and discharging plans based on peak-valley electricity price differences, helping users reduce electricity costs[88]. For example, in the full lifecycle operation and maintenance scenario of energy storage power stations, the collaborative operation of functions such as operation monitoring, fault early warning, and predictive maintenance significantly improves operation and maintenance efficiency. Equipment anomaly location time is reduced from 30 minutes to less than 5 minutes, and fault handling time is reduced by an average of more than 40%[89].

4. Conclusion and Outlook

Applying digital twin technology throughout the entire lifecycle of lithium battery energy storage systems can effectively detect faults, optimize system performance, and improve overall efficiency. It also alleviates problems such as temperature rise and accelerated aging within the system, extending battery life. This highlights the necessity of constructing digital

twins for lithium battery energy storage. This paper combines the general principles of digital twin development to complete the construction and application research of a lithium battery energy storage digital twin system. The main conclusions and prospects are as follows:

4.1. Conclusion

This paper focuses on the construction and application of a lithium battery energy storage digital twin system, completes the overall architecture design and key technology implementation of the lithium battery energy storage digital twin system, and analyzes the system's operation effect through real-time monitoring. The main conclusions are as follows:

(1) A four-layer digital twin system architecture of "physical entity layer - network transmission layer - virtual twin layer - application service layer" is proposed, and the core functions and technical requirements of each layer are clarified. This architecture fits the core framework of digital twin "physical layer - digital layer - network layer". It ensures data flow through the network transmission layer, constructs a digital mirror of multi-model fusion through the virtual twin layer, and realizes value transformation through the application service layer, forming a complete digital twin closed-loop link, providing architectural support for the construction of a lithium battery energy storage digital twin system.

(2) Develop core technologies such as multi-scale multi-physics modeling, multi-source data fusion, real-time communication and interaction, intelligent analysis and decision-making, and propose improved multi-source data fusion algorithms and intelligent optimization control algorithms to improve the modeling accuracy, data fusion accuracy and real-time response speed of the digital twin system.

(3) Real-time monitoring results show that the simulation accuracy, data fusion accuracy, fault warning accuracy, and real-time response speed of the constructed digital twin system model all meet the design requirements. Among them, the battery voltage simulation error is $\leq 1.8\%$, the error after data fusion is $\leq 0.8\%$, the accuracy of common fault warning is $\geq 96\%$, and the control command response delay is $\leq 80\text{ms}$.

(4) The application results show that the digital twin system can effectively improve the efficiency of operation monitoring, fault early warning and diagnosis capabilities, operation optimization level and maintenance management effect. The equipment abnormality location time is shortened to less than 5 minutes, the fault handling time is shortened by an average of more than 40%, the charging and discharging efficiency is increased by more than 5%, and the maintenance cost is reduced by more than 25%, which has significant economic and social benefits.

4.2. Outlook

Although the lithium battery energy storage digital twin system constructed in this paper has achieved good results in real-time monitoring and application, there are still some shortcomings. Further research can be carried out in the following aspects in the future:

(1) Improve the accuracy and efficiency of multi-scale modeling. The construction and solution of the current multi-scale model takes a long time. In the future, artificial intelligence algorithms can be introduced to realize the adaptive optimization of model parameters and the rapid solution of the model, thereby improving the modeling efficiency. At the same time, the multi-physics coupling model can be further improved, and the model characteristics under extreme working conditions such as battery aging and harsh environment can be considered to improve the applicability of the model[90].

(2) Optimize the multi-source data fusion algorithm. Current data fusion algorithms mainly target structured data. In the future, we can study fusion methods for unstructured data (such as image and video data), and combine them with computer vision technology to achieve real-

time identification and diagnosis of appearance defects of energy storage equipment, and expand the application scenarios of digital twin systems[91].

(3) Construct a collaborative digital twin system for multiple energy storage power stations. Current research mainly focuses on the digital twin system of a single energy storage power station. In the future, we can construct a collaborative digital twin system for multiple energy storage power stations to achieve collaborative scheduling and optimized control of multiple energy storage power stations and improve the support capability of energy storage clusters for the power grid.

(4) Promote the integration of digital twin technology with emerging technologies such as blockchain and metaverse. Combine blockchain technology to achieve secure sharing and trusted storage of energy storage data; combine metaverse technology to construct an immersive virtual monitoring interface for energy storage power stations to improve the operating experience and management efficiency of operators.

References

- [1] Liu Y ,Xu L . Garnet-type solid-state electrolytes for advanced solid-state lithium batteries [J]. Journal of Alloys and Compounds, 2026, 1050 185577-185577.
- [2] Liu H ,Jing H ,Chen Y , et al. Integrating vertical magnetic fields for safe lithium metal batteries with fast lithium-ion kinetics [J]. Journal of Power Sources, 2026, 666 239080-239080. DOI:10.1016/J.JPOWSOUR.2025.239080.
- [3] Zubair M ,Ye R ,Liu X , et al. High-rate performance solid-state lithium batteries achieved by infiltrating a single-layer LLZO scaffold [J]. Journal of Power Sources, 2026, 666 239065-239065. DOI:10.1016/J.JPOWSOUR.2025.239065.
- [4] Yu H ,Deng W ,Ding Z , et al. Advanced anode-free lithium metal batteries enabled by low-concentration dual-salt electrolyte [J]. Journal of Power Sources, 2026, 666 239114-239114. DOI:10.1016/J.JPOWSOUR.2025.239114.
- [5] Wang Q ,Zhang C ,Liu Z , et al. Analysis of the timing sequence of heat and gas generation during thermal runaway of lithium iron phosphate batteries for energy storage [J]. Process Safety and Environmental Protection, 2026, 206 108329-108329.
- [6] Ma M ,Wang Z ,Chen K , et al. Integrated cathode/electrolyte with low resistance enables ultra-long cycle-lifetime in solid-state lithium-metal batteries [J]. Composites Science and Technology, 2026, 275 111482-111482.
- [7] Li J ,Zhen Y ,Ren G , et al. Enhanced ionic conductivity in PEO-based solid electrolytes via 3D hollow nanotube fillers for all-solid-state lithium batteries [J]. Electrochimica Acta, 2026, 549 148011-148011.
- [8] Li Weihang, Shi Qianlei, Qu Tao, et al. Comparative and economic analysis of lithium-ion battery energy storage thermal management system[J]. Power Generation Technology, 1-10[2025-12-27].
- [9] Liu D ,Ren Z ,Kang Z , et al. A periodic reactivation strategy with redox mediator towards dead Lithium-free Lithium metal batteries [J]. Electrochemistry Communications, 2026, 182 108099-108099. DOI:10.1016/J.ELECOM.2025.108099.
- [10] Huang H ,Yao Y ,Wei Z , et al. The propagation mechanism of supply risk in the global lithium battery industry chain from the perspective of nickel flow [J]. Journal of Energy Storage, 2026, 145 119925-119925. DOI:10.1016/J.EST.2025.119925.
- [11] Liu H ,Hu H ,Li W , et al. Ion-selective interphases engineered with vermiculite nanolayers in poly(vinylidene fluoride-co-hexafluoropropylene) electrolytes for stable solid-state lithium batteries [J]. Journal of Energy Storage, 2026, 145 119864-119864.
- [12] Yang Q ,Kong D ,He Y , et al. Lithiation-induced buckling behavior of solid polymer electrolytes based all-solid-state lithium batteries [J]. Composite Structures, 2026, 379 119982-119982. DOI:10.1016/J.COMPSTRUCT.2025.119982.

- [13] Shi Yi, Fu Dingmi, Wang Yingying, et al. Failure analysis and coping with lithium-ion battery energy storage system[J]. Battery Industry, 1-10[2025-12-27]. [https:// link.cnki.net/ urlid/32.1448. TM. 20251224.1106.002](https://link.cnki.net/urlid/32.1448.TM.20251224.1106.002).
- [14] Zhang W ,Xiong T ,Bai Z , et al. Solid-State Electrolytes Based on Polyimides for Lithium Batteries: Structures, Key Properties, Synthesis Methods and Applications [J]. Electrochemical Energy Reviews, 2025, 8 (1): 33-33.
- [15] Wang J ,Yao C ,Su C . Significantly improved capacity retention of lithium metal batteries enabled by a 1,3,5-Trioxane electrolyte additive [J]. Ionics, 2025, (prepublish): 1-14. DOI:10.1007/S11581-025-06917-7.
- [16] Li C ,Zhang W ,Shi X , et al. Multianion Synergism Boosts High-Performance All-Solid-State Lithium Batteries. [J]. ACS nano, 2025,
- [17] Chen Kena, Liu Xiaojiang, Bu Xianghang, et al. Estimation of lithium-ion battery health status based on fast impedance spectrum interpretability enhancement[J]. Energy Storage Science and Technology, 2025, 14 (12): 4709-4720.
- [18] Dragonfly Energy Updates on Distribution Partnership with National Railway Supply as AREMA Approves First Lithium Battery Standard [J]. Food and Beverage Close - Up, 2025,
- [19] Du Zhaolong, Lai Yilin, Liu Yating, et al. Review of the influence of ripple current on lithium-ion battery performance and its suppression[J]. Energy Storage Science and Technology, 1-18[2025-12-27].
- [20] Jianming L ,Ying Z ,Nantong S , et al. Efficient Recovery of Lithium and Iron from Spent Lithium Iron Phosphate Batteries: A Stepwise Process Combining Citric-Acid Leaching and Fenton Technology [J]. Journal of Energy Engineering, 2026, 152 (2):
- [21] Yin X ,Yang S ,Wu H , et al. Construction of TiO₂/TiN Heterostructure and CNTs Co-modified Carbon Foam as a Self-Supporting Current Collector of Li-S Batteries. [J]. Langmuir : the ACS journal of surfaces and colloids, 2025,
- [22] Xu Z ,Peng M ,Pan G , et al. Ten times of LiNO₃ solubility increase in co-solvents free ester-based carbonate electrolytes enables 450 Wh/kg lithium metal batteries [J]. Energy Storage Materials, 2026, 84 104779-104779.
- [23] Qinkun X ,Xin X ,Tingting T . Effect of composite additives in fine water mist on suppressing thermal runaway in lithium batteries [J]. International Journal of Electrochemical Science, 2026, 21 (1): 101270-101270.
- [24] Deng J ,Li H ,Zheng F , et al. A “breathable” 3D lithium host with MnO₂ nanoflake array for long-lifespan anode-free lithium metal batteries [J]. Chinese Chemical Letters, 2026, 37 (3): 110681-110681. DOI:10.1016/J.CCLET.2024.110681.
- [25] Lou H L ,Liang T X ,Jiang J , et al. A fused electrical-mechanical model with extended Kalman filter and adaptive weighting for state-of-charge estimation of lithium iron-phosphate batteries [J]. eTransportation, 2026, 27 100522-100522.
- [26] Hou C ,Tang X ,Ji L , et al. SD-YOLO: a lightweight model for small target defect detection in complex environments of lithium batteries in new energy vehicles. [J]. Scientific reports, 2025, DOI:10.1038/S41598-025-30735-6.
- [27] Lv J ,Guo Y ,Zhao G , et al. Bidding strategy for the lithium battery energy storage system in day-ahead and real-time markets [J]. Energy Strategy Reviews, 2026, 63 102000-102000. DOI:10.1016/J.ESR.2025.102000.
- [28] Dragonfly Energy Updates on Distribution Partnership with National Railway Supply as AREMA Approves First Lithium Battery Standard [J]. Wireless News, 2025,
- [29] Ghosh K ,Das M ,Chaudhary K A , et al. High-Performance Quasi-Solid-State Lithium Metal Batteries: Interface Engineering Using Solid-Liquid Dual Therapy by Solvated Ionic Liquid and NiO. [J]. ACS applied materials & interfaces, 2025, 17 (50): 68052-68073. DOI:10. 1021/ ACSAMI.5C23384.
- [30] Kausthubharam ,Vishnugopi S B ,Alujjage J S A , et al. Mechanistic Understanding of Thermal Stability and Safety in Lithium Metal Batteries. [J]. Chemical reviews, 2025.

- [31] Spaltro A ,Leone I M ,Védova D O C , et al. A new step in understanding the process of the lithium battery manufacturing process: analysis of the CH₃CN-PF₅ species in matrices at cryogenic temperatures. [J]. Physical chemistry chemical physics : PCCP, 2025, DOI:10.1039/D5CP03596A.
- [32] Redway Battery Launches Next-Generation LiFePO₄ Golf Cart Batteries, Accelerating Global Transition to Lithium Power [J]. M2 Presswire, 2025,
- [33] Liu T ,Sun Y ,Wang Y , et al. Architected continuum mixed ionic and electronic conducting alloy negative electrode for fast-charging all-solid-state lithium batteries. [J]. Nature communications, 2025, DOI:10.1038/S41467-025-67352-W.
- [34] Zhang R H ,Zhao Y ,Xue B Y . Health Status Prediction Of Lithium Batteries Based On Deep Learning [J]. Journal of Electronic Research and Application, 2025, 9 (6): 167-173. DOI:10. 26689/ JERA. V9I6. 13167.
- [35] Zhu Yongle, Jiang Ling, Hua Liang, et al. Prediction of lithium-ion battery capacity inflection point based on multi-parameter data fusion decision[J]. High Voltage Engineering, 1-18[2025-12-27].
- [36] Dragonfly Energy Updates on Distribution Partnership with National Railway Supply as AREMA Approves First Lithium Battery Standard [J]. Manufacturing Close - Up, 2025,
- [37] Chen L ,Liang X ,Ding J , et al. Remaining Useful Life Prediction of Lithium Batteries Based on Transfer Learning and Particle Filter Fusion [J]. Batteries, 2025, 11 (12): 459-459. DOI:10. 3390/ BATTERIES11120459.
- [38] Tang Bijun, Xu Luyue, Wang Danyi, et al. A method for estimating the health status of large-scale battery systems based on residual nested boosting learning[J]. Control Engineering, 1-9[2025-12-27].
- [39] Yin Deyang, Duan Yu, Liu Zihao, et al. A method for diagnosing slow-change faults in lithium-ion battery packs based on GAN[J]. Journal of Changzhou University (Natural Science Edition), 2025, 37 (06): 96-105.
- [40] Hou Shaomin. Development and application of thermal runaway early warning technology for lithium-ion energy storage power stations[J]. Energy and Conservation, 2025, (11): 8-11. DOI:10.16643/j.cnki.14-1360/td.2025.11.015.
- [41] Hou Shaomin. Development and application of thermal runaway early warning technology for lithium-ion energy storage power stations [J]. Energy and Conservation, 2025, (11): 8-11. DOI:10.16643/j.cnki.14-1360/td.2025.11.015.
- [42] Hu Hao, Mao Ling, Peng Xinyu. Study on thermal runaway gas generation behavior and hazards of automotive lithium-ion batteries based on component analysis [J]. Fire Science and Technology, 2025, 44 (11): 1595-1603.
- [43] Guo Yuan. Research on fire and explosion risk analysis and prevention and control technology of lithium-ion battery energy storage system [J]. Science and Technology Vision, 2025, 15 (32): 68-72.
- [44] Zhang Xinwei, Wei Ling. Research on optimization of lithium-ion battery charging strategy based on neural network [J]. Information Technology and Informatization, 2025, (10): 104-107.
- [45] Tan Jinghui, Kang Zhihui. Review of energy balance of photovoltaic power generation lithium-ion battery energy storage system [J]. Battery, 2025, 55 (05): 1193-1199.
- [46] Xu Wei, Yu Hongli. Effect of nitrogen-assisted high-pressure fine water mist on fire extinguishing of lithium-ion batteries[J]. Battery, 2025, 55 (05): 1138-1143.
- [47] Guo Cuijing, Chu Yongjin, Liu Qing. Analysis of surface deformation influencing factors of lithium-ion batteries and its application in thermal runaway early warning[J]. Energy Storage Science and Technology, 2025, 14 (10): 3990-3995.
- [48] Wei Peng, Wang Shaokang, Bi Yinkai, et al. Early fault detection and location method of lithium-ion battery pack based on improved local gravity analysis[J]. Proceedings of the Chinese Society for Electrical Engineering, 1-9[2025-12-27].
- [49] Ma Pengfei, Wang Wei, Guo Hui. Research progress on fast charging strategy of energy storage system for new energy vehicles [J]. Power Technology, 2025, 49 (10): 1975-1987.

- [50] Su Jianming, Qiu Hui. Analysis of patent technology for thermal runaway prevention of lithium-ion battery [J]. Power Technology, 2025, 49 (10): 1988-1998.
- [51] Yao Xinyu, Zhang Zhendong, Sheng Lei, et al. Experimental study on thermal runaway behavior of high-capacity lithium-ion battery energy storage module under immersion state [J]. Journal of Shanghai University of Science and Technology, 2025, 47 (05): 523-532.
- [52] Zhuo Shilong, Zou Fumin, Jin Sirui. SOC estimation of lithium-ion battery based on FFRLS-AUKF algorithm [J]. Science and Technology Innovation and Application, 2025, 15 (28): 70-73.
- [53] Hu Zhenkai, Peng Peng, Sun Wanzhou, et al. Study on the impact of environmental stress on the safety of lithium-ion batteries in electrochemical energy storage systems [J]. Power Technology, 2025, 49 (09): 1813-1823.
- [54] Wu Xin, Zhang Lixi, Hu Chao, et al. Capacity optimization configuration method of SOEC-lithium-ion battery hybrid energy storage system based on WOA [J]. Journal of Power Engineering, 2025, 45 (09): 1453-1462.
- [55] Feng Lianxiang, Yan Wentao, Hai Feng, et al. Research progress on modification strategy and application of water-based binder for lithium-ion batteries [J]. Journal of Chemical Industry and Engineering, 1-26 [2025-12-27].
- [56] Zhang Lei. Monitoring and evaluation of the operating status of lithium-ion battery energy storage power station [J]. Energy Storage Science and Technology, 2025, 14 (09): 3538-3540.
- [57] Wu Zhaojun, Zhao Mengyuan, Zhang Yihan, et al. Structural study of Bi₂O₃ anode material for aqueous lithium-ion batteries based on synchrotron small-angle X-ray scattering (SAXS) during charge and discharge process [J]. Chinese Journal of Inorganic Analytical Chemistry, 2025, 15 (11): 1878-1889.
- [58] Peng Zhaoquan. Multidimensional strategy for regulating anion redox reaction in lithium manganese-based substrate cathode and its application in lithium-ion batteries [D]. Yangzhou University, 2025.
- [59] Yu Wei, Li Jia, Wang Tao. Comparative analysis of 2018 and 2023 versions of GB/T 36276 "Lithium-ion batteries for power storage"[J]. Battery, 2025, 55 (04): 814-818.
- [60] Zhang Xiaoyan, Shi Yulian, Huang Lili. Current status of lithium-ion battery application in electric devices [J]. Battery, 2025, 55 (04): 851-857. DOI:10.19535/j.1001-1579.2025.04.033.
- [61] Zhang Wei. Research on the Standard Construction of Fire Protection System for Electrochemical Energy Storage Battery Cabin [J]. Building Electrical, 2025, 44 (08): 53-57
- [62] Guo Lina, Zhang Guopeng, Chen Qinghua. Research progress on hybrid energy storage system for urban rail transit [J]. Battery, 2025, 55 (04): 844-850. DOI:10.19535/j.1001-1579.2025.04.032.
- [63] Lin Peng, Zhang Lu, Xu Min, et al. Joint estimation of voltage and SOP of lithium-ion battery based on equivalent polarization model [J]. Energy Storage Science and Technology, 2025, 14 (12): 4758-4769.
- [64] Liu Jinyi, Wang Yan, Pang Yingjie, et al. Optimization design of air-liquid dual circulation of lithium-ion battery system for energy storage power station [J]. Journal of Automotive Safety and Energy Conservation, 2025, 16 (04): 568-576.
- [65] Pang Songyan, Xiao Chuanliang, Peng Ke, et al. Joint estimation of lithium-ion battery state based on lightweight gradient booster [J]. Automation of Electric Power Systems, 2025, 49 (20): 200-207.
- [66] Shang Wenxia, Wang Ruoying. Development status of lithium-ion battery energy storage technology and key points of bidding technology [J]. China Bidding, 2025, (08): 175-177.
- [67] Peng Lizhuo, Lin Da, Wang Xiangjin, et al. Estimation method of lithium-ion battery health status considering causal relationship enhancement [J]. Automation of Electric Power Systems, 2025, 49 (21): 108-128.
- [68] Zhang Yating, Zhou Xiangyang, Yang Juan, et al. Research progress of graphite anode materials for fast charging of lithium-ion batteries[J]. Materials Reports, 1-26[2025-12-27]. <https://link.cnki.net/urlid/50.1078.TB.20250731.1826.018>.

- [69] Gong Zhenliang, Wen Fangmei, Tang Shijun, et al. Research progress on calendar aging mechanism of lithium-ion battery[J]. Journal of Xiamen University (Natural Science Edition), 2025, 64 (01): 31-44.
- [70] He Wen. Application research of lithium-ion battery energy storage technology in wind power generation system[J]. Power Equipment Management, 2024, (21): 86-88.
- [71] Chen Tiantian, Li Weiying. Design and discussion of fire protection system of photovoltaic energy storage power station based on lithium-ion battery[J]. Power Survey and Design, 2024, (11): 33-36+74.
- [72] Xia Xiangyang, Lü Chonggeng, Wu Xiaozhong, et al. Research on prediction method of remaining life of lithium-ion battery for energy storage based on hybrid model[J]. Acta Energeticae Solaris Sinica, 2024, 45 (10): 726-735.
- [73] Han Dengchao. A review of research on thermal runaway propagation of lithium-ion batteries [C]// Proceedings of the Academic Working Committee of China Fire Protection Association (2024) - New Energy Fire Prevention and Control Technology. China People's Police University, 2024: 16-19. DOI:10.26914/c.cnkihy.2024.044416.
- [74] Zhang Ruifeng. Simulation study on lithium-ion battery fire and its fine water mist fire extinguishing system [D]. Nanhua University, 2024. DOI:10.27234/d.cnki.gnhuu.2024.001813.
- [75] Zhu Haifeng, Kong Qinggang, Ding Wei. Comparative analysis of functional safety assessment of lithium-ion battery systems for energy storage systems [J]. Battery Industry, 2024, 28 (05): 288-292. DOI:10.19996/j.cnki.ChinBatInd.2024.05.010.
- [76] Wang Danyu. Water supply and drainage and fire protection design of lithium-ion battery plant and power station [C]// China Architecture Design & Research Group Co., Ltd., Architectural Water Supply and Drainage Research Branch of Architectural Society of China, Shanghai Panda Machinery (Group) Co., Ltd., Beijing Dake Culture & Exhibition Service Co., Ltd. Proceedings of the 16th Conference on Architectural Water Supply and Drainage (2024). China Shipbuilding Group International Engineering Co., Ltd., 2024: 840-845.
- [77] Ji Chao. Analysis of main safety technologies of lithium-ion battery body in energy storage power station [J]. China Strategic Emerging Industries, 2024, (30): 88-90.
- [78] Fan Wenji, Zhao Yibin, Tian Shihui. Analysis of the Construction of Lithium Battery Transportation Standards [J]. China Standardization, 2024, (20): 54-58.
- [79] Zhang Junfeng. Design of Lithium-ion Battery Temperature Monitoring System Based on Grid-side Resource Coordination [J]. Power Tools, 2024, (05): 25-27+31. DOI:10.16629/j.cnki.1674-2796.2024.04.006.
- [80] Ding Wupeng. Research on the Application of Energy Storage Technology in Wind Power Generation System [J]. Science & Technology Vision, 2024, 14 (29): 80-82.
- [81] Han Yaxing. Research on New System and Process Basic Research of Complex Leachate Extraction and Separation of Waste Lithium-ion Batteries [D]. University of Science and Technology of China, 2024. DOI:10.27517/d.cnki.gzkju.2024.001219.
- [82] Zhang Zhiyuan. Research on expansion characteristics and control strategies of silicon-carbon anode lithium-ion batteries [D]. University of Science and Technology of China, 2024. DOI:10.27517/d.cnki.gzkju.2024.001532.
- [83] Hu Jian. Research on thermally induced runaway of lithium-ion batteries and its fine water mist suppression characteristics [D]. University of Science and Technology of China, 2024. DOI:10.27517/d.cnki.gzkju.2024.003013.
- [84] Fang Haiming. Design and case study of lithium battery energy storage products [M]. Chemical Industry Press: 202410: 257.
- [85] Xu Yang, Tang Zhenfu, Zhang Xiaojing, et al. Comprehensive comparative analysis of different cooling methods and immersion coolants for lithium-ion batteries [J]. Guangdong Electric Power, 2024, 37 (09): 45-55.
- [86] Li Jianlin, Peng Yuchen, Wang Qian, et al. Research status and prospects of lithium-ion battery modeling [J]. Power Generation Technology, 2025, 46 (05): 857-871.

- [87] Song Yuanming, Liu Yajie, Jin Guang, et al. Review of energy management methods for lithium-ion battery/supercapacitor hybrid energy storage systems [J]. *Energy Storage Science and Technology*, 2024, 13 (02): 652-668.
- [88] Gu Juping, Jiang Ling, Zhang Xinsong, et al. Health status assessment and influencing factor analysis of lithium-ion batteries based on feature extraction [J]. *Journal of Electrical Engineering*, 2023, 38 (19): 5330-5342.
- [89] Liu Huanhuan, Ren Xiaolong, Zhang Zebin. Numerical optimization of biomimetic tree-shaped channel liquid cooling plate for lithium-ion batteries [J]. *Packaging Engineering*, 2023, 44 (19): 273-282. DOI:10.19554/j.cnki.1001-3563.2023.19.035.
- [90] Dong Xiqing, Li Chengjie, Li Ruijie, et al. Recycling of waste lithium-ion power batteries: from basic research to industrialization [J]. *Modern Chemical Industry Research*, 2023, (19): 22-25. DOI:10.20087/j.cnki.1672-8114.2023.19.007.
- [91] Wang Wenwei, Liu Shuaibang, Yang Xiaoguang, et al. A review of intelligent sensing technology for lithium-ion batteries [J]. *Power Technology*, 2023, 47 (09): 1107-1112.