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Digital twins for battery health prognosis: A comprehensive review of recent advances and challenges

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ABSTRACT

This review systematically examines the integration of Digital Twin (DT) technology with lithium-ion battery health prognosis systems. As electrification accelerates across multiple domains, accurate prediction of battery health indicators – including State of Charge (SOC), State of Health (SOH), Remaining Useful Life (RUL), and fault conditions – becomes increasingly critical for ensuring safety, reliability, and optimal performance. The core contribution of this review lies in proposing a novel four-layer conceptual framework, comprising the Physical, Data & Communication, Virtual Model, and Twin Service layers, as an analytical tool for structuring the field. After establishing the theoretical foundations of DTs and battery aging, we leverage this framework to systematically survey recent advancements in data augmentation, online state estimation, and fault diagnosis. Through this structured analysis, we then identify critical implementation challenges, including performance in extreme degradation phases, battery pack inconsistencies, and operation under complex conditions. We conclude by proposing future research directions focused on enhancing model generalization and creating standardized architectures through the integration of cloud computing and IoT technologies, and applying federated learning to solve potential privacy and security problems. This review serves as a critical reference by providing a structured, application-centric understanding of DTs in battery health management.

1. Introduction

Lithium-ion batteries (LIBs) have become indispensable in a wide range of applications [1], including electric vehicles (EVs) [2], portable electronics, renewable energy [3], and grid-level energy storage systems [4]. Their high energy density, relatively long cycle life, and low self-discharge rate make them a preferred power source for many modern technologies [5–8]. However, as electrification and large-scale energy storage solutions become more prevalent, the safety, reliability, and lifetime of LIBs demand careful attention. Accurate prediction of battery health – encompassing State of Charge (SOC) [8,9], State of Health (SOH) [10,11], Remaining Useful Life (RUL) [12], and potential faults [13] – plays a pivotal role in ensuring that batteries operate within safe limits, maintain optimal performance, and avoid catastrophic failures such as thermal runaway [14,15].

Despite extensive research in battery modeling and on-board Battery Management Systems (BMSs), accurately predicting the health and fault conditions of battery systems remains a formidable challenge. Traditional methods for estimating SOC, SOH, RUL, and detecting faults are typically divided into model-based and data-driven approaches [16–19]. Model-based methods, such as equivalent circuit models [20–22] and electrochemical models [23,24], depend on predefined mathematical representations to simulate battery behavior. However, these methods often struggle to encapsulate the complex, nonlinear, and time-varying degradation processes, particularly under dynamic operating conditions like fast charging, abrupt load changes, or temperature fluctuations. Their reliance on fixed parameters limits their adaptability and parameter correction over the battery's lifespan, reducing their effectiveness in real-world scenarios. Conversely, data-driven methods, including machine learning and statistical techniques, exploit historical data to predict battery states [25–27] but require extensive, high-quality datasets [28–30] that are challenging to acquire due to inconsistent usage patterns and scarce labeled data [31]. These approaches also suffer from limited interpretability, obscuring the physical mechanisms driving degradation. Compounding these issues, most conventional BMSs operate on resource-constrained microcontrollers, employing simplified algorithms that compromise accuracy and offer minimal fault diagnosis capabilities [32,33]. Collectively, these limitations highlight the need for more advanced and flexible solutions to better address the complexities of battery health prognosis.

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The concept of Digital Twins (DTs) offers a promising solution to these challenges. First conceived by Michael Grieves in 2002 [34] and later refined by NASA in 2012, DTs are broadly understood as real-time, synchronized virtual representations of physical systems. Leveraging advanced modeling, sensor fusion, big data analytics, and cloud-based computational resources, a DT enables continuous monitoring, diagnostic analysis, and predictive prognosis of its physical counterpart. Recent studies have highlighted the capability of DTs to enhance system efficiency in numerous domains, including mechanical manufacturing [35], structural health monitoring [36], energy optimization [37,38], and smart city planning [39,40].

For lithium-ion batteries, DTs provide distinct advantages over conventional approaches. By fusing physics-based and data-driven techniques within a coherent structure, DTs enhance the robustness and accuracy of health predictions while preserving interpretability—addressing the opacity of purely data-driven models. Real-time sensor data enable DTs to dynamically update and correct model parameters, offering superior adaptability to evolving battery conditions compared to static model-based methods. Additionally, DTs leverage richer data management and augmentation strategies, such as synthetic data generation [41,42] and transfer learning [43,44], to mitigate the data scarcity and variability that hinder standalone data-driven approaches. Harnessing cloud-based computational resources, DTs can process large datasets and execute complex algorithms infeasible on traditional BMS hardware, significantly improving the precision and scope of battery health management [32,45].

Although extensive research exists on battery modeling and DT technology, a significant gap persists in the literature concerning a structured application framework for battery health prognosis. Existing reviews [32,46] provide a broad overview but often lack a focused examination of specific health indicators within a unified DT architecture. To address this, as a primary contribution, this review introduces a novel four-layer DT architecture as an analytical tool to classify and evaluate current technologies. Specifically, we aim to (i) propose and detail this conceptual framework for battery DTs, (ii) systematically analyze state-of-the-art methodologies for health prediction and fault diagnosis within this framework, including data augmentation and online estimation, and (iii) identify research gaps and propose future directions to enhance the robustness and applicability of DTs in battery health prognosis.

In this paper, we present a structured review of DT technologies tailored for lithium-ion battery health prognosis. We begin by introducing our proposed conceptual framework for battery DTs (Section 2). Next, we discuss the aging mechanisms of LIBs and examine existing detection methodologies (Section 3). We then leverage our framework to analyze the integration of DTs with battery health prognosis (Section 4), examining each layer's contribution, from the foundational Physical Layer and the data-centric operations in the Data & Communication Layer to the core modeling engine in the Virtual Model Layer. This is followed by a detailed review of the applications delivered by the Twin Service Layer, including advancements in online estimation and fault diagnosis. Finally, we summarize major challenges and prospective areas of research (Section 5) before drawing our overall conclusions. We believe this review will serve as a critical reference for researchers and industry practitioners, offering clear insights into how DTs can revolutionize battery health management.

2. Digital twins

This section establishes foundational knowledge of DTs, including basic definitions, evolutionary developments, and practical applications. Furthermore, a four-layer conceptual framework of battery digital twin will be clarified. This framework serves as the basis for discussion in subsequent sections.

2.1. Conceptual evolution and primary applications of digital twins

DTs have emerged as a focal point in frontier domains with the advent of the informational and intelligent era. First conceptualized by Michael Grieves in 2002 [34], a DT was initially described as a digital construct that mirrors a physical system. In 2012, NASA provided a more precise definition, describing DTs as simulations that integrate multiple physical models, sensor data, and historical datasets to monitor or predict the behavior of real-world systems. Since then, DTs have evolved with the integration of other computer-aided technologies, such as the Internet of Things (IoT), CAD, and CAE, and are now defined as real-time, synchronized virtual representations of products, processes, or environments. Table 1 reveals different definitions of DTs during each stage.

Nowadays, DTs are widely used in design, manufacturing, and service phases of various domains gradually, due to their ability to assist in system adjustment, diagnostics, lifetime prediction, and defect detection. They provide iterative improvements in design processes, production efficiency, and asset management. For instance, in mechanical manufacturing and industrial designing domain, Fang et al. [35] proposed a DT-driven intelligent gear surface degradation assessment method. They constructed a DT using a dynamic model and compared it with a real-world gear system to update parameters, enabling precise, non-destructive assessment of surface degradation severity. Moreover, according to recent research on energy management, Li et al. [51] introduced a new DT framework based on a backpropagation neural network (BPNN) to predict lithium-ion battery discharge voltage curves and assess real-time battery capacity and degradation using a CNN-LSTM-Attention-based model. Pooyandeh and Sohn [38] created a complex DT system for EV BMS, enabling comprehensive prediction of battery SOH, SOC, and thermal variation. Other applications of DTs are posed in Fig. 1.

While DTs are increasingly vital across diverse modern industrial productions and scientific research, this paper specially focuses on their construction, optimization, and utilization for lithium-ion battery and BMS.

2.2. A conceptual framework for battery digital twins

Applying the broad concept of a Digital Twin to the specific and complex domain of battery systems necessitates a structured framework. To provide a systematic perspective for analyzing the role of DTs in battery health prognosis, we propose a conceptual four-layer architecture, as illustrated in Fig. 2. This framework deconstructs the complex DT system into distinct, interconnected levels. At the base is the Physical Layer, which comprises the actual lithium-ion battery pack, its cells, and the embedded sensors (e.g., for voltage, current, temperature) that capture real-world operational data via the Battery Management System (BMS). The second level is the Data and Communication Layer, which serves as the nervous system connecting the physical and virtual worlds. This layer is responsible for data acquisition, secure and low-latency transmission (e.g., via CAN or cloud gateways [45]), pre-processing, and crucially, data augmentation techniques to enrich sparse or incomplete datasets. Above this sits the Virtual Model Layer, the core of the digital twin. It hosts a suite of models (from high-fidelity electrochemical models to computationally efficient equivalent circuit models and data-driven algorithms, e.g., LSTMs, CNNs) that create a synchronized, high-fidelity virtual representation of the battery's state and aging behavior [32]. Finally, the Twin Service Layer leverages the insights from the virtual model to deliver actionable applications. These services include the real-time estimation of key health indicators (SOC, SOH, RUL), advanced fault diagnosis and prognosis, and optimization strategies for charging and thermal management [46]. This layered architecture provides a clear roadmap for developing, integrating, and evaluating battery DT systems, and serves as the analytical lens for this review.

Table 1
Variation of definitions about digital twins.

Authors	Time	Definitions of digital twins
Michael Grieves	2002	A digital informational construct about a physical system could be created as an entity on its own.
NASA	2012	Simulations that integrate multiple physical models, sensor data, and historical datasets to monitor or predict the behavior of real-world systems.
Michael Grieves John Vickers	2017	A set of virtual information constructs that fully describes a potential or actual physical manufactured product from the micro atomic level to the macro geometrical level.
Georg Goldenits et al. [47]	2024	Digital Twins replicate a real entity in a virtual representation and allow for simulating and optimizing tasks and events supported by machine learning models.
Ye Yiming et al. [48]	2024	Digital twin is a digital representation or model of a physical object, system, or process. It is designed to simulate the behavior and performance of the real-world counterpart, integrating real-time data from sensors and IoT devices.
Fu Xiangfu et al. [49]	2025	The digital twin concept centers on constructing a virtual model to analyze a physical entity's state and inform decision-making, facilitating real-time interaction between physical and virtual spaces.
Luo Junjie et al. [50]	2025	A digital twin includes the detailed replication and virtual representation of objective physical entities, thereby facilitating the establishment of a mirrored mapping relationship between the virtual and the physical.

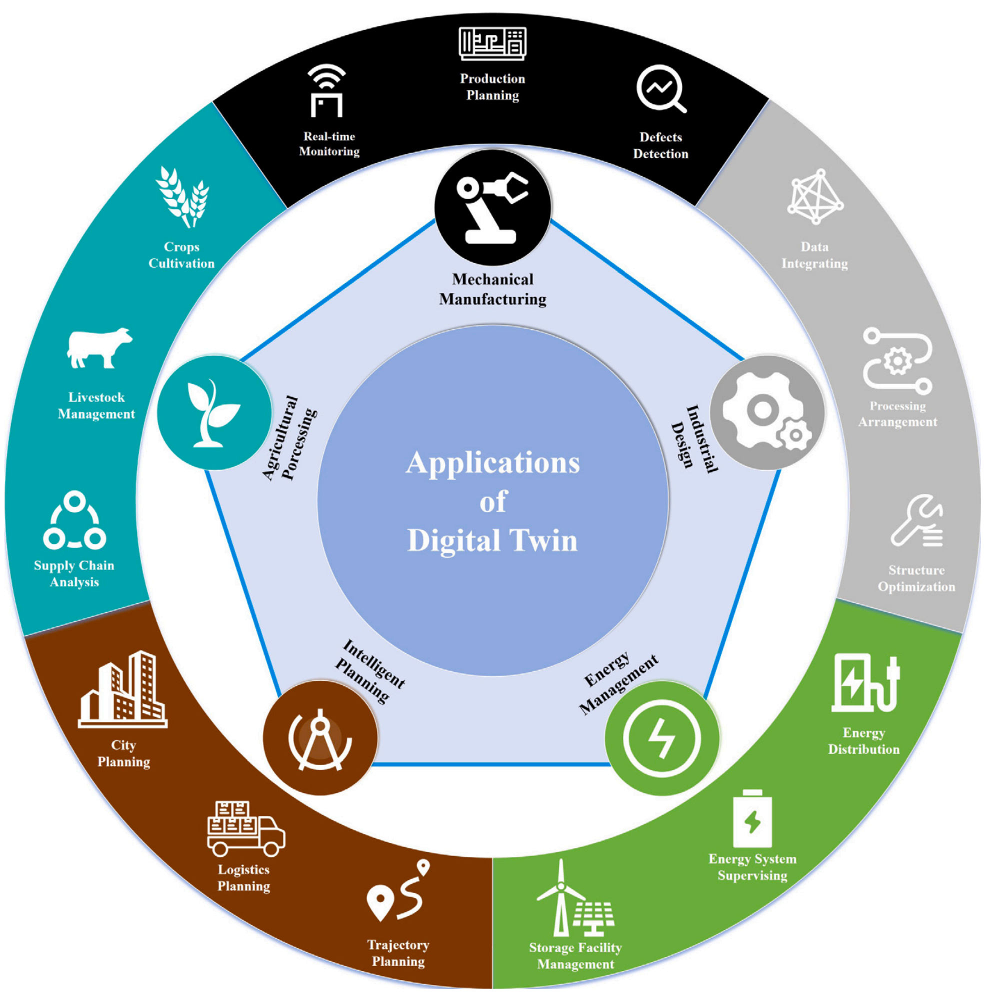

Fig. 1. Applications of Digital Twins in different domains.

2.3. Strengths and challenges of battery digital twins

The primary strength of the Digital Twin paradigm lies in its capacity to create a holistic, dynamic, and data-driven representation of a physical asset. For battery systems, this enables a shift from static, offline analysis to continuous, real-time health prognosis. By synergizing multi-physics models within the Virtual Model Layer with live data streams from the Physical Layer, a DT can capture complex, nonlinear

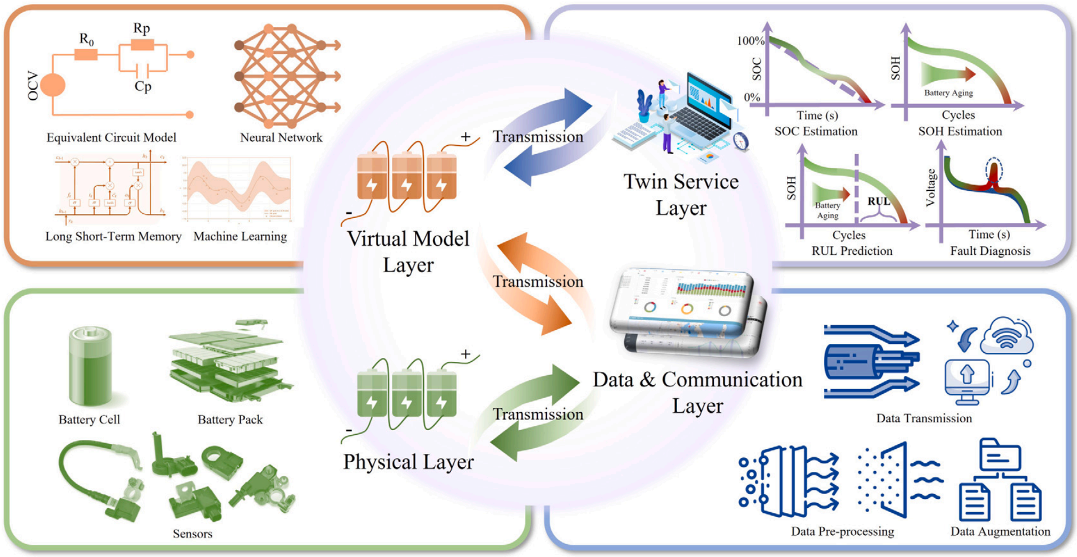

Fig. 2. The proposed four-layer conceptual framework for a battery Digital Twin system, consisting of the Physical, Data & Communication, Virtual Model, and Twin Service layers.

aging phenomena that traditional models often miss. This integrated approach facilitates superior predictive accuracy for battery health indicators, enables preemptive fault detection, and provides a platform within the Twin Service Layer for optimizing operational strategies like fast charging and thermal management, thereby maximizing both performance and lifespan.

However, the practical implementation of battery DTs faces significant hurdles that can be contextualized within the proposed four-layer architecture. A fundamental challenge originates at the Physical Layer: the cost, stability, and placement of sensors. Insufficient or noisy data can compromise the entire twin's accuracy. In the Data & Communication Layer, ensuring real-time, low-latency synchronization between the physical battery and its virtual counterpart is non-trivial, especially for large, distributed battery fleets connected via cloud–edge infrastructure. Additionally, data pre-processing technologies and procedures in this layer remain vague. Finally, data security vulnerabilities are critical concerns that must be addressed. The greatest technical complexity often resides in the Virtual Model Layer. A persistent challenge is the trade-off between model fidelity and computational feasibility. High-fidelity electrochemical models offer deep physical insight but are often too computationally intensive for real-time applications, while purely data-driven models may lack interpretability and struggle to generalize to unseen operating conditions. Furthermore, the lack of robust optimization algorithms for model validation and reparametrisation, contributes to an obstacle in maintaining the twin's accuracy over the battery's entire lifecycle. In the Twin Service Layer, the absence of health prediction accuracy and insufficient model information interpretation, both represent significant impediments to profound advancement and development of battery DTs. Addressing layer-specific and systemic challenges mentioned above, is essential for realizing the full potential of DTs in industrial battery management systems.

3. Battery health prognosis

Battery health prognosis aims to ensure the long-term sustainability, reliability, and safety of battery-powered systems. It is generally divided into two main areas: battery health prediction and battery fault diagnosis. Battery health prediction concentrates on forecasting the degradation trajectory of the battery over time. This involves modeling the aging mechanisms and estimating future performance metrics such as capacity fade or internal resistance increase. Battery fault diagnosis, on the other hand, focuses on the early detection, identification, and classification of abnormal conditions or failures within the battery system. These faults can include issues such as internal short circuits, thermal runaway risks, electrode material degradation, or sensor malfunctions.

3.1. Identifying degradation pathways in Lithium-ion batteries

Digital twins often serve to provide the diagnosis of the health prediction of batteries. There are several advantages to applying digital twins for battery aging mechanism diagnosis, such as:

(1) Proactive Battery Maintenance: Early identification of aging signs allows for timely interventions, reducing the risk of unexpected failures. Proactive maintenance strategies can significantly lower costs compared to reactive replacements [52].
(2) Advancing Battery Safety Measures: Aging can lead to thermal instability or mechanical failure, increasing the risk of fire or explosion. Effective aging detection helps mitigate risks of thermal runaway and catastrophic failures [15].
(3) Battery Recycle and Sustainability: Accurate aging detection facilitates efficient recycling and supports the development of second-life applications for partially aged batteries, reducing waste and environmental impact [53].
(4) Economy Efficiency and Optimization: By understanding the aging mechanism, operational strategies to avoid reducing battery lifespan such as a smarter battery management system can be designed [54].

Battery aging detection methods can be broadly categorized into invasive and non-invasive approaches [55]. Invasive methods involve disassembling or directly intervening with the battery to assess its internal physical and chemical properties, providing insights into aging and performance degradation. On the other hand, non-invasive methods do not require battery cell modifications and major add-ons in a system [56]. Instead, it evaluates aging and performance degradation by analyzing external signals or characteristics of the battery. This literature review will focus on non-invasive methods, as they are more practical and widely applicable.

3.1.1. Invasive characterization of aging mechanisms

The most direct invasive aging diagnosis methods utilize techniques like X-ray analysis [57]. X-ray technology is employed both during electrical activation and after the usage phase to analyze the relationship between electrical characteristics and the actual physical state [58]. X-ray tomographic microscopy enables precise examination of microstructural morphology and the distribution of individual coating components, including active materials, binders, and etc [59]. The research by [59] used segmentation of X-ray tomographic microscopy images of graphite-silicon composite electrodes to perform a statistically significant analysis of the microstructural evolution within the carbon black and binder domain during battery operation, providing information on the aging mechanism. Research [60] proposes an X-ray computed tomography to visualize and quantify the morphological degradations of Si-based electrodes from the microscale, which includes the SEI layer growth, formation of gas, and consumption of electrolyte. Research by [61] reveals the strong impact of particles, specifically the species distribution for zinc–oxygen batteries with X-ray tomography. While these methods enable direct observation of battery material degradation, they typically require dismantling the battery, causing irreversible damage and rendering it unusable. Additionally, applying invasive X-ray methods can harm the battery cell and result in beam-induced damage [62]. As a result, non-invasive methods have gained considerable attention from researchers as effective approaches to studying and quantifying battery aging mechanisms.

3.1.2. Non-invasive characterization of aging mechanisms

Non-invasive aging mechanism diagnosis is valuable for evaluating battery degradation by analyzing external signals such as voltage, current, temperature, and impedance. This method provides insights into battery health without causing harm to the battery itself. It is particularly beneficial for BMSs, as it allows for continuous monitoring, early detection of performance degradation, and timely interventions without interrupting the battery's use [63]. Non-invasive aging mechanism detection methods are broadly classified into model-based and data-driven approaches, which together form a preliminary framework resembling a digital twin of the battery for diagnostic purposes. Model-based methods utilize physical or equivalent models, such as electrochemical impedance spectroscopy (EIS) [64,65] or equivalent circuit models (ECM) [66,67], to analyze external signals. In contrast, data-driven approaches employ machine learning or statistical techniques to identify patterns and predict aging behavior from large datasets [68].

The recent advancement of model-based methods includes enhancing the EIS, ECM, and physics-based models. Research by [69] proposed an innovative migration-based macro–micro SOH prediction method for LIBs, enabling a systematic, non-invasive, and quantitative assessment of aging mechanisms and life prediction using reduced-order physics-based models. Research [70] proposed a non-invasive equation-based analysis framework, grounded in failure modes, for measuring battery data to identify battery failures and aging mechanisms. Research by [71] identified two major degradation modes, Loss of Active Material (LAM) and Loss of Lithium-ion Inventory (LLI), demonstrated through differential voltage and incremental capacity analysis under varying temperatures. Generally, the current model-based methods focus on enhancing the model description and proposing a hybrid model to improve battery applications. Model-based methods are favored over data-driven approaches for their reliability in describing process dynamics with a solid physical understanding. However, their dependence on physical foundations can become a limitation when dealing with complex systems [72].

Recent advancements in data-driven methods emphasize improving mathematical algorithms to enhance real-world battery health prognosis. Research by [73] integrates convolutional neural networks with transformer networks to develop a model for real-world battery pack health degradation. Research by [74] assessed the prediction accuracy of nonlinear autoregressive with external input (NARX) recurrent neural networks (RNN) and time delay neural networks (TDNN) for SOH prediction using the NASA dataset. Research [75] integrates a fusion-based selection method with Gaussian Process Regression (GPR) and noise reduction techniques for battery SOH estimation. Research [76] proposed a novel physics-informed machine learning approach that integrates a physics-based model with a long short-term memory (LSTM) network for online degradation modeling and RUL prediction. These approaches collectively represent essential components toward realizing battery digital twins, as they enable accurate health state prediction, uncertainty quantification, and physics-data fusion. Nonetheless, purely data-driven models require extensive, high-quality data for effective training, highlighting the importance of DT formation strategies and data augmentation techniques to bridge this gap.

3.2. Battery health prediction indicators

A battery's health generally reflects its effectiveness, measured by its ability to deliver voltage and current over time compared to a new battery. To ensure equipment operates safely, the battery management system must deliver accurate information about the battery's status, including its state of charge (SOC), state of health (SOH), and remaining useful life (RUL). SOH estimation targets short-term predictions of capacity or internal resistance; therefore, it is usually calculated based on the battery capacity of internal resistance. In contrast, RUL derived from the end of live (EOL), offers a long-term forecast of the battery's remaining useful life, indicating how many cycles it can complete before performance degradation leads to potential failure. The degradation trajectory offers a more detailed perspective, tracking changes in parameters such as cycle count, capacity, and resistance, thus enabling more comprehensive battery management. Fig. 3 illustrates the roles of each component in battery health prognostics.

3.2.1. State of charge

Knowing a battery's actual SOC is essential for its proper use, as it helps prevent harmful operating conditions, such as overcharging, that can damage the battery [78]. SOC is typically defined as the ratio of the actually available charge in a battery to the maximum charge it can deliver after 100% full charging cycles [79]. The battery SOC at time t, SOC_t can be calculated by coulomb counting as shown in Eq. (1) below [80]:

$$SOC_t = SOC_{t-1} + \frac{I(t) * \Delta t}{Q} \tag{1}$$

where $I(t)$ represents the battery current in ampere, Q represent the battery capacity in the current time step t.

3.2.2. State of health

Battery SOH is defined as a criterion to make a statement about the performance, capacity, and loss of power [81]. Generally, the SOH calculation is formulated by the battery capacity, using the charging data as Eq. (2) below:

$$SOH_C = \frac{Q_c}{Q_{new}} \tag{2}$$

where Q_c represents the current capacity in cycle c, and Q_{new} is the rated capacity. This is the most commonly used method for estimating SOH_c battery SOH based on capacity; however, it has several limitations. Capacity-based SOH estimation overlooks the impact of battery degradation caused by increasing internal resistance. Additionally, real-world data may lack complete or detailed charging profiles necessary for accurate SOH estimation.

Researchers are also focusing on developing suitable SOH estimation for their application to overcome the limitations of traditional SOH estimation. Research by [82] establishes the SOH model based on ohmic internal resistance and capacity fade as shown as Eq. (3)

$$SOH_R = \frac{R_{eol} - R_{cur}}{R_{eol} - R_{new}} \tag{3}$$

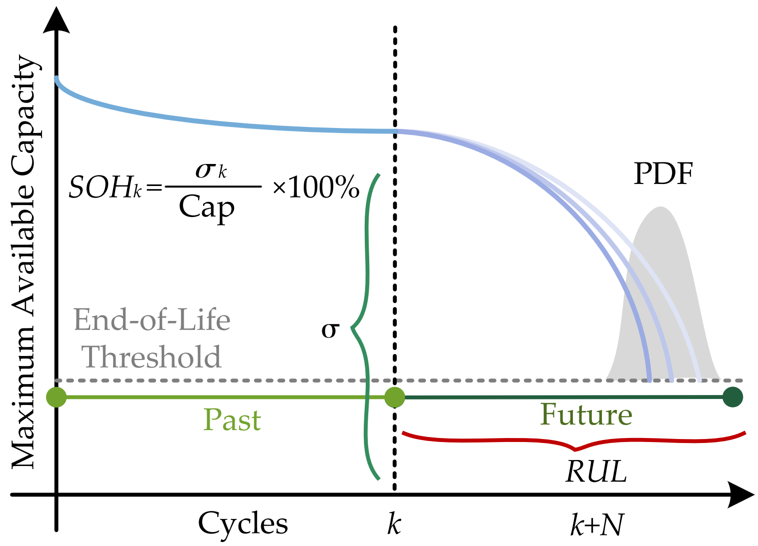

Fig. 3. Battery Health Prediction Indicators. In the figure, k is the time period used for SOH_k, where $k+N$ is the future long-term period where RUL is applied [77].

where SOH_r is the battery SOH based on internal resistance, R_{eol} is the ohmic internal resistance at the end of its lifetime, R_{cur} is the current ohmic internal resistance and R_{new} is the ohmic internal resistance when the battery is new. This method presented a mathematical explanation of the battery SOH degradation model based on internal resistance, however, the calculation of R_{eol} ohmic internal resistance at the end of its lifetime is difficult. Research by [83] introduced an attenuation SOH model that incorporates monthly average temperature and mileage, making it applicable to real-world EVs. However, this method relies on comprehensive data for effective SOH model development, including detailed mileage and temperature information. Research by [73] proposed a SOH model that uses charging energy delivered to estimate real-world EV SOH, relying only on minimal charging profile data.

3.2.3. Remaining useful life

RUL is defined as the number of remaining cycles during which a lithium-ion battery is expected to operate reliably while minimizing the risk of catastrophic failure [84]. Accurately predicting the RUL is crucial for ensuring the safety and reliability of lithium-ion batteries, offering valuable guidance for maintenance planning [85]. While SOH estimation primarily relies on historical performance data and predefined end-of-life criteria. Remaining Useful Life (RUL) estimation is concerned with forecasting future battery behavior and supporting proactive health management strategies. The calculation of RUL can be quantified as :

$$RUL = n_{EOL} - n \tag{4}$$

where n is the number of current cycles and n_{EOL} is the cycle which the battery reaches failure. RUL estimation has several strengths compared with the SOH estimation:

(1) Predictive Maintenance: RUL estimation forecasts the future operational lifespan of a battery, enabling proactive maintenance and reducing unexpected failures.
(2) Operational Planning: RUL predictions offer critical insights for scheduling battery replacements and optimizing lifecycle cost management, facilitating informed decision-making in battery management systems [86].

3.3. Nature of aging mechanism

The main components of a lithium-ion battery (LIB) are the cathode, anode, electrolyte, and separator [87]. The cathode is usually made of transition metal oxides or phosphates, while the anode consists of materials like graphite or silicon. The electrolyte, which enables ion transport, can be an organic liquid or a solid-state material. The separator serves as a barrier between the cathode and anode, preventing short circuits. The performance of LIBs inevitably declines over time due to aging and degradation. Although LIB aging is a complex process influenced by various factors, it generally manifests in two key phenomena: capacity loss and power fade [77].

Capacity fade refers to the gradual decline in a battery's ability to store and deliver energy over time, reducing the total runtime available for use [88]. This is typically caused by processes such as loss of lithium inventory (LLI) and loss of active material (LAM), primarily at the negative electrode [89]. LLI loss refers to the depletion of active lithium ions that can no longer participate in the battery's cycling process. This loss is often caused by parasitic side reactions, including surface film formation, decomposition reactions, lithium plating, and other similar mechanisms. LAM involves the structural degradation or loss of usable anode or cathode material. Contributing factors may include the growth of surface layers on electrodes or cracks induced by repeated cycling. LAM impacts the battery's performance by contributing to both capacity reduction and power fade [90].

Power fade, on the other hand, signifies a reduction in the battery's ability to supply energy quickly, impacting its performance under high-power demands [91]. Power fade is often attributed to increased internal resistance, SEI layer growth, and conductivity loss (CL). CL is associated with the corrosion of the current collector and the decomposition of the binder during battery operation [92]. This rise in resistance negatively impacts the battery's ability to deliver power efficiently, especially under high-load conditions. Together, these degradations affect the battery's overall functionality and efficiency as shown in Fig. 4.

3.4. Battery health fault diagnosis

During the operation of lithium-ion batteries (LIBs), various faults may occur, compromising both battery health sustainability and vehicle safety. From a control perspective, battery fault models can be categorized into battery faults, sensor faults, and actuator faults [13]. Battery

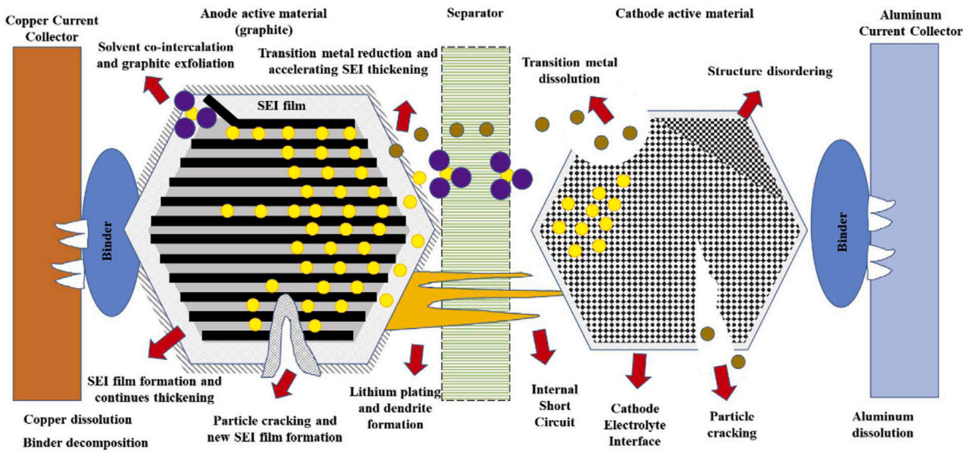

Fig. 4. Internal aging mechanism of a lithium-ion battery [93].

faults arise from internal issues within the battery itself, including overcharging, overdischarging, overheating, and short circuits. Sensor faults occur when measurement devices, responsible for providing critical feedback to the BM,S malfunction, with common examples being voltage, current, and temperature sensor faults [94]. Actuator faults, such as terminal connector failures, cooling system malfunctions, controller area network bus errors, high-voltage contactor failures, and fuse faults, typically have a more immediate impact on control system performance compared to battery or sensor faults [95]. Based on progression speed, battery system faults can be classified as gradual faults, which develop over time, or burst faults, which are sudden and severe [96].

Nevertheless, fault modeling faces significant challenges due to the limited fault data, and implementing fault-tolerant control demands high accuracy and rapid response from BMS fault diagnosis [97]. Unlike the battery health prediction, the fault data generation at the battery system level is both time and cost-consuming [98]. The emergence and application of the DT concept offer a promising approach to address this issue by generating fault data through digital models, thereby alleviating the slow data acquisition process inherent in large-scale physical experiments.

4. Digital twins for battery health prognosis in the four-layer conceptual framework

This section analyzes the application of Digital Twin (DT) technology to battery health prognosis through the lens of the proposed four-layer framework. Rather than merely categorizing existing research, the following subsections are structured to provide a deeper analysis of the DT as an integrated system. We will examine the critical synergies and interdependencies between the layers: how the quality and resolution of data from the Physical Layer directly constrain the Data & Communication Layer; how this processed data, in turn, dictates the necessary complexity and fidelity of the Virtual Model Layer; and ultimately, how these foundational layers collectively determine the accuracy, reliability, and value of the applications delivered by the Twin Service Layer. This analytical approach aims to illuminate not just what has been accomplished, but how the distinct components of a DT must work in concert to achieve robust battery health management.

4.1. The physical layer as the foundation of digital twins

The Digital Twin (DT) framework is fundamentally based on its Physical Layer [99,100], which consists of the tangible, real-world asset being monitored. For battery health prognosis, this layer comprises the complete lithium-ion battery system, including its individual cells, modules, and the final assembled pack. The Physical Layer is the source of empirical data, representing the complex electrochemical and thermal dynamics that occur during operation. Critically, this layer also includes the embedded sensory infrastructure, a network of sensors that captures high-frequency measurements of voltage, current, and temperature, orchestrated by the onboard Battery Management System (BMS) [101]. The raw data stream generated here serves as a primary input for the DT and is essential for all subsequent layers. Therefore, the fidelity of the entire DT system is highly dependent on the quality, accuracy, and resolution of the data originating from this foundational layer, as any inaccuracies can propagate through the architecture [102].

4.2. Data augmentation in data and communication layer

Real-world LIB health prognosis is significantly more complex than analyzing experimental data. This complexity arises from the often incomplete nature of real-world data, its random charging and discharging profiles, and the presence of unlabeled data. This challenge leads to poor data quality in the data layer of digital twins. To address these challenges, data augmentation techniques can be utilized to enhance the data and information in the information layer. In the context of battery digital twins, the application of data augmentation can be broadly categorized into functional themes, which are (1) virtual battery and feature generation; and (2) data enrichment for model robustness and accuracy. Regardless of the approach, the ultimate goal is to improve model accuracy and generalization through augmented data, as shown in Fig. 5.

Virtual battery and feature generation focus on synthesizing realistic or missing data such as creating incomplete run-to-fail (RTF) datasets or extracting battery health features. Research by [103] applied dynamic time wrapping to augment the data obtained from different operating conditions to the current system, which plays the role of virtual RTF data for real-world LIB health prognosis. Research by [104] employed gaussian process regression to restore past states and ensure continuity in SOH estimation algorithms. Research by [105] developed universal health indicators for various battery types, which are later adapted for specific batteries using their standard deviation as an input feature for data augmentation. Besides, real-world datasets often lack labeled target data, such as capacity or internal resistance, which are costly and time-consuming to generate. To address this, research by [106] proposed a deep learning framework that integrates estimations from a swarm of DNNs to provide reliable SOH predictions without relying on labeled data from specific batteries. Research [107] generated pseudo-labeled data which were combined later with laboratory data to re-train and predict the field unlabeled data. Research [108] generated synthetic battery packs with limited labels, simulating the dynamic behavior of the battery pack under different aging conditions and levels of cell inconsistency. From the above discussion, it can be concluded

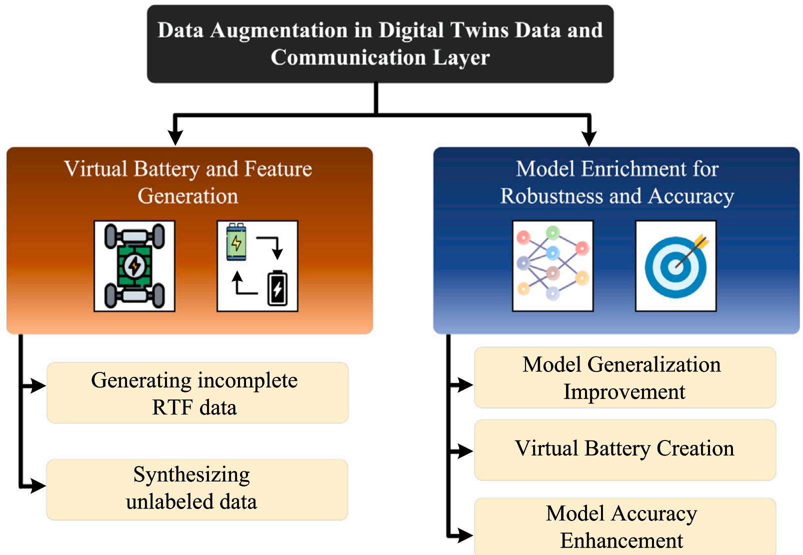

Fig. 5. Data augmentation in battery digital twins.

that virtual battery and feature generation is a data augmentation method that addresses incomplete data, limited labels, or the absence of target data by generating synthetic data. This approach aims to enhance the quality of input data for data-driven health prognosis.

Data enrichment for model robustness and accuracy focuses on generating additional or refined data, such as introducing noise or generating virtual batteries, to enhance both model accuracy and resilience. Research by [109] incorporates random noise supervision into Gated Recurrent Unit (GRU) networks for SOH estimation, effectively reducing overfitting. Similarly, research by [110] employs Gaussian noise through data augmentation in neural networks to mitigate overfitting and improve generalizability. A Generative Adversarial Network (GAN)-based approach by [41] expands sparse datasets to enhance SOC and SOH estimation. Research [111] combines GAN-based augmentation with LSTM to capture and generate temporal characteristics of battery cycles, further improving SOC estimation. Research [112] further utilizes a GAN-based framework enhanced with a Wasserstein loss function, resulting in better battery capacity estimation. Research by [113] generates virtual battery samples by multi-distribution global trend diffusion algorithm addressing health prognosis challenges related to user anxieties and arbitrary charging behaviors. Research by [114] introduces a quantum assimilation algorithm to uncover latent commonalities between abnormal and normal samples, enhancing health prognosis by prioritizing abnormal data. The data enrichment process aims to enhance model accuracy and generalization by generating additional data or introducing noise into data-driven health prognosis models, ultimately improving real-world battery health prognosis.

4.3. The virtual model layer as the core engine of digital twins

The Virtual Model Layer serves as the core engine of the battery DT, responsible for simulating, predicting, and analyzing the battery's behavior. It is here that the raw data from the Physical Layer, refined by the Data & Communication Layer, is transformed into the high-level insights that power the Twin Service Layer. This layer hosts a diverse suite of computational models that create a synchronized, high-fidelity virtual representation of the battery's internal electrochemical state and long-term aging trajectory.

The models housed within this layer can be broadly classified into three categories. First are the physics-based models, such as equivalent circuit models (ECMs) and complex electrochemical models, which offer high interpretability by representing the underlying physical laws governing battery operation [16]. Second are the data-driven models, which leverage machine learning and deep learning algorithms like Long Short-Term Memory (LSTM) networks, Convolutional Neural Networks (CNNs), and transformers to identify complex patterns and correlations in historical data without requiring explicit physical formulations [68]. Third are **hybrid models**, which synergize the two approaches to leverage the strengths of both. These can range from Physics-Informed Neural Networks (PINNs) that embed physical equations into the loss functions of neural networks [76], to modular frameworks that combine distinct model types. For example, some approaches integrate physics-based ECMs with neural networks to correct for aging-related parameter drift [115], while others couple state estimators like the Extended Kalman Filter (EKF) with machine learning models like XGBoost to enhance robustness [116]. Another strategy involves embedding data-driven algorithms like AdaBoost and LSTM within a semi-empirical battery model to improve predictive accuracy while retaining a physical basis [117].

A central challenge in designing the Virtual Model Layer is navigating the critical trade-off between model fidelity and computational feasibility. High-fidelity electrochemical models provide deep physical insight but are often too computationally intensive for the real-time requirements of a DT. Conversely, purely data-driven models can be computationally efficient but may lack robustness when extrapolating to unseen conditions and often function as "black boxes" with limited interpretability. The DT architecture directly addresses this challenge by enabling the offloading of computationally expensive models to cloud-based resources, allowing the use of more sophisticated algorithms than would be possible on a resource-constrained onboard BMS. Crucially, this selection is not made in a vacuum; the richness, granularity, and quality of the data provided by the Data & Communication Layer directly dictate the required complexity and achievable fidelity of the models that can be effectively implemented. The selection of an appropriate model or ensemble of models is therefore a crucial design decision that directly impacts the performance and practicality of the entire DT system.

4.4. Twin service layer: Online estimation for health prediction

The primary function of a battery Digital Twin is to deliver actionable insights, a task executed by the Twin Service Layer. This layer provides critical estimations of key health indicators: State of Charge (SOC), State of Health (SOH), and Remaining Useful Life (RUL). These estimations are the culmination of a multi-layer process. It begins at the Physical Layer, where sensors capture raw operational data (voltage, current, temperature). This data is then managed by the Data & Communication Layer, which handles transmission, pre-processing, and augmentation. Subsequently, the data feeds into the Virtual Model Layer, where sophisticated models simulate and predict the battery's state. Finally, the Twin Service Layer translates these complex model outputs into the clear, interpretable health indicators essential for battery management. This section reviews recent advancements in the implementation of these services.

4.4.1. Digital twin-based SOC estimation

SOC estimation is a cornerstone of BMS in EVs, providing a critical measure of the remaining battery capacity, analogous to a fuel gauge. Delivering this information accurately is a fundamental service provided by the DT's Twin Service Layer. Accurate SOC estimation is vital for optimizing battery performance, ensuring operational safety, and prolonging the lifespan of LIBs. Traditionally, SOC estimation relies on algorithms executed within onboard BMS, which are hampered by limited computational resources. These constraints often result in estimation inaccuracies that compromise battery efficiency and safety. The DT architecture overcomes these limitations by hosting computationally intensive models in the Virtual Model Layer, which leverages off-board resources (e.g., the cloud) to deliver a more precise and adaptive SOC estimation service [32].

One prominent DT-based approach employs a hybrid framework that integrates on-vehicle and cloud-based systems for SOC estimation. As outlined in [118], this methodology utilized coulomb counting, where current is integrated over time, to provide real-time SOC assessments directly on the vehicle. This hybrid implementation perfectly exemplifies the DT architecture's strength: the on-vehicle system serves as a responsive edge component within the Data & Communication Layer for immediate estimates, while more complex, SOH-aware models run in the cloud-hosted Virtual Model Layer to provide a periodically corrected, high-fidelity estimation service. Implemented on platforms like Microsoft Azure with hardware support from Raspberry Pi boards, this approach demonstrates the practical deployment of DTs in real-world EV applications, offering a scalable solution for accurate SOC monitoring.

Advanced filtering techniques further enhance DT-based SOC estimation. For instance, [119] introduces a joint H-infinity filter and particle filter (HIF-PF) algorithm that operates within the Virtual Model Layer of a DT-driven framework. Conducted under the Beijing Bus Dynamic Stress Test (BBDST) conditions, this cloud-based method achieves a mean absolute error (MAE) of 0.14%, significantly outperforming traditional Extended Kalman Filter (EKF) approaches. This superior accuracy is a direct result of the DT's ability to execute computationally demanding algorithms and process extensive datasets within its Virtual Model Layer, a capability that circumvents the data-sharing and processing bottlenecks of conventional, isolated BMS.

Data-driven methodologies are powerful tools for constructing the Virtual Model Layer to deliver SOC estimation services. The work by Pooyandeh et al. [42] is a case in point, embedding an LSTM algorithm within a DT as a core component of the Virtual Model Layer to deliver precise SOC predictions. This approach eliminates the need for additional sensor calibration by relying on a cloud-based IoT network, where the DT operates alongside the physical BMS. A notable innovation is the use of a time-series generative adversarial network (TS-GAN) to generate synthetic data, a technique that enriches the Data & Communication Layer. This highlights a key synergy: a more robust data layer directly enables a more accurate virtual model, which in turn delivers a higher quality service. Similarly, Njoku et al. [120] employs LSTM and deep neural networks (DNNs) within a DT framework, achieving reliable SOC estimates. The integration of explainable artificial intelligence (XAI) techniques, such as SHapley Additive exPlanations, ensures model transparency, adding value and trustworthiness to the Twin Service Layer.

Furthermore, Saba et al. [121] integrated a Deep Deterministic Policy Gradient (DDPG)-driven DT within an Intelligent Transportation Systems (ITS)-enabled vehicle-to-grid framework to enhance SOC estimation under dynamic load conditions. This approach utilizes the Virtual Model Layer to capture the complex interplay between SOC, cell voltage, and health indicators (HI), and performs "virtual discharge" experiments to probe the actual remaining capacity. The Ensemble Weighted Network (EWN) proposed in [122] combines multiple SOC estimation learners within a unified Virtual Model Layer. By employing accuracy weight scaling and time weight scaling, this model mitigates variability across different estimation algorithms and time periods. Experimental results report root mean square error (RMSE), MAE, and mean absolute percentage error (MAPE) values of less than 1.10%, 0.96%, and 1.92%, respectively, highlighting its robustness across diverse temperatures and battery types.

Hybrid models offer another avenue for improving SOC estimation accuracy. The Digital Twin Hybrid Model (DTHM) described in [115] integrates an Equivalent Circuit Model (ECM) with a Neural Network Model (NNM) within the Virtual Model Layer. Using a residual technique and dynamic calibration informed by DT technology, this approach addresses parameter uncertainties due to battery aging. Under varied operational and temperature conditions, the DTHM achieves a synchronization error of less than 0.2% between the Physical Layer and Virtual Model Layer, with maximum MAE and RMSE values of 0.0057 and 0.0065, respectively, at the end of the battery lifecycle.

Innovative signal processing techniques have also been incorporated into DT frameworks. Di et al. [123] proposed a method to estimate internal complex impedance as a function of SOC by applying wavelet analysis to filter voltage and current signals. This pre-processed data from the Data & Communication Layer informs a feedforward neural network-based Virtual Model, which generates realistic voltage outputs for accurate SOC estimation, validated using NASA's prognostics dataset.

These DT-based methodologies are outlined as illustrated in Fig. 6. They collectively enhance the SOC estimation service by providing real-time, accurate insights that surpass traditional onboard BMS. By integrating advanced techniques such as filtering, data-driven modeling, and hybrid modeling within the Virtual Model Layer, and leveraging the seamless data flow enabled by the Data & Communication Layer, DTs offer a dynamic and adaptive solution for online health prediction. These advancements not only improve operational efficiency but also contribute significantly to the sustainability and reliability of battery-powered systems.

4.4.2. Digital twin-based SOH estimation

Parallel to SOC, SOH estimation is another critical application delivered by the Twin Service Layer, providing a measure of battery degradation over time. By integrating real-time sensor data from the Physical Layer through the Data & Communication Layer, virtual battery models in the Virtual Model Layer, and advanced algorithms, DT-based approaches enable continuous monitoring and prognosis of battery degradation, thereby supporting proactive maintenance and improving the overall reliability of EVs, smart grids, and other battery-reliant systems [45,116]. The following sections present key contributions from existing literature, illustrating diverse methods used to achieve robust and accurate SOH prediction.

Several studies emphasize combining multiple estimation algorithms to improve SOH accuracy. For instance, [116] integrates an Extended Kalman Filter (EKF) with an Extreme Gradient Boost (XGBoost) model within a DT architecture to estimate incremental SOH from historical battery data. By situating this hybrid model in the Virtual Model Layer, the framework capitalizes on the strengths of both algorithms: the XGBoost model excels at capturing complex, non-linear degradation patterns from data, while the EKF refines the outputs by dynamically correcting for system noise and uncertainties. This synergy demonstrates how the Virtual Model Layer can host ensemble methods

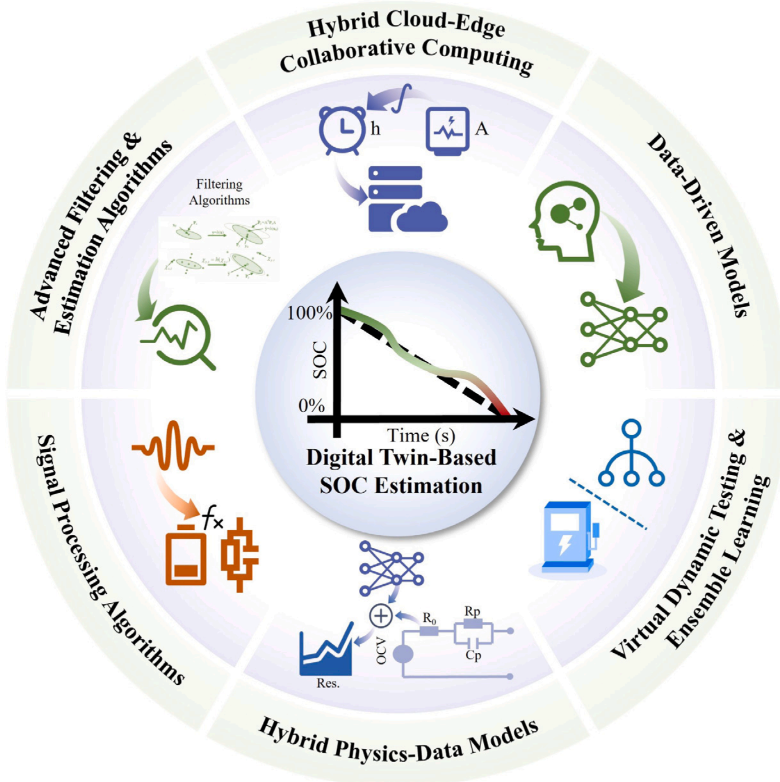

Fig. 6. Digital twin-based SOC estimation.

to deliver a more robust SOH estimation service than either algorithm could achieve alone. A similar approach was proposed in [124], where a hybrid EKF and Particle Swarm Optimization (PSO) method was used for joint SOC and SOH estimation in a DT framework, creating a powerful hybrid model in the Virtual Model Layer where the EKF tracks the battery state while PSO optimizes model parameters online, thus enhancing the quality of the SOH estimation service.

Cloud-based DT implementations are essential for realizing the full potential of the proposed architecture, providing the necessary computational resources for the sophisticated Virtual Model and Twin Service Layers. Ref. [45] employs a cloud-based DT to estimate SOC using an adaptive H-infinity filter and SOH via particle swarm optimization. This architecture showcases a well-defined data flow where raw signals from the Physical Layer's sensors are collected by a slave BMS. This data then traverses the Data & Communication Layer, first moving via CAN bus to a Raspberry Pi acting as an edge gateway, and then is relayed to the cloud-hosted Virtual Model Layer using the MQTT protocol. Testing on a real UPS yielded mean absolute errors (MAEs) of 0.49% for SOC, 0.74% for capacity, and 1.7% for resistance. A key analytical insight here is that the cloud-centric framework enables the Virtual Model Layer to be a living entity. It can be retrained or updated with new data over the battery's lifespan, ensuring long-term adaptability to aging dynamics in a way that a static, embedded BMS model cannot.

The integration of cloud platforms with DTs is also discussed in [99], which introduces a cloud-side-end collaboration model for BMS. This model utilizes cloud-based computational power to overcome the limitations of traditional BMS and proposes a Particle Filter (PF)-based method for both SOC and SOH estimation within its Virtual Model Layer. The model then leverages the Twin Service Layer to control cell balancing. This framework enables seamless interaction between the local, cloud, and end components of the battery system, thus optimizing battery management. Other works, such as [125,126], and [127], have also employed cloud-based DT models, leveraging the data storage and computational capabilities of cloud platforms to achieve accurate SOH estimation.

Machine learning (ML) and deep learning methods have also been successfully integrated into the Virtual Model Layer to enhance SOH estimation. The study in [128] utilizes a LSTM-based battery DT for virtually discharging batteries to estimate capacity, achieving an SOH MAE of 2.86%. Ref. [129] leverages random forest, light gradient boosting, and deep neural network (NN) techniques for DT-based SOC and SOH estimation, achieving MAEs of 0.549% and 0.603%, respectively. This approach demonstrates the flexibility of the Virtual Model Layer to host an ensemble of data-driven models, which in turn yields a more robust estimation service.

Recent advancements have turned to building sophisticated deep learning (DL) architectures within the Virtual Model Layer to further enhance SOH estimation. In [100], a time-attention LSTM model regresses on the Maximum Available Capacity (MAC) by considering the temporal importance of different sampling points. Coupled with energy discrepancy-aware temporal warping for data synchronization (a preprocessing step in the Data & Communication Layer), the approach achieves reliable real-time SOH predictions, even when future data are partially unavailable. Ref. [130] further addresses the challenge of catastrophic forgetting and overfitting in continuous learning for EV battery SOH prediction by introducing a memory buffer to preserve historical data distributions. This acts as an intelligent data management strategy within the Data & Communication Layer, ensuring that the Virtual Model Layer is trained on diverse, high-quality data over the battery's lifespan. The model, once fine-tuned, is deployed to the cloud, where this dynamic interaction between data and model enables continuous improvement of the prediction service.

Additionally, Schmitt et al. [131] develop a recurrent encoder–decoder model within the Virtual Model Layer that is trained solely on unstructured BMS signals, enabling virtual incremental capacity experiments from routine voltage–current profiles. This approach allows the Twin Service Layer to offer advanced diagnostic capabilities (virtual experiments) without requiring dedicated physical tests, drawing its power from a model adept at interpreting raw data streams from the

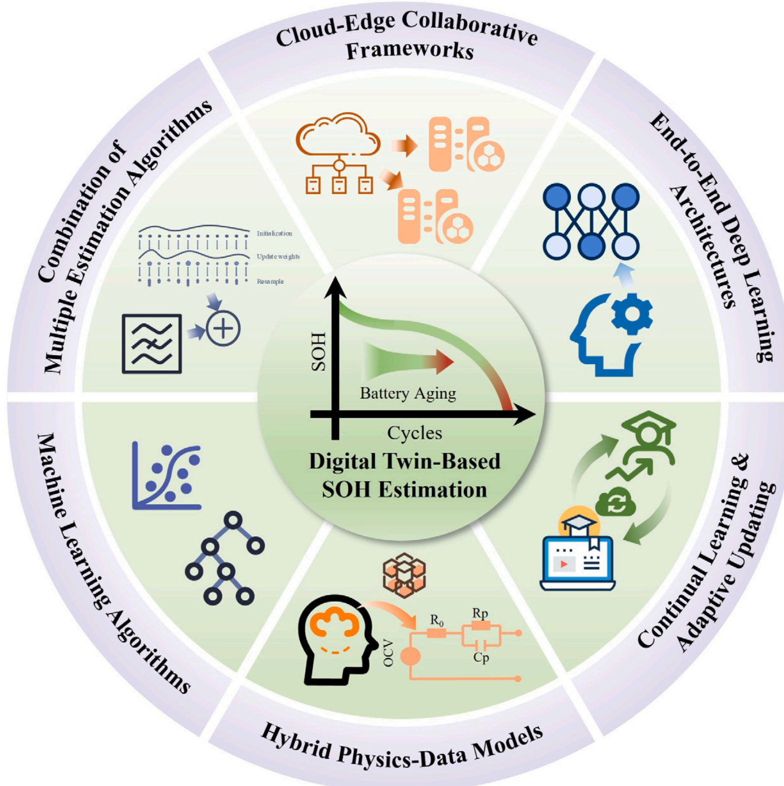

Fig. 7. Digital twin-based SOH estimation.

Data & Communication Layer. By either applying a steady shift of load sequences (average SOH deviation 0.36%) or a random alignment of subsequences (1.04%), their method achieves high accuracy. More recently, Li et al. [51] introduce a CNN–LSTM–attention framework that constitutes a multi-stage Virtual Model Layer: a back-propagation neural network first reconstructs partial discharge curves (a data enrichment function), and then an attention-augmented CNN–LSTM predicts maximum available capacity with over 99% accuracy. This demonstrates a sophisticated, pipeline-based approach to data-driven SOH estimation.

Beyond sequence modeling, hybrid DT architectures integrating physical insights with data-driven methods have emerged as promising solutions for building a high-fidelity Virtual Model Layer. For example, Nair et al. [117] propose an AI-driven DT that embeds AdaBoost and LSTM within a semi-empirical battery model, with hyperparameters optimized via antlion and grey wolf algorithms. Analytically, this design showcases a powerful synergy within the Virtual Model Layer, where the physics-based component provides a structural backbone and interpretability, while the data-driven models capture complex, non-linear dynamics that are difficult to model from first principles. This fusion, fine-tuned by metaheuristic optimizers, exemplifies the DT's capacity for creating highly customized and accurate virtual representations for superior real-time SOH tracking. Validated on the NASA battery aging dataset through ten-fold cross-validation, their IGWO–AdaBoost DT achieves both MAE and RMSE of 0.01 in discharge capacity prediction.

These DT-based SOH estimation strategies are summarized as shown in Fig. 7. They showcase the importance of fusing modeling techniques (e.g., EKF, PF) with data-driven ML and DL methods (e.g., random forest, XGBoost, LSTM) within the Virtual Model Layer, all supported by a cloud-enabled digital infrastructure. By continuously integrating sensor inputs, refining predictions through feedback loops, and incrementally updating model parameters, DT-based systems can dynamically adapt to battery aging processes. Ultimately, the synergy between an adaptive, data-rich Virtual Model Layer and a responsive Data & Communication Layer is what empowers the Twin Service Layer to deliver accurate, reliable, and truly predictive health prediction.

4.4.3. Digital twin-based RUL prediction

RUL estimation is a pivotal component of battery health prediction, offering a predictive measure of the operational cycles a LIB can withstand before its capacity degrades to a critical threshold, typically around 80% of its nominal value [32]. This represents a key forward-looking service within the Twin Service Layer. Unlike SOH, which captures the battery's present condition, RUL forecasts its future degradation trajectory and remaining lifespan, facilitating proactive maintenance strategies and optimized lifecycle management. Despite significant progress in academic research, the integration of dedicated RUL estimation functionalities into commercial BMSs remains limited. DTs emerge as a powerful solution to bridge this gap by leveraging the Data & Communication Layer for centralized data management and the Virtual Model Layer for scalable computation, enabling real-time model updates that are essential for accurate long-term forecasting.

The algorithmic foundation of RUL estimation spans multiple paradigms, including physics-based models that simulate degradation mechanisms, data-driven approaches that infer patterns from historical data, and hybrid methods that synergize both techniques. A detailed examination of these methodologies and their theoretical underpinnings is available in [132]. Recent trends have increasingly harnessed DTs to refine RUL predictions, capitalizing on their ability to integrate diverse data streams and computational resources to address the nonlinear and stochastic nature of battery aging.

One significant advancement is the development of a DT-driven framework that employs adaptive model evolution to capture the dynamic and uncertain characteristics of battery degradation. As explored in [133], this approach constructs a sophisticated Virtual Model Layer comprising a suite of models–including capacity degradation, stochastic degradation, and life prediction models–to account for randomness in aging processes and variability across multiple cells. The analytical

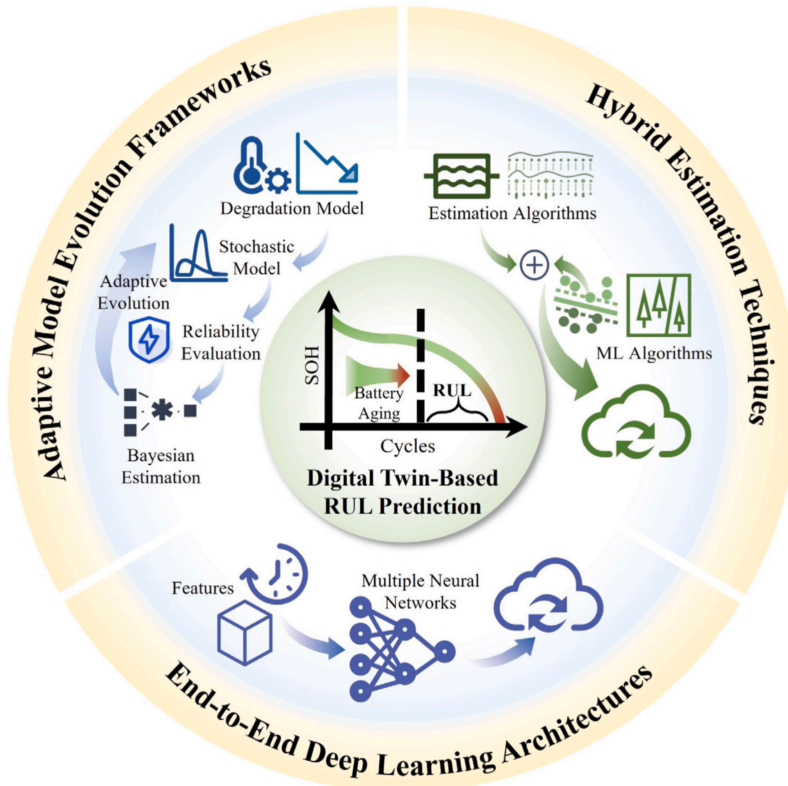

Fig. 8. Digital twin-based RUL prediction.

contribution of this work lies in its use of Bayesian algorithms to create an adaptive Virtual Model Layer. As new data streams in from the Data & Communication Layer, the models are not static. They evolve, updating their parameters to reflect the battery's most current degradation trajectory. This adaptive learning process is fundamental to the DT concept and is what enhances prediction precision over time. Experimental results indicate that this technique achieves a prediction error of approximately 5%, demonstrating its efficacy in managing the inherent uncertainties of battery life cycles and supporting reliability evaluations critical for predictive maintenance.

Complementing this, hybrid DT-based strategies integrate traditional estimation techniques with machine learning (ML) models to deliver real-time RUL forecasts [134]. For example, Kalman filters, known for their effectiveness in state estimation, are paired with advanced ML algorithms such as least squares support vector machines or artificial neural networks. In this DT architecture, the battery sensors constitute the Physical Layer, while remote sensing links form the Data & Communication Layer. The KF and ML algorithms work in tandem within a hybrid Virtual Model Layer, with computationally intensive tasks offloaded to cloud infrastructure. This integration allows the Twin Service Layer to provide robust RUL forecasts that are continuously refined, improving accuracy and adaptability to varying operational conditions.

The advent of deep learning has further elevated the capabilities of the Virtual Model Layer for RUL prediction, with techniques like those presented in [44]. This method employs a Temporal Convolutional Network (TCN) coupled with LSTM networks within a DT-supported framework to estimate battery states, including RUL. The TCN-LSTM algorithm excels in extracting temporal and spatial features from sequential battery data, reducing dependence on initial state assumptions. Through transfer learning, the model dynamically adjusts its neural network parameters in the Virtual Model Layer using fresh data, ensuring real-time accuracy. Testing across 90 cycles reveals an average root mean square error (RMSE) of 0.9% for RUL, alongside 1.1% for SOC and 0.8% for SOH, markedly outperforming traditional convolutional neural networks (CNNs) with RMSE values of 3.6%, 2.2%, and 2.0%, respectively. This superior performance highlights the efficacy of integrating advanced deep learning with DT technology for robust and precise health prediction.

Collectively, DT-based RUL prediction frameworks are presented as depicted in Fig. 8. They leverage real-time sensor data, cloud scalability, and versatile modeling strategies to tackle the intrinsic uncertainties of battery degradation. Whether through adaptive evolution, hybrid estimation, or deep learning approaches implemented in the Virtual Model Layer, these methods aim to enhance the RUL prediction service delivered by the Twin Service Layer. Looking ahead, the evolution of DT-based RUL prediction will likely prioritize enhanced model interpretability, efficient processing of large and diverse datasets, and the incorporation of contextual factors such as temperature variations and usage profiles.

4.5. Twin service layer: Fault diagnosis

Fault diagnosis in battery systems is a cornerstone of ensuring the safety, reliability, and efficiency of energy storage systems, particularly in high-stakes applications such as EVs and renewable energy grids. Within the DT framework, fault diagnosis is a critical offering of the Twin Service Layer. Traditional onboard BMS employs straightforward fault detection methods, typically monitoring voltage, current, and temperature variables against fixed thresholds to identify issues like over-discharge, over-charge, or short circuits. While these techniques suffice for basic fault detection, their reliance on single-variate analysis and disregard for historical performance data limit their effectiveness in diagnosing complex or evolving faults. In contrast, the DT architecture enables advanced, multi-variate, and physics-informed fault diagnosis schemes by integrating high-resolution data from the Physical Layer with sophisticated models in the Virtual Model Layer, offering deeper insights into degradation pathways and incipient fault indicators [32, 33].

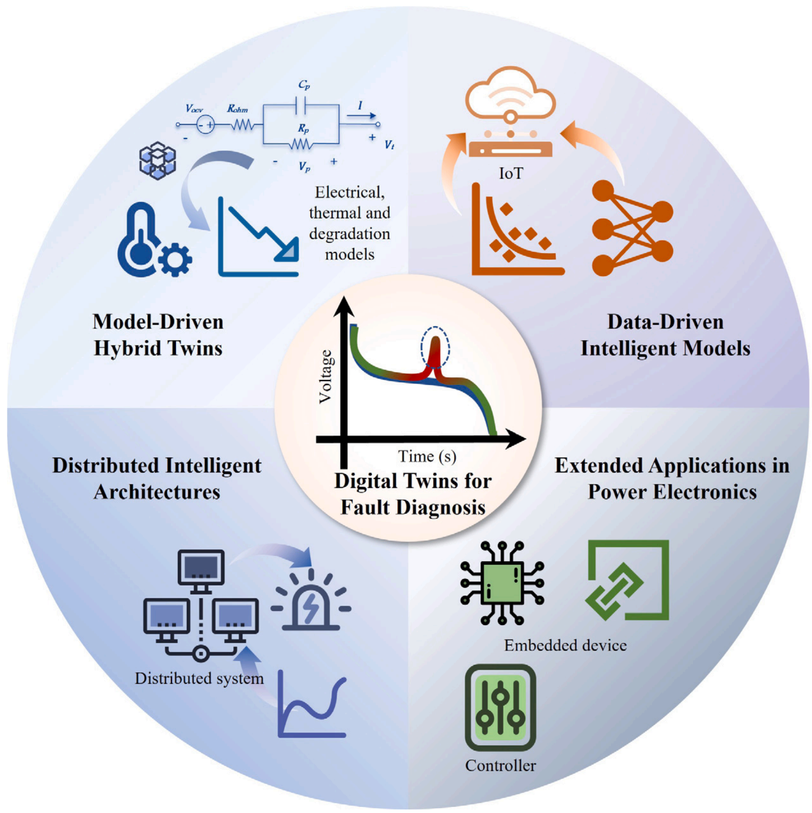

Fig. 9. Digital twins for fault diagnosis.

DT-enabled model-based approaches populate the Virtual Model Layer with reduced-order electrical, thermal, and degradation models to detect incipient faults at the cell or module level. Miguel et al. [135] propose a cloud-based platform where cell-level thermo-electric aging models are aggregated into a module-level DT, enabling continuous comparison between measured and simulated responses for fault isolation and trend analysis. Similarly, Sancarlos et al. [136] develop a hybrid twin that employs a POD model and sparse-Proper Generalized Decomposition (s-PGD) in its Virtual Model Layer to achieve real-time fault prediction, showcasing its adaptability to dynamic operating conditions. Analytically, these model-centric DTs provide a physics-grounded baseline of expected behavior. Faults are detected as deviations from this baseline, allowing for earlier and more sensitive detection than simple thresholding.

The incorporation of intelligent, data-driven monitoring further elevates the fault diagnosis service. By embedding ML models within the Virtual Model Layer, vast datasets from battery sensors can be analyzed to detect patterns or anomalies signaling incipient faults. Cheng et al. [137] developed an intelligent battery operation and maintenance system using IoT and DT technology, where IoT devices form the Data & Communication Layer for real-time monitoring. Based on inputs from a Virtual Model, the Twin Service Layer delivers multi-level alarm modes and actionable insights, directly facilitating the efficient deployment of maintenance personnel.

Recent innovations have pushed this frontier further. Jin et al. [138] apply Willems' fundamental lemma to derive a Kalman-filter-equivalent residual generator directly from raw input–output trajectories, creating a purely data-driven model in the Virtual Model Layer that bypasses the need for first-principles parametrization. Their scheme achieves robustness to stochastic disturbances and noise, outperforming existing data-driven methods in three-cell pack simulations. Meanwhile, El et al. [43] introduced a distributed intelligent DT architecture for EV powertrains, which exemplifies a sophisticated implementation of the Data & Communication and Twin Service Layers, employing transfer learning to diagnose faults in real time while ensuring scalability and driver safety.

The versatility of the DT framework extends beyond batteries to enhance diagnostics in power electronics, serving as versatile tools for energy systems. This highlights the flexibility of the Virtual Model and Twin Service Layers to be adapted for health monitoring across various system components. Milton et al. [139] developed a controller-embedded DT for power electronic converters, enabling real-time probabilistic fault diagnosis with compact implementation. Similarly, Peng et al. [140] designed a DT for DC/DC converters, using cluster-data analysis to predict faults in components like IGBTs or MOSFETs as a non-invasive, cost-effective approach.

In summary, DT-based fault diagnosis, powered by a sophisticated Virtual Model Layer and enabled by an efficient Data & Communication Layer, offers superior sensitivity for detecting both abrupt and gradual faults. These techniques are summarized as shown in Fig. 9. By employing model-based residuals and data-driven predictors within the Virtual Model Layer, these systems provide a Twin Service that identifies and localizes anomalies early, supporting the reliability and longevity of EVs and large-scale energy storage systems. Future efforts should focus on standardizing feature extraction, quantifying fault severity, and integrating multi-component DTs under a unified diagnostic framework.

5. Key challenges

The aforementioned research findings demonstrate distinct advantages of DT technology in lithium-ion battery health prediction and fault diagnosis. The establishment of comprehensive frameworks based on extensive historical datasets and multiple methods, combined with continuous model optimization through real-time sensor data, enables DT to become a more precise, robust, and operational virtual platform.

Nevertheless, there are still some challenges that have received insufficient attention, requiring prioritized investigation. As Figs. 10

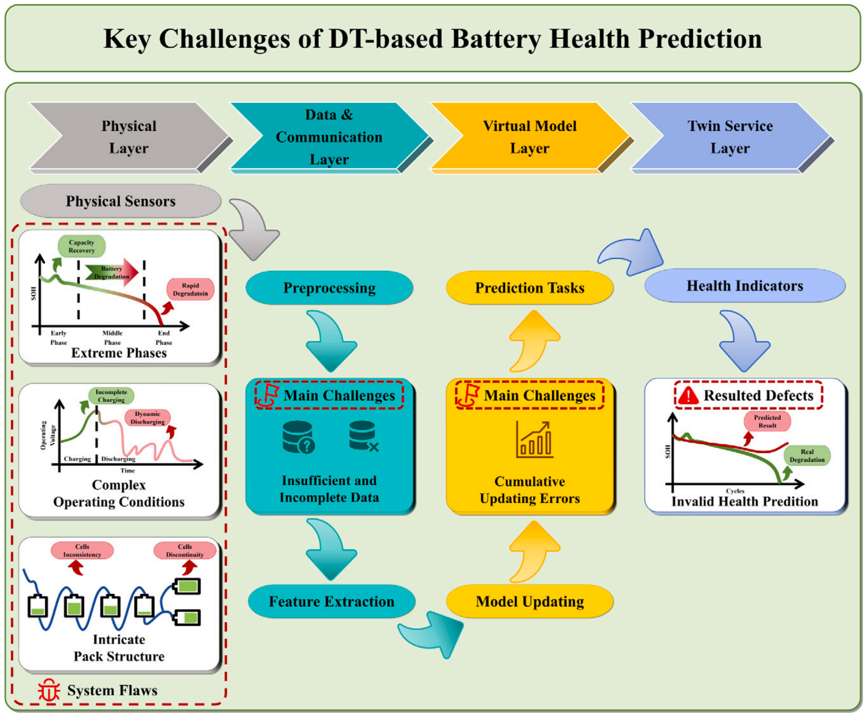

Fig. 10. Main Challenges of DT-based Battery Health Prediction. Intrinsic challenges are highlighted with red dashed rectangles. Additionally, system flaws in the Physical Layer that trigger these challenges, along with resulted defects in the Twin Service Layer, are similarly marked. As illustrated, complex physicochemical reactions, operating conditions and battery structures within the Physical Layer, contribute to poor data quality in the Data & Communication Layer, and cumulative updating errors in the Virtual Model Layer. These challenges ultimately lead to invalid health predictions in the Twin Service Layer.

and 11 exhibit, DT-based battery health prediction is troubled by the degradation trend of extreme phases and data extracted from real-world operational conditions, while fault diagnosis is disturbed by feature problems, functional requirements, and measurement difficulties. These unresolved issues impose substantial constraints on the progressive development and practical applications of DT technologies to some extent.

5.1. Limited generalization ability of DT-based health prediction

For DT-based health prediction systems, the primary challenge lies in inadequate generalization capability while handling complex physical structures and diverse operating conditions. This limitation frequently leads to substantial prediction errors in the Twin Service Layer, thereby restricting the practical deployment of DTs.

5.1.1. Extreme phases in battery lifespan

Comparative analysis of extant articles reveals that, predominant researches focus on mid-cycle phase data in lithium-ion battery degradation experiments. Cells, operating within this intermediate range, typically exhibit stabilized physicochemical reactions, enabling researchers to extract favorable voltage features for the Virtual Model Layer via the Physical Layer and the Data & Communication Layer. However, emerging evidence suggests that, when the Physical Layer contains a brand-new battery, distinct electrochemical mechanisms dominate the initial and terminal phases, which are induced by varied charge–discharge conditions and may result in unpredictable fluctuations of capacity. Commonly, battery capacity typically declines at the slowest rate during the early degradation phase, while the most rapid aging occurs in the late phase [141].

However, it should be noted that, in some cases, even within the same phase, capacity can exhibit unexpected variations. As depicted in Fig. 12(a) and (b), the early aging behavior of batteries can be divided into two stages: battery formation and SEI film growth [142]. Specifically, Gyenes et al. [141] report that in the initial stage of the early degradation phase–often within the first few cycles–the battery electrode undergoes rapid but insufficient SEI formation. This reaction enhances lithium-ion exchange and interaction efficiency. The coulombic efficiency(CE) of cathode is consequently improved, finally leading to a temporary capacity recovery. In the subsequent stage, excessive SEI growth consumes available lithium-ions, aggravating LLI in the electrolyte, and capacity gradually declines at a steady rate. This phenomenon is subject to multiple factors. Research by Jia et al. [143] and Lewerenz et al. [144] demonstrates that capacity recovery phenomena in $LiFePO_4$ are particularly evident under conditions of shallow depth-of-discharge, moderate C-rates, and elevated storage temperatures. Additionally, diverse polarization and degradation modes manifest across distinct voltage plateaus during the discharge process [142], as illustrated in Fig. 13.

In DT-based battery health prediction, ephemeral extreme degradation phases correspond to sparse data. Moreover, indicative signals of minor physicochemical reactions are readily obscured by noise. These inevitable flaws in the Physical Layer contribute to insufficient data of specific phases in the Data & Communication Layer. Finally, with a high updating frequency, DTs exhibit substantial cumulative error. Such unexpected variation introduces significant challenges in health indicator prediction accuracy for DTs. For instance, complementary research by Ji et al. [115] further reveals limitations and suboptimal behavior of the current hybrid DT architecture, when it predicts end-of-life battery aging trend.

These findings collectively underline the necessity for developing adaptive DT health prediction frameworks incorporating multi-phase degradation mechanisms of the battery. From our perspective, modifying the Virtual Model Layer by incorporating physicochemical theories, presents a promising approach. A concrete method is utilizing Physics-Informed Neural Networks (PINN). PINNs refer to thermodynamic laws and physicochemical equations governing special reactions (such as

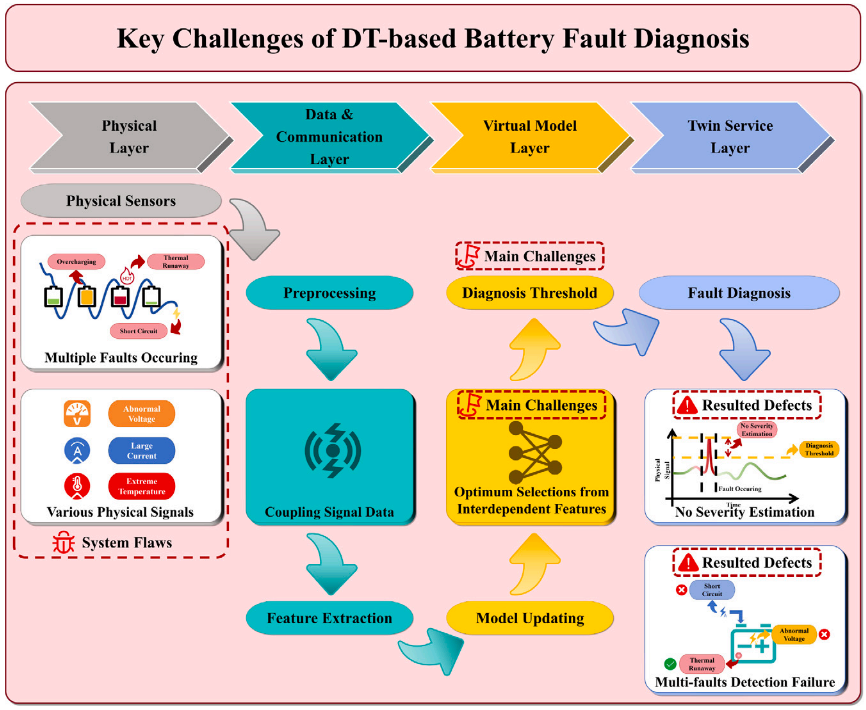

Fig. 11. Main Challenges of DT-based Battery Fault Diagnosis. Intrinsic challenges are highlighted with red dashed rectangles. Additionally, system flaws in the Physical Layer that trigger these challenges, along with resulted defects in the Twin Service Layer, are similarly marked. Multiple faults occurring in the Physical Layer lead to coupling signal data in the Data & Communication Layer. These inevitable phenomena hinder optimal feature selection, and uniform diagnosis threshold confirmation in the Virtual Model Layer. Consequently, these challenges contribute to inadequate multi-fault detection capability and severity estimation functionality in the Twin Service Layer.

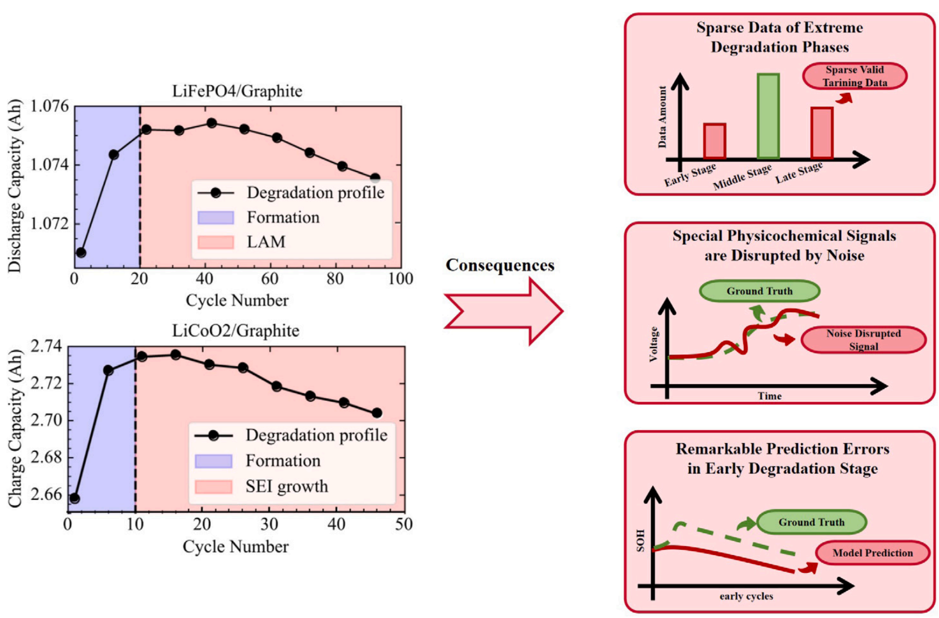

Fig. 12. Specific battery aging behavior and consequent challenges. Subfigures on the left exhibit aging behavior of $LiFePO_4$ and $LiCoO_2$ during the early degradation phase [142]. As illustrated in the right subfigures, the short duration of battery formation phase during early degradation stage, results in sparse training data. Moreover, environmental noise overlaps the micro voltage signal that captures capacity recovery to a large extent. Consequently, significant prediction errors occur in the Twin Service Layer.

battery formation and SEI decomposition), to formulate penalty terms, thereby establishing novel loss functions as optimizing targets [145–148]. Furthermore, this methodology can integrate attention mechanisms to dynamically assess the significance of individual features during distinct degradation phases, thus identifying features with better correlations [149].

5.1.2. Lack of consideration about battery package

At present, the predominant health prediction researches with DTs, focus on single-battery experiments. However, the Physical Layer of DTs practically applied in real-world EVs and physical energy storage systems, prefers a battery package to an independent battery cell. Such a layer involves more intricate constructions, but not simple serial

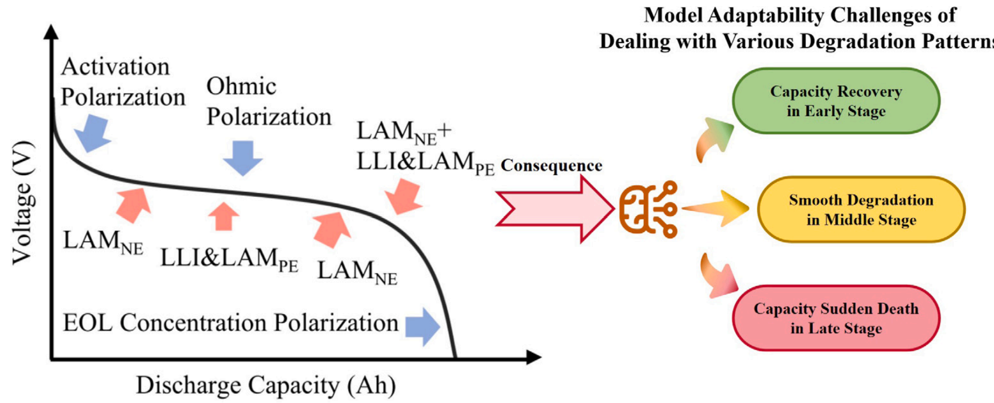

Fig. 13. Different aging modes and consequent challenges. Subfigures on the left show aging modes and polarization during voltage plateau phase in battery discharge [142]. As illustrated in the right subfigures, different degradation phases are dominated by various physicochemical reactions. This inherent characteristic presents challenges for model adaptability in handling diverse degradation patterns.

or parallel connections. The internal variations in voltage, current, capacity, and physicochemical states across individual cells, inevitably lead to systemic inconsistencies and discontinuities at the package level. Therefore, applying a conventional single battery health indicator estimation virtual model to a package, is particularly prone to cause significant errors.

Addressing this critical challenge necessitates a primary focus on Data & Communication Layer. The most direct approach involves extracting inconsistency and discontinuity features from individual cells as a supplement. Applying correlation analysis to identify dynamical differences of voltage, temperature, and remaining capacity among each cell, can provide model a mathematical basis to grasp battery package degradation pattern [150–152]. Furthermore, system identification algorithms, like Forgetting Factor Recursive Least Squares (FFRLS), can clarify variations of ohmic and polarization resistance in representative individual cells, offering a physical interpretation for model optimization. Though, extensive features excavation corresponds to significant computational demands, DT offers robust capability for handling large-scale data. Consequently, this methodology is worth further investigations in subsequent research.

5.1.3. Problems with complex working conditions

Contemporary battery datasets are predominantly derived from laboratory-controlled cyclic charge–discharge experiments. Under these operating conditions, idealized voltage and capacity measurements can be reliably extracted. Fig. 14 corresponds with a single battery working under a typical CC-CV condition. It is obvious that, charging and discharging curves move to the left of figure gradually and regularly, with the number of cycles increasing.

However, when a DT framework is employed in real-world conditions, practical operation exposes battery in the Physical Layer to dynamic and heterogeneous operating environments and complicated working conditions. For example, irregularly charging or discharging cycling, and also, abnormal temperature and humidity, induce unexpected SOH and RUL variations by impacting on electrode materials and electrolyte components. Additionally, inherent hardware limitations in sensing precision and system stability in the Physical Layer, with persistent measurement noise from the working environment, disrupt data acquisition integrity, result in inconsistent or fragmented detecting datasets in the Data & Communication Layer, and hinder valid feature extraction for the Virtual Model Layer. Fig. 15 shows an EV battery package working under real operational conditions. We can easily find that, there is a harsher condition of fast charging, and, interval and insufficient discharging are more common. These fundamental challenges bring difficulties in timely and precise updating for battery health predicting DT.

Employing precise and stable sensors within the Physical Layer of DT, offers notable benefits for overcoming this challenge. However, this approach entails cost surge. Thus, implementing appropriate signal processing technologies in the Data & Communication Layer, presents a viable method. Reconstructing is a prevalent approach. This technique employs interpolation or fitting methods, coupled with optimization algorithms such as Kalman Filter (KF), to reconstruct and reshape battery charging/discharging voltage curves [153,154]. The processed curves yield more reliable and information-rich features. Alternatively, special filtering algorithms like Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) can be applied to decompose raw signals, thereby enriching feature datasets [155,156]. Such signal processing methods effectively extract valid degradation information from raw data and prevent data waste.

5.1.4. Brief summary

Based on the aforementioned analysis, we highlight that, the primary challenges confronting battery health prediction grounded in DT methodologies, lie in enhancing generalization capabilities and advancing practical applications. The intricate battery structures and working conditions in the Physical Layer pose significant challenges for feature extraction and construction, ultimately leading to compromised accuracy and stability in prognostic performance. To mitigate these limitations, we pinpoint valid modifications within the Data & Communication Layer and the Virtual Model Layer. The core enhancement for two layers is leveraging the inherent capability of DTs to process extensive historical data, consequently excavating more physical insights and refining existing algorithms, models, and frames. These methodologies provide DT-based health prediction with reliable model interpretations and clear optimization directions.

5.2. Lack of further research about DT-based battery fault diagnosis

The primary challenge for DT-based fault diagnosis systems is a deficiency in functional versatility. Insufficient investigations about optimal feature selection, multi-fault diagnosis, and severity estimation ultimately constrain practical applications of DTs.

5.2.1. Difficulties in feature extraction and choice

Lithium-ion battery suffers multiple faults throughout its lifespan. Primary failure mechanisms, including overcharge, overdischarge, internal and external short circuits, thermal runaway, could occur at all operational phases [157]. These faults correlate with complex diagnosis physical features, involving voltage fluctuations, extreme currents, and abnormal local thermal variations. However, these features demonstrate strong interdependencies and implicit relationships. A single

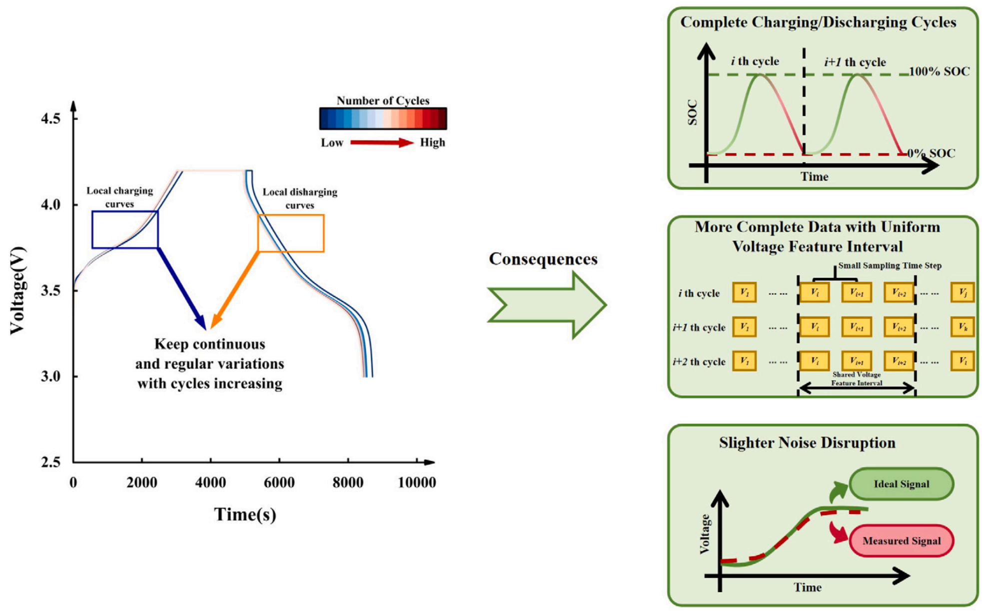

Fig. 14. Single Battery Working under Typical CC-CV Conditions. Obviously, experimental environments offer more complete data with less noise interference. Therefore, researchers can extract reliable training data within a shared voltage range.

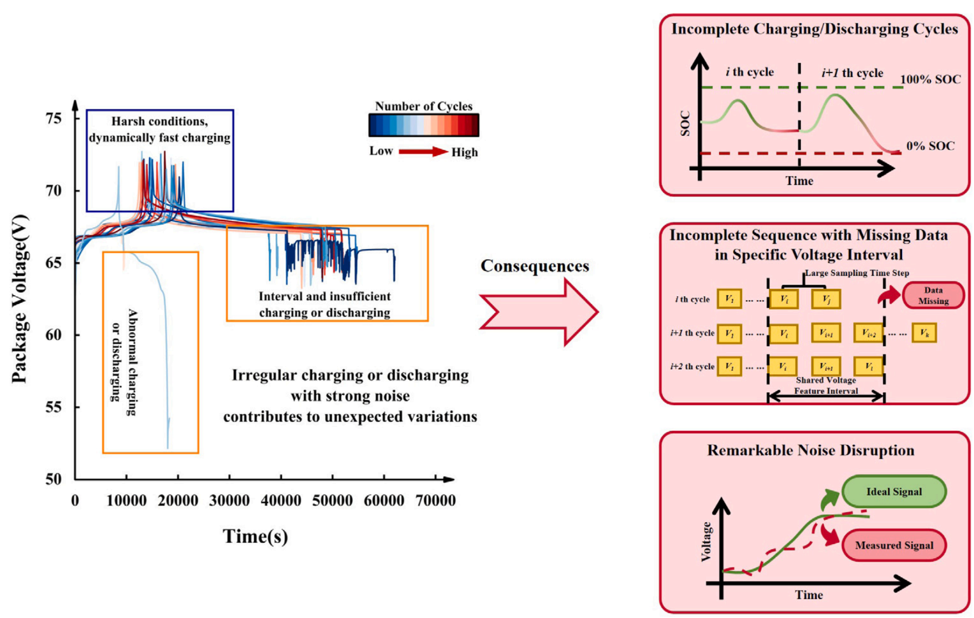

Fig. 15. EV Battery Working under Real-world Conditions. Subfigures on the left demonstrate that, real-world operating conditions are consistently characterized by incomplete charging/discharging cycles and significant noise inference. These unavoidable factors contribute to data gaps within specific voltage intervals, consequently resulting in feature extraction difficulties.

feature may indicate multiple battery faults. Current diagnosis approaches based on DT, lack systematic methodologies for identifying optimal feature-fault correlations. This limitation in selecting optimal features persists as a critical challenge in battery fault prognosis area. Contriving to overcome this shortcoming will further improve accuracy and interpretation of DT fault diagnosis models and frames, thus clarifying optimization directions when encountering a bottleneck.

Considering distinct types of battery with random faults, to ensure generalization ability of the Virtual Model Layer under multi-function demands, utilizing computational platforms and resources in the Data & Communication Layer, to preprocess data sufficiently, is essential. We recommend to construct an abundant feature pool and take a thorough analysis of feature correlations. This process facilitates the identification of optimal features and enhances the efficiency of data interaction, thus leading to faster training and prediction in the Virtual Model Layer.

5.2.2. Challenges in multiple fault diagnosis

As widely recognized, lithium-ion batteries are susceptible to diverse faults across all degradation stages. Establishing a generalized diagnosis framework, which is capable of identifying and locating multiple faults rapidly, proves crucial for ensuring battery health and preventing safety accidents. However, current DT models and frames are predominantly provided with single-fault detection capability. This limitation in Twin Service Layer substantially constrains the applications of DT technology in comprehensive battery fault diagnosis, thereby impeding advancements toward generalized fault diagnosis frameworks.

The most straightforward approach to address this challenge involves integrating classifiers, such as K-Nearest Neighbors (KNN), Support Vector Classification (SVC), and Random Forest (RF), within the Virtual Model Layer [158]. Training dedicated classifiers for each fault type and systematically evaluating diagnosis model outputs effectively resolves this limitation. Furthermore, employing an ensemble model framework offers a robust solution. This comprehensive methodology enables the integration of optimal models for each specific fault, thereby facilitating wide multi-fault diagnosis.

5.2.3. Lack of unified standard measurement and severity estimation

Lithium-ion battery fault diagnosis requires standardized criterion to measure diagnosis features in order to confirm whether a fault is occurring. Current methodologies primarily employ threshold-based and statistics-based methods. However, on the one hand, the empirical subjectivity among different researchers causes the absence of a universally accepted detection standard, thus, enabling undetected minor faults during battery utilization. On the other hand, a proportion of detected faults may originate from environmental interference or sensor distortion. Moreover, some transient faults with marginal severity may dissipate instantly without substantial influence. The diagnosis of such insignificant faults often induces unnecessary computational overhead in DT systems.

This flaw in DT battery fault diagnosis systems significantly compromises battery longevity through cumulative degradation effects. In our opinion, future research should leverage data acquisition, management, and calculation capability in Data & Communication Layer, combined with statistical methods (including analysis of probability distributions for an unique fault occurs under varying thresholds), to investigate historical data and confirm an unified measurement both for severity and action time of faults [159,160]. Implementing this standard will enable DT-based battery fault diagnosis to acquire adaptive sensitivity, detect and locate faults more rapidly, and achieve balanced frameworks, thus effectively prolonging battery durability.

5.2.4. Brief summary

In general, diagnosis systems employing DTs for battery fault detection, demonstrate an urgent need to advance detection accuracy, enable multi-fault identification, and strengthen intelligent severity estimation. Within the Data & Communication Layer, based on historical data and statistical methods, a systematic clarification of the physical interpretations associated with diverse diagnosis features, coupled with the identification of optimal features related to a specific fault, is essential to enhance the precision and stability of DT-based systems. Moreover, strategic optimizations targeting the Virtual Model Layer, such as integrating multiple fault classifiers, are recommended. Such enhancements can effectively improve the real-time responsiveness of DTs in practical implementations.

5.3. Prospect and suggestions

Comprehensive analysis reveals that, shortcomings and complexities within the Physical Layer of DTs employed in BMS, frequently constrain performance behaviors of the Virtual Model Layer and limit functional scopes of the Twin Service Layer. To address these crucial limitations, we propose several feasible research methods targeting the aforementioned key challenges. However, these approaches necessitate extensive analysis of both real-time and historical operational data and system states, resulting in substantial computational resource consumption and persistent challenges in data management.

To address these constraints, extensively combining systems with state-of-the-art technologies, like cloud computing and IoT, is recommended. Cloud computing platform demonstrates exceptional capability in secure storage of historical data at scale, while simultaneously enabling intelligent computational resources distribution. This platform enhances data processing velocity, thereby relieving local DT systems' computational burdens and facilitating timely updating. Concurrently, IoT technology empowers DTs with continuous system monitoring and real-time data generation capabilities, thereby enhancing model-data interaction. Such integration shows potential for improving both timeliness and reliability in DT-based BMS.

Nevertheless, specific and systematic integration of these advanced technologies within DT frameworks is not clear enough. Another notable challenge is the absence of standardized definitions, architectures, and functional requirements for battery DTs, which elevates risks associated with data privacy disclosure. Furthermore, persistent security vulnerabilities persist due to insufficient safeguards against thermal runaway incidents and operational failures, within existing DT frameworks coupled with these technologies. Implementation complexity and cost also emerge as a substantial barrier, where the integration of multi-layered subsystems, coupled with expensive hardware requirements, creates technical obstacles. This challenge ultimately limits the practical applicability of DTs.

To standardize and offer the construction of cloud- or IoT-based DT battery, we suggest that an independent Cloud Layer is essential, based on the aforementioned four-layer conceptual framework. Positioned between the Data & Communication Layer and the Virtual Model Layer, this layer functions as a platform for both storage and calculation of massive historical data and complex preprocessing algorithms. Such an isolated design can be integrated by a uniform information communication protocol, thus reducing the implementation cost and complexity for DT battery. To address data privacy and security issues, federated learning methods can be incorporated into the new layer above. Such approaches allow several companies or institutions to share large-scale databases via a universal model. This model aggregates parameters with special weighted aggregation algorithms, to avoid data transmission, thereby ensuring robust privacy and security protection. While numerous novel techniques could enhance existing DT battery frameworks, the proposed direction remains among the most straightforward to implement. Consequently, comprehensive investigations in this domain are recommended [161,162].

6. Conclusions

This comprehensive review has explored the convergence of Digital Twin (DT) technology with battery health prognosis systems, highlighting significant advancements and persistent challenges through the lens of a proposed four-layer conceptual framework. The evidence presented demonstrates that DTs, when structured into the Physical, Data & Communication, Virtual Model, and Twin Service layers, offer a powerful paradigm for enhanced battery health management by integrating multi-physics modeling, real-time data, and advanced computational resources.

Our analysis, structured by this framework, reveals three key findings. First, DT-based approaches significantly outperform traditional BMS in accuracy and adaptability across all health indicators (SOC, SOH, RUL) by effectively linking real-world data from the Physical Layer to sophisticated algorithms in the Virtual Model Layer. Second, data augmentation techniques, situated within the Data & Communication Layer, are critical for addressing the limitations of incomplete or unrepresentative real-world datasets, thereby improving model robustness. Third, the Twin Service Layer delivers superior fault diagnosis capabilities by leveraging advanced hybrid models and deep learning architectures hosted in the virtual space.

However, several challenges persist across the DT architecture. The limited generalization of models in the Virtual Model Layer across extreme degradation phases, insufficient consideration of battery pack structures in the Physical Layer, and the complexity of real-world operating conditions all constrain practical implementation. Furthermore, the services for fault diagnosis require improvements in optimum feature selection, multi-fault identification, standardized measurement protocols, and severity estimation.

In order to overcome aforementioned challenges, future research for different layers and directions, should be explored. The Data & Communication Layer needs enhancement to integrate cell-level and pack-level features for system-wide health assessment. Furthermore, adaptive Virtual Model Layers that account for multi-phase degradation mechanisms, should be developed. Achieving multiple functions in the Twin Layer, especially for fault diagnosis, is essential. Finally, it is crucial to establish standardized DT architectures and protocols, potentially by introducing a dedicated Cloud Layer, combined with federated learning, to optimize resource allocation and ensure data security. Addressing these layer-specific challenges is crucial for the widespread adoption of DTs.

As DT technology continues to mature, its structured integration with battery management systems promises to revolutionize health prognosis in electric vehicles, renewable energy storage, and other critical applications, ultimately enhancing safety, extending battery life, and supporting sustainable energy transitions.

CRediT authorship contribution statement

Yujie Wang: Writing – original draft, Project administration, Investigation, Funding acquisition, Conceptualization. **Jiayin Xiao:** Writing – original draft, Visualization, Investigation. **Yin-Yi Soo:** Writing – original draft, Visualization, Investigation. **Yifan Chen:** Writing – original draft, Visualization, Investigation. **Zonghai Chen:** Writing – review & editing, Supervision, Conceptualization.

Declaration of competing interest

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

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Data availability

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

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