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Advancing Lithium-Ion Battery Health Prognostics With Deep Learning: A Review and Case Study

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ABSTRACT Lithium-ion battery prognostics and health management (BPHM) systems are vital to the longevity, economy, and environmental friendliness of electric vehicles and energy storage systems. Recent advancements in deep learning (DL) techniques have shown promising results in addressing the challenges faced by the battery research and innovation community. This review article analyzes the mainstream developments in BPHM using DL techniques. The fundamental concepts of BPHM are discussed, followed by a detailed examination of the emerging DL techniques. A case study using a data-driven DLinear model for state of health estimation is introduced, achieving accurate forecasts with minimal data and high computational efficiency. Finally, the potential future pathways for research and development in BPHM are explored. This review offers a holistic understanding of emerging DL techniques in BPHM and provides valuable insights and guidance for future research endeavors.

INDEX TERMS Deep learning (DL), health and life-cycle analysis, lithium-ion battery (LIB) management system, prognostics and health management (PHM), remaining useful life (RUL) prediction, state of charge (SOC) estimation.

NOMENCLATURE

ATE	Aging trajectories estimation.
BMS	Battery management systems.
BPHM	Battery prognostics and health management.
C	Capacity.
CNN	Convolutional neural networks.
DBN	Deep belief networks.
EOL	End-of-life.
EV	Electric vehicle.
FOBSS	Monitoring Data from a Modular Battery System.
GAN	Generative adversarial networks.
GRU	Gated recurrent unit.
LIB	Lithium-ion battery.
LSTM	Long short-term memory.
P2-D	Newman's pseudo-2-D model.
PCoE	NASA Ames Prognostics Center of Excellence.
RNN	Recurrent neural network.
RUL	Remaining useful life.
SOC	State of charge.
SOE	State of energy.
SOH	State of health.
SOM	Self-organizing maps.
SOP	State of power.
SPM	Single-particle model.
TCN	Temporal convolutional network.

I. INTRODUCTION

Nowadays, lithium-ion batteries (LIBs) are among the foremost technological innovations in contemporary society. This is attributed to their notable safety, high gravimetric and volumetric densities, long durability, reusability, and recyclability, as illustrated in Fig. 1 [1]. In 2019, the LIB market stood at 36.7 billion, and it is anticipated to soar to an impressive 128.3 billion by 2027. This surge, projected at a compounded annual

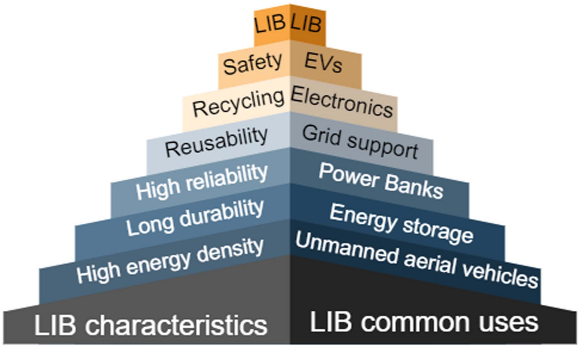

FIGURE 1. LIB characteristics and usage.

rate of 18% from 2020 to 2027, is predominantly propelled by the shift from combustion engine cars to hybrid and electric vehicles (EVs) [2]. LIBs play a crucial role in promoting the proliferation of diverse technologies, including EVs, portable electronic gadgets, renewable energy integration, and grid stability support, as shown in Fig. 1. However, the foreseeable growth of LIBs in our highly electrified world underscores the need for accurate and reliable estimation of battery performance parameters. In fact, the health degradation of LIBs during charging and discharging cycles, attributed to their complex aging mechanisms, can curtail their lifespan [3]. Studies indicate that by 2030, the number of retired LIBs from EVs will surpass 12 million tons [4]. Thus, it is imperative to promote battery prognostics and health management (BPHM) systems to ensure that the batteries operate with utmost safety and reliability [5].

BPHM's primary objective is to monitor, predict, and maintain the health and performance of LIBs throughout their operational life incorporating a myriad of algorithms and tools [6]. Within BPHM, key battery internal states, such as state of charge (SOC), state of health (SOH), and state of power significantly influence the safety, efficiency, and overall longevity of the battery storage system [7]. As a result, the development of advanced algorithms and methods for efficient BPHM has emerged as a pivotal research area in the realm of battery management systems (BMS) [8]. BPHM estimation models are taxonomized into three classes: Model-based, data-driven, and hybrid approaches [9]. The model-based techniques leverage the complicated physical processes or mathematical models to represent battery degradation behaviors [10]. Model-based techniques offer benefits, such as lower data requirements and insensitivity to external disturbances. Hence, these model-based techniques are relatively complex. Methods such as the coulomb counting method, electric equivalent circuit models (ECMs), and electrochemical impedance spectroscopy (EIS) tests, which fall under direct calibration model-based methods, rely on extensive physical and chemical knowledge [11]. However, they face challenges in fully capturing the intricate, dynamic, and static characteristics of LIB.

In contrast, data-driven methods, which view the LIB as a black-box system, have gained notable prominence in recent years with the abundance of operational battery data. Researchers have directed and implemented machine learning (ML) techniques for BPHM, crafting data-driven solutions adaptable to diverse battery chemistries, operating conditions, and aging mechanisms [12]. These methods utilize statistical and ML techniques to analyze historical battery performance and operational data, with the aim of providing patterns and relationships for accurate prognostics [13]. In particular, shallow ML methodologies are generally more flexible and convenient than model-based approaches. By employing various ML algorithms, such as regression analysis, support vector machines, or random forests, these methods enable the prediction of key battery parameters, such as remaining useful life (RUL). These predictive models offer valuable insights for proactive maintenance, optimized battery utilization, and improved reliability in various BPHM applications. However, their performance is heavily contingent upon the quantity and quality of available data. Despite having access to large-scale aging data, the classical ML models might not always generalize effectively under novel conditions [14].

Traditional ML schemes for LIB face challenges in capturing degradation characteristics [15], leading to potential inconsistencies in the accuracy and robustness of the degradation process estimation. With the large volume of data, deep artificial neural networks (DNNs) have gained significant attention in the field of BPHM due to their ability to learn feature representations on their own, thus, avoiding potentially biased hand-crafted features [16]. Deep learning (DL) models have been utilized to extract and analyze complex patterns and temporal dependencies in battery data [17]. By leveraging large-scale datasets and powerful computational capabilities, DL algorithms can effectively learn and predict battery degradation behavior. Moreover, DL methods have demonstrated their ability to handle high-dimensional and multimodal battery data, which includes voltage, current, temperature, and impedance, thereby enabling comprehensive and accurate battery health assessments. Therefore, DL methods offer a promising avenue for advancing BPHM techniques.

A. BACKGROUND AND MOTIVATION

Proper LIB diagnostic assessment can help prevent unexpected shutdowns, extend battery life, optimize BMSs, and enhance user experience [18]. Traditional BPHM methods, such as empirical, electrochemical, and analytical models, have limitations in terms of accuracy, computational complexity, and adaptability to varying operating conditions [19]. DL models have emerged as promising alternatives due to their ability to decipher complex relationships from data, adapt to changing conditions, and refine assessment accuracy [20]. Moreover, there has been a notable surge in DL models to bolster the precision of battery health prognostic systems. Table 1 explicitly compares this review with the recently published review works in the past three years on LIB informatics, enumerating the applicable cases and scenarios in BPHM where ML can make a viable impact [18], [19], [20], [21], [22], [23], [24], [25], [26], [27], [28], [29], [30], [31], [32]. This

TABLE 1. List of the Related Review Papers on Battery Health Prognostics

Reference		[18]	[19]	[20]	[21]	[22]	[23]	[24]	[25]	[26]	[27]	[28]	[29]	[30]	[31]	[32]	Ours
Year		2022	2022	2020	2021	2021	2022	2023	2023	2023	2022	2021	2020	2020	2021	2021	2023
Covered scope	SOC	●	●	●	●	●	○	●	●	●	●	○	◐	○	●	○	●
	DL	●	○	●	○	○	○	◐	○	○	○	◐	○	○	○	◐	●
	LIB	●	◐	●	●	●	●	●	●	●	●	●	●	●	●	●	●
	SOH	○	●	○	●	○	●	●	●	○	●	●	●	●	●	○	●
	RUL	○	○	○	●	○	●	●	●	○	◐	○	●	●	●	○	●
	BPHM	◐	●	○	●	●	○	●	◐	●	●	○	●	◐	◐	○	●
	LIB fault detection	○	●	○	●	○	○	●	○	○	○	○	◐	●	●	○	●
	LIB aging trajectories	○	○	○	○	●	●	◐	○	○	●	○	●	○	●	○	●
	Case study	○	○	○	○	○	○	○	●	○	○	○	○	○	○	○	●

●Fully addressed ◐ Partially addressed ○ Not addressed

comparison is based on coverage of topics: DL and LIB and SOH and RUL and BPHM and LIB fault detection and LIB aging trajectories, and a case study. Despite the increasing focus on DL models, most of these reviews only dedicate a brief paragraph or section to discuss their integration with BPHM. To the best of the authors' knowledge, comprehensive reviews dedicated to the study of the combined potential of DL and BPHM with a case study on a real-world dataset do not exist in the current literature. Unlike existing review works, this article provides extensive coverage of the wide spectrum of BPHM algorithms that integrate the pioneering works on DL. This work is supported by a case study for the SOH estimation using a recent data-driven model and compared with several benchmark models. This review delves into various DL models, their applications, and the challenges they encounter in RUL and SOH assessments. Furthermore, future research pathways in the context of emerging battery technologies and the increasing intricacy of LIB systems are identified. This article is intended to be a valuable resource for researchers, engineers, and practitioners in the domain of BPHM.

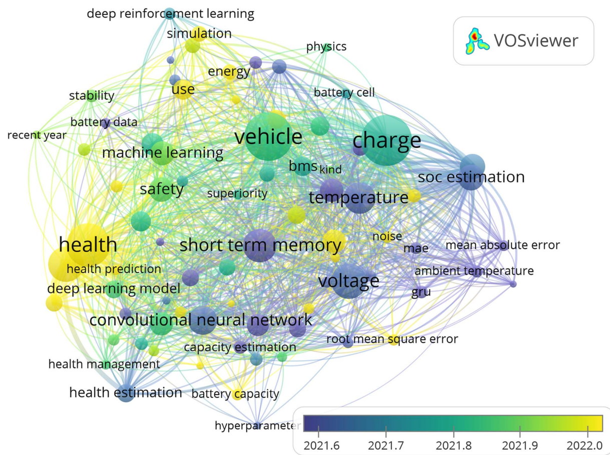

FIGURE 2. Keywords map for BPHM methods.

This structure is influenced by the identified keywords. Fig. 2 highlights two topic clusters: DL models and their integration on BPHM. These clusters guide the organization of the review in the subsequent section.

B. OBJECTIVES AND SCOPE OF THE REVIEW

This article provides a comprehensive analysis of recent advances in BPHM using DL techniques. The introduction covers the fundamentals of battery aging processes, followed by a brief overview of traditional methods employed in these estimations. The discussion, then, delves into state-of-the-art techniques applied to battery state estimation, highlighting the strengths, weaknesses, and practical implications of each. Further exploration reveals the impact of different factors on the accuracy and performance of these techniques, including considerations, such as feature extraction and selection, data preprocessing, model architecture, and training strategies. The text identifies existing challenges, knowledge gaps, and potential future directions by finding synergies between DL and LIB storage systems to enhance the accuracy, robustness, and scalability of estimation models. A bibliometric analysis has been conducted using a thesaurus file from the WoS website to define the review's structure, as depicted in Fig. 2.

C. LIST OF CONTRIBUTIONS AND ARTICLE ORGANIZATION

The article primarily focuses on offering an in-depth review of contemporary literature on DL techniques with application to BPHM systems.

1) A systematic literature review of the emerging BPHM solutions is provided using the most advanced DL methods. Despite the numerous papers applying DL for LIB informatics in the last three years, these models have not been sufficiently reviewed and analyzed.
2) The study highlights unaddressed research areas and potential challenges in existing BPHM studies. Multiple key technical bottlenecks are depicted to solidify the applicability of DL in LIBs.
3) An efficient data-driven model is exploited for SOH estimation. The proposed model uses limited data to provide accurate forecasts on a real-world dataset with the merits of competitive performance and high-computational efficiency. To the best of the authors'

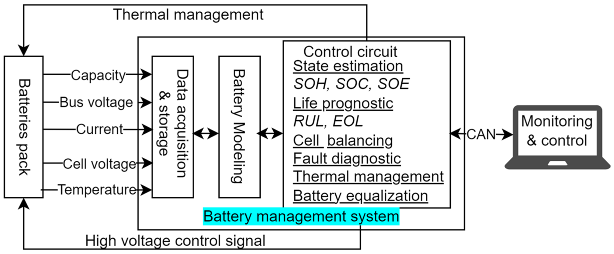

FIGURE 3. Flowchart of the commonly-used BMS.

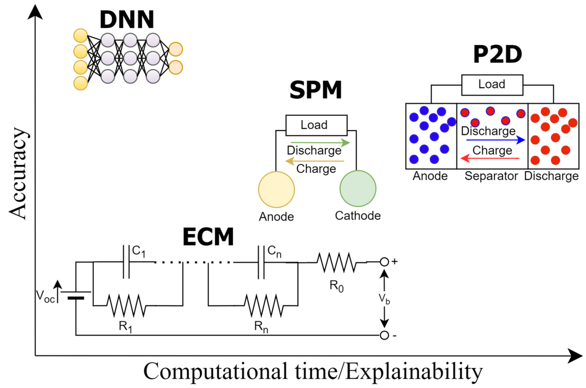

FIGURE 4. Accuracy versus computational time and explainability for ECM, SPM, DNN, and P2D model.

knowledge, this is the first time the DLinear model is applied to a LIB dataset.

The rest of this article is organized as follows. Section II provides an in-depth analysis of the used models to simulate LIB operation and the degradation mechanisms involved. The DL network structures for BPHM are detailed in Section III. Section IV taxonomizes the use of DL techniques in BPHM. Section V provides a detailed analysis of a specific use-case scenario. Section VI discusses the challenges and potential future directions in BPHM-based DL. Finally, Section VII concludes this article.

II. BATTERY MODELING APPROACHES

The BMS is pivotal for modeling and controlling LIBs. The BMS monitors and manages battery packs, as shown in Fig. 3. It tracks parameters, such as capacity, voltage, and temperature, and performs functions like cell balancing and fault diagnostics. Through battery modeling, it predicts performance, ensures safety through thermal management, and communicates with other systems via the controller area network protocol. Battery modeling involves understanding the electrochemical, thermal, and electrical behavior of a battery. Effective models capture essential features such as voltage, current, temperature, and aging. At present, commonly used battery models fall into three categories: ECMs, electrochemical, and data-driven models. ECMs use ordinary differential equations to reflect the phenomenology of the electrical circuits. These methods are efficient for real-time applications, but accuracy varies based on the circuit's complexity.

For instance, the second-order resistor–capacitor ECM model has garnered significant attention from scholars and practitioners due to its optimal balance between complexity and accuracy [33]. To accurately simulate high-dynamic electrochemical processes and aging effects, electrochemical models are derived from electrochemistry principles and offer detailed insights into internal processes in the electrodes and the electrolyte, such as chemical reactions and charge conservation laws [34]. Therefore, the electrochemical-based model is anticipated to supersede the ECM, serving to observe and estimate the states and properties of the battery throughout its aging process [35]. These models can record variations induced by temperature fluctuations as such variations elicit distinct responses from an electrochemical standpoint. Newman's pseudo-2-D (P2D) model is one of the widely used electrochemical models.

The P2D model incorporates over 20 parameters, employing nonlinear and partial differential equations to meticulously explore the behavior of LIBs [33]. This presents a notable computational expense and optimization difficulty as significant hurdles when implementing this electrochemical-based model within BPHM systems in real-time scenarios. From a technical point of view, ECMs perform with reduced computational demands compared with P2D models [36]. To strike a balance between modeling accuracy and computational efforts, a simplified LIB electrochemical-based model, namely, the single-particle model (SPM) is proposed [37]. The SPM originates from the comprehensive full-order electrochemical model, thereby inheriting several crucial properties. Within the SPM, each of the two electrodes is conceptualized as a singular spherical solid particle. Unlike the P2D models, the SPM does not take electrolyte dynamics into consideration and the LIB concentration in the electrolyte reaction is assumed to be uniform [37]. The SPM exhibits a more limited dynamic behavior compared with the full-order model, particularly excluding mechanical responses. The impact of these responses on diffusion becomes notably significant when the electrode material possesses a high modulus and elevated partial molar volume [37]. Nonetheless, the accuracy of the SPM commonly diminishes at elevated charge/discharge rates due to its inability to account for electrolyte dynamics. To mitigate this limitation, integrating electrolyte dynamics can be an effective approach [38]. Data-driven models use empirical data and ML to depict battery behavior, balancing accuracy and computational efficiency. The Thevenin model is one of the most commonly used ECMs. Fig. 4 illustrates a fair comparison of the common LIB models (DNN, SPM, ECM, and P2D) in terms of accuracy, computational time, and explainability. From Fig. 4, it is evident that the DNN model stands out in delivering superior accuracy. However, this high accuracy comes at the cost of skyrocketing computational time. This suggests that while DNN offers precise predictions, it might require more resources or time to process, which could be a consideration for real-time applications or systems with limited computational power.

ECMs predict battery behavior using electrical components. These models describe voltage changes in response to current changes. By simulating the internal resistance and other processes, ECMs offer insights into battery performance and lifespan. The choice of an ECM depends on battery chemistry, desired accuracy, and application. Battery degradation affects performance and longevity, especially in LIBs. Degradation mechanisms include capacity fade, power fade, and solid-electrolyte interphase (SEI) formation. Capacity fade results from the loss of active material, whereas power fade arises from increased internal resistance. SEI layer formation can increase resistance and reduce capacity. Factors such as temperature and operating conditions affect these degradation mechanisms, thereby influencing the overall battery performance and lifespan.

III. EXISTING DL METHODS IN BPHM

In this section, DL methods are classified based on data structure into sequential and nonsequential methods. Sequential methods, such as recurrent neural network (RNN) and long short-term memory (LSTMs), process time series or ordered data. In contrast, nonsequential methods, such as feedforward neural networks and convolutional neural networks (CNNs), handle fixed-size data without emphasizing sequence or order.

A. SEQUENTIAL NEURAL NETWORKS

Sequential neural networks (SNNs) process time-series data by assuming that the state at any given time step depends on prior states. SNNs consider the time-ordered or sequential aspects of data. The following sections describe the commonly used SNNs for BPHM systems.

1) RNN AND THEIR DERIVATIVES

RNN model, designed for time series data, uses feedback loops in hidden layers to retain past state information. For input sequences x_t and output vectors y_t, the hidden states are h_t [39]. The current hidden state, h_t, is computed using the input, previous hidden state, and associated weights and biases. The output is expressed as $y_t = W_{hy}h_t + b_y$, where W and b represent the weights and bias, respectively. LSTMs excel in temporal feature extraction, attributed to three gates: input i_t, forget f_t, and output o_t [39]. Each gate uses specific weights, biases, and the sigmoid activation function. Elementwise multiplication is denoted by $\odot$. Gated recurrent units (GRUs) designed to reduce the LSTM's computational load, utilize two gates. The update gate functions similarly to the LSTM's forget gate, deciding on information retention, whereas the reset gate determines information preservation. In the vast majority of papers applying the RNN models, the memory gates improve the model accuracy [40].

Li et al. [39] delved into an innovative approach leveraging LSTM and the ECM to diagnose LIBs faults in EVs. The ECM provides a detailed representation of the battery's internal dynamics, enhancing diagnostic accuracy. However, the proposed approach was primarily tested through simulations or lab settings, with limited verification in real-world EV implementations. In [40], the authors introduced an improved SOC estimation model based on a two-hidden-layer GRU trained with the one-cycle policy. The proposed model has demonstrated satisfactory outcomes with a low error rate under various EV drive cycles at different ambient temperatures. Nonetheless, the proposed GRU model involves significant hyperparameters selection, and there is a lack of studies highlighting the influence of these hyperparameters on model performance.

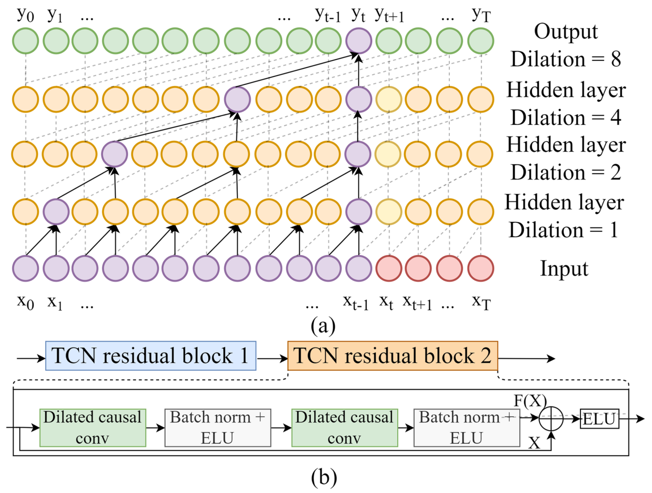

FIGURE 5. (a) Conceptual diagram of a stack of dilated causal convolutions with dilation factors $d = 1, 2, 4, 8$. (b) Architecture of the TCN consisting of two residual blocks.

2) TEMPORAL CONVOLUTIONAL NETWORKS

Temporal convolutional networks (TCN) are designed to handle time series sequences [41]. TCN consists of a stack of residual blocks hierarchically distributed, as shown in Fig. 5(a). The TCN architecture contains causal (dilated) convolutions, as shown in Fig. 5(b). The dilated convolutions ensure that the output at time t is convolved only with information up to time t as follows:

$$y_t = f(x_{t-d}, x_{t-d+1}, \ldots, x_t) \tag{1}$$

where f is a function implemented by the TCN layers, x is the input sequence, and d is the size of the receptive field. TCNs can be used for forecasting battery health by processing sequential battery usage and health data to predict future states or RUL.

A conditional temporal convolutional encoder–decoder (CTCED) is proposed for predicting the available capacity of LIBs under various scenarios, including different battery chemistries and changing conditions [41]. The CTCED model is nonrecursive, making it faster than traditional models on modern hardware optimized for vectorized computations. Unfortunately, the CTCED's GPU RAM usage is higher during training, especially when longer sequences are involved. Zhou et al. [42] addressed the challenges of predicting the SOH and

RUL for LIBs. By applying the TCN model, the dilated convolution improves the training speed and memory caused by network depth. However, obtaining accurate measurements of impedance, which are essential for battery health monitoring, is challenging and costly.

3) BIDIRECTIONAL RNNS

Bidirectional RNN processes sequences in both directions: From past to future and vice versa [43]. This gives them a wider context for each time point [44]. The output of the forward hidden unit $\overrightarrow{h_t}$ and the backward hidden unit $\overleftarrow{h_t}$ are computed as [43]

$$\overrightarrow{h_t} = \overrightarrow{f}(x_t, \overrightarrow{h_{t-1}}) \tag{2}$$

$$\overleftarrow{h_t} = \overleftarrow{f}(x_t, \overleftarrow{h_{t+1}}) \tag{3}$$

where $\overrightarrow{f}$ and $\overleftarrow{f}$ are forward and backward RNN functions, respectively. This approach can be utilized to incorporate both historical and anticipated usage patterns in estimating the health of batteries.

Zhang et al. [43] proposed a bidirectional GRU (BiGRU) method to map LIB measurements, such as voltage, current, and temperature, directly to the SOC. The proposed BiGRU learns the effects of ambient temperature variations, resulting in accurate SOC estimations with a root mean square error (RMSE) values less than 2.5% and 3.5% for different battery types. However, the bidirectional architecture might start to overfit after a certain point. Such model has a trade-off between performance and computational cost, with larger models requiring more floating point operations per second and runtime. Zhang et al. [45] proposed a ground-based LIB state estimation technique for low Earth orbit satellite systems. This technique utilizes an unscented Kalman filter-based model that leverages battery current and voltage predictions made by the bi-directional LSTM (Bi-LSTM) network. The proposed technique's SOC estimation RMSE converges to about 1.7 A for current and 0.2 V for voltage. However, in the early stages, when there is insufficient training data, the SOC estimation error can increase to about 9%.

4) TRANSFORMER MODELS

Transformers use self-attention mechanisms to weigh the relevance of different parts of the input sequence when producing an output. The attention mechanism is mathematically represented as [46]

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V \tag{4}$$

where Q, K, and V are query, key, and value matrices, respectively. Transformers can process irregular time series data from batteries and consider long-range dependencies, which might be crucial for accurate prognostics. In [46], a transformer-based model has been proposed to capture both local and global temporal dependencies in the data. The transformer model can efficiently process the entire sequence in parallel, leading to faster training times compared with RNN-based models. Chen et al. [47] introduced a multiview information perception transformer (MVIP-Trans) framework for LIB SOH estimation. This framework combines local information perception (LIP) and global information perception to enhance noise tolerance and long-term feature learning. Despite the high training time of the proposed approach, the MVIP-Trans model outperforms other models in prediction accuracy, especially on certain datasets, such as B0005.

5) CONVOLUTIONAL RNN

A combination of CNNs for feature extraction and RNN for sequential processing is introduced in the literature to boost the prediction system performance on time series LIB data [48]. While the CNN layers capture spatial patterns, the RNN layers capture temporal patterns. CNN-RNN are used for batteries that have spatial and temporal data, like arrays of sensors spread across large batteries, to capture both spatial degradation patterns and temporal usage patterns. A convolutional GRU framework is proposed for SOH by extracting key features from segments of voltage, current, and temperature curves during the charging process [49]. While the CNN-GRU model offers a low mean absolute error (MAE) of 0.013, there are still some outliers observed in the results. A CNN-LSTM-DNN model has been proposed for RUL, offering a data-driven, self-adaptive, and nonlinear approach [50]. Experimental validation on datasets from the National Aeronautics and Space Administration (NASA) and Center for Advanced Life Cycle Engineering (CALCE) demonstrates its superior prediction accuracy over single ML methods, offering both high accuracy and acceptable execution time. However, the method's reliance on historical data might not account for unforeseen changes or anomalies in battery behavior variations, such as heat and aging. Navigating through the complexities of LIB behavior, a combination of CNN and GRU enriched by the potency of transfer learning is proposed in [51]. It was proven that transfer learning aids the CNN-GRU model by utilizing pre-existing knowledge, enhancing generalization and accuracy, and improving model performance. Nonetheless, If the domains are significantly different, the benefits of transfer learning might be diminished.

6) ATTENTION RNN

RNN can be enhanced with attention mechanisms by focusing on specific parts of the input sequence when producing each output, similar to transformers but in RNN framework [52]. The attention mechanism in this enhanced RNN model can be mathematically represented by [52]

$$c_t = \sum_i \alpha_{ti} h_i \tag{5}$$

where c_t is the context vector and α_{ti} are the attention weights. Attention RNN can be utilized when certain periods or events in the battery's life are more critical than others, allowing the model to focus on those crucial moments for prognostics. A calendar health prognostic based on knowledge-data-driven attention is proposed in [6]. The model integrates battery empirical knowledge, which significantly improves prognostics performance, especially for unwitnessed conditions. Unfortunately, potential biases in semiempirical models for the proposed framework might need further refinement. An integrated attention mechanism leveraged with a Bi-LSTM network is proposed for SOC [53]. The authors claim that the proposed method may not be as effective for datasets with very long sequences, and further refinements are needed to handle such scenarios.

B. NON-SNN

The nonsequential networks extract features related to space and interaction. Moreover, they can represent temporal data either by modeling the end state or by assessing the entire history of observed states, without presuming a conditional dependence on earlier states. This section delves into the key nonsequential networks for LIB systems.

1) CONVOLUTIONAL NEURAL NETWORKS

The CNN model consists of an input layer, multiple convolution layers, pooling layers, a rectified linear unit with a fully connected layer, and the output layer [47]. For BPHM, CNNs can be employed to analyze image or time series data to detect anomalies or predict battery failures [54]. Mathematically, the convolution operation in CNNs is given as [55]

$$(Y * X)[i, j] = \sum_m \sum_n Y[m, n] \cdot X[i - m, j - n] \quad (6)$$

where Y is the kernel and X is the input. Xu et al. [55] proposed 1-D CNNs for estimating the SOC of LIBs. The 1-D CNN model takes the voltage, current, and temperature values of a battery corresponding to specific timesteps as inputs and predicts the SOC value at a given timestep. 1-D CNNs stride only in one dimension, which is the temporal dimension in this context. This ensures that the network captures patterns relevant over time, which is crucial for battery SOC estimation. However, the CNNs might potentially face challenges in handling long-term dependencies in the data or require fine-tuning for accurate SOC.

2) BOLTZMANN MACHINES AND DBNS

Boltzmann machines are stochastic RNN [56]. In the context of BPHM, they can be used for feature learning or modeling complex interactions in battery data. The energy of a state in a Boltzmann machine is computed as [57]

$$E(\mathbf{v}, \mathbf{h}) = -\sum_i a_i v_i - \sum_j b_j h_j - \sum_{i,j} v_i w_{ij} h_j. \quad (7)$$

Deep belief networks (DBNs) are composed of multiple layers of stochastic, latent variables [58]. They are trained greedily, one layer at a time. In BPHM, DBNs can model complex relationships and detect intricate patterns in battery datasets. The energy function of a Restricted Boltzmann machine (RBM) (the building block of DBNs) is calculated as follows [57]:

$$E(v, h) = -\sum_i a_i v_i - \sum_j b_j h_j - \sum_{i,j} v_i w_{ij} h_j \quad (8)$$

where v and h are visible and hidden units, respectively. Massaoudi et al. [59] introduced a DBN method for estimating the capacity of LIBs based on features derived from the charging process. Health indicators are extracted from charging curves, optimized using grey relation analysis, and then processed with a DBN. The proposed approach is limited to the heavy computational requirements of DBN training. Meanwhile, Cao et al. [60] combined the partial incremental capacity (IC) with a DBN optimized by particle swarm optimization for the health diagnosis of LIBs. The IC curve's evolution, which correlates well with the battery's SOH as the number of cycles increases, is used. Peaks and valleys in the IC curves are applied as input features. The estimation errors are mostly below 2.5%, with the best estimation results corresponding to fully charged and discharged operating conditions, reaching less than 1%. However, there are occasional outlier points with larger estimation errors.

3) AUTOENCODERS AND THEIR DERIVATIVES

The autoencoders learn to encode inputs into a reduced dimensional space and then decode them back [61]. In BPHM, they can be used for feature reduction or anomaly detection by analyzing the reconstruction error [62]. Given an input x, an encoder function f, and a decoder function g, the reconstruction is given as [63]

$$\hat{x} = g(f(x)). \quad (9)$$

Jiao et al. [64] introduced a stacked denoising autoencoder (SDAE) combined with clustering by fast search to select significant features for LIB RUL prediction. This approach effectively reduces the dimensionality of the data, which is beneficial for improving the efficiency of the prediction model. Unfortunately, the challenge of the SDAE model is rooted in the high complexity, which might make it harder to interpret compared with simpler models.

An improved variational autoencoder (VAE) method is proposed to reconstruct the inconsistency of multidimensional parameters of battery packs [65]. The VAE-based method can generate parameters with better similarity to the original data using a small sample size (95 samples). It can be noticed that the temperature standard deviation error of the proposed method can reach up to 4.53%, which might be significant in certain applications.

4) GENERATIVE ADVERSARIAL NETWORKS

GANs consist of two networks: A generator and a discriminator [66]. The generator produces fake data, whereas the discriminator tries to distinguish between real and fake data [67]. For BPHM, GANs can generate synthetic battery data to augment datasets. A capacity forecast GAN (CFGAN) is proposed for forecasting the calendar aging of LIBs [68].

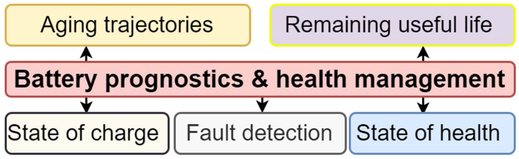

FIGURE 6. Application of DL for BPHM.

The CFGAN aims to model the joint distributions of forecasting targets at different lead steps. The model is trained to be consistent with the electrochemical theory of calendar aging. Unfortunately, the CFGAN model requires alternating training, which can be computationally intensive and challenging to implement and optimize. Zhao et al. [69] introduced a GAN-based SOC estimator for synthetic battery operation data generation. This method aims to produce synthetic data that closely resembles real battery operation data. However, the synthetic data generated by GAN, no matter how well generated, might not capture all the nuances of real-world data.

5) SELF-ORGANIZING MAPS

Self-organizing maps (SOMs) are unsupervised neural networks that produce a low-dimensional representation of the input space [16]. For BPHM, SOMs can cluster similar battery states or behaviors together, aiding in visualization and analysis. Given a weight matrix W and an input x, the best matching unit (BMU) is computed as

$$\text{BMU}(x) = \arg\min_i ||x - w_i||. \tag{10}$$

A SOM is employed to identify aging conditions in LIBs [70]. The methodology can be employed to depict the aging process in batteries intended for the second-life market, even if their past uses are unknown. This approach can assist in identifying suitable second-life applications for used cells based on their performance capabilities. However, the technique's accuracy might be affected if the battery has been subjected to varied conditions not covered in the training dataset.

IV. APPLICATIONS OF DL IN BPHM

This review divides the BPHM methods into five classes, namely, SOC estimation, RUL estimation, battery fault detection and diagnosis, SOH estimation, and aging trajectories estimation (ATE), as shown in Fig. 6. In this section, each class is described and demonstrated through real applications from the literature. Additionally, Table 2 presents a compilation of DL approaches used for battery performance prediction. Each model's unique benefits and constraints are discussed, with considerations of computational demands and environmental conditions factored into their practical applicability.

A. SOC ESTIMATION-BASED DL

With the fast-changing electromechanical features, SOC is a way to measure the current state of a battery varying in a short time span. SOC is defined as the ratio of its remaining capacity and its initial capacity [71]. The SOC estimation is a crucial factor in BMS, as it directly influences the performance and lifespan of batteries [51]. DL techniques have emerged as promising approaches for accurately estimating SOC, thus, enhancing the overall efficiency of battery systems and preventing catastrophic thermal runaway. The SOH represents the percentage of the battery cell's available capacity, and it is calculated using the formula below [42]:

$$\text{SOH}(t) = \frac{C_t}{C_0} \tag{11}$$

where C_o and C_t denote the initial capacity and the capacity at the tth cycle, respectively. DL techniques, such as CNNs, RNN, and LSTM networks, have demonstrated their prowess in capturing complex temporal relationships in battery data. By harnessing the power of DL methodologies, researchers have made significant strides in overcoming the potential discrepancies of traditional SOC estimation techniques, paving the way for more reliable, efficient, and intelligent BMS.

Flores et al. [72] introduced a method for estimating the SOH of lithium ionphosphate batteries. One of the significant advantages of the proposed method is its ability to utilize images as input, which has been shown to help the DL model capture and learn features more effectively than using sequences as input. However, a limitation was observed for specific datasets, such as R5. The difficulty in transferring degradation model (DM) knowledge from synthetic datasets to real datasets like R5 restricts further improvement in SOH estimation accuracy. A bilateral branched visual transformer with dilated self-attention is introduced in [73]. This innovative framework considers partial charging segments of different SOC ranges, enhancing its applicability to real-world scenarios. It is worth mentioning that traditional direct calibration methods, such as coulomb counting and open-circuit voltage methods are time-consuming, costly, and less practical for real-world EV applications, being more suited for lab settings. Yang et al. [74] offers a novel approach that leverages advanced algorithms for accurate predictions. One of the key advantages of this method is its ability to provide precise SOH estimations, as evidenced by its performance metrics like RMSE and MAE.

B. RUL ESTIMATION-BASED DL

The battery's RUL in the early-cycle stage refers to the number of operational cycles from the current working cycle before the battery's capacity degrades to the failure threshold. Lu et al. [75] indicates that a battery approaches its end of life (EOL) when its capacity declines to between 70% and 80% of its original rating. Degradation processes, including metal erosion, expansion of the protective surface coating on the electrodes, and the depletion of reusable lithium ions, influence the lifespan of the LIB. RUL estimation is a critical

TABLE 2. Comparative Analysis of DL Models for Battery Performance Prediction

Ref.	Model	Best error	App.	Multi-T	Advantages	Limitations
[95]	TCN	RMSE=0.87%	SOC	0, 10, and 25°C	- Predicts SOC under varied conditions - Applies transfer learning to other SOC types	- Requires specific SOC speed estimation -'s computing capacity is unspecified.
[96]	LSTM	MAE=0.7%	SOC	0, 10, and 25°C	- Self-learns network parameters - Encapsulates temperature behaviors	- Cumbersome hyperparameter tuning - Computationally expensive and memory-intensive
[14]	AE-CNN-LSTM	RMSE=5.03%	RUL	NA	- Deep information mining and - Continuous and stable output Effective training of CNN and LSTM.	- Prediction accuracy may be affected by sparse - degradation data and the complex definition of - degradation index thresholds.
[97]	GNN	R^2=0.9674	Capacity	NA	- Ability to model complex relationships - Ability to handle incomplete data and non-Euclidean data	- Difficult to interpret and understand - Prone to overfitting
[98]	GRU	RMSE=1.07 at T=40°C	SOC	0, 10, 20, 30, 40, and 50°C	- Adapts to diverse battery materials - Manages regeneration, hysteresis, and degradation	- Prone to overfitting May face concept drift problems
[99]	DNN	RMSE=3.68%	SOC	0,25,45°C	- Predicts SOC for unseen drive cycles	- Prone to overfitting
[67]	RGAN	RMSE=1.24%	SOH	25C	- Works with varied battery specs -Efficiently bypasses time consuming and costly anomaly collection.	- High computational demand - Valid only at room temperature - Works with varied battery specs - Needs CC charging for specific voltage segments
[62]	CVAE-PF	RMSE=1.8095	RUL	NA	- Able to handle different uncertainty levels - Learn latent representations of the input data	- The model is not considering otherstress conditions such as usage patterns and environmental conditions.
[100]	MRSN	RMSE=0.18% at T=25°C	SOC	20,0,10,25	- High accuracy - Better generalization potential	- Noise Sensitivity - Diffuclt to Interpret

aspect of battery health and safety management, as it supports quality inspection, optimal operation, maintenance, and replacement decisions. The RUL is calculated as follows [42]:

$$\mathrm{RUL}(t) = t - t_{\mathrm{EOL}} \tag{12}$$

where EOL denotes the number of cycles at the end of battery life, and t is the tth cycle number. Likewise, end users could estimate their battery life expectancy. DL techniques have emerged as powerful tools for accurately predicting the RUL of batteries, leveraging complex patterns and correlations hidden in historical and real-time data. By exploiting the wealth of data generated by sensors monitoring battery performance, these algorithms can predict the deterioration of battery capacity, voltage, and internal resistance, ultimately leading to a more precise estimation of the RUL. This improved understanding of battery health not only enhances the reliability and safety of power systems but also contributes to cost reduction, resource optimization, and the extension of battery lifetimes. As such, the application of DL techniques for RUL estimation represents a significant stride toward more efficient and sustainable power systems.

Fei et al. [76] introduced a novel attention-assisted temporal convolutional memory-augmented network framework for predicting the RUL of LIBs. This method boasts superior accuracy, speed, and generalizability, even with limited data, setting it apart from existing models. It adeptly processes high-dimensional battery data by integrating attention mechanisms, temporal convolution, and memory augmentation. However, its effectiveness is primarily demonstrated in laboratory settings with ample training samples. The model requires separate training for different battery types due to inherent degradation discrepancies. A particle filter-temporal attention mechanism-BiGRU (PF-BiGRU-TSAM) is proposed in [77]. By seamlessly merging model-based and data-driven strategies, this innovative approach not only provides timely data feedback and correction but also utilizes the BiGRU-TSAM predicted value to refine the PF model, ensuring more accurate RUL predictions. Furthermore, it can determine a 95% confidence interval for battery RUL at various prediction junctures. However, a notable limitation is its design for individual batteries. In [78], a capsule network and transfer learning (TL) are leveraged for RUL using the curves of battery charging and discharging cycles. Capsule networks are believed to be adept at extracting numerical data from images, similar to human cognition. The method offers the potential for high estimation accuracy with limited knowledge of the studied cell, making it suitable for BMS or health-conscious fast-charging protocols. The use of images as inputs to the capsule network can create more robust and reliable networks by minimizing data preprocessing. Despite its potential, the capsule network architecture is not yet mainstream, primarily due to its high computational demands and challenging implementation compared with more established architectures like CNNs and LSTMs.

C. BATTERY FAULT DETECTION AND DIAGNOSIS-BASED DL

The abusive use of LIBs can result in over-charging/discharging, overheating, and internal short circuits [79]. DL methods can be harnessed to monitor and predict LIB faults with a higher degree of accuracy and reliability compared with traditional methods [80]. By training DL models on large datasets reflecting a variety of operational states and fault scenarios, these models can learn to recognize early fault indicators and distinguish between different types of faults [81]. This ability not only enhances fault diagnosis precision but also offers opportunities for proactive intervention, therefore increasing battery lifespan, improving safety, and optimizing performance [7], [82].

Xiong et al. [83] introduced a Lebesgue sampling-based DBN model for diagnosing LIBs. This data-driven framework combines DBN and particle filter (PF). DBN, with its deep architecture, learns the state evolution and Lebesgue time transition models, whereas PF estimates the fault state. Together, they predict the battery's RUL. While the proposed method offers cost-efficiency, reduced computation, and better uncertainty management, it faces challenges in accurately modeling the dynamic degradation patterns of modern batteries. Hong et al. [84] introduced a many-to-one LSTM architecture for fault prognosis of battery systems. Tested across different seasons, the model demonstrates robustness and adaptability, offering a promising solution for battery voltage prediction in varied conditions. In [85], the authors proposed an intelligent diagnostic framework for li-ion battery packs. The method leverages the Pearson correlation coefficient (PCC) improvements and transforms the improved PCC series into pseudo images. These images, which visualize fluctuations indicative of different faults, are then processed using CNN to judge fault occurrence, type, and grade. Experimental results demonstrate high accuracy rates for fault type isolating, reaching up to 99.63% on Gramian angular field images (GAFIs) and 99.75% on Markov transition field image (MTFIs). However, the method has limitations. The CNNs used require similar image texture backgrounds for stability, and images for model training and testing should come from the same pair of cells in both pre and postfault injection due to potential differences in electrochemical characteristics among healthy cells.

D. SOH ESTIMATION-BASED DL

Understanding and estimating the SOH of LIBs on the long-term timescale is a crucial area of research that aids in their effective management, extends their operational life, and prevents irreversible damage [86]. DL models are trained on vast datasets using early-cycle data encompassing parameters, such as voltage, current, temperature, and charge-discharge cycles, among others, and output precise SOH estimations. A convolution transformer-based multiview information perception framework is proposed for SOH prediction of LIBs [47]. The MVIP-Trans framework provides an enhanced noise tolerance through LIP, and improved long-term feature learning via GIP. However, potential limitations might encompass computational demands, dataset dependencies, and optimal performance conditions.

Cai et al. [87] presented a novel method for estimating the SOH of LIBs. The approach employs an evolutionary multi-objective method to simultaneously find the best combination of features, attention layer, and hyperparameters of the network. An LSTM neural network is utilized to establish the data-driven model, with an added attention layer to finalize feature selection. Future paper work should focus on refining solution selection based on different charging scenarios and improving the generalization of the effect of temperature on the estimation. An encoder–decoder model-based SOH estimation is proposed in [88]. The encoder part of the model is constructed using a hybrid neural network that combines CNN, ultra-lightweight subspace attention mechanism (ULSAM), and simple recurrent unit (SRU) structures. This encoder is adept at extracting features from the input data. The article introduces three different decoders, with the third decoder (decoder 3) incorporating an attention mechanism. This attention mechanism allows the model to generate attention weights corresponding to encoding vectors at different moments, ensuring that the resultant new context vector effectively captures the information of the entire sequence. The attention mechanism, while beneficial for longer encoding sequences, might introduce unnecessary complexity for shorter sequences.

To use the attention mechanism more effectively, a convolutional block attention module (CBAM) is proposed to meticulously focus on distributing attention across both channel and spatial dimensions [86]. The CBAM consists of two submodules: The channel attention module (CAM) and the spatial attention module (SAM) [86]. The CAM identifies and prioritizes input data, whereas SAM emphasizes different feature map areas, enhancing attention distribution. This meticulous attention distribution along the channel and spatial dimension ensures a nuanced, selective prioritization and learning from the most relevant data during training and prediction, thereby enhancing the accuracy and robustness of the SOH estimation model.

E. ATE-BASED DL

The operational longevity of LIBs is hindered by complex aging mechanisms, which can precipitate critical failures, such as power loss, fire, or explosion, resulting in substantial economic damage [89]. The SOH is typically viewed as an important clue to reflect the battery aging process, Nevertheless, merely determining a LIB's present SOH is not sufficient to investigate the aging behavior of LIBs. In essence, the operators attempt to get insights into the LIB's future aging trajectory to alleviate concerns about its lifespan. It is important to note that the projected aging patterns are not directly derived from the current SOH. LIB ATE-based DL is a critical aspect of BPHM [90]. As the LIB ages nonlinearly, capacity declines linearly until a "knee point" where the aging trajectory accelerates. Predicting the knee point effect is crucial, but early-stage data-driven solutions are scarce [91].

Xu et al. [92] introduced a sequence-to-sequence DL method for predicting battery capacity degradation trajectory. The proposed framework consists of three main steps: Feature extraction, clustering and data augmentation, and prediction. However, the proposed model performance is untested under varying external conditions or with different battery chemistries. In [93], a novel approach for early prediction of LIB degradation trajectory using CNN and a synthetic dataset generated through a polynomial function. With only limited initial data, the validation on a large dataset with over 100 cells demonstrated the method's robust performance, achieving less than 2% MAE and RMSE in most cases. Nonetheless, the choice of the pretraining dataset might influence the method's accuracy. Specifically, pretraining with a dataset that closely matches the target dataset yielded superior results. Zhao et al. [94] presented a LIB health prognostic method using aging trajectory matching with ensemble deep TL. By incorporating a bidirectional LSTM network the proposed method features its robustness to incomplete data, superior performance compared with other methods, adaptive recognition of battery degradation patterns, and accurate trajectory matching. Nevertheless, the original model and the transfer model should be applied to identical battery types, leading to potential performance deterioration when applied to batteries with uncertain operational conditions.

V. CASE STUDY: A NOVEL SOH ESTIMATION APPROACH UTILIZING DLINEAR MODEL AND BAYESIAN OPTIMIZATION

A. EXPERIMENTAL DATA

The testing dataset for LIBs was derived from the Prognostics Center of Excellence's data repository at the National Aeronautics and Space Administration's (NASA) Ames Research Center. In the experiment, the LIB data were collected at the Idaho National Laboratory using multiple commercial li-ion 18650 LIBs tested on a specialized prognostics testbed [101]. The process of charging a battery adheres to the constant-current constant-voltage methodology. The acquired time series data contains 34 866 measurements including the voltage, current, temperature, current load, voltage load, and SOH values. The testbed comprises a suite of diagnostic tools including a power supply, programmable DC electronic load, voltmeter, thermocouple sensor, environmental chamber, EIS, and a PXI-based data acquisition system [102]. Operational tests at ambient temperature involved charge, discharge, and impedance profiles. At a room temperature of 24 °C, a steady current of 1.5 A is used for charging until the voltage hits the 4.2 V threshold [102]. Following this, the voltage is maintained steady at 4.2 V, while the charging continues until the current reduces to 20 mA. Discharge occurred at a constant 2 A down to specific voltage thresholds for each battery. Impedance assessments were performed via EIS spanning a frequency range of 0.1 to 5 kHz. Such cycles expedited wear, terminating the experiment when the batteries reached a 30% capacity reduction, indicative of EOL. The experiments were stopped when the batteries hit the EOL threshold, fading in the rated capacity (from 2 to 1.4 Ah). Four battery types (B0005, B0006, B0007, and B0018) with different capacity degradation behavior are provided and shown in Fig. 7. The battery aging conditions are provided in Table 3, including the charge/discharge cut-off voltage (C/DCV), minimal charge current (MCC), and constant discharge current (CDC).

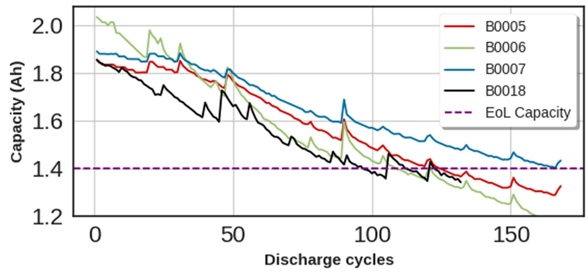

FIGURE 7. Capacity degradation (at a temperature = 24 °C).

TABLE 3. Battery Aging Conditions in the Experiment

Battery Type	Failure Threshold	Cycles	C/DCV	MCC	CDC
B0005	1.38 Ah	128	4.2/2.7 V	20 mA	2 A
B0006	1.38 Ah	112	4.2/2.5 V	20 mA	2 A
B0007	1.42 Ah	159	4.2/2.3 V	20 mA	2 A
B0018	1.38 Ah	100	4.2/2.5 V	20 mA	2 A

B. PROPOSED METHODOLOGY

Consider a historical instance of a multivariate time series, denoted as $\chi_h = [x_1, x_2, \ldots, x_n] \in \mathbb{R}^{n\times c}$, where n is the length. The objective of time series forecasting tasks is to estimate the values of the next m steps, represented as $\chi_f = [x_{n+1}, x_{n+2}, \ldots, x_{n+m}] \in \mathbb{R}^{m\times c}$, across all c channels. These tasks necessitate the learning of a mapping function $\psi : \chi_h^{n\times c} \to \chi_f^{m\times c}$, where χ_h and χ_f are sequential. To address this requirement, the DLinear model, introduced in 2022, offers an innovative approach. Known for its high precision, DLinear has a straightforward structure, which only comprises a decomposition scheme and two linear networks. In other words, it predicts the output of a given input by simply combining the input features in a linear fashion. However, unlike traditional linear models, the DLinear model uses

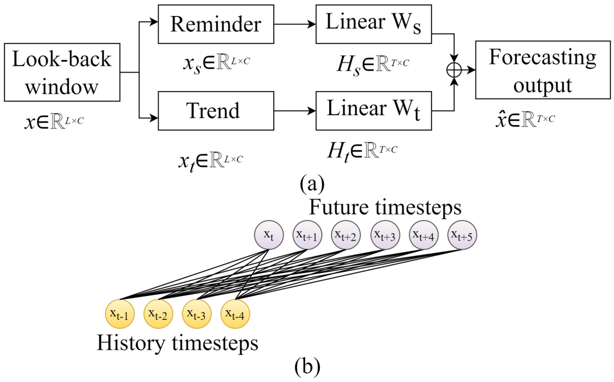

FIGURE 8. Graphical model representation of the DLinear network. (a) Structural design of DLinear. (b) Configuration of a single-layer linear network.

a deep neural network to learn the weights of the linear combination. This allows the DLinear model to learn more complex relationships between the input features and the output. Thus, it outperforms the more intricate transformer model in terms of predictive accuracy. During the forecasting process, DLinear initially decomposes the original sequence X into a trend component X_t and a residual component $X_r (X_r = X - X_t)$. Following this, two single-layer linear networks are employed to predict each component separately. Finally, each subsequence is predicted by the novel DLinear algorithm individually. The structure of the model, which effectively maps χ_h to χ_f, is depicted in Fig. 8.

DLinear breaks down the time series into a trend sequence and a remainder series. It then employs two singular-layer linear networks to predict based on these sequences. The DLinear model first decomposes historical time series data into a trend (Trend) data and remaining (Remainder) data, and then, applies a single-layer linear network to the two sequences obtained by decomposing [103] as

$$H_s = W_s X_s \in R^{T\times C}, W_s \in R^{T\times L} \tag{13}$$

$$H_t = W_t X_t \in R^{T\times C}, W_t \in R^{T\times L} \tag{14}$$

$$\hat{X} = H_s + H_t \tag{15}$$

where H_r and H_t denote the output values of the single-layer linear networks corresponding to the residual and trend components, respectively. In a similar vein, W_r and W_t symbolize the single-layer linear networks associated with the residual and trend components. The model generates at the end the summation of the outputs of the two single-layer linear networks. Also, if the variables of the dataset have different characteristics, i.e., different seasonality and trends, then sharing weights between different variables may not perform well. Therefore, two kinds of DLinear were proposed: DLinear-S where each variable shares the same linear layer, and DLinear-I: In which each variable has an independent linear layer. Fig. 9 presents the adopted methodology for the proposed model. According to the figure, the DL framework is conducted through data collection and preprocessing, DL model implementation, model comparison, and error metrics assessment.

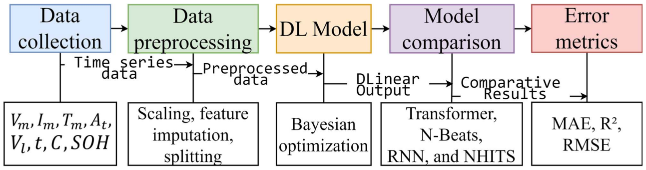

FIGURE 9. DL framework for LIB SOH prediction.

C. RESULTS AND DISCUSSIONS

The feature vector in the database is formulated as $\Psi_k = [V_m(k), I_m(k), T_m(k), A_t, C_l, V_l, t, C]$, where $V_m(k)$, $I_m(k)$, and $T_m(k)$ signify the voltage measured, current measured, and temperature measurement of the battery at each time step k, respectively; A_t is the ambient temperature, C_l is the current load, V_l is the voltage load, t is the time, and C represents capacity, all of which contribute to a comprehensive evaluation and monitoring of the performance and health status of a battery system. In this article, we use the LIB data of B0018 in this dataset. The prediction model is trained using a dataset $D = (\Psi_1, SOC_1), \ldots, (\Psi_N, SOC_N)$, where SOC_k is the ground-truth value or the observable SOC value at time step k and Ψ_k is the vector of inputs at the same time step, k. For the B0018 battery, 80% and 20% of the total cycle data are selected as the training and testing samples, respectively.

The Bayesian optimization (BO) technique is valuable when the cost of function evaluation is high due to its efficiency in evaluations [104]. The technique involves surrogate and acquisition functions. The surrogate functions commonly used include Gaussian Processes (GPs) and tree-structured Parzen estimators (TPE). A GP is a distribution over functions, parameterized by a mean and covariance function. The function values are drawn from a normal distribution considering the prior observations [105]. Random forest and TPE serve as alternatives to GP. Acquisition functions are employed to choose the next point of function evaluation in a way that the optimization progresses toward the maximum. This is often achieved by maximizing the expected improvement. The likelihood of the improvement is computed from the normal density function.

Table 4 presents the search space for the hyperparameters used in each of the models studied in this work, where ICL, OCL, and RS denote the input chunk length, the output chunk length, and the random states, respectively. The implemented models include neural basis expansion analysis for time series (N-BEATS), RNN, GRU, LSTM, neural Hawkes integrated temporal self-attention (NHITS), and DLinear models. [106], [107], [108]. For instance, the DLinear model performed best when the ICL is set to 42, the OCL is set to 7, the number of epochs is set to 284, and the RS is set to 100.

In order to evaluate the performance of DNN models, multiple dependent scales and independent scale score metrics were introduced. These metrics comprise the RMSE, coefficient of

TABLE 4. Search Space of the Proposed Models

Model Name	Optimized Hyperparameters	Search Space
N-BEATS	ICL: 15, OCL: 9, N. epochs: 145, RS: 100	ICL: [12, 48], OCL: [6, 24], N. epochs: [100, 300], RS: [0, 15, 42, 100]
NHiTS	ICL: 15, OCL: 9, N. epochs: 145, RS: 100	ICL: [12, 48], OCL: [6, 24], N. epochs: [100, 300], RS: [0, 15, 42, 100]
LSTM	ICL: 20, OCL: 19, N. epochs: 138, RS: 0, dropout: 0.31, N. RNN layers: 4, hidden dim: 18	ICL: [12, 48], OCL: [6, 24], N. epochs: [100, 300], RS: [0, 15, 42, 100], hidden dim: [10, 50], N. RNN layers: [1, 5], dropout: [0.1, 0.5], lr: [1e-4, 1e-2], batch size: [10, 30], training length: [200, 400]
GRU	ICL: 25, OCL: 4, N. epochs: 106, RS: 0, dropout: 0.32, N. RNN layers: 5, hidden dim: 87	ICL: [12, 48], OCL: [6, 24], N. epochs: [100, 300], RS: [0, 15, 42, 100], hidden dim: [10, 50], N. RNN layers: [1, 5], dropout: [0.1, 0.5], lr: [1e-4, 1e-2], batch size: [10, 30], training length: [200, 400]
RNN	ICL: 48, OCL: 8, N. epochs: 126, RS: 15	ICL: [12, 48], OCL: [6, 24], N. epochs: [100, 300], RS: [0, 15, 42, 100], hidden dim: [10, 50], N. RNN layers: [1, 5], dropout: [0.1, 0.5], lr: [1e-4, 1e-2], batch size: [10, 30], training length: [200, 400]
DLinear	ICL: 47, OCL: 13, N. epochs: 278, RS: 15	ICL: [12, 48], OCL: [6, 24], N. epochs: [100, 300], RS: [0, 15, 42, 100]
Transformer	ICL: 24, OCL: 12, N. epochs: 200, RS: 15	ICL: [12, 48], OCL: [6, 24], N. epochs: [100, 300], RS: [0, 15, 42, 100]

determination (R^2), and MAE as follows [109]:

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=0}^{n-1} |y_i - \hat{y}_i| \tag{16}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum\nolimits_{i=0}^{n-1} (y_i - \hat{y}_i)^2} \tag{17}$$

$$R^2 = 1 - \frac{\sum_{i=0}^{n-1} (\hat{y}_i - y_i)^2}{\sum_{i=0}^{n-1} (\bar{y}_i - y_i)^2}, \bar{y} = \frac{1}{n}\sum_{i=0}^{n-1} y_i \tag{18}$$

where y_i, $\hat{y}_i$, and n illustrate the actual SOH values, the predicted values, and the total number of samples. For a more fair comparison, ten-fold cross-validation (10-CV) is performed to evaluate the model universality. All experiments have been implemented via Google Colab Pro Plus High-RAM and background execution options enabled. Preinstalled packages, which reduce potential errors due to the compatibility of all the versions. The BO is implemented using Optuna Python library [110]. In contrast, DLinear is implemented using the Darts library [111].

Fig. 10 illustrates the models' performance for SOH. Regarding Fig. 10, the DLinear model interestingly outperforms all N-BEATS, RNN, Transformer, and NHITS models. Particularly, the NHITS overfits to noise and miss simpler patterns that are more indicative of the SOH. This is because the NHITS's complexity allows it to fit the small fluctuations that do not generalize well outside of the training dataset. Table 5 illustrates that the proposed DLinear model surpasses the benchmark models N-BEATS, RNN, Transformer, and NHITS in performance across several evaluation metrics, namely R^2, MAE (10^2), RMSE (10^2), and computation time. The obtained results clearly show that the DLinear model improves the accuracy of the SOH estimation. Alternatively, the Transformer model performs reasonably well in tracking the general trend of the SOH but may need improvements for finer accuracy, especially in predicting sudden changes or long-term trends.

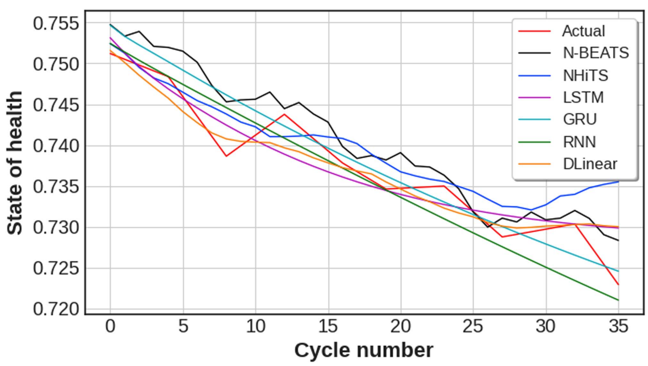

FIGURE 10. Diagrams of the estimated SOH results using NASA LIB degradation data.

TABLE 5. Comparison Results

Model	R²	MAE	RMSE	TrT (s)	TeT (s)
N-BEATS	77.24	0.31	0.35	328.92	0.28
NHITS	74.31	0.28	0.38	53.16	0.10
LSTM	89.50	0.19	0.24	65.62	0.11
GRU	87.46	0.20	0.26	82.14	0.11
RNN	83.61	0.24	0.30	43.79	0.12
Transformer	90.05	0.19	0.23	170.40	0.12
DLinear	91.91	0.15	0.21	105.11	0.09

Regarding Table 5, the DLinear model achieved an impressive R^2 of 91.91%, indicating high predictive accuracy. Furthermore, it demonstrated a superior prediction precision, with the smallest MAE and RMSE values, 0.15 and 0.21 (10^{-2}), respectively. The high accuracy of the DLinear is due

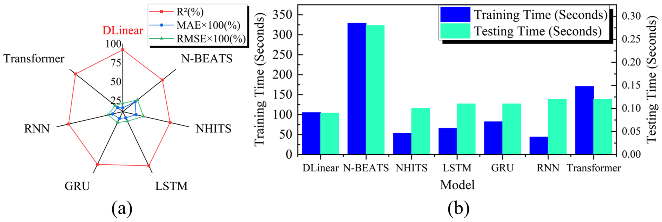

FIGURE 11. **(a) Radar plot of DL models metrics (b) Computational training time results (s).**

to its potential to capture the periodicity and seasonal effects. On the other side, NHITS has a relatively lower $\mathbf{R}^2$ of 74.31%, indicating less predictive accuracy compared with DLinear. According to Table 5, NHITS has a notably short training time of 53.16 s, which is significantly less than that of N-BEATS at 328.92 s but more than DLinear at 105.11 s. DLlinear, while it has the best prediction accuracy, still has a competitive testing time of 0.09 s. The Transformer model achieves an R^2 of 90.05%. The experimental findings indicate that the attention mechanism is unnecessary for capturing temporal dependencies.

Fig. 11(a) illustrates the radar plot of the ML models used for predicting the SOH. From the radar plot, we observe that the DLinear model outperforms the others across all three key predictive performance metrics: R^2, MAE, and RMSE. R^2, which reflects the proportion of variance explained by the model, is particularly high for DLinear, indicating a strong predictive power. The MAE and RMSE values are lowest for DLinear, suggesting high precision and reliability in its predictions. The radar plot reveals that the Transformer model closely rivals the DLinear model in terms of R^2, albeit with slightly higher error rates as indicated by MAE and RMSE. Meanwhile, models like N-BEATS and NHITS show larger errors and lower R^2 values, hinting at less accurate predictions for SOH.

Fig. 11(b) shows the comparison of the computational efficiency of the models. According to Fig. 11(b), it is evident that the N-BEATS model requires the most extended training time, which could be a significant drawback in scenarios where model retraining is frequent or computational resources are limited. On the contrary, NHITS stands out as the most time-efficient model for training, though this comes at the cost of predictive accuracy. The Transformer model requires a training time of 170.40 s, which is significantly longer than the DLinear's training time of 105.11 s. This difference suggests that the Transformer model may have a more intricate or expansive training process, potentially due to a more complex architecture or a greater volume of parameters to optimize during training. On the other hand, the testing times for both models are very close, with the Transformer model at 0.12 s and the DLinear model slightly faster at 0.09 s. The similarity in testing times indicates that once trained, both models can perform predictions with nearly equal speed, making them both suitable for real-time or near-real-time SOH estimation where rapid decision-making is critical.

VI. CHALLENGES AND FUTURE RESEARCH PATHWAYS

Despite the advances that have been made with regard to DL methods for BPHM, there are still many challenges that need to be addressed. In this section, we highlight some of those challenges and give insight as to how they can be addressed.

A. RESEARCH CHALLENGES

Numerous challenges exist in this field, including the nonlinear and complex nature of battery behavior, the impact of various operational factors (e.g., temperature, aging, and cycling), and the difficulty in obtaining accurate and robust measurements.

1) Data Quality and Quantity Limitations: High-quality, large-scale LIB data is essential for training robust DL models. According to [112], this data must be representative of various operating conditions and LIB states to ensure the model is robust and generalizable to real-world scenarios. However, obtaining such data from the material community can be challenging due to the complex nature of batteries, varied usage conditions, and the time-consuming process of collecting LIB degradation data [113]. Only a handful of material properties have been properly cataloged in sufficient quantity and quality. For instance, Cobalt, a key component in lithium cobalt oxide and lithium nickel manganese cobalt oxide (NMC) batteries, is a limited resource and most of it comes from politically unstable regions, which can create supply chain uncertainties [114], [115]. Several publicly available datasets are employed by pioneering researchers to develop prediction models for the RUL of LIBs, as provided in Table 6. The variety in datasets reflects diverse testing conditions and battery types, from the smaller 2 Ah 18650 to larger 10 Ah $LiFePO_4$ batteries, across various temperature conditions [116]. The main challenge identified is the high cost associated with data collection. As DL necessitates substantial computational resources, the BPHM algorithms require powerful computational capabilities to process and analyze the data effectively, which might not always be readily available or economically feasible, especially in real-time or on-board applications where computational resources might be limited [112].

2) Integration With Physics-Informed DL Models: Relying solely on battery tests or simulation data in a completely data-driven manner to learn the LIB behaviors can be inefficient with the current test setup limitations and the high uncertainties existing in real-world driving profiles [125]. Ensuring the robustness of DL models against uncertainties, such as sensor noise, operational variations, and environmental changes remains a challenging task in BPHM [126]. Physics-informed neural networks combine physical laws with data-driven insights to provide comprehensive and reliable BPHM [127]. With LIB data scarcity, physics-guided DL can conserve a high performance of DL algorithms under unseen conditions [68]. Typically, as a battery model encompasses more physical phenomena, it becomes increasingly complex. Therefore, the ongoing challenge is to create a simplified multiphysics model that enhances computational

TABLE 6. Public Lithium-Ion Battery Datasets

Ref.	Features	T(°C)	Battery type
[101]	V(t), C(t), T(t)	43, 4	2 Ah 18650
[117]	V(t), I(t), T(t)	Variant	LFP; NCA; NMC 811
[118]	V(t), I(t), T(t), time	22, 23, 24	LiNiMnCoO_2
[119]	I(t), Charge/Discharge C, Charge/Discharge Energy	0, −5, −10, −40	1.1 Ah, LiCoO_2, 1.5 Ah, LiCoO_2, 1.35 Ah, LiCoO_2, 2.4 Ah, LiFePO,4, 2.23 Ah, LiFePO_4, 2.3 Ah, LNMC
[120]	T(t), C(t), V(t), Charge, discharge	30	1.1 Ah, LiFePO4
[121]	V(t), T(t), I(t), power	40, 25, 10, 0, −10, −19	3 Ah, LG HG2
[122]	V(t), I(t), time, power	40, 25, 10, 0, −10, −20	1.35 Ah, LiCoO22.4 Ah, LiFePO42.23 Ah, LiFePO42.3 Ah, LNMC
[123]	V(t), C(t), I(t)	25	3 Ah, LG HG2
[124]	V(t), C(t), time	25	10 Ah, LiFePO4

efficiency without compromising accuracy. For instance, Wei et al. [128] presented a novel and effective method for optimizing the fast charging of LIBs. The proposed model leverages a deep reinforcement learning strategy combined with an improved deep deterministic policy algorithm.

3) Interpretability and Generalizability: DL models, which are often referred to as “’black boxes,” inherently lack interpretability [129], [130]. In the context of BPHM, this lack of transparency can be problematic, particularly in safety-critical applications, as it becomes challenging to understand and justify the model’s prognostic predictions [131]. Also, DL models may struggle to generalize to unseen battery types, usage conditions, or failure modes. While a model might excel in its training data, its performance may degrade significantly when confronted with scenarios not covered in the training set [132].

4) Computational Efficiency and Cybersecurity Consideration: End-to-end DL models often require significant computational resources, which may not be available in all BPHM applications, particularly in embedded systems or edge devices. Furthermore, with the growing integration of internet connectivity and communication channels for battery monitoring, cybersecurity becomes essential, especially when relying on extensive data [133]. Malicious hackers can trigger battery fires or explosions by manipulating BMS parameters and measurement information through online access. Typically, a dual-phase approach is essential to counter intrusions. The initial phase focuses on promptly detecting fraudulent data, which includes replay attacks and noise-injection attacks [54]. The second phase involves taking actions to lessen the effects of the attack [134]. Blockchain platforms (e.g., Hyperledger-Fabric [135]) can play a vital role in ensuring the trustworthiness of battery sensors and communication data [135]. On the other hand, federated learning is a promising method for battery informatics by aggregating locally computed updates from LIB apparatus for privacy preservation [136]. Nonetheless, cybersecurity threats of the LIBs are usually overlooked according to the existing literature.

B. FUTURE RESEARCH DIRECTIONS

In light of recent advancements in DL for BMSs, it is imperative to delve deeper into specific methodologies for BPHM. The integration of these cutting-edge approaches can significantly improve the performance and applicability of current DL techniques in this domain. This section provides some potential aspects for more efficient LIB informatics.

1) Hybrid Estimation Methods: Future research should explore the development of hybrid estimation methods that combine the strengths of both DL techniques [137]. This approach could lead to more accurate and robust SOC and RUL estimations, taking advantage of the complementary capabilities of these techniques. The study of hybrid systems introduces a myriad of BPHM strategies that can be broadly categorized into two groups [138]. The first group uses heuristic rule-based or fuzzy logic strategies, offering low computing complexity and resilience to driving behaviors but lacking optimal vehicle control. The second category applies optimization techniques to power-splitting decisions, using methods, such as dynamic programming, Pontryagin’s minimum principle, and convex programming. While these offer optimal solutions, they rely on prior knowledge of future driving conditions, limiting their real-time application. For practical feasibility, real-time optimization methods, such as the adaptive equivalent consumption minimization strategy and model predictive control have been studied, though they come with their own set of challenges.

2) Explainable DL and Model Interpretability: The European Union released ethics guidelines for AI, mandating models to be lawful (compliant with regulations), ethical (upholding values), and robust (stable under varied conditions) [139]. As battery state monitoring techniques evolve, understanding the multiple interconnections between key processes and battery variables remains challenging due to their intricacy. There is an increasing need for trustworthy AI and DL interpretability spurred by governmental policies and subsidies. Currently, interrelations among key processes. Future research should focus on developing models that not only provide accurate estimations but also offer insights into the underlying mechanisms of battery degradation and performance [140]. In essence, we have to remain vigilant whether the operators are able to discern features that affect the action [141]. Nevertheless, the investigations conducted in this review indicate that the use of explainable DL in this domain is still in its infancy, with only a few attempts documented. For instance, an uncertainty-guided LSTM model-based EOL estimation is proposed in [142]. Through an explainability analysis, the model highlights the significance of specific input features for varying battery lifespans. These insights correlate with known chemical degradation effects, ensuring the model is not just a "black box" but offers meaningful interpretations of its predictions.

3) Real-Time Implementation and Big Data Tools Considerations: For batteries deployed on-site, the development of computationally efficient algorithms and hardware solutions that enable real-time state estimation requires further investigations [94]. To accurately depict battery behavior, DNNs necessitate vast datasets and significant computational efforts. As a result, when developing DMs, it is crucial to factor in the computational capabilities of onboard hardware. Most DMs that utilize DNNs depend on recursive computations. Thus, by creating a noniterative model that matches the precision of iterative ones, both training and prediction speeds can be boosted. However, crafting such a noniterative approach for LIB state modeling is challenging, given the need to correlate both historical cycling data and upcoming conditions with future behavior change stages. Big data tools and cloud computation can provide an excellent alternative to reduce the computational burden of BPHM [143]. It is of conspicuous importance to emphasize data privacy for management based on cloud-connected health monitoring and data analysis. In this context, encryption and access control technologies have been implemented in real-world applications [144]. Through data encryption or the use of access control measures, only those with authorization can access the extensive battery data, thereby bolstering data security.

4) Battery Calendar Health Prognostics (BCHP): After manufacturing, a LIB operates in two main modes: Calendaring and cycling [145]. Continuous efficient BCHP advancements in AI and battery technologies are expected to make better efficiency for BPHM [146]. In practical use cases such as EVs, LIBs experience degradation via both calendar and cycling modes [3]. Given that more than 70% of an automotive battery's lifespan is consumed under storage conditions, there is an urgent need for effective solutions to monitor and manage battery health under calendar degradation mode [3], [6]. For instance, a transferred RNN (TRNN) approach has been proposed for predicting the future calendar capacity of LIBs [147]. The TRNN structure ensures that the base model provides foundational mapping information, which guides the transfer model, enhancing prediction performance for unwitnessed storage scenarios. The transfer model part is fine-tuned using only a small portion of starting capacity data from unwitnessed conditions.

VII. CONCLUSION

This article navigates through the contemporary advancements and methodologies permeating BPHM across a spectrum of applications, with a discerning lens focused on DL approaches. This study diligently underscores the pivotal role of DL in addressing the multifaceted challenges tethered to battery state estimation while also shedding light on its inherent strengths and limitations. This article has unearthed the quintessential characteristics and requisites of efficacious LIB state monitoring systems, encapsulating accuracy, robustness, adaptability, and computational efficiency. Furthermore, this work has delved into the emerging DL approaches, including CNN, RNN, and LSTM networks, which have shown promising results in handling complex, nonlinear, and high-dimensional battery data. DL techniques have shown the potential to overcome these limitations by automatically extracting relevant features from raw data, resulting in improved accuracy and adaptability. The harmonious amalgamation of DL, edge computing, and federated learning collaborations heralds a transformative era for LIB research. This triumvirate not only ignites innovation but also acts as a cornerstone for the broader journey to design next-generation state estimation models. Despite the strides made in DL toward assiduously monitoring the operational status of batteries, a myriad of challenges and prospects for future research linger on the horizon. These include the need for larger and more diverse battery datasets, improved interpretability and explainability of DL models, and the development of real-time monitoring systems that can adapt to changing operating conditions and battery degradation mechanisms. In addition, the integration of domain knowledge and physics-based models with data-driven techniques could lead to more accurate and reliable BPHM. Nonetheless, considering LIBs stochastic degradation behavior, prevailing temperature, and testing conditions, DNN models in practical applications emerge not merely as a trend but as an imperative, steering the future course of BPHM systems toward enhanced precision and reliability.

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