Journal of Energy Storage 73 (2023) 109069

Contents lists available at ScienceDirect

Journal of Energy Storage

journal homepage: www.elsevier.com/locate/est

Review article

Advancements in Artificial Neural Networks for health management of energy storage lithium-ion batteries: A comprehensive review

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ARTICLE INFO

Dataset link: https://data.matr.io/1/, https://web.calce.umd.edu/batteries/data.htm, https://ti.arc.nasa.gov/tech/dash/pcoe/prognostic-datarepository/#battery, http://howey.eng.ox.ac.uk/data-and-code/

Keywords:
Lithium-ion battery
Energy storage
ANN
Health management

ABSTRACT

Lithium-ion batteries, growing in prominence within energy storage systems, necessitate rigorous health status management. Artificial Neural Networks, adept at deciphering complex non-linear relationships, emerge as a preferred tool for overseeing the health of these energy storage lithium-ion batteries. This paper presents a comprehensive review of the current research in this field. The discussion initiates with the distinctions between energy storage batteries and power batteries, the composition and management of battery energy storage systems, and common evaluation metrics such as State of Health, State of Charge, and Remaining Useful Life. This is followed by outlining common open datasets, data preprocessing techniques, health feature extraction methods, and battery health prediction approaches. Emphasis is laid on the utilization of Artificial Neural Networks for lithium-ion battery health management, encompassing a spectrum of networks from Feedforward Neural Network, Extreme Learning Machine, Convolutional Neural Network, Recurrent Neural Network (with Long Short-Term Memory and Gated Recurrent Unit) to Transformer and methodologies like transfer learning and the integration of traditional techniques with Artificial Neural Networks. Concluding remarks ponder over the future prospects and challenges of using Artificial Neural Networks for lithium-ion battery health management.

1. Introduction

As global demand for sustainable and clean energy intensifies, ensuring the stability and reliability of power supply has become increasingly critical, highlighting the growing importance of energy storage systems (ESSs). Compared to traditional energy storage methods like pumped hydro storage and compressed air energy storage, lithium-ion batteries have become one of the preferred choices within battery energy storage systems (BESS) due to their high energy density, outstanding modularity, superior energy conversion efficiency, and rapid response times [1–3].

BESSs can store energy generated from solar panels, wind turbines, or other renewable sources, providing households, industries and businesses with a reliable and cost-effective power supply during power outages or periods of high electricity prices [4,5]. Recent analyses have revealed that the deployment of BESS offers a promising strategy for the seamless integration of renewables into the power grid, where lithium-ion batteries are making a significant impact [6–8].

Lithium-ion batteries have also emerged as the preferred choice for electric vehicle (EV) power batteries [9]. However, the requirements for this application differs generally from energy storage. Power batteries in EVs must provide high energy density [10,11], fast charging capabilities [12,13], while also ensuring safety and thermal management under vibration and structural damage scenarios [14,15]. In contrast, Lithium-ion batteries for energy storage applications require long cycle life [16,17], low self-discharge rate [18,19], and tolerance to a wide range of operating conditions [20].

The degradation of lithium-ion batteries is a complex process influenced by various factors, including operating conditions, design, and chemistry. Over time, these factors contribute to a decline in the battery's capacity, power, and overall performance [21,22]. The challenge of managing the health of lithium-ion batteries lies in the complexity of these degradation processes and the interdependence of various factors [23,24].

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https://doi.org/10.1016/j.est.2023.109069
Received 16 May 2023; Received in revised form 2 September 2023; Accepted 19 September 2023
Available online 3 October 2023

Nomenclature

Q_{max}	Battery's current maximum capacity.
Q_{rated}	Battery's rated capacity.
Q_{remain}	Battery's current remaining capacity.
$\tilde{\mathbf{h}}_t$	New gate of the GRU at time t.
$\mathbf{r}_t$	Reset gate of the GRU at time t.
$\mathbf{z}_t$	Update gate of the GRU at time t.
$\mathbf{c}_t$	Cell gate of the LSTM at time t.
$\mathbf{f}_t$	Forget gate of the LSTM at time t.
$\mathbf{i}_t$	Input gate of the LSTM at time t
$\mathbf{o}_t$	Output gate of the LSTM at time t.
$\mathbf{h}_t$	Hidden state at time t associated with input x_{t+1}.
$\mathbf{W}^l$	Weight matrix between layers $l-1$ and l.
$\sqrt{d_k}$	Scaling factor of the Transformer.

The complex nature of battery degradation mechanisms, combined with the diverse and dynamic operating conditions of BESSs, necessitates advanced modeling techniques that can capture and predict the State of Health (SoH) [25], State of Charge (SoC) [26], and Remaining Useful Life (RUL) [9] of lithium-ion batteries. Artificial Neural Networks (ANNs) have risen to prominence as an invaluable tool in the health management of lithium-ion batteries within BESSs. Their effectiveness stems from their ability to model non-linear relationships [27], a crucial aspect given the intricacies of battery behaviors influenced by factors like temperature, charge–discharge cycles, and aging. Moreover, ANNs possess an innate capacity for feature learning, enabling them to discern and extract significant patterns from raw data that indicate battery health or potential degradation [28]. Their adaptable nature allows them to fine-tune predictions based on incoming data [29], ensuring consistent accuracy even with evolving battery conditions or the introduction of new battery types. Additionally, they offer impressive scalability [30], efficiently processing vast amounts of data, which becomes essential as the scale of energy storage monitoring expands. Beyond these capabilities, ANNs can be integrated seamlessly with other machine learning strategies, like reinforcement learning for decision-making or clustering algorithms for health-based battery categorization. Collectively, these attributes highlight ANNs as a preferred solution for overseeing the health of lithium-ion batteries in diverse energy storage scenarios.

In Fig. 1, the comprehensive approach of using ANNs for managing the health of energy storage lithium-ion batteries is elucidated. The process begins with 'Data Collection', where pertinent metrics such as charge and discharge current, voltage, temperature, and others, are gathered from the batteries. This collected data is then directed through an intricate 'Data Pre-procession' phase, during which it is filtered, normalized, resampled, and subsequently divided into subsets for analysis, training, and testing. In the 'Feature Extraction' stage, a multitude of techniques including domain-specific knowledge extraction, principal component analysis, classification methods, clustering methods, and even ANNs, are employed to cull crucial features from the raw data. The 'Model Development' phase incorporates a varied set of methods, ranging from model-based approaches such as electrochemical, equivalent circuit, and impedance models, to data-driven methodologies. While ANNs are emphasized, alternative techniques like the Kalman Filter (KF), Particle Filter (PF), Support Vector Regression (SVR), Gaussian Process Regression (GPR), and Random Forest Regression (RFR) are also potential additions. The culmination of the process is the 'Health Management' phase, which meticulously manages the battery's health metrics. This phase delineates the SoH, SoC, and RUL facets, each encompassing a suite of strategies and actions. For instance, SoH covers performance estimation, end-of-life prediction, adaptive operation, and failure detection, while SoC is centered on energy estimation, charge optimization, discharge planning, and safety assurance. RUL, on the other hand, prioritizes degradation forecasting, usage pattern modifications, proactive maintenance scheduling, and cost management. The application of ANNs is growing within various stages of lithium-ion battery health management, from data collection to health-centric strategic actions.

To obtain a thorough understanding of the current landscape of lithium-ion battery health management, we initiated a comprehensive literature search across five prominent databases: WebofScience, Sciencedirect, IEEEExplore, Springer, and MDPI. Utilizing a combination of targeted keywords including "energy storage", "lithium-ion battery", "SoH", "SoC", "RUL", "health management", and "prognostics", we focus on articles published between 2020 and 2022. This meticulous process, illustrated in Fig. 2, yielded 437 relevant pieces of literature from major journals. This collection comprises 32 survey reports, 390 research papers, 62 publications specific to BESSs, and 128 articles centered on EVs. Notably, within these works, 118 studies leverage ANNs for modeling battery state, whereas 131 predominantly adopt traditional machine learning methodologies.

The literature selection for this study followed these steps:

1. Identification: Using the specified keywords, we initiated a preliminary search and identified 764 articles across the databases.
2. Screening: After removing duplicate and similar papers from the preliminary set of 764 articles, 437 unique articles remained.
3. Eligibility: By assessing the titles and abstracts, we excluded 121 articles that deviated from the research focus on battery health management, leaving 316 articles.
4. Included: Based on our specified inclusion criteria, we thoroughly reviewed the remaining articles, eventually selecting 119 that met all the criteria.

ANNs have demonstrated remarkable success in a wide range of applications, such as computer vision, speech recognition, finance, and business data analysis [31,32]. Consequently, our survey primarily focuses on the current state of research employing ANNs for lithium-ion energy storage battery health management. By honing in on this rapidly advancing field, we aim to provide a comprehensive overview of the latest methodologies, techniques, and findings, as well as to identify potential avenues for future research and innovation in the realm of ANN application of lithium-ion battery health management for energy storage applications.

In this study, a systematic and detailed overview of the recent advancements in ANNs for health management of energy storage lithium-ion batteries is provided, with the key contributions enumerated as follows.

1. This paper provides an overview of ANN applications in lithium-ion battery health management for BESSs.
2. The paper highlights the distinctions between energy storage and power application scenarios for lithium-ion batteries.
3. A summary of public datasets, common features, indicators, and methods employed in lithium-ion battery health management is provided.
4. The paper concludes by discussing future challenges in applying ANNs for prognostics and health management of lithium-ion storage batteries.

The remainder of this paper unfolds systematically to offer a comprehensive insight into ANN application in lithium-ion battery health management for energy storage. Section 2 elucidates the nuances of energy storage batteries versus power batteries, followed by an exploration of the BESS and the degradation mechanisms inherent to lithium-ion batteries. This section culminates with an introduction of key battery health metrics: SoH, SoC, and RUL. In Section 3, we pivot

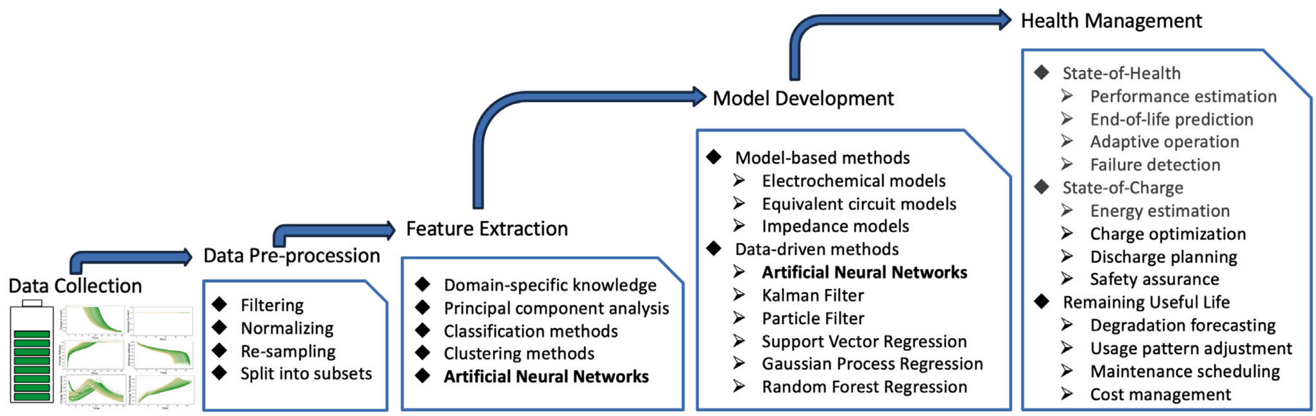

Fig. 1. ANN application for energy storage lithium-ion battery health management. This figure delineates the comprehensive application of ANNs in the health management of energy storage lithium-ion batteries. Beginning with the collection of pertinent battery metrics, the process undergoes phases of data preprocessing, feature extraction, model development, and ultimately, health management. Each phase integrates varied methodologies, with ANNs underscoring its significance in feature extraction and model development in optimizing and ensuring battery health.

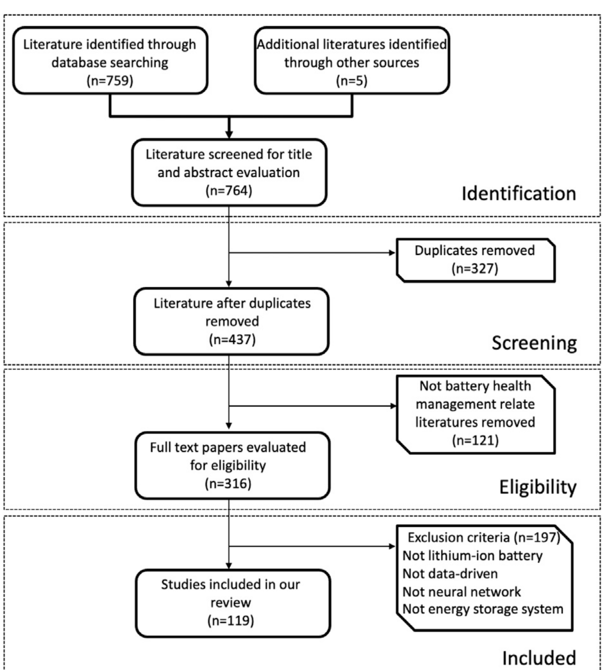

Fig. 2. Flowchart of the literature selection. This figure presents a flowchart detailing our literature selection process for energy storage battery health management. Initiating with a broad search across five major databases, we systematically narrowed down our selection through stages of identification, screening, eligibility assessments, and final inclusions. By the end of the rigorous process, 119 articles met our stringent criteria, reflecting the most pertinent literature in the domain.

to the methodologies, delving into public datasets, pre-processing techniques, feature extraction, and a range of health prediction methods tailored for these batteries. Section 4 hones in on the application of ANNs, showcasing a spectrum from Feedforward Neural Networks (FNNs) to Transformers, and touches upon advanced methodologies like transfer learning and ensemble strategies. The paper wraps up with a summary in Section 5, encapsulating the key takeaways.

2. Health management of lithium-ion batteries for energy storage

2.1. Energy storage battery versus power battery

Generally, lithium-ion batteries can be classified into consumer, power, and energy storage batteries based on their application scenarios, with power and energy storage batteries representing the most promising areas for growth and innovation [33,34].

Batteries employed in EVs and those utilized in energy storage devices are fundamentally energy storage batteries. However, their specific application contexts dictate the performance and service life requirements for each type. Power batteries, often referred to as EV batteries, must provide high power [35], high energy density [36], and fast charging capabilities [37] to ensure adequate acceleration and driving range. In contrast, energy storage batteries are designed to store and release energy over extended periods of time, prioritizing high energy efficiency [38,39] and long cycle life for applications such as grid support and renewable energy integration.

As summarized briefly in Table 1, although both power and energy storage batteries share the overarching objective of storing electrical energy, their unique performance and service life demands necessitate tailored designs and optimizations to ensure optimal operation within their respective application contexts.

2.2. Battery energy storage system

BESS are complex and intricately designed to ensure efficient storage, management, and utilization of energy. As shown in Fig. 3, the primary components of a BESS include the Battery System (BS), the Power Conversion System (PCS), and the Battery Management System (BMS) [4,5].

BS constitutes the core of a BESS and is responsible for storing electrical energy. Typically comprising an array of lithium-ion battery cells or modules, the BS provides the necessary energy capacity and power output to respond the demands of the specific application. The performance of the BS is determined by factors such as energy efficiency, power density, and cycle life, which are influenced by the chemistry, materials, and design of the individual battery cells.

PCS serves as the interface between the BS and the utility grid or load. The primary function of the PCS is to convert the electrical energy stored in the BS to the appropriate form required for grid integration or load consumption. This may involve converting DC from the batteries to AC for grid connection or vice versa, as well as voltage regulation and power factor correction. The PCS is essential for ensuring the

Table 1
Energy storage battery versus power battery.

	Power battery	Storage battery
Application scenarios	Electric vehicles, electric bicycles, and other electric-powered equipment	Peak regulation and frequency control, renewable energy grid integration, and microgrids
Performance requirements	High energy density, power density, safety, and thermal management	Mobility not required; energy density varies; power density depends on specific requirements
Service life	Cycle life ranges from 1000 to 3000	Cycle life typically exceeds 8000 cycles
Battery type	Lithium Iron Phosphate (LiFePO4) batteries are frequently chosen for safety and economic reasons	Wide range of battery types, including Lithium Nickel Manganese Cobalt Oxide (NMC), LiFePO4, and Lithium Titanate (LTO)
Competition	Competing with traditional combustion engines	Facing competition from traditional peak and frequency modulation technologies such as flywheels, fuel cells, and pumped hydro storage

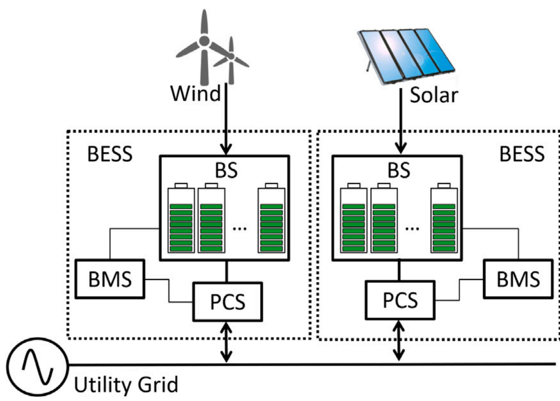

Fig. 3. Battery Energy Storage System. This figure showcases the integral components of a BESS: BS, PCS, and BMS. The BS stores energy, the PCS manages its conversion and distribution, and the BMS oversees its safety and optimization. These components work together to ensure efficient and reliable storage, conversion, and delivery of electrical energy.

efficient and reliable operation of the BESS, as it manages the flow of electrical energy between the BS and the grid or load.

BMS is a crucial component of the BESS, responsible for monitoring, controlling, and safeguarding the operation of the BS. The BMS continuously tracks vital parameters such as voltage, current, temperature, and SoC for each battery cell or module, and utilizes this information to optimize performance, prevent over-charging or over-discharging, and ensure thermal stability. Furthermore, the BMS provides diagnostic data for battery health estimation and prognostics, enabling the early detection of potential issues and facilitating proactive maintenance to extend the life and reliability of the Battery System.

2.3. Degradation of lithium-ion batteries

The degradation of lithium-ion batteries is a complex process influenced by various factors, including operating conditions, design, and chemistry. Over time, these factors contribute to a decline in the battery's capacity, power, and overall performance.

The primary mechanisms contributing to lithium-ion battery degradation can be broadly categorized into two groups: capacity fade and power fade. Capacity fade refers to the gradual loss of a battery's ability to store energy, which is mainly caused by the loss of active lithium and the deterioration of the electrode materials [40]. On the other hand, power fade is associated with the increase in the internal resistance of the battery, which results in reduced power output and efficiency [41].

Several factors contribute to these degradation mechanisms. One major factor is the cycling of the battery, which involves repeated charging and discharging. During cycling, side reactions may occur, leading to the formation of a solid electrolyte interface on the electrodes [22], which increases internal resistance and contributes to capacity fade. Ambient temperatures can also accelerate degradation by increasing the rate of these side reactions and causing thermal stress on the battery materials [42].

Another critical factor is the SoC of the battery. It is common for BESSs to be at a high SoC in order to respond to unpredictable demand. Operating at high SoC levels for extended periods can cause lithium plating on the anode, leading to irreversible capacity loss [43]. Similarly, over-discharging the battery can result in excessive voltage drops, which can cause structural and chemical changes in the electrode materials, further contributing to degradation [43].

The challenge of managing the health of lithium-ion batteries lies in the complexity of these degradation processes and the interdependence of various factors. Accurately predicting the SoH and RUL of a battery requires the development of advanced models that can capture the various degradation mechanisms and consider the impact of operating conditions and battery design [25].

Furthermore, in practical energy storage applications, lithium-ion batteries are often subjected to diverse and dynamic operating conditions, individual batteries tend to exhibit unique degradation patterns [44]. This variability adds a layer of complexity to the task of estimating the health condition of energy storage lithium-ion batteries. As the demand for energy storage batteries continues to grow, further research and innovation in battery health management are essential to meet the challenges associated with their widespread deployment.

2.4. SoH

SoH is a vital metric for gauging the condition of a lithium-ion battery, and it is conventionally defined in terms of capacity [45]. Specifically, SoH is the ratio of the battery's current maximum capacity to its rated capacity, expressed as a percentage:

$$SoH = \frac{Q_{max}}{Q_{rated}} \times 100\%, \tag{1}$$

where Q_{max} and Q_{rated} represent the rated capacity and the battery's current maximum capacity.

A higher SoH value indicates that the battery is closer to its original capacity, while a lower value signifies a greater degree of degradation. When the capacity of a battery at full charge declines by 20%–30% of the rated capacity, it is normally considered to have reached End of Life (EOL) and needed to be retired [46]. In addition to capacity-based SoH, there are also definitions of SoH from a power perspective, which consider factors such as internal resistance and discharge power capability. This alternative approach to defining SoH can provide additional insights into a battery's overall performance and efficiency.

Prior to estimating the SoH of a lithium-ion battery, it is recommended to cycle the battery several times in order to stabilize its capacity [47]. Once stabilized, a quantitative approach such as coulomb counting can be employed to measure the maximum discharge capacity of the battery over a full charge and discharge cycle. Subsequent measurements of the amount of capacity discharged by the battery represent its current Q_{max}.

However, real-world applications often do not permit batteries to undergo full charging and discharging cycles. In such cases, machine learning methods are typically employed to estimate the current SoH by integrating experimental data and operational parameters from the battery's usage history. This approach can inform decisions related to battery maintenance, replacement, and optimization in various practical contexts.

When the SoH declines, the aging of the battery may begin to accelerate significantly. The point at which this accelerated aging occurs, which may not always be readily apparent, is referred to as the SoH knee-point.

It is important to note that the SoH of an energy storage battery is a dynamic metric that evolves over time. A dramatic decline in SoH within a short period may suggest the presence of an internal fault within the battery, necessitating further investigation and potential remediation. Ultimately, accurate and reliable assessment of SoH plays a critical role in maximizing the performance and lifespan of lithium-ion batteries across various applications.

2.5. SoC

The SoC serves as a metric for evaluating a battery's current remaining capacity, providing insights into its operational status and informing decisions related to charging, discharging, and battery management. SoC is typically defined as the ratio of the battery's current remaining capacity to its current maximum capacity, expressed as a percentage. The definition of SoC can be expressed as

$$SoC = \frac{Q_{remain}}{Q_{rated}} \times 100\%, \tag{2}$$

where Q_{remain} and Q_{rated} represent the battery's current remaining capacity and the rated capacity.

A higher SoC value indicates that the battery has more capacity remaining, while a lower value signifies that the battery has been partially or substantially depleted. SoC can be conceptualized as a time-varying nonlinear function of remaining capacity that is influenced by factors such as temperature, charging, and discharging. Consequently, the SoC provides valuable short-term information on battery capacity, which is crucial for optimizing battery performance and ensuring safe operation.

Maintaining the energy storage battery within a reasonable SoC range during use is essential for avoiding damage, prolonging its lifespan, and effectively fulfilling its energy storage function. Straying outside this optimal range, either through overcharging or deep discharging, can lead to accelerated degradation or even catastrophic failure, compromising both the safety and efficiency of the battery system.

Accurately estimating the SoC of a battery can be challenging, as the calculation implies that the battery will be completely depleted, which is not always the case in real-world applications. Moreover, factors such as ambient temperature, battery temperature, and discharge power requirements can vary during the discharging process, further complicating the estimation of SoC.

2.6. RUL

The RUL of a lithium-ion battery is an metric employed to estimate the number of cycles a battery has left before it reaches EoL.

Estimating the actual RUL of a battery typically involves analyzing SoH in conjunction with the battery's degradation path under its specific usage scenario. This approach accounts for the consideration of various factors that influence battery degradation, such as temperature, charging and discharging patterns, and the battery's usage history.

Batteries with long RUL are essential for energy storage applications due to the high capital investment, dependability and reliability requirements, environmental considerations, regulatory requirements, and reduced maintenance costs. Ensuring a long RUL for batteries used in energy storage applications is crucial for maximizing the overall performance, sustainability, and cost-effectiveness of these systems.

3. Approaches to lithium-ion battery health management

3.1. Public datasets

Publicly available datasets [48] provide valuable information on battery performance degradation and usage patterns, enabling researchers to develop and refine models, algorithms, and techniques for estimating battery health indicators such as SoH, SoC, and RUL. Here are some notable public datasets in the field of battery health assessment.

Stanford-MIT dataset [49] compiled through a collaboration between Stanford University and the Massachusetts Institute of Technology, offering two consecutive groups of tests. Group 1 comprises 124 batteries of the same specification, tested in three batches under the same environmental conditions. In each cycle, the "C1(Q1)-C2" protocol was used for fast charging, begins by charging the battery at a constant current of "C1" until it reaches a SOC of "Q1%". Upon reaching "Q1%" SOC, the charging rate switches to a constant current of "C2" and continues until the battery achieves 80% SOC. After this, the battery adopts a 1C Constant Current-Constant Voltage (CC-CV) charging approach until it is fully charged. Then, a 4C rate was applied for discharging. The purpose of this group was to verify the RUL of the battery under different charge protocols [47]. Group 2 consists of 224 APR18650M1ALFP cells, tested in five batches at a controlled ambient temperature of 30 °C. The testing protocol employed for fast charging and discharging involved a "CC1-CC2-CC3-CC4" sequence, with a 4C discharge rate for each cycle. The "CC1-CC2-CC3-CC4" testing protocol goes further and breaks the charge of first 80% SOC progression into four equal segments, each representing a constant current charging step over a 20% SOC window. Specifically, CC1 charges the battery from 0% to 20% SOC, CC2 from 20% to 40%, CC3 from 40% to 60%, and CC4 from 60% to 80%. The goal is to fine-tune these four steps to establish a optimized charging protocol that enhances the battery's RUL. The first four batches of batteries underwent 100–120 cycles, while the final batch was cycled to battery failure in order to verify the close loop optimization of fast charge protocol [50].

Centre for Advanced Life Cycle Engineering (CALCE) datasets [51] provided by the University of Maryland, focus on battery performance, aging, and failure mechanisms. Among these datasets, the CS2 dataset [52–54] is particularly well-known, as it encompasses a diverse range of tests designed to simulate various operating conditions and user behaviors. The CS2 dataset comprises six different types of tests: Type 1 for constant 0.5C cycling; type 2 for constant 1C cycling; type 3 for discharging at six different current levels, allowing for the evaluation of battery performance under varying discharge rates; types 4 to 6 employ different cutoff voltages to simulate user-determined battery usage. These tests explore the impact of variations in charging and discharging voltage thresholds on battery performance and degradation.

NASA datasets [55] are provided with two well-known studies involving the testing of NCA type 18 650 batteries with a rated capacity of 2Ah in 2008, and LCO type 18 650 batteries with a rated capacity of 2.1Ah in 2014, with the objective to estimate battery performance and degradation in aerospace applications. 2008 test involved 34 NCA type 18 650 batteries [56], which were cycled at various conditions until the SoH dropped to 80% or 70%. By investigating the effects of various factors on battery performance and degradation, this dataset provides valuable insights into the influence of operating conditions on battery health.

Oxford datasets [57] offered by the University of Oxford are conducted by two separate battery performance and degradation studies. In Soft Pack batteries dataset, batteries were charged using a "CC-CV" (Constant Current - Constant Voltage) protocol and discharged using the urban Artemis profile, simulating real-world driving conditions. The aging characteristics of the batteries were measured after every 100 cycles, providing insights into battery degradation over time. Another dataset used 28 NCA-type 18 650 batteries, dividing into four groups. Each group was subjected to different cyclic aging and calendar aging processes to assess the path dependence of battery aging [58]. This approach allowed researchers to evaluate how different usage scenarios and environmental conditions affect the rate at which batteries degrade.

3.2. Data pre-processing

Data pre-processing is a common step in creating accurate and reliable battery health estimation [59], as it ensures that the data used for model development is clean and consistent, which is suitable for machine learning algorithms.

Battery data may contain noise, outliers, or errors resulting from measurement inaccuracies, sensor malfunctions, or other factors. Data cleaning involves identifying and addressing these issues, typically by filtering or smoothing the data, removing or correcting erroneous data points, or interpolating missing values.

Different battery parameters may have different units, scales, or ranges, which can affect the performance of modeling algorithms. Data normalization is the process of transforming the data to a common scale, typically by scaling the values to a specific range (e.g., 0 to 1) or by standardizing the data [60].

Moreover, battery data may be collected at different rates or intervals, depending on the application, measurement equipment, or other factors. Data re-sampling involves adjusting the data to a consistent sampling rate [61], either by aggregating data points (down-sampling) or interpolating between existing data points (up-sampling).

To train and validate battery models, it is necessary to split the data into separate subsets for training, validation, and testing. Data partitioning involves dividing the data into these subsets in a way that ensures a representative distribution of battery conditions, operating scenarios, or other factors across all subsets.

3.3. Feature extraction

Raw battery data often contains a large number of variables, not all of which may be relevant for modeling battery performance, degradation, or health. Therefore, feature extraction [62] is crucial for identifying the most relevant variables (features) or combinations of variables that capture the essential information about the battery's behavior. Techniques such as principal component analysis (PCA) [63], auto-encoders [64], or domain-specific knowledge can be employed to achieve this.

As numerous studies have focused on extracting health features from the battery charging or discharging process to assess the battery's state, some approaches involve using the incremental capacity (IC) curve to extract features and employing a Back Propagation Neural Network (BPNN) to predict the SoH while taking temperature into account [65]. In contrast, another approach uses the voltage from 10 min to 80% SoC during the fast charging phase as a feature, combining it with the number of cycles and using Long Short-Term Memory (LSTM) networks for online capacity prediction.

Moreover, other researchers have extracted the curve of the differential temperature during charging and used timestamps of peak values of differential temperature as health characteristics [66]. Additionally, some researchers have combined the maximum, minimum, and average values of voltage and current, the category number after clustering using K-means, along with time, current variation, and current, as input for neural networks to examine the performance of different neural networks in predicting RUL [17].

3.4. Lithium-ion battery health prediction methods

There are two common approaches for predicting the SoH of lithium-ion batteries [4,25]: model-based methods and data-driven methods. Referring to Table 2, each method is characterized by its respective suitable and unsuitable scenarios. These approaches offer essential perspectives on battery performance, degradation, and RUL, serving as pivotal tools in shaping battery management strategies and enhancing ESSs.

Model-based methods for predicting battery SoH involve the use of electrochemical models (EM) [67], equivalent circuit models (ECM) [68], and impedance models (IM) [63,69] to estimate SoC, SoH, and RUL. Each of these methods has unique advantages and limitations, which must be considered when applied to battery degradation analysis.

EMs capture the nonlinear internal characteristics of batteries by simulating their electrochemical reactions and internal mechanical and physical structures. While these models can be highly accurate, they often require complex testing procedures and substantial computational resources. Furthermore, the EM approach necessitates the selection of a suitable model for the specific battery chemistry and configuration, which can be challenging for large battery packs.

ECMs use simple electronic components to simulate the dynamic behavior of batteries. Common ECMs include the internal resistance (Rint) model and the first or second-order Thevenin model. Although ECMs are generally easier to implement and computationally less demanding than EMs, they may struggle to accurately represent abnormal behaviors caused by temperature variations and internal mechanical deformation. High-order Thevenin models also come with increased computational costs.

IMs are based on electrochemical impedance spectroscopy (EIS), an experimental technique that measures changes in battery impedance under different AC voltages. EIS can provide valuable insights into the electrochemical mechanisms underlying electrical degradation. However, EIS testing requires specialized hardware, is time-consuming, and is not easily performed on batteries during operation, limiting its practical applicability.

Data-driven methods leverage machine learning, statistical analysis, and other data-driven techniques to predict battery SoH based on historical and real-time data. Data-driven methods do not require explicit knowledge of the electrochemical processes involved in battery degradation, making them more flexible and adaptable to different battery chemistries and operating conditions. Examples of data-driven methods include ANNs, SVR [70], GPR [71], KF [72], RFR [73], PF [74], and other regression techniques.

SVR is a popular method for regression analysis, offering the ability to model complex, nonlinear relationships between input variables and the target output, such as SoH or RUL. However, its efficiency may be compromised with excessively large datasets or if there is a lack of clear margins between data points.

GPR is a probabilistic model that provides not only point estimates for SoH and RUL, but also uncertainty estimates, which can be useful for battery management and decision-making. Its drawback, however, is scalability; as large datasets can considerably slow down its computations.

KF is a recursive estimation algorithm that can efficiently incorporate new data into existing models, making it well-suited for online battery health monitoring. Its limitation, however, is that it presumes Gaussian noise, making it less effective in scenarios with non-Gaussian or nonlinear dynamics.

RFR is an ensemble method that combines the predictions of multiple decision trees, offering robustness against overfitting and the ability to model complex relationships between inputs and outputs. However, interpretability can be a challenge given the model's ensemble nature.

PF is a sequential Monte Carlo method, which can be used to estimate the state of a dynamic system, such as a battery, by propagating

Table 2
Comparison of methods for lithium-ion battery modeling.

		Features	Suitable scenarios	Unsuitable scenarios
Model-based methods	Electrochemical models (EM)	Simulate nonlinear internal battery characteristics by accounting for electrochemical reactions and internal structures.	Situations requiring high accuracy, analyzing specific battery chemistries and configurations.	Large battery packs, situations with limited computational resources or lacking complex testing facilities.
	Equivalent Circuit Models (ECM)	Use simple electronic components to simulate dynamic battery behavior.	Applications needing quick implementations, general battery behavior estimations.	Precision modeling of batteries under temperature variations or internal mechanical deformations.
	Impedance Models (IM)	Measure battery impedance variations with different AC voltages.	Understanding underlying electrochemical mechanisms of battery degradation.	Real-time/on-the-go monitoring due to the requirement of specialized hardware and time-intensive nature.
Data-driven methods	Support Vector Regression (SVG)	Models complex nonlinear relationships.	Situations with defined margins between data points.	Extremely large datasets.
	Gaussian Process Regression (GPR)	Probabilistic model offering point and uncertainty estimates.	Battery management requiring decision-making based on uncertainties.	Large dataset analysis due to scalability issues.
	Kalman Filter (KF)	Recursive estimation suitable for online health monitoring.	Applications where Gaussian noise assumptions hold true.	Non-Gaussian or nonlinear dynamics scenarios.
	Random Forest Regression (RFR)	Ensemble method combining multiple decision trees.	Modeling complex input–output relationships.	Situations demanding high interpretability.
	Particle Filter (PF)	Sequential Monte Carlo method suitable for nonlinear and non-Gaussian systems.	Complex system analyses with dynamic changes.	Scenarios with limited computational power due to high resource requirements.
	Artificial Neural Networks (ANN)	General data-driven technique for state estimation with adaptability to various battery chemistries and operating conditions.	Diverse scenarios given the flexibility of ANNs.	Situations with very limited datasets or where interpretability is crucial.

a set of particles through time. PF is particularly useful for nonlinear and non-Gaussian systems, where traditional filtering methods, such as the KF, may struggle. On the flip side, PF demands substantial computational resources, particularly when handling a large number of particles.

Beyond these methods, and considering the extensive data collection capabilities of BMS, ANNs have become a prevalent tool for battery health assessment. They represent an additional category of data-driven techniques dedicated to battery state estimation. A more in-depth discussion on these methods will be provided in the subsequent section.

4. Application of ANNs in energy storage lithium-ion battery health management

In online applications, only battery data up to the current cycle can be accessed, making it challenging to directly estimate the health of lithium-ion battery. To address this issue, ANNs can be trained using data generated from experimental tests and combined with current online data to predict the SoH of a battery.

Various ANN architectures have been employed to predict the state of batteries, including FNN, Extreme Learning Machine (ELM), Convolutional Neural Network (CNN), Recurrent Neural Network (RNN) with LSTM and Gated Recurrent Unit (GRU) and Transformers. These networks leverage their inherent properties to identify and transform features within battery data into latent states or direct inputs. Each ANN architecture offers unique advantages and caters to different scenarios: FNNs effectively learn complex patterns, ELMs enable rapid learning with a single hidden layer, CNNs specialize in analyzing spatial patterns and are ideal for pattern recognition applications, while GRUs and LSTMs handle sequential data, making them suitable for time-series analysis and forecasting tasks. Transformers, with their self-attention mechanism, excel in capturing long-range dependencies in sequences. Additionally, transfer learning techniques have been employed to enhance the performance of these architectures by leveraging pre-trained models or knowledge from related tasks, improving generalization and reducing the need for large amounts of training data.

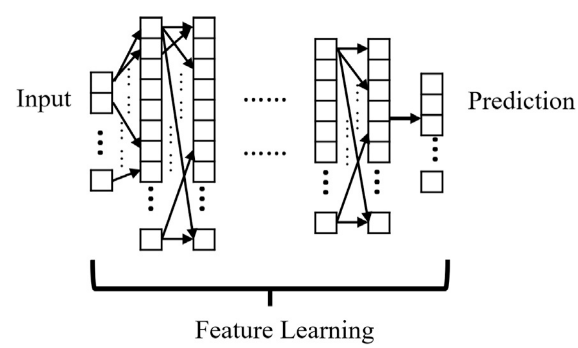

Fig. 4. Feedforward Neural Network. The FNN consists a structured arrangement of an input layer, multiple hidden layers, and an output layer. Through its layers and activation functions, FNN captures intricate nonlinear relationships, processing and transforming the input data into meaningful battery state predictions.

4.1. FNN

Illustrated in Fig. 4, FNNs consist of an input layer, which is responsible for receiving the input data; an output layer, which represents the predicted battery state; and multiple hidden layers in between. These layers form a multi-layer network structure with activation functions that establish the nonlinear relationship between the input data and the state of lithium-ion batteries.

The hidden layers within the FNN enable the extraction of increasingly complex features from the input data as it passes through the network. This hierarchical learning process allows FNNs to capture intricate patterns and relationships in the battery data. the computation of FNN can be depicted as

$$F(\mathbf{x}) = o^L(\mathbf{W^L} o^{L-1}(\mathbf{W^{L-1}} \cdots o^1(\mathbf{W^1 x} + \mathbf{b}^1) \cdots + \mathbf{b}^{L-1}) + \mathbf{b}^L), \quad (3)$$

where $\mathbf{x}$ represents the input vector of features, L represents the number of layers, $\mathbf{W}^l$ represents the weight matrix between layer $l-1$ and l, o^l represents the activation function at layer l, and $\mathbf{b}^l$ represents the bias at layer l.

The loss of the FNN is provided by the cost function:

$$C(\mathbf{y_i}, f(\mathbf{x_i})) \tag{4}$$

where $\mathbf{x_i}$ represents the input of a specific sample, $\mathbf{y_i}$ represents the target output, and C represent the loss function to evaluate the difference between the output from FNN and the target output. The train the model, FNNs typically employ gradient-based back propagation algorithms to train the weights and biases within the network. This training process allows the loss function to converge continuously, improving the accuracy of the model.

Researchers have used custom-designed FNNs to predict SoH with high reliability in various scenarios, such as constant voltage constant current mode and random current mode. A FNN is developed to estimate complete charging curves using small portions of charging curves as inputs [75]. In another approach, FNNs are used to predict the battery's capacity degradation trajectory based on data from a single cycle, demonstrating promising results with an error of just 8.6% over the first 100 cycles [76]. Additionally, an FNN is employed to establish the relationship between SoH, estimated capacity, and temperature [77], suggesting that FNNs can effectively model complex relationships between various input data and the state of lithium-ion batteries, even with limited information.

4.2. ELM

ELM [78] is a type of neural network that consists of only a single hidden layer. Unlike traditional neural networks, ELMs do not require an gradient-based backpropagation training process to update the weights and biases. Instead, the weight values and bias values for the hidden layer are randomly assigned during the training phase.

The output layer of an ELM does not contain any bias values. Instead, the output layer weight values are calculated by solving a linear system, which can often be done using standard linear algebra techniques. This approach makes ELMs faster to train than traditional neural networks, as the computational complexity is reduced. The output function of ELM can be expressed as

$$F_L(\mathbf{x}_j) = \sum_{i=1}^{N} \beta_i g(\mathbf{w}_i \cdot \mathbf{x}_j + \mathbf{b}_i), j = 1, 2, \dots, N, \tag{5}$$

where N represents the sample number, β_i represents the weight vector connecting the ith hidden layer neuron, and $\mathbf{w}_i$ represents the weight vector between the ith hidden layer neuron and the output.

ELMs have been shown to provide good generalization performance in various applications, including SoH prediction for lithium-ion batteries. While their simpler architecture may not always yield the same level of accuracy as deeper neural networks, ELMs can still be an efficient and effective option for certain prediction tasks, particularly when computational resources or training time are limited.

To enhance the performance of ELM and prevent it from getting trapped in local optima, an improved Sparrow Search Algorithm (ISSA) optimized ELM network is developed for predicting the SoH of lithium-ion batteries under random load conditions [79]. In addition, a Salp Swarm Algorithm (SSA) is utilized for hyperparameter search in the ELM, leading to the development of an improved ELM-based SoC estimation model [80]. A novel feature extraction technique for obtaining features characterizing battery aging is also developed, along with an improved ELM algorithm [81].

4.3. CNN

CNNs, as shown in Fig. 5, are known for their powerful representation learning capabilities and have found widespread application in areas such as image recognition and object detection [82]. The architecture of a CNN typically consists of several key components, including convolutional layers, pooling layers, and fully connected layers.

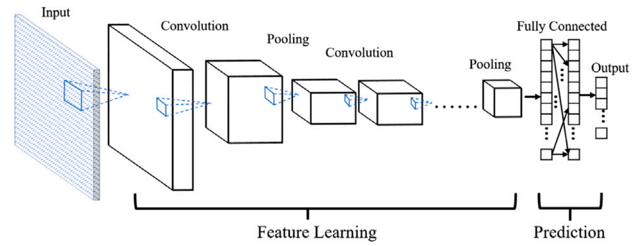

Fig. 5. Convolutional Neural Network. CNNs employ convolutional layers to detect specific patterns in battery health data using filters. Pooling layers subsequently compress this data, preserving crucial health indicators. Fully connected layers synthesize these insights, allowing the network to derive a comprehensive understanding of the battery's health state from various features.

Convolutional layers are responsible for detecting local features in the input data by applying a series of filters or kernels to the input. This process enables the CNN to learn various patterns within the data. Pooling layers are used to reduce the spatial dimensions of the input data while retaining important information. This downsampling process helps to reduce the computational complexity of the network and control overfitting.

Fully connected layers are used to combine the features learned by the previous layers, enabling the network to make decisions based on a global understanding of the input data. The fully connected layer combines the extracted features to form a nonlinear output, allowing the network to learn complex relationships between different features.

Finally, the loss function calculates the error between the predicted output and the true output, quantifying the performance of the CNN. In the CNN training process, the parameters Θ are learned for a composite nonlinear function $F(x|\Theta)$, connecting the input $\mathbf{x}$ to the corresponding output $\mathbf{y}$:

$$\mathbf{y} = F(\mathbf{x} \mid \Theta) = f_L\left(\cdots f_2\left(f_1\left(\mathbf{x} \mid \theta_1\right) \mid \theta_2\right) \mid \theta_L\right), \tag{6}$$

where each operation $F_l(\cdot|\Theta_l)$ in the network is associated with the convolutional layer, pooling layer and their respective parameters Θ. The loss value is used to update the network's weights through back propagation, aiming to minimize the overall error and improve the network's performance on the task at hand.

In the context of battery health prediction, researchers can leverage the strong feature extraction capabilities of CNNs to analyze time series data, such as voltage, current, and temperature, and extract relevant features that help predict the state of lithium-ion batteries. A study presents an end-to-end prognostic framework for SoH estimation and RUL prediction, employing a hybrid ANN consisting of a one-dimensional CNN and LSTM to capture hierarchical features and temporal dependencies in battery degradation variables [83]. Addressing the limitations of traditional physical models in describing complex battery behavior, a multi-scale deep CNN offers enhanced feature extraction capabilities [84]. Additionally, a quantitative analysis of degradation patterns in lithium batteries reveals loss of active matter, lithium ion loss, and conductivity loss; by feeding this information into a CNN-LSTM prediction model, better results are obtained in analyzing the internal mechanistic effects of low temperature and near-adiabatic conditions [85].

Temporal Convolutional Networks (TCN) have also emerged as a development in the domain of CNN. For tasks that involve sequential data, TCNs utilize a convolutional approach, ensuring fixed-sized receptive fields and offering several advantages such as parallelism during training and more flexible memory size. [86] proposes a TCN network leveraging a convolutional structure for precise SOH monitoring and RUL prediction of lithium batteries, improving upon traditional models by addressing local regeneration phenomena and integrating Empirical Mode Decomposition (EMD) to enhance prediction accuracy. Following

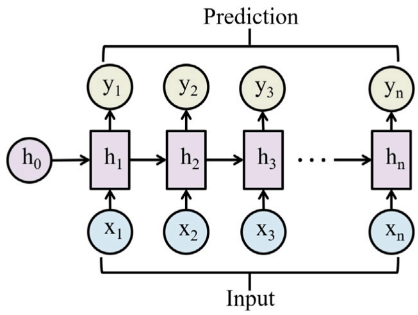

Fig. 6. Recurrent Neural Network. RNNs uniquely model temporal relationships in battery health data through hidden states, maintaining a running context of the input data over sequential time steps. This ability enables them to forecast battery states, like the SoH for upcoming cycles, by learning and adjusting weights during training to minimize discrepancies between predicted outputs and actual values.

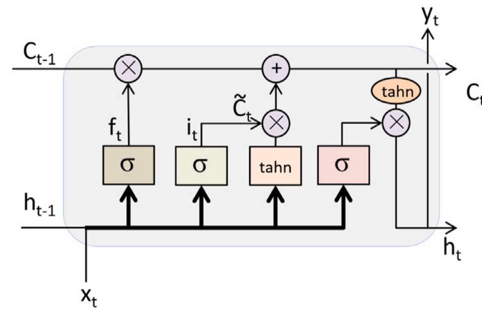

Fig. 7. Long Short-Term Memory Cell. LSTMs are engineered with unique gates, like the forget gate, which smartly filters past information, enhancing training stability. Additionally, the input and output gates collaboratively manage the assimilation of new data and the relay of pertinent information, optimizing the cell's capability to recognize and retain long-term dependencies in battery health data.

a similar vein, [87] develops a generic TCN framework designed to process raw sensor data for SOH estimation of lithium-ion batteries across different aging scenarios, optimized using Bayesian hyperparameter tuning and validated via stratified K-Fold cross-validation, eliminating the need for additional feature engineering, making it suitable for on-board operations and BMS applications; the work also delves into the influence of partial load cycles from various SOC ranges on the accuracy of the SOH estimation.

4.4. RNN

RNNs [88] are designed to have time series memory, which makes them especially well-suited for processing time series data. As shown in Fig. 6, their autoregressive architecture enables them to maintain a hidden state that can capture information from previous time steps, allowing them to effectively model temporal dependencies in the data. This characteristic is particularly useful when working with data that has a sequential nature, such as time series data from battery tests and operation.

In an RNN architecture, the hidden state $\mathbf{h}_t$ at each time step t is crucial for capturing the temporal dependencies within the sequence. This hidden state is passed to the subsequent $t+1$ time step with the input x_{t+1}. By using the hidden state $\mathbf{h}_t$ with the input x_{t+1}, the RNN block computes a new hidden state $\mathbf{h}_{t+1}$ and an output $\mathbf{y}_{t+1}$ for the current time step. This process is repeated for each time step within the sequence, allowing the RNN to maintain a running context of the input data and to better model the temporal relationships between time steps.

The hidden state,

$$\mathbf{h}_t = \phi(\mathbf{x}_t W_{ih}^T + \mathbf{b}_{ih} + \mathbf{h}_{t-1} W_{hh}^T + \mathbf{b}_{hh}), \tag{7}$$

is updated using an activation function $\phi()$, such as a hyperbolic tangent (tanh) or a sigmoid function, which allows the network to learn non-linear patterns in the data. The weights and biases within the RNN are learned during the training process, where the network is optimized to minimize a loss function that measures the difference between the predicted outputs and the actual target values, such as SoH of next cycle.

One popular variant of the RNN is the LSTM network [89], which is specifically designed to address the vanishing gradient problem that can occur in traditional RNNs. This issue can make it difficult for RNNs to learn long-term dependencies in the data. As presented in Fig. 7, LSTMs incorporate special gating mechanisms that allow them to better retain information over longer sequences, making them a popular choice for many time series prediction tasks, including battery health estimation.

For input $\mathbf{x}_t$, the LSTM cell computes the following functions:

$$\begin{aligned}
\mathbf{i}_t &= \sigma\left(W_{ii}\mathbf{x}_t + \mathbf{b}_{ii} + W_{hi}\mathbf{h}_{t-1} + \mathbf{b}_{hi}\right),\\
\mathbf{f}_t &= \sigma\left(W_{if}\mathbf{x}_t + \mathbf{b}_{if} + W_{hf}\mathbf{h}_{t-1} + \mathbf{b}_{hf}\right),\\
\mathbf{g}_t &= \tanh\left(W_{ig}\mathbf{x}_t + \mathbf{b}_{ig} + W_{hg}\mathbf{h}_{t-1} + \mathbf{b}_{hg}\right),\\
\mathbf{o}_t &= \sigma\left(W_{io}\mathbf{x}_t + \mathbf{b}_{io} + W_{ho}\mathbf{h}_{t-1} + \mathbf{b}_{ho}\right),\\
\mathbf{c}_t &= \mathbf{f}_t \odot \mathbf{c}_{t-1} + \mathbf{i}_t \odot \mathbf{g}_t,\\
\mathbf{h}_t &= \mathbf{o}_t \odot \tanh\left(\mathbf{c}_t\right),
\end{aligned} \tag{8}$$

where $\mathbf{i}_t$, $\mathbf{f}_t$, $\mathbf{c}_t$, $\mathbf{o}_t$, represents the input, forget, cell, and output gates, respectively. σ represent the sigmoid function, and $\odot$ represent the Hadamard product.

The forget gate in an LSTM block determines which information from the previous hidden state should be discarded or retained. By selectively forgetting information, the LSTM can better focus on the relevant inputs and maintain a more stable gradient during the training process.

The input gate controls the flow of new information into the cell state, ensuring that only relevant information is added to the cell state. The output gate then determines the information that should be passed to the next block, based on the updated cell state and the input data.

Several studies have demonstrated the effectiveness of LSTMs in predicting the SoH and RUL of lithium-ion batteries. Researchers demonstrate the efficiency and effectiveness of battery monitoring by accurately predicting the lifespan of a specified lithium-ion battery using an LSTM model [90]. For volatile battery data, [91] employs a LSTM-based neural network to understand the battery's electrical behavior and subsequently adapt virtual battery experiments to actual load conditions. In a different approach, a novel SoH estimation method employs improved LSTM and health indicators extracted from the charging–discharging process, selecting high-correlation parameters with Pearson coefficient, reducing computational burden with neighborhood component analysis, and optimizing hyperparameters in LSTM models using differential evolution grey wolf optimizer [92].

For better SoH estimation, an improved LSTM-based data-driven method utilizes particle swarm optimization for network topology estimation, selects four health indicators, employs grey relational analysis to quantify their correlations with battery SoH, and establishes an LSTM model to map the relationship [93]. A hybrid ALF-PF-LSTM approach accurately predicts the RUL of LIBs, with experimental results demonstrating improved prediction performance, robustness, and superiority over popular PF-based algorithms [94].

A study evaluates the impact of three methods for characterizing future operating conditions in probability-based prognostic algorithms, specifically LSTM, Markov Chain, and constant usage, considering their influence on the system's RUL evaluation [95]. To reduce the requirement of degradation data for early RUL prediction, an ADLSTM-MC algorithm is proposed, combining adaptive dropout long short-term

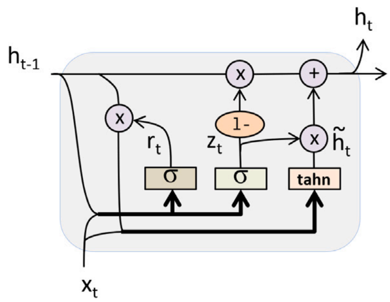

Fig. 8. Gated Recurrent Unit Cell. GRUs employ a more streamlined architecture than LSTMs with only two crucial gates: the update and reset gates. These gates jointly manage information retention and influence from previous states, enabling GRUs to adeptly capture extended temporal patterns in battery health data, all while ensuring computational efficiency.

memory (optimized by Bayesian optimization) and Monte Carlo simulation for accurate RUL prediction while accounting for uncertainties in the results [96].

GRUs, as shown in Fig. 8, are another popular RNN architecture. Like LSTMs, GRUs are designed to address the vanishing gradient problem in traditional RNNs, also have gating mechanisms that help in controlling the flow of information through the network. However, GRUs have a simplified architecture compared to LSTMs, as they only have two gates: an update gate and a reset gate. A GRU cell computes the following functions:

$$\begin{aligned}
\mathbf{r}_t &= \sigma(W_{ir}\mathbf{x}_t + \mathbf{b}_{ir} + W_{hr}\mathbf{h}_{(t-1)} + \mathbf{b}_{hr}),\\
\mathbf{z}_t &= \sigma(W_{iz}\mathbf{x}_t + \mathbf{b}_{iz} + W_{hz}\mathbf{h}_{(t-1)} + \mathbf{b}_{hz}),\\
\tilde{\mathbf{h}}_t &= \tanh(W_{in}\mathbf{x}_t + \mathbf{b}_{in} + \mathbf{r}_t \odot (W_{hn}\mathbf{h}_{(t-1)} + \mathbf{b}_{hn})),\\
\mathbf{h}_t &= (1-\mathbf{z}_t) \odot \tilde{\mathbf{h}}_t + \mathbf{z}_t \odot \mathbf{h}_{t-1},
\end{aligned} \tag{9}$$

where $\mathbf{r}_t$, $\mathbf{z}_t$, $\tilde{\mathbf{h}}_t$ represents the reset, update, and new gates, respectively. σ represent the sigmoid function, and $\odot$ represent the Hadamard product.

The update gate controls the extent to which previous hidden states are retained, while the reset gate controls the influence of the previous hidden state on the current hidden state. This gating mechanism allows GRUs to better capture long-range dependencies in time series data while maintaining a simpler and more computationally efficient structure than LSTMs.

In the context of battery state estimation, researchers have found that GRUs can provide comparable performance to LSTMs in certain scenarios while requiring fewer model parameters and computational resources. As a result, GRUs have become a popular alternative to LSTMs in many applications, including the prediction of battery health and lifespan.

One study proposes a novel RUL prediction approach that employs a FNN for the low-frequency part and a self-designed improved Res2Net-Bidirectional Gated Recurrent Unit-Fully Connected (IRes2Net-BiGRU-FC) for the high-frequency part [97]. In contrast, another study suggests an approach utilizing a hybrid neural network, GRU-CNN, to estimate SoH based on CC charging curves, as this method can learn shared information and time dependencies of the charging curve, capturing capacity-related insights from voltage, current, and temperature data [98]. Optimized through a momentum gradient algorithm for faster convergence, a GRU-RNN model is constructed for SoC estimation using voltage and current inputs [99].

Moreover, a comparative study evaluates the performance of various RNN architectures, such as simple RNN, LSTM with GRU, and LSTM with a bidirectional structure, in SoH estimation. The results show that LSTM and bidirectional LSTM models tend to exhibit greater insensitivity to charge–discharge conditions and higher accuracy in predicting SoH.

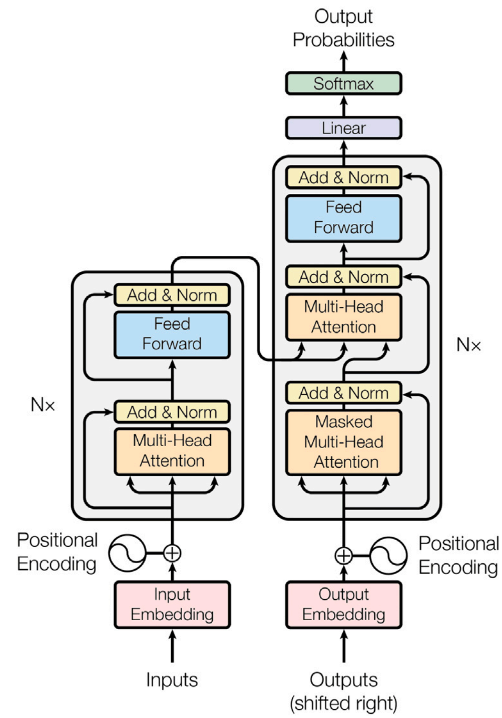

Fig. 9. The Transformer encoder–decoder. The Transformer architecture, introduced in the seminal paper "Attention Is All You Need", [100] revolutionized sequence-to-sequence tasks with its unique self-attention mechanism. The encoder ingests the input sequence, processing it through stacked layers of attention and feed-forward networks, while the decoder generates the output, utilizing both its own layers and the encoder's representations, facilitating intricate battery health state interpretations and predictions.

4.5. Transformer

As shown in Fig. 9, Transformers [100] are a type of encoder–decoder architecture initially designed for natural language processing tasks. They have gained popularity due to their ability to handle long-range dependencies and their scalability, which is achieved through the use of self-attention mechanisms. The multi-head self-attention mechanism allows the Transformer to consider multiple positions of the input sequence simultaneously, making it highly parallelizable and efficient in capturing long-range dependencies. This is in contrast to traditional RNN-based architectures, which process sequences sequentially and may struggle with long-range dependencies due to vanishing or exploding gradients.

As a crucial component in the Transformer architecture, the self-attention function is computed on a collection of queries simultaneously, consolidated into a matrix Q. Correspondingly, the keys and values are also combined into matrices K and V. The resulting output matrix is calculated as follows:

$$\mathrm{Attention}(Q,K,V) = \mathrm{softmax}(\frac{QK^T}{\sqrt{d_k}})V, \tag{10}$$

where $\sqrt{d_k}$ represents the scaling factor.

A study introduces a Temporal Transformer Network (TTN) for lithium-ion battery RUL prediction, integrating self-attention, denoising autoencoder for noise reduction, and a temporal encoding layer to incorporate operating time in the input [101]. In contrast, another study suggests a hybrid battery health prediction method that merges Transformer and online correction, employing multi-scale health features and dimension reduction, while integrating a specialized filter layer in the Transformer for managing diverse features [102].

A unique approach using a Transformer neural network and an adaptive observer for battery SoC estimation is presented, capitalizing on richer information from input sequences and rectifying learning fluctuations for enhanced accuracy [103]. Lastly, a novel SoH estimation method is introduced, utilizing data pre-processing techniques and a CNN-Transformer framework, selecting and reducing features through PCC and PCA, followed by min–max scaling, before being input into the CNN-Transformer model [104].

4.6. Transfer learning

Once the neural network has been trained on a set of battery data, its learned knowledge can be transferred to evaluate the health status of different batteries under various operating conditions. This enables the trained ANN to generate more accurate predictions by leveraging the general rules obtained during training and applying them to the specific operating data of the battery under evaluation.

In [105], an LSTM network-based transfer learning model is introduced for adaptive online capacity prediction under fast charging, featuring a novel voltage attribute enabling 80% SoC in roughly 10 min, integrating voltage features and cycle numbers through a sliding window, and optimizing hyperparameters with cross-validation and fine-tuning as new battery data becomes available to address cell-to-cell differences. [106] employs early battery aging data for degradation pattern recognition and transfer learning to improve SoH estimation accuracy, extracting four features from discharge capacity curves for this purpose.

A novel transfer learning approach using cross-manifold embedding [107] tackles battery characteristic differences and model migration challenges by leveraging minimal target battery data and incorporating information from related tasks, allowing for small sample SoH estimation and better generalization, overcoming overfitting issues faced by traditional machine learning methods. [108] introduces a deep CNN based method for estimating the capacity of lithium-ion batteries using a limited dataset by integrating transfer learning and ensemble learning, demonstrating superior accuracy and robustness compared to other data-driven approaches. In addition, a Controllable Deep Transfer Learning (CDTL) network [109] uses controllable Multiple Domain Adaptation (MDA) with adaptive regularization to enable short and long-term SoC estimations at early degradation stages, enhancing target LSTM generalizability by transferring knowledge between target and historical source cells while minimizing negative transfer learning and ensuring controllability and convergence.

A new transfer learning strategy combined with cycle life prediction technology [110] addresses accurate long-term aging trajectory prediction for LFP lithium-ion batteries in a two-stage aging process, employing feature extraction, deep learning, Bayesian model migration, and incorporating prior cycle life information for precise and uncertain quantification of aging trajectories with limited data. In contrast, [111] introduces an accurate SoC estimation algorithm for lithium-ion batteries using LSTM and transfer learning, allowing knowledge sharing across batteries with less training data and integrating a rolling learning method to update model parameters as battery capacity degrades, providing precise estimation across diverse aging states and temperatures.

4.7. Ensemble of ANNs with other machine learning

ANNs have been effectively combined with other SoH estimation methods in several studies, resulting in improved performance.

A framework integrating a FNN with knowledge transfer and ARIMA forecasting is proposed, using Pearson correlation coefficient and LASSO regression for efficient feature selection and applying Savitzky–Golay filtering for noise reduction, achieving high estimation accuracy (96%) with limited training data (25%) [112]; however, additional training with more data shows no significant improvement. In contrast, another study [113] characterizes LIHC dynamics using a first-order RC equivalent circuit model and employs a VFF-RLS algorithm to update model parameters adaptively, while an LSTM neural network model corrects OCV to estimate SoC, RUE, and SOE under dynamic conditions across various temperatures.

A multi-feature fusion model [114] combines SVR and long short-term memory network (LSTM) to estimate battery SoH by extracting feature parameters from the constant voltage charging stage, constructing primary SVR models, and employing LSTM as a secondary learner to improve multi-feature fusion performance. Also, a novel parameter identification method [115] combines a 1D CNN with a genetic algorithm to learn the dynamics between input current and simulated voltage, enabling the recommendation of highly probable parameter candidates for building an electrochemical model.

Neural network and ordinary differential equation-based models [116] are utilized to forecast battery SoH and predict end of life, with discoveries and predictions made using various neural ODEs compared against established RNN models such as LSTM and GRU. A hybrid data science model [117] combines empirical mode decomposition, grey relational analysis, and deep RNNs for lithium-ion battery RUL prediction, using EMD and GRA for feature extraction and various deep RNNs for SoH and RUL forecasting, with Bayesian optimization for hyperparameter tuning.

[118] presents a high-precision SOC estimation approach using an LSTM neural network with attention mechanism, optimized by a Bayesian optimizer, while leveraging the isolation forest anomaly detection for data preprocessing and the sliding window method to enhance time-series data accuracy. In another approach, a temperature-compensated second-order equivalent circuit model [119] is developed, using a particle swarm optimization algorithm for adaptive parameter identification, and an LSTM for accurate battery capacity prediction, with dynamically updated model parameters and capacity estimates inputted to a square root cubature KF for SoC estimation.

5. Summary

Lithium-ion battery health estimation is of critical importance in various applications, including BESSs, EVs, and portable devices. Energy storage lithium-ion batteries differ inherently from power and customer battery application scenarios in terms of reliability, efficiency and cycle life, making their health state estimation a topic of interest for many researchers.

Degradation of lithium-ion batteries is a complex process, involving various mechanisms that can lead to changes in capacity, impedance, and cycling performance. Addressing the challenges of battery health management requires a thorough understanding of these degradation mechanisms and the development of reliable estimation models.

Deep learning has emerged as a powerful tool for lithium-ion battery health estimation, offering advantages over traditional methods due to its ability to learn complex relationships between input data and health indicators. Neural network architectures, such as FNNs, CNNs, RNNs, LSTMs, GRUs, and Transformers have been recently used in data-driven battery health estimation models with promising results. These neural network-based models, coupled with advanced machine learning techniques, can be employed for energy storage lithium-ion battery health estimation tasks, potentially improving the performance of estimation models.

We believe that employing ANNs in battery health assessment and prediction can help address several existing challenges, warranting further study to unlock their full potential:

1. As lithium-ion battery manufacturing processes and material technologies advance, leading to evolving operating temperature ranges, cycle times, and charging and discharging rules, ANNs can play a crucial role in extracting more effective features representing the degradation state, enhancing battery health monitoring.

2. Long-life energy storage lithium-ion batteries demand data-driven models with strong generalization capabilities. ANNs can help develop models that, even with limited experimental data, can be applied to online health prediction for batteries with varying aging paths.
3. In BESSs supporting renewable energy power generation equipment, which consist of numerous battery cells, ANNs can facilitate the planning of long-term, reliable operation of the entire BESS through early prediction of battery cell life, addressing a critical task for future BESSs.
4. Applying contrast learning techniques in conjunction with ANNs can enforce that similar instances have similar representations while dissimilar instances have distinct representations in the latent space. This approach holds promise for more accurate fault detection and diagnosis by distinguishing between healthy and faulty battery states, improving lithium-ion battery health management.

CRediT authorship contribution statement

Yuntao Zou: Conceptualization, Validation, Visualization, Writing – original draft. **Zihui Lin:** Investigation, Resources, Writing – original draft. **Dagang Li:** Investigation, Resources, Writing – review & editing. **ZhiChun Liu:** Validation, Writing – review & editing, Supervision, Project administration, Funding acquisition.

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.

Data availability

Data availability All data used in this study are publicly available. The datasets were sourced from the following repositories:
• Stanford-MIT dataset: Available at https://data.matr.io/1/
• CALCE dataset: Available at https://web.calce.umd.edu/batteries/data.htm
• NASA dataset: Available at https://ti.arc.nasa.gov/tech/dash/pcoe/prognostic-datarepository/#battery
• Oxford dataset: Available at http://howey.eng.ox.ac.uk/data-and-code/

Acknowledgments

This work was supported by the National Key Research and Development Program of China (No. 2022YFB4003801), the National Natural Science Foundation of China (Grant No. 52076088) and the Key-Area Research and Development Program of Hubei Province (No. 2023BIB017).

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