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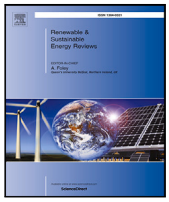

Prognostics and health management of Lithium-ion battery using deep learning methods: A review

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ABSTRACT

Prognostics and health management (PHM) is developed to guarantee the safety and reliability of Lithium-ion (Li-ion) battery during operations. Due to the advantages of deep learning on nonlinear modeling and representation learning, it gains considerable attentions in the PHM of Li-ion battery. To provide a comprehensive view of deep learning-based PHM of Li-ion battery, this paper summarizes these applications on the basis of current research. Deep learning-based PHM of Li-ion battery roughly involves three steps, namely data acquisition, deep learning methods and performance evaluation. Firstly, regular data types and public datasets are introduced. Secondly, brief introductions of deep learning methods and their applications to PHM of Li-ion battery are summarized. These deep learning methods include autoencoder, deep neural network, deep belief network, convolutional neural network, recurrent neural network and generative adversarial network. Thirdly, commonly-used evaluation metrics are presented. Finally, the paper draws a conclusion and presents the prospects of PHM of Li-ion battery with deep learning techniques.

1. Introduction

The lithium-ion (Li-ion) battery has achieved a wide range of applications across fields, e.g., electric vehicles, satellites and aircrafts, due to its advantage of high energy density, longevity and low self-discharging rate [1]. The failure of battery could give rise to huge economic losses, or even serious disasters. Therefore, it is crucial to develop prognostics and health management (PHM) method to guarantee the battery operating in safety and reliability.

In the past decades, much efforts have been devoted to the PHM of Li-ion battery [2–4], which significantly advances the development of this research field. The PHM of Li-ion battery aims to assess and predict the operating state of a Li-ion battery and further to enhance their reliability on operation [5]. Approaches to the PHM of Li-ion battery typically include physical models and data-driven models [6]. Establishing physical models, e.g., electrochemical models, equivalent circuit based models, analytical model, for PHM of Li-ion battery usually requires the assistance of prior knowledge and experience for quantitative reasoning, and insufficient prior knowledge could degrade the performance of these models [7]. By contrast, data-driven methods demands minimal knowledge or information of physical degrading mechanisms of Li-ion battery. They can effectively refine more high-representative information from historical monitoring data.

Data-driven approaches mainly consist of statistical modeling methods, machine learning methods and neural networks [8]. Conventional data-driven methods conduct PHM by four steps. They are illustrated in Fig. 1. In the step of data acquisition, voltage, current, temperature and several other data are usually measured by sensors during charging or discharging of a battery due to their sensitivity to the variation of battery health state [9]. With the aging degradation of Li-ion battery, voltage, current and temperature presents different fluctuations. Then features are extracted from collected data to represent the health state efficiently. Prior knowledge is demanded on feature selection to guarantee sensitive features extracted. After feature extraction, they are projected by data-driven models to conduct PHM of Li-ion battery, including state of health (SoH) estimation, state of charge (SoC) estimation, end of life (EoL) prediction and remaining useful life (RUL) prediction. These problems can be formulated as regression problems or classification problems. Finally, these methods are quantitatively evaluated by appropriate metrics to assess their performance in the PHM of Li-ion batteries.

Deep learning, as an important branch of machine learning, has achieved significant advances in theory [10] and applications to many fields, e.g., image processing [11], automatic driving [12], natural language processing [13,14], etc. It also receives substantial attentions in the PHM of Li-ion battery in recent years in view of its powerful ability on nonlinear modeling for complex systems [15]. These networks are composed of a collection of linear or nonlinear transformations,

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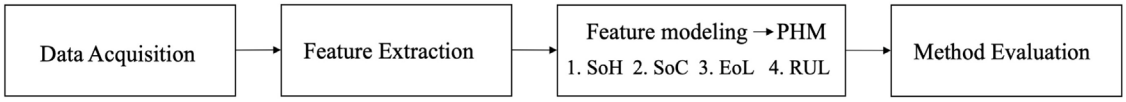


Fig. 1. The general procedure of data-driven-based PHM of Li-ion battery.

enabling high-representative features to be extracted from multiple levels [16]. The basic procedures of deep learning-based PHM of Li-ion battery are illustrated in Fig. 2, including data acquisition, deep learning-based PHM and method evaluation [17]. Data are also the basis of the PHM modeling based on deep learning. The data that are sensitive to the variation of health condition should be collected first. The category of data in the deep learning based modeling is identical to that of traditional methods. However, the advantages of deep learning methods over conventional data-driven methods in PHM is that they can perform feature extraction from raw signals automatically by unsupervised learning. It can effectively avoid the inappropriate feature selection caused by the absence of prior knowledge. These deep learning methods used in PHM of Li-ion battery are outlined in Fig. 3. It mainly includes auto-encoder (AE), deep neural network (DNN), deep belief network (DBN), convolutional neural network (CNN), recurrent neural network (RNN) and generative adversarial network (GAN). They were adopted in extensive research aiming to solve different problems facing PHM of Li-ion battery.

This paper presents an organized and comprehensive overview of deep learning-based PHM of Li-ion battery. The contributions can be summarized as follows.

1. This review gives an organized view of deep learning based PHM of Li-ion battery from the steps of data acquisition, deep learning model and method evaluation.
2. The categories of data that are used in PHM of Li-ion battery are provided. The data includes current, voltage, temperature and several other types. The open-access datasets that are utilized in the PHM are summarized.
3. Deep learning techniques and their applications are summarized to give a comprehensive view of PHM development of Li-ion battery. These methods are comprised of AE, DNN, DBN, CNN, RNN, GAN as well as their variants.
4. The summary of commonly used metrics and their indications are listed to facilitate method validations.

The reminder of this paper are organized as follows. The tasks of PHM of Li-ion battery are described in Section 2. Section 3 lists the category of data that used in PHM. Section 4 summarizes various deep learning methods and their applications to PHM of Li-ion battery. Section 6 concludes the paper and points out the potential future directions of PHM of Li-ion on the basis of deep learning.

2. The tasks of prognostics and health management of Li-ion battery

The tasks of PHM of Li-ion battery include SoH, SoC, EoL estimation and RUL prediction. Capacity, e.g., in [21] is a common measurement to indicate the performance of Li-ion battery [22]. Coulomb counting and open circuit voltage based techniques are two basic methods to calculate the discharging capacity by integrating the discharging current [23,24]. Coulomb counting is given by Eq. (1).

$$C = \int_{t=1}^{T} i(t)\,\mathrm{d}t \tag{1}$$

where $i(t)$ denotes the current at time t and T is the sum of discharging time. C is the discharging capacity.

1. State of Health : SoH is used to describe the health state of a battery from long term. It is defined as the ratio of the maximum available capacity of each cycle to the initial capacity, which is denoted as Eq. (2).

$$SoH(t) = \frac{C_{max}(n)}{C(0)} \tag{2}$$

where $C(0)$ denotes the initial capacity of a Li-ion battery and $C_{max}(n)$ is the maximum capacity of a battery at cycle n.
The SoH tends to decrease over cycles, which indicates the degradation of a battery. A battery normally can be considered reaching failures when the capacity at the full charging state decreases by 20%–30% of the nominal capacity [25].
2. State of Charge : SoC is defined as the remaining charge within the battery and is given by the available residual capacity of the battery divided by its nominal capacity of current discharging cycle as Eq. (3). In general, the estimation of SoC is a nonlinear function that varies with temperature and discharge/charge currents.

$$SoC = \frac{Q_{avail}}{C_{max}(n)} \tag{3}$$

where Q_{avail} represents the available capacity of a battery in a cycle and $C_{max}(n)$ is the maximum capacity of battery at cycle n.
3. End of Life : EoL can be defined as the time instance at which the battery can no longer operate normally. It can be denoted by a cycle number [26] and calculated as follows.

$$EoL = n_{end} \tag{4}$$

where n_{end} is the cycle number that a battery reaches a failure.
4. Remaining Useful Life : The RUL is typically defined as the remaining cycles that a Li-ion battery is estimated to be functional with the purpose of minimizing catastrophic failures [27]. The following equation is used to calculate the RUL.

$$RUL = n_{end} - n \tag{5}$$

where n is the number of current cycle.

These tasks of PHM of Li-ion are interlinked. The variables applied in these PHM tasks are shown in Fig. 4 to facilitate the understanding of each definition of tasks. Fig. 4(a) shows an overall variation of capacity in the whole cycle life and Fig. 4(b) demonstrates an capacity variation over a cycle.

3. Data acquisition

The degradation of a battery could be arisen from many factors, e.g., the loss of reusable lithium, the loss of electrode active materials or resistance growth of a cell [6]. The internal change can be reflected on external phenomena. With the aging progressing, the battery capacity decreases. Sensitive data that can reflect the operating condition of Li-ion can be collected to indicate the degradation. The degradation can be implied by the charging/discharging fluctuations of voltage, current and temperature. Therefore, these data can be collected from battery to monitor the internal change of a Li-ion battery. This section presents the data that are used for PHM modeling of Li-ion battery.

1. Voltage. An example of a battery complying with constant current (CC)-constant voltage (CV) charge is taken as an example. Figs. 5(a) shows charging variations of battery voltage over cycles. It can be seen from this figure that the voltage demonstrates

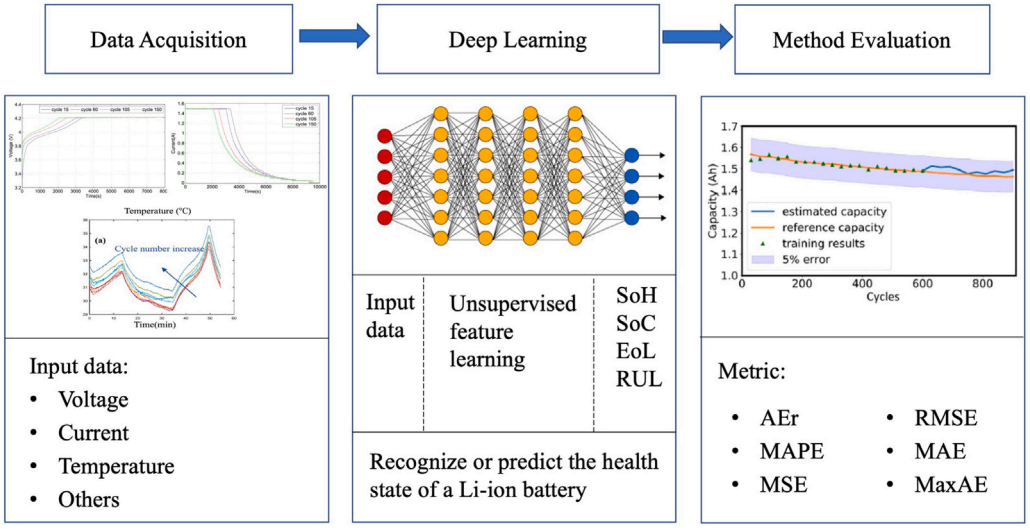


Fig. 2. The basis procedure of PHM of Li-ion battery [18–20].

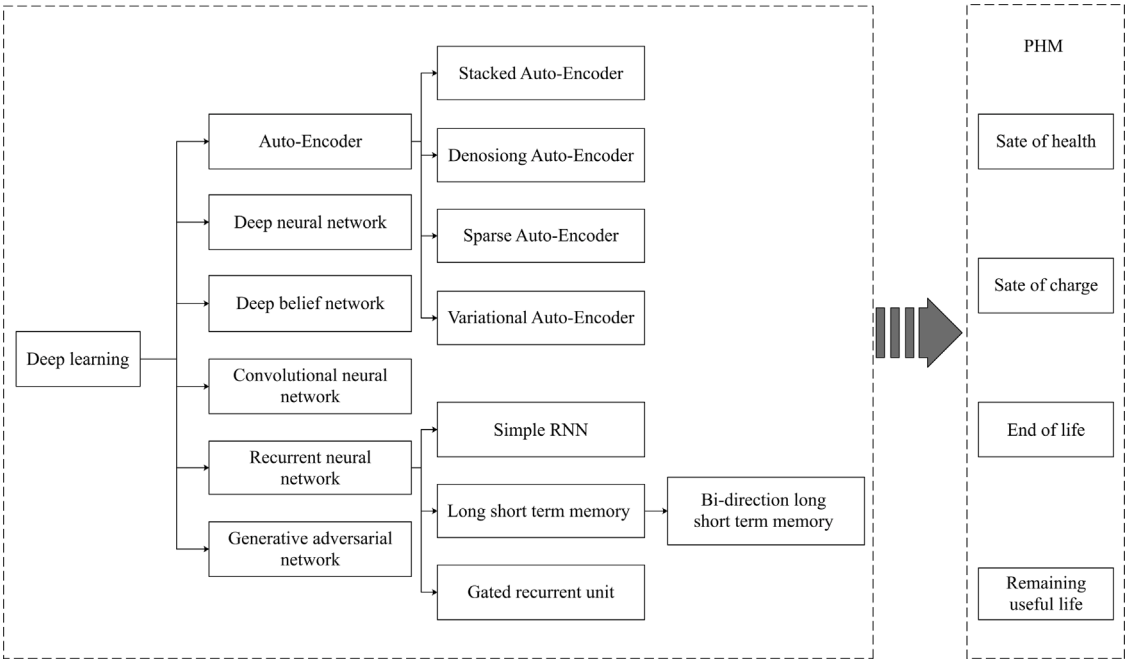


Fig. 3. The category of deep learning methods for PHM of Li-ion battery.

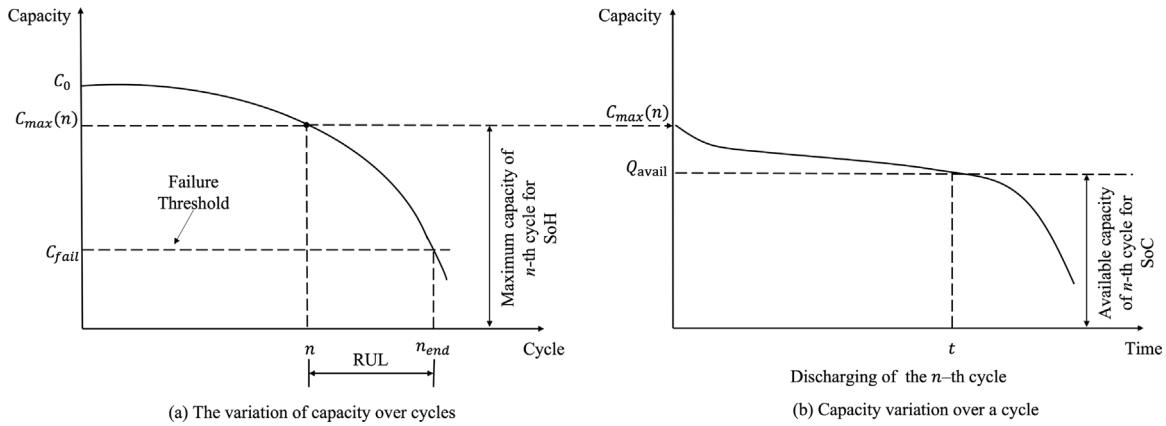
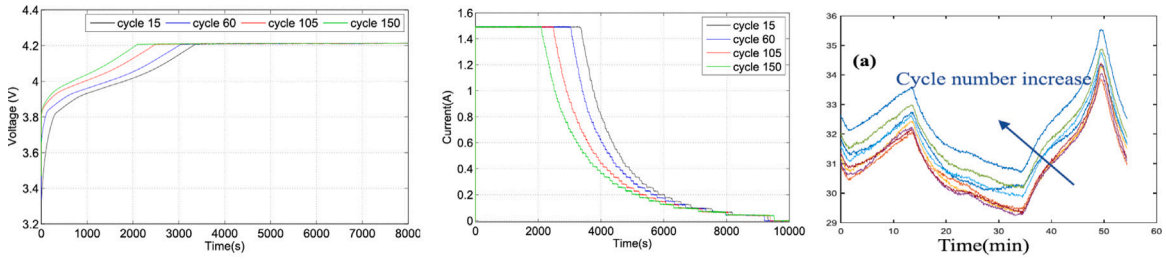


Fig. 4. Illustration of capacity variation of a battery.



(a) Voltage [18] (b) Current [18] (c) Temperature [19]

Fig. 5. Charging/discharging profiles of battery.

differences for different cycles. With the increase of the cycling number, the terminal voltage becomes higher at the same time instance during charging, and reaches the cut-off voltage earlier than it at the previous cycles. An early cut-off of CC charge gives rise to a low battery capacity. This indicates that the voltage variation is sensitive to the degradation of a battery. It can reflect the health state of a battery with effective information extracted.

2. Current. An example of a battery complying with CC-CV charge is taken as an example. The current variation is illustrated in Fig. 5(b). With the same charging profile, a battery reaches the threshold of CC charging faster. Capacity can be calculated by the integration of the close area below each current curve. With the cycle increasing, the area becomes smaller. Therefore, the current can be collected to reveal and predict the health condition of Li-ion battery.
3. Temperature. Temperature is another effective indicator to reflect the battery aging process. Fig. 5(c) displays a temperature profile of a cell over multiple cycles. Two peaks can be observed in Fig. 5(c); the left peak occurs in the charging process, while the right peak appears in the discharging process. The battery temperature presents an upward growth during the charging and discharging, respectively. With the number of cycle evolving, the peak of temperature tends to be larger and can be achieved within a shorter time duration. This mainly arises from the reduction of electrolyte conductivity and the Li-ion diffusivity [28].
4. Others. Apart from the aforementioned data, some other types of data are also applied in the PHM of Li-ion batteries, e.g., electrochemical impedance spectroscopy (EIS) [29] and incremental capacity analysis (ICA) [30]. Two open access datasets are also provided in the two literatures. Compared with the current, voltage and temperature data, EIS can obtain rich information about material properties, interfacial phenomena and electrochemical reactions and further reflect possible degradation of a battery [29]. In addition, the ICA is defines as differential capacity in proportion to differential voltage (dQ/dV). The extraction of ICA can reflect the variation of electrochemical property more straightforwardly. This data can also be integrated with other data driven methods to improve the PHM performance.

Various experiments have been conducted by research communities to collect data. These data are available to the public. Classic datasets include NASA dataset [31], CALCE dataset [32], Oxford dataset [33], MIT dataset [34], Panasonic 18 650PF dataset [35], Aging dataset [36]. The information of these public datasets are summarized briefly as follows and in Table 1.

1. NASA: NASA provides a collection of battery degradation datasets which were acquired under cycling of various temperatures. The most widely used datasets are B0005, B0006, B0007 and B0018; they cycled at room temperature via charge, discharge and impedance processes and complied to CC-CV charging profile. These data can be applied to research in RUL and SoH estimations.
2. CALCE: CALCE Battery Research Group provides abundant datasets for SoC estimations of Li-ion battery. The dataset were collected from cell INR 18 650-20R under various dynamic stress conditions, namely Dynamic stress test (DST), Federal Urban Driving Schedule (FUDS), US06 Highway Driving Schedule and Beijing Dynamic Stress Test (BJDST). They can be used to examine the effectiveness of SoC estimation methods. Another typical dataset was collected from cell CX2 under various charging/discharging currents, voltages or temperatures. These data can be used for RUL prediction.
3. Oxford: This experiment was conducted by Oxford University. It contains degrading data of 8 Kokam (SLPB533459H4) 740 mAh Li-ion pouch cells. These data were all measured at 40 ℃. They were exposed to a CC-CV charging profile and followed by a drive cycle discharging profile obtained from the urban Artemis profile. Measurements were conducted every 100 cycles.
4. MIT: The public data collection consists of 124 commercial lithium-ion batteries and divided into three batches. All cells in this dataset are charged with a one-step or two-step fast-charging policy. The target of the dataset is to improve the PHM performance of Li-ion battery of fast charging. The temperature measurements were performed by attaching a Type T thermocouple with thermal epoxy (OMEGATHERM 201) and Kapton tape to the exposed cell can after stripping a small section of the plastic insulation.
5. Panasonic: This cycling experiment was performed at the University of Wisconsin-Madison. A brand new 2.9Ah Panasonic 18 650PF cell was tested in an 8 cu.ft. thermal chamber with a 25 A, 18 V Digatron Firing Circuits Universal Battery Tester channel. A series of tests, including HPPC, drive cycles, and impedance spectroscopy, were performed at five different temperatures. The battery was charged after each test at a 1C rate to 4.2 V, 50 mA cut off, with battery temperature 12 ℃ or greater. These data can be used to test SoC algorithms.
6. Aging: This data was initially built for assessing machine learning method of recovering large-scale battery aging dataset. This experiment was accomplished with three types of battery, namely FST-3350, ME-2600 and SY-2150. These batteries all followed the CC-CV charging profiles and CC discharging profiles. The collected data are categorized into 3 groups. The first group is marked with A, which were collected by accelerated aging tests. The referenced capacities are available for each cycle. The second group is marked with W. It can be used for weakly supervised learning with partial referenced capacities provided. The third group is marked with T. They are used for model evaluation. More detailed information is provided in the supplemental information of Ref. [36].

Though these open access datasets facilitate the validation of PHM methods, it is still worth noting that difficulties exist in data collection. One problem is that sometimes it is time-consuming on data labeling by hand craft and partial data may be absent of label, so it is necessary to develop datasets that can be used to validate weakly supervised

Table 1
Summary of the public datasets and PHM measures used in different studies.

Dataset	Studies	PHM			
		SoH	SoC	RUL	EoL
NASA	Ding et al. [21], Jiao et al. [38], Khumprom et al. [39], Ren et al. [40], Tian et al. [41], Wang et al. [42], Ding et al. [43], Shen et al. [44], Zhang et al. [45], Song et al. [46], Wang et al. [47], Ma et al. [48], Naaz et al. [49], Tong et al. [50], Ungurean et al. [51], Cui et al. [52], Tan and Zhao [53]	√	√	√	√
CALCE	Jiao et al. [38], Tian et al. [41], Ma et al. [48], Tan and Zhao [53], Zhao et al. [54], Liu et al. [55], Li et al. [56], Liu et al. [57], Qian et al. [58], Yang et al. [59], Hannan et al. [60], Deng et al. [61], Shen et al. [62], Huang et al. [63], Bian et al. [64]	√	√	√	
Oxford	Tian et al. [41], Naaz et al. [49], Li et al. [65]	√	√		
MIT	Xu et al. [19], Li et al. [20], Deng et al. [61], Li et al. [65], Che et al. [66], Hong et al. [67]		√		√
Panasonic	Chemali et al. [24], Bian et al. [64], Vidal et al. [68], De et al. [69], Chemali et al. [70], Bhattacharjee et al. [71], Hannan et al. [72], Ma et al. [73]		√		
Aging	Tang et al. [36]	√		√	

learning method. Among the listed dataset, the Aging dataset can be used for the validation of weakly supervised learning methods. Another problem could be the small sample of data. This will cause an insufficient training of model and thus undermine the performance in PHM of Li-ion batteries. Developing reliable methods of data generation could be an effective means to solve the problem and some scholars has pioneered the related research, e.g., Zhang et al. [23] and Tang et al. [36].

The above mentioned datasets can be used for both supervised learning and unsupervised learning. There exist some other datasets that can only be used for unsupervised learning, e.g., dataset in Ref. [37]. These data can be acquired from the national monitoring and management centre for EVs (China). They can assist the validation of fault detection methods.

4. Deep learning methods

The battery degradation presents high nonlinearity due to the complex electrochemical mechanism [74]. Deep learning methods are applied to the PHM of Li-ion battery for the purpose of extracting high-representative and non-linear information from raw data by complex non-linear transformations. This section summarizes deep learning methods and their applications to the research field. Deep learning methods include autoencoder, deep neural network, deep belief network, convolutional neural network, recurrent neural network and generative adversarial network. These methods are adopted to handle different problems. This section introduces these methods and their applications to the research field.

4.1. Auto-encoder and its variants

Auto-encoder is a generative model and it refines desirable information from data by unsupervised learning [75]. Fig. 6 presents the basic structure of AE, which consists of an encoder and a decoder. The number of neurons in the input layer is identical to that in the output layer. A reconstruction error is supposed to be selected to measure the similarity between the input and the output. The encoder projects the raw input into a low-dimensional representation and obtains the results in the bottleneck layer. This manipulation can be referred to as Eq. (6).

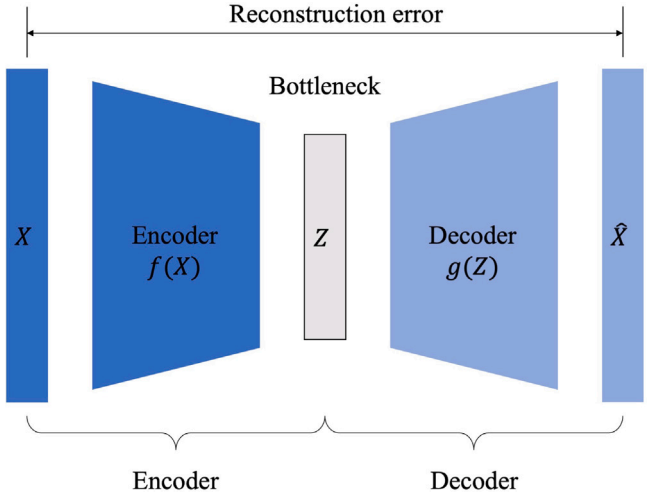


Fig. 6. The basic AE structure.

$$z = f(X) \tag{6}$$

where $f(\cdot)$ denotes an encoder function, which can be convolutional operations [76] or dense functions [21]. The input X can be mapped to the low-dimensional results z in the bottleneck layer by $f(\cdot)$. The decoder reconstructs signals from the lower-dimensional representations to the output layer. This can be expressed by

$$\hat{X} = g(z) \tag{7}$$

where $g(\cdot)$ refers to a decoder function. After decoding, $\hat{X}$ is calculated and obtains identical dimensions to X. Loss functions are selected to calculate the reconstruction error. Eq. (8) shows a regular selection of the loss function.

$$loss = L\left(X, \hat{X}\right) \tag{8}$$

where L is a loss function to measure the dissimilarity between X and $\hat{X}$. The optimal parameter can be obtained by iterations of training and minimization of the reconstruction error. Ding et al. [21] proposed a stacked auto-encoder (SAE) to estimate the capacity fading of Li-ion battery. Charge current data, discharge voltage data and charge time data under constant voltage was recorded and input into the SAE. Then the SAE performs multi-layer information fusion from the data layer and feature layers. The effectiveness and superiority of the proposed method was validated on the NASA dataset. Results demonstrated that the representativeness of information can be effectively enhanced from multiple levels. The SAE variant can be obtained by stacking multiple AEs. Deeper information can be refined from SAE than AE. Valantet al. [76] applied a 1 dimensional CNN autoencoder to SoC estimations of Li-ion battery. The Terminal battery voltage and current waves were collected as observable variables to predict the SoC. The proposed method was evaluated on five different simulations of driving profiles, and results validated its performance in anomaly detection. Convolutional operation is adopted in the CNN-AE. This allows share weights to be used in the encoder and decoder, thereby increasing the computing efficiency.

Various AE methods have been proposed upon the above basic version for PHM of Li-ion battery. They are organized as follows.

Sparse autoencoder is applied in PHM to explore the sparse information from monitoring data. It can be achieved by enforcing a sparsity

penalty $\Omega(z)$ on the bottleneck layer [77]. Then the loss function can be referred to as

$$loss = L\left(X, \hat{X}\right) + \Omega(z) \tag{9}$$

Liu et al. [78] proposed a technique for RUL forecast of Li-ion batteries based on the voltage and current data. This method used sparse autoencoder to reconstruct signals at a fixed internals. The result proved that the proposed method outperformed K nearest neighbor and support vector regression in RUL of Li-ion batteries. Sun et al. [79] proposed a novel machine learning structure involving a sparse autoencoder and backward propagation neural network. This method established a relationship between the battery terminal voltage at the late stage of charging and SoH. Experimental results showed that SOH estimation errors can be restrained within the range of ±5% by the proposed method, which significantly enhances the performance in PHM. Sparse autoencoder enforces the low-dimensional representation to be sparse by adding a $L1$ regularization into the loss function. This method attempted to explore more useful information from sparse representation.

Denoising autoencoder (DAE) is applied to improve the robustness of results [80]. In this method, certain forms of noise is utilized to corrupt the raw data X into $\tilde{X}$, then the low-dimensional representation can be calculated as

$$\tilde{z} = f\left(\tilde{X}\right) \tag{10}$$

where $\tilde{X}$ and $\tilde{z}$ indicate the corrupted signal and the low-dimensional representation calculated from the corrupted signal, respectively. The decoder can be expressed by

$$\hat{X} = g(\tilde{z}) \tag{11}$$

The loss function can be given by

$$loss = L\left(X, g\left(f\left(\tilde{X}\right)\right)\right) \tag{12}$$

Xu et al. [19] proposed a stacked denoising autoencoder (SDAE). Features were firstly extracted from discharge temperature waves and voltage waves. Then these features were fused by SDAE to predict the remaining useful life of a battery. This method can remove or alleviate the negative influence of redundant information generated in measurements and further enhance the robustness of the PHM result. The structure of SDAE includes a set of DAEs. DAE can remove the noise of raw data by corruption and then implement data reconstruction. This operation can enhance the robustness of the reconstructed results.

Variational autoencoder (VAE) is developed on the basic AE, but it encourages training a parametric encoder, which maps the parameter of data distribution into the bottleneck layer instead of a lower-dimensional feature of raw data. The calculation of VAE can be described as follows [75]. A sample z is first drawn from the code distribution $p_{model}(z)$, then $g(z)$ is obtained via a generator network. Finally, $\hat{x}$ is sampled from $p_{model}(x; g(z)) = p_{model}(x|z)$. The network can be trained by maximizing the lower bound of variation, and the loss function can be given by

$$loss = \mathbb{E}_{Z\sim q(z|x)} \log p_{model}(x|z) - D_{KL}\left(q(x|z) \parallel p_{model}(z)\right) \tag{13}$$

where D_{KL} is the Kullback–Leibler divergence.

Jiao et al. [38] proposed a conditional variational autoencoder particle filter (CVAE-PF). The CVAE was embedded into the PF as the prior distribution to alleviate particle degradations. CALCE dataset was employed to validate the proposed method. The result demonstrated the exceptional performance of the proposed method. VAE projects the parameters of data distribution in the latent space rather than a low dimensional feature of raw data in the AE.

To summarize, auto-encoder conducts information extraction in PHM of Li-ion batteries by unsupervised learning. Data labels are not required in the training. The AE consists of a set of variants, including sparse autoencoder, stack autoencoder, denoising autoencoder and variational autoencoder. The variants of autoencoder were designed to resolve different problems existing in PHM of Li-ion battery. Sparse AE can discover more sparse information from raw data; stack AEs are able to refine deeper information from raw signals by stacking a set of AE; denoising AE preserves more pure and robust information for PHM of Li-ion batteries by corrupting raw data; variational AE projects parameters of monitoring data distribution into the latent space to enhance the robustness of PHM results. The AE and its variants can effectively accomplish PHM of Li-ion with a high performance.

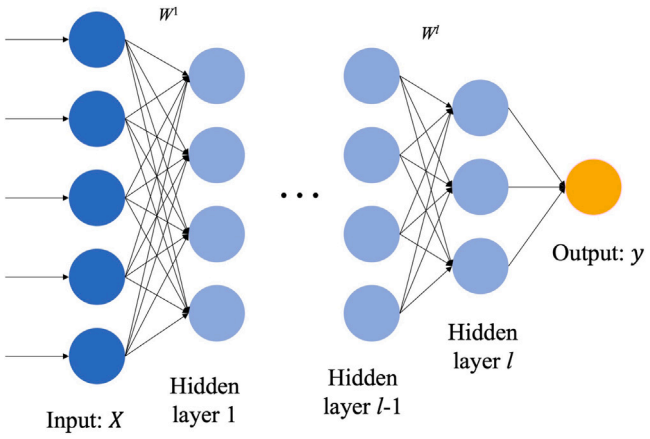


Fig. 7. An example of DNN.

4.2. Deep neural network

Deep neural network is an important method of deep learning. It is generally composed of a set of hidden layers instead of a single hidden layer in the artificial neural network [81]. This method can attain deep representations of raw inputs by complex nonlinear projections in parallel. One example of DNN structure is shown in Fig. 7.This network includes an input layer, a collection of hidden layers and an output layer. The output of the lth layer is calculated from $(l-1)$th layer and this can be given by

$$a^l = \sigma\left(W^l a^{l-1} + b^l\right) \tag{14}$$

where W^l and b^l represent weight matrices and bias vectors of th lth layer, respectively; they map the data of the $(l-1)$th layer to the lth layer. a^l is a node in the lth hidden layer. σ is an activation to operate nonlinear transformation. Commonly-used activation function are referred to [82]. This network can be optimized by back-propagation algorithm [83]. The number of hidden layer can be designed in terms of the performance in different applications.

The effectiveness of DNN on PHM of Li-ion battery has been proved in different research. Khumprom et al. [39] used DNN to perform the RUL and SoH of Li-ion batteries. This method was validated on database of NASA Ames Prognostics Center. Vidal et al. [68] designed a novel estimator for the SoC based on a deep feedforward neural network. This proposed method can effectively remove the added errors and further obtained a robuster health indicator for SoC estimation. Nguyen et al. [84] proposed an effective DNN method to predict the SoC of the single-cell battery. DNN was applied to evaluate the charge and discharge capacities, from which SoC can be derived. DNN is effective to perform different tasks of PHM. To further enhance the performance of DNN, De et al. [69] presented an empirical study of SoC based on DNN. In the DNN, the stochastic optimization was adopted in training stage. This method was then validated on the ten driving cycles of Panasonic dataset. The results proved its excellent performance in SoC estimations. To comprehend more useful information, Chemali et al. [70] proposed a DNN with multiple sources of data as the input.

As voltage, current and temperature data are sensitive to the variation of health condition of Li-ion batteries, they were adopted as the input of the DNN. This method was proved that it can accomplish SoC prediction of Li-ion batteries effectively.

However, the combination of DNN with other deep learning method can contribute to a better performance of PHM. Ren et al. [40] proposed a method integrating auto-encoder with DNN to operate RUL of Li-ion battery. Liu et al. [78] applied DNN to implement RUL prediction. It was combined with sparse AE to refine sparse information. Voltage and current data of three datasets were used to validate the proposed method. Tian et al. [41] proposed a 1D-CNN-based DNN to estimate the entire charging curve. The proposed method allows flexible dimensions of inputs measured from daily charging. Critical states or even incremental capacity curves of Li-ion batteries can be accurately derived from the approach. Duan et al. [85] proposed a CNN-based DNN to predict the fully-discharged impedance spectra using inputs of incomplete constant-current charging curves. In these studies, data were first pre-processed by other networks, e.g., CNN and AE, then input into DNN to implement the tasks of PHM. These data from other networks can signify more useful and compact features. With these data as input, DNN could attain more confident results.

To summarize, in the DNN-based PHM of Li-ion batteries, a single variable or combinations of voltage, current and temperature can be used in the tasks of PHM. DNNs can adopt these data directly for PHM of Li-ion batteries or employs handled data from other networks to refine effective information. DNN is suitable to handle one-dimensional monitoring data of Li-ion battery. Information can be refined by a collection of non-linear transformations in each layer of DNN. The representativeness of extracted features from monitoring data of Li-ion battery increases over layers with information of data fully captured in each layer. Using high representative features allow deep information to be reflected and thus improves the performance of PHM of Li-ion batteries. However, with the layer going deeper, the number of parameters grow explosively, which causes large computation burdens for PHM of Li-ion batteries.

4.3. Deep belief network

The DBN is proposed by Hinton in 2009 [86]. It is composed of a stack of restricted Boltzmann machine (RBM) and each RBM consists of a visible layer and a hidden layer. The output of the prior RBM is the input of the following one. The structure of DBN is demonstrated in Fig. 8. $V = \left(v_1, v_2, \ldots, v_{m_v}\right)$ and $H = \left(h_1, h_2, \ldots, h_{m_h}\right)$ are units in the visible and hidden layers respectively. W are weight matrix connecting hidden layers and visible layers. $a = \left(a_1, a_2, \ldots, a_{m_v}\right)$ and $b = \left(b_1, b_2, \ldots, b_{m_h}\right)$ are biases of visible layer and hidden layers. The energy function of RBM can be denoted as

$$E(v,h) = -\sum_{i=1}^{m_v} a_i v_i - \sum_{j=1}^{m_h} b_j h_j - \sum_{i=1}^{m_v}\sum_{j=1}^{m_h} h_j w_{i,j} v_i \tag{15}$$

The joint probability of visible unit and hidden unit is

$$p(v,h) = \frac{\sum_h e^{-E(v,h)}}{Z} \tag{16}$$

where $Z = \sum_{v,h} e^{-E(v,h)}$ is a normalization function. The conditional probability between hidden units and visible units can be denoted as

$$p(v = 1|h) = \sigma\left(b_j + \sum_j w_{i,j} h_j\right) \tag{17}$$

$$p(h = 1|v) = \sigma\left(a_i + \sum_i w_{i,j} v_i\right) \tag{18}$$

where σ denotes an activation function. Parameters of DBN can be updated by gradient descent [86].

Wang et al. [42] proposed a DBN-based battery aging assessing method. Several statistical features were extracted from discharging voltage curves, then DBN was used to fused features in depth and reduced the feature dimension. The DBN implements the dimension reduction of features and fuse the feature in depth. In addition, Zhao et al. [54] employed DBN to extract features from raw signals. Relevance vector machine (RVM) was used to perform the RUL prediction based on the battery capacity. The proposed method was validated on the CALCE battery datasets. Li et al. [56] utilized a DBN for Li-ion battery RUL prediction. The proposed method is trained with historical battery capacity data. The DBN can track capacity degradation and predict the RUL effectively. DBN were used to extract features self-adaptively from raw signals in these research. Liu et al. [55] proposed a method for hybrid state of charge estimation for lithium-ion battery under dynamic operating conditions. The electric current, terminal voltage and temperature of battery are used as the input of the proposed model. The DBN explored the relationship between the measured variables and SoC by non-linear modeling. Multi-source data can also applied in DBN modeling to implement PHM of Li-ion battery. Niu et al. [87] proposed method that integrating the DBN with particle filter to estimate the RUL of a Li-ion battery. The framework combines the DBN method with state space modeling, which can further enhance the PHM performance of Li-ion battery.

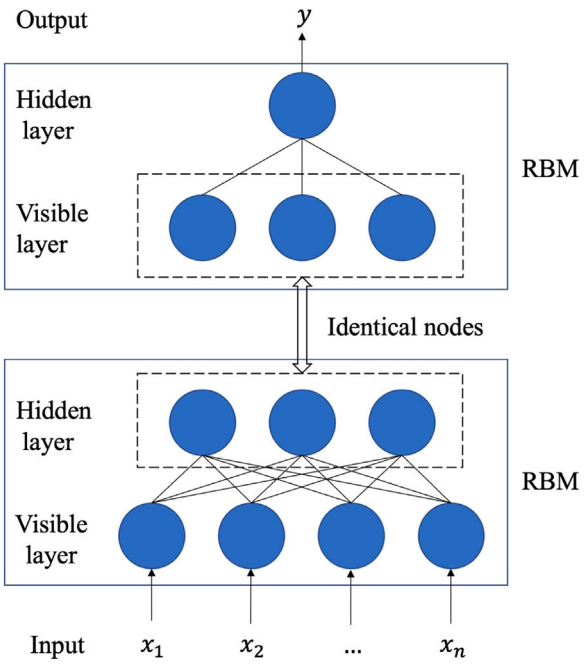


Fig. 8. The structure of DBN.

DBN contains the un-directional graph model, namely RBM, which is a big difference from other networks on structure. This unique structure of DBN enables it to utilize the interactive information of neighboring layers in the PHM modeling of Li-ion battery. However, it also sacrifice more computational resources than other networks during training. This could pose a further obstacle in the application of deep learning methods to the online PHM of Li-ion battery.

4.4. Convolutional neural network

Fig. 9 illustrates a structure of CNN. It basically consists of convolutional layers, pooling layers and fully connected layers [88]. The convolutional layer operates by two steps, namely convolution and activation.

$$z_i^l = x_i^l * w^l + b^l \tag{19}$$

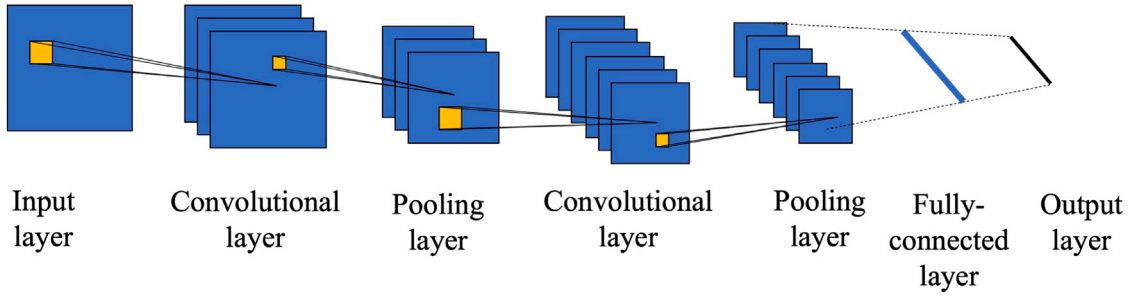


Fig. 9. An example of CNN.

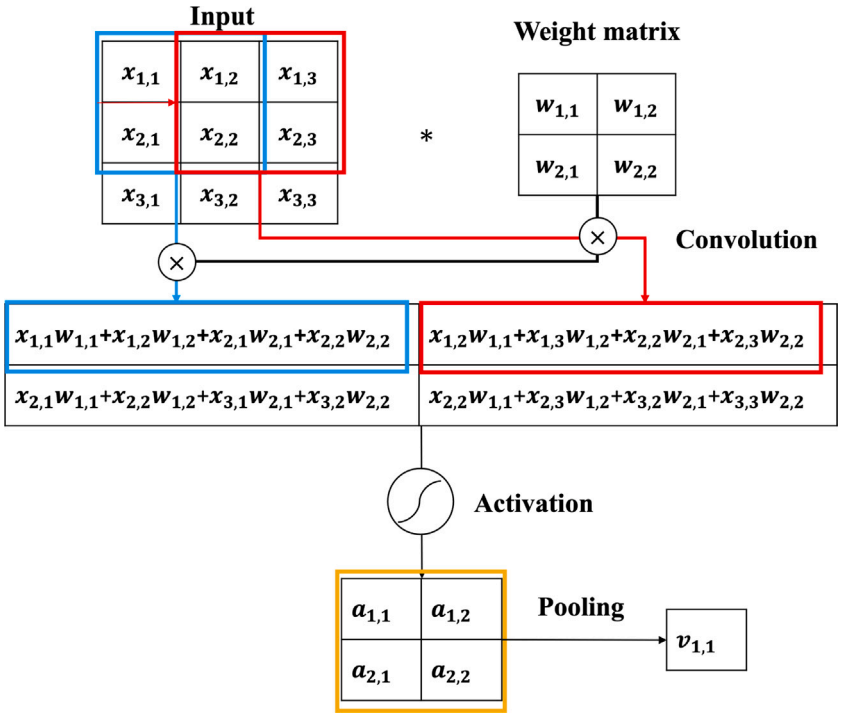


Fig. 10. A demonstration of CNN operation.

where w^l and b^l denote the weight and bias in the lth layer, respectively. Then the results were input into an activation function for non-linear transformations.

$$a_i^l = a\left(z_i^l\right) \tag{20}$$

where a is an activation function. Then pooling is performed to downsample the data.

$$v_{i,j}^l = pool\left(a_{m,n}^l\right), \vee (m,n) \in R_{ij} \tag{21}$$

where R_{ij} are locations around (i, j). Finally, a fully connected layer is added to the network to concatenate all the calculated elements for high-level reasonings. Fig. 10 gives a brief example to demonstrate the operation of CNN and more details of CNN can refer to [89].

Qian et al. [58] proposed a 1D-CNN to carry out SoC of Li-ion battery. Effective information was calculated from charging voltage curve, differential charging voltage curve and charging current curve of a single charge cycle by one-dimensional CNN. Shen et al. [90] proposed an online estimation method of Li-ion battery capacity based on randomly selected segmentations of charging curves, including capacity curves, voltage curves and current curves from the identical charging cycle. SoH was predicted on the basis of the predicted capacity. Shen et al. [62] used a deep CNN for online SoH of Li-ion battery pack. It adopted voltage, current and charge capacity as the input and the CNN were composed of five convolutional layers and three fully-connected layers. Li et al. [65] proposed a method that only needs partial charging segmentations of voltage, current and temperature signals as input data. Raw data was transformed into images and input into CNN for capacity estimation. The proposed method can implement fast capacity estimations of battery with high efficiency. Hong et al. [67] proposed a method based on dilated CNN and 1D-CNN. This method can accomplish swift prediction of RUL with 25 times faster than conventional methods. In addition to optimizing the network from structure, Hannan et al. [72] proposed a learning rate optimization strategy for CNN and enhanced its performance of SoC of Li-ion batteries. The advantage of CNN is that it can not only handle one-dimensional data, but also handle two-dimensional data of PHM. This method could preserve more spatial–temporal invariant information of data.

In addition, CNN can integrate with other methods for improve the performance in the PHM of Li-ion battery. For instance, Yang et al. [59] proposed a hybrid network which combined CNN with Bi-LSTM. In this method, CNN was used to extract features as the input of Bi-LSTM, while Zhao et al. [91] proposed a RNN-CNN method to accomplish the SoC estimation of batteries. Features were first calculated from voltage, current and temperature data by RNN to encompass time dependency information. Then these feature vectors were input into CNN to further extract abstract features and to determine the SoC result. In this method, features from RNN was regarded as the input of

CNN. CNN can also handle data along with signal processing method. Ding et al. [43] integrated the wavelet package decomposition (WPD) and a two-dimensional CNN to determine the state of battery. In this approach, charging and discharging currents were decomposed into a collection of sub-signals by WPD to highlight the nonlinearity information of battery degradation, then features were learnt from CNN by unsupervised learning. These features were applied to assess the RUL of a battery.

CNN can also be applied with transfer learning to contribute to the training on small sample of data and improve the generalization ability. Shen et al. [44] proposed a deep CNN with ensemble learning and transfer learning to estimate the capacity of batteries and further assist the SoH prediction. This network ensembled the current, voltage and charge capacity information of partial charging cycles, and CNN was trained by source domain data and applied to the target domain data. This method can effectively reduce the effort on data collection, and ensembling multi-source information can improve the accuracy of SoH result. Li et al. [20] proposed a compact CNN with parameters pruned and transfer learning incorporated. The optimized CNN was trained on a large battery dataset including voltage, current and cumulative charge capacity, and then it was transferred to a small dataset of target batteries for capacity estimation. This method significantly reduced the computational complexity of algorithm and enhanced the performance of CNN in PHM. Bhattacharjee et al. [71] proposed a one-dimensional CNN for SoC estimations of battery. This method combined the transfer learning mechanism to enhance the generalization ability of the proposed method.

To summarize, CNN performs feature extraction from PHM data of Li-ion battery by convolutional and pooling operations. This method can preserve more spatial–temporal information of raw data. In convolution layer, shared weight matrices are used, which can enhance the computational efficiency. The function of pooling is downsampling. CNN is competent to handle one-dimensional or two-dimensional data. By applying shared weights, the computational burden can be decreased considerably. However, it inevitably causes the leakage of useful information of PHM. Aiming to enhance the performance of PHM of Li-ion battery, CNN can be further optimized by integrating with other deep learning methods or signal processing methods. Transfer learning can also be incorporated in the CNN-based methods to facilitate PHM on small sample of monitoring data.

4.5. Recurrent neural network and its variants

RNN is a classic network that can handle sequential data with variable sizes of input data [92]. It can refine time dependency information from historical data. Fig. 11 presents the basic structure of a RNN. A RNN can be denoted by the right term and it is equivalent to the unfolded part in the left part of the figure. The RNN calculates feature by Eq. (22). where $x = [x_1, x_2, \ldots, x_N]$ represents the RNN input with sequence length of N. W is the weight matrix and b denotes the bias. $\mathcal{H}$ means the activation function. Parameters of RNN can also be optimized by gradient descent. Zhao et al. [91] proposed a RNN-CNN method to accomplish SoC of battery. Features were calculated from RNN to preserve more sequential information from battery signals. Whereas, gradient vanishing problem may happen in the training process for the PHM of Li-ion battery.

$$\begin{aligned} h_t &= \mathcal{H}\left(W_{xh}x_t + W_{hh}h_{t-1} + b_h\right) \\ y_t &= W_{hy}h_t + b_y \end{aligned} \tag{22}$$

The LSTM is a variant of RNN [93]. One LSTM cell is shown in Fig. 12a. The LSTM is put forward to mitigate the gradient vanishing problem of conventional RNN [94]. It includes an input gate, an output gate and a forget gate. The structure is demonstrated in Fig. 12a. Eq. (23) shows the manipulation of LSTM on information extraction.

$$\begin{aligned} \mathrm{i}_t &= \sigma\left(W_{xi}x_t + W_{hi}x_{t-1} + W_{ci}x_{t-1} + b_i\right) \\ \mathrm{f}_t &= \sigma\left(W_{xf}x_t + W_{hf}x_{t-1} + W_{cf}x_{t-1} + b_f\right) \\ \mathrm{c}_t &= \mathrm{f}_t c_{t-1} + \mathrm{i}_t \tanh\left(W_{xc}x_t + W_{hc}x_{t-1} + b_c\right) \\ \mathrm{o}_t &= \sigma\left(W_{xo}x_t + W_{ho}h_{t-1} + W_{co}c_t + b_o\right) \\ h_t &= \mathrm{o}_t \tanh\left(c_t\right) \end{aligned} \tag{23}$$

where c_t is the updated output of cell; i_t, f_t and o_t denote the input gate, forget gate and output gate, respectively; W_{xi} and W_{hi} mean the weight matrix of input–input gate and the weight matrix of hidden-input gate and likewise of other weight matrices; b_i denotes the bias vector of input gate and likewise of other bias vectors.

Chemali et al. [24] used the LSTM to estimate the SoC of a battery. The LSTM mapped the voltage, current and temperature of a battery to a SoC value. Ma et al. [73] applied a LSTM to SoC of Li-ion batteries and it was validated under various working conditions. Zhang et al. [45] applied the LSTM to RUL prediction and SoH prediction. It can implement multi-step-ahead prediction based on the time-series input of capacity with flexible dimensions. Compared with other deep learning method, including DNN and RNN, this paper proved the superiority of LSTM. However, the traditional LSTM used a fixed learning rate in the optimization. To further enhance the performance, a dynamic learning rate was adopted in the PHM of Li-ion battery. Wang et al. [47] proposed a dynamic LSTM to conduct online RUL prediction of Li-ion battery. Adaptive moment estimation and $L2$ regularization was used to optimize the parameter of LSTM dynamically. The dynamic LSTM employed the measured discharge voltages instead of capacity to construct an indirect health index for PHM of battery. Apart from varying the optimizer, dropout technique was adopted in Ref. [50]. Tong et al. proposed an adaptive dropout LSTM for early prediction of Li-ion battery RUL. The adaptive dropout was conducted by the Bayesian optimization to have the uncertainty considered. Additionally, LSTM can be combined with other methods e.g., statistical models and deep learning methods, to enhance the performance. Liu et al. [57] proposed an ensembled LSTM to predict the RUL of a battery on the basis of capacity data. This method took the uncertainty into account with Bayesian model averaging. Ren et al. [95] integrated LSTM with particle swarm optimization (PSO) to implement SoC of Li-ion batteries. PSO was used to calculate the parameters of LSTM and allowed the parameters to match the network topology better. Ma et al. [48] proposed a hybrid method based on CNN and LSTM. LSTM is used to analyze the RUL of a battery from a series of features calculated by CNN. Ensemble scheme or integration of methods enable more comprehensive information being extracted for Li-ion battery PHM. Li et al. [96] developed a deep LSTM capacity estimation model for SoH and EoL of Li-ion batteries under real-world working conditions. LSTM can also be introduced into transfer learning to resolve small sample of data. Tan and Zhao [53] developed a novel LSTM which was combined with fully connected layers. This model was regarded as the base model in transfer learning to perform SoH of Li-ion batteries. Typically, the state of a battery in the previous time step affects that of the following steps in PHM. Time dependency information can be considered in the RNN method. However, conventional RNN tends to cause gradient vanishing, which undermines the performance in the application of PHM of Li-ion battery. Therefore, LSTM is proposed as a variant of RNN. This method can alleviate the gradient vanishing problem in optimization and enhance the applicability to PHM of Li-ion batteries.

To make a further improvement, bi-directional LSTM (Bi-LSTM) was proposed. This method considers the time dependency information from bi-directions of signal. Bian et al. [64] introduced a stacked and bidirectional LSTM to SoC of Li-ion battery. This method fully explored the temporal information hidden in collected data. In contrast to unidirectional RNN-based methods, the proposed model can capture battery temporal information from both forward and backward directions. Yang et al. [59] proposed a hybrid network which combined CNN

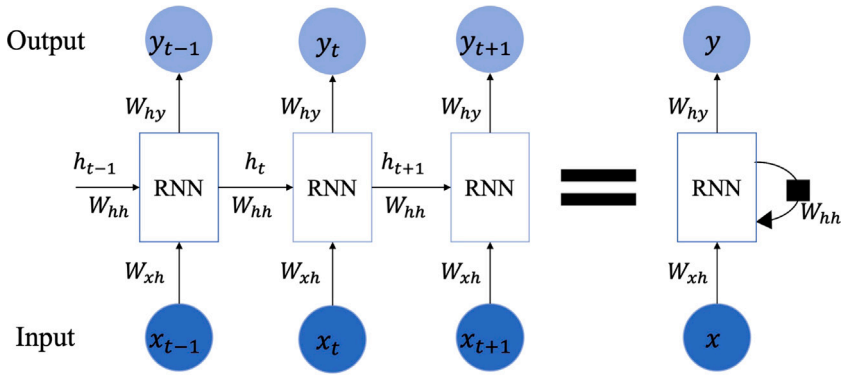
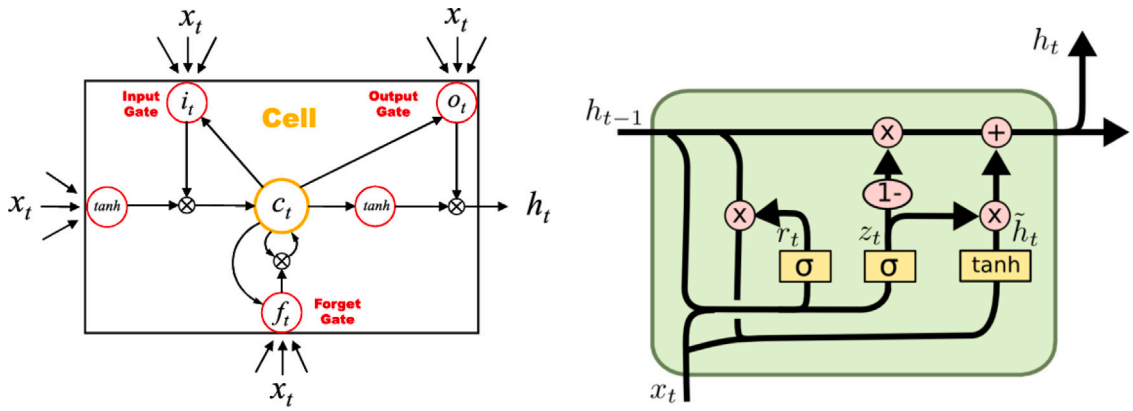


Fig. 11. RNN structure.



(a) A cell of LSTM [45] (b) The structure of GRU [46]

Fig. 12. Two variants of RNN.

and Bi-LSTM. CNN extracted features from integrated charging and discharging current. Bi-LSTM calculated bi-directional time dependency information from raw data, which enhanced the precision of capacity prediction for RUL. Zhang et al. [23] proposed a Bi-LSTM-based algorithm for battery SoC. Images were generated from historical charging or discharging data of Li-ion battery and they were used to train Bi-LSTM for battery state predictions. Bi-LSTM frames the PHM problem from bi-direction of time-series data rather than from single direction in LSTM. This encourages hidden time dependency information of raw data to be explored from bi-directions. Whereas, LSTM extracts useful information by a complex mechanism of calculation, which could attribute to a high computing cost.

Aiming to solve the above-mentioned problem of LSTM, the RNN with the GRU was used in the PHM of Li-ion battery. This method simplifies the calculation mechanism of LSTM, and increase the computation efficiency. It consists of two gates, namely a reset gate r_t and a update gate z_t [97]. x_t represent the input of GRU and h_{t-1} indicates the output of the previous unit. Reset gates are used to remove irrelevant information of h_{t-1} and update gates are used to determine the information absorbed in the current unit. Reset gate, update gate and output are given by the following three equations and the structure of GRU is exhibited in Fig. 12b.

Reset gate:

$$r_t = \sigma\left(W_t \cdot \left[h_{t-1}, x_t\right]\right) \tag{24}$$

Update gate:

$$z_t = \sigma\left(W_z \cdot \left[h_{t-1}, x_t\right]\right) \tag{25}$$

Output:

$$\tilde{h}_t = \tanh\left(W_{\tilde{h}} \cdot \left[r_t * h_{t-1}, x_t\right]\right) \tag{26}$$

Song et al. [46] proposed a method based on GRU to perform RUL. This method used historical capacity data to train GRU models, and the well-trained model was then applied to predict RUL. Ungurean et al. [51] applied GRU to SoH of battery. Hannan et al. [60] implemented SoC estimations under variable ambient temperatures. GRU adopted voltage, current and temperature as inputs, which incorporates more comprehensive information of PHM. This method was evaluated on three datasets and the experimental analysis demonstrated the effectiveness of the network. Huang et al. [63] proposed a convolution GRU to estimate the SoC of a battery. Cui et al. [52] developed a deep learning method which introduced attention mechanism to GRU for SOH estimation of Li-ion batteries. GRU includes a simpler structure than LSTM. It can find reliable long-term relationships hidden in the time series monitoring data of Li-ion battery with lower computational cost. This can significantly increase the computation efficiency of PHM of Li-ion batteries.

To summarize, RNN and their variants are suitable to handle time series signals. Useful time-dependency information can be extracted from PHM data of Li-ion batteries. Due to the gradient vanishing problem, LSTM is proposed by adding gates to the original RNN. This exerts a better control on the information extraction. As the complicated structure of LSTM causes a heavy burden of computation, GRU using a simplified structure was applied to the PHM modeling. Though this method enhances the computing efficiency, it is at the expense of information loss.

4.6. Generative adversarial network

The generative adversarial network was proposed by Goodfellow in 2014 [75]. Fig. 13 shows the structure of GAN. This network is

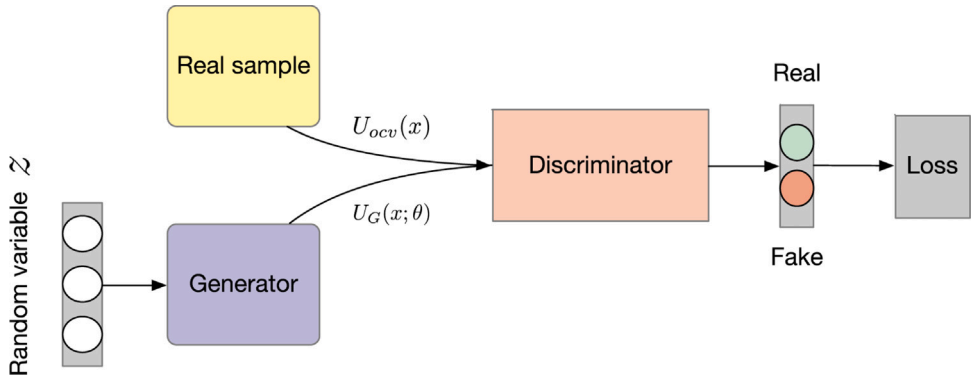


Fig. 13. The structure of GAN [23].

composed of a discriminator network D and a generator network G. A generator is constructed to generate data, while a discriminator is used to discriminate the real data and the fake data. When the discriminator makes a mistake by a probability of 50%, it can be considered that the generated data achieves a high similarity to the real samples, and it is difficult for the discriminator to distinguish the fake data from the real data. In this figure, $U_{ocv}(x)$ indicates the distribution of measured data; $U_G(x;\theta)$ represents a distribution where new data is generated with the random input vector. The generator can be optimized by Eq. (27).

$$G^* = \arg\min_G \max_D V(G, D) \tag{27}$$

The competing mechanism can be accomplished by Eq. (28).

$$\min_G \max_D V(G, D) = E_{x\sim U_{ocv}(x)}\left[\log D(X)\right] + E_{x\sim U_z(z)}\left[\log(1 - D(G(z)))\right] \tag{28}$$

where U_z represents the prior distribution of generated data.

Naaz et al. [49] introduced a GAN-based approach for data augmentation in PHM of Li-ion batteries. GAN expanded sparse datasets for network training. With augmented dataset, the generalization ability of networks was then improved in the SOC and SOH predictions. Zhang et al. [23] proposed an improved GAN algorithm for battery SoC value. This method can generate images from historical charging/discharging data of voltage and current by GAN. Then the generated data was used to predict the SoC value of a battery. Kim et al. [98] proposed a fully unsupervised methodology for reliable extractions of latent variables that were used to represent the characteristics of lithium-ion batteries by GAN. Then the relationship between extracted latent variables and capacity degradation progress were investigated by Gaussian process regression, then the SoC was calculated based on estimated capacities.

To summarize, GAN, as a generative model, can be adopted to generate data that is difficult to be distinguished from the real data. With the PHM monitoring data augmented by an adversarial mechanism, PHM methods can be trained to reach a better performance. The generalization ability and robustness of PHM methods can be improved significantly, especially only when limited amount of data for PHM is available. With the advance of technology and the continuous improvement of Li-ion battery quality, the amount of run-to-failure data could considerably drops. The GAN method shows great potentials in the future PHM of Li-ion battery. Thus it is essential to develop methods for data augmentations.

To make a summary of this section, Table 2 lists references that used different deep learning methods as well as the advantages and disadvantages of these methods in the PHM of Li-ion batteries. Fig. 14, it can be seen that few research pays attention to the PHM of Li-ion batteries based on small sample of data.

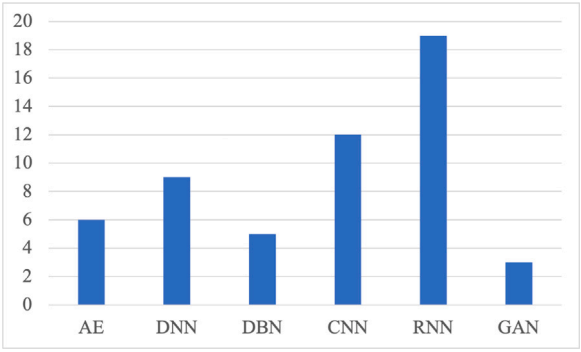


Fig. 14. The number of publications under each deep learning methods.

5. Method evaluation

Evaluation metrics are used to quantify the performance of proposed methods. Six typical metrics are listed here, including absolute error (AEr), mean absolute percentage error (MAPE), mean square error (MSE), root mean square error (RMSE), mean absolute error (MAE) and max absolute error (MaxAE).

1. AEr. This metric measures the difference of a predicted value and its true value. It is suitable to analyze the error of individual sample. AEr can be expressed by

$$AEr = \left|\hat{Y}(i) - Y(i)\right| \tag{29}$$

where $\hat{Y}(i)$ and $Y(i)$ represent the prediction and the ground truth, respectively.

2. MAPE. This metric evaluates the mean percentage of error over the true value. It can reflect the average deviation degree from the ground truth. This can be used for regression analysis, e.g., SoC. A larger value means a less reliable result. This metric is defined as

$$MAPE = \frac{1}{N_s}\sum_{i=1}^{N_s}\frac{\left|Y(i) - \hat{Y}(i)\right|}{|Y(i)|} \times 100\% \tag{30}$$

3. MSE. MSE can measure the average square errors of the predicted value and its true value. As this metric tends to give square weights to errors, it is more sensitive to large errors. The MSE function is defined as

$$MSE = \frac{1}{N_s}\sum_{i=1}^{N_s}\left\|Y(i) - \hat{Y}(i)\right\|_2^2 \tag{31}$$

4. RMSE. RMSE is the square root of the MSE. It assigns lower weights to large values than MSE. This function is defined as

Table 2
Summary of PHM on different deep learning methods.

Method	Studies	Advantages	Disadvantages
AE	Xu et al. [19], Ding et al. [21], Jiao et al. [38], Valant et al. [76], Liu et al. [78], Sun et al. [79]	-AE is a generative model that can be used to generate new and robust data based on raw data with various targets for PHM of Li-ion batteries. -Data labels are not required in the training. -This method can implement data dimension reduction by the encoder part.	In data dimension reduction, the PHM data to be compressed is supposed to follow the same distribution of training data. Otherwise, the compressed data deviates from the desirable result greatly.
DNN	Khumprom et al. [39], Ren et al. [40], Tian et al. [41], Vidal et al. [68], De et al. [69], Chemali et al. [70], Liu et al. [78], Nguyen et al. [84], Duan et al. [85]	Layers are fully connected by parameters. It can preserve more comprehensive information for PHM of Li-ion battery.	The number of parameters tends to be increase explosively, and thus causes a heavy computational burden in PHM of Li-ion batteries. This could not be suitable to online PHM of Li-ion batteries.
DBN	Wang et al. [42], Zhao et al. [54], Liu et al. [55], Li et al. [56], Niu et al.[87]	DBN considers the interactive information between layers during modeling for PHM.	DBN affords a high computation expense due to the RBM component. This could not be suitable to online PHM of Li-ion batteries.
CNN	Li et al. [20], Ding et al. [43], Shen et al. [44], Qian et al. [58], Yang et al. [59], Shen et al. [62], Li et al. [65], Hong et al. [67], Bhattacharjee et al. [71], Hannan et al. [72], Shen et al. [90], Zhao et al. [91]	CNN can efficiently process two-dimensional PHM data of Li-ion battery and can preserve spatial–temporal information. By applying shared weight, the computational burden can be decreased considerably.	Pooling layers is designed for down sampling. Though it enhances the computation efficiency, it is likely that useful information is lost.
RNN	Zhang et al. [23], Chemali et al. [24], Zhang et al. [45], Song et al. [46], Wang et al. [47], Ma et al. [48], Tong et al. [50], Ungurean et al. [51], Cui et al. [52], Tan and Zhao [53], Liu et al. [57], Yang et al. [59], Hannan et al. [60], Huang et al. [63], Bian et al. [64], Ma et al. [73], Zhao et al. [91], Ren et al. [95], Li et al. [96]	RNN and its variants are suitable to handle time-series problems. Time dependency information can be extracted from raw monitoring data to enhance the PHM performance.	Gradient vanishing is a problem existing in the training of RNN. This will decrease the training efficiency. –Though LSTM overcomes the above problem, it enhances the computation burden. –GRU increases the computation efficiency, whereas it could present incompetence when handling high diversity of Li-ion battery PHM due to its simpler structure.
GAN	Zhang et al. [23], Naaz et al. [49], Kim et al. [98]	GAN can generate new data that is more difficult to be distinguished from real PHM data following different distributions.	GAN is difficult to be trained. It holds the risk that training fails to reach Nash equilibrium, which affects the generation of new data.

$$RMSE = \sqrt{\frac{1}{N_s}\sum_{i=1}^{N_s}\left\|Y(i) - \hat{Y}(i)\right\|_2^2} \tag{32}$$

5. MAE. MAE measures the average difference of the predicted value and the corresponding true value. It is given by

$$MAE = \frac{1}{N_s}\sum_{i=1}^{N_s}\left\|Y(i) - \hat{Y}(i)\right\| \tag{33}$$

   Compared with MSE, MAE shows better performance on the evaluation of small variation in the PHM of Li-ion battery.
6. MaxAE. MaxAE is the maximum difference among the predicted value and the corresponding true value. To an extent, it can reflect the robustness of a method in the application of Li-ion battery. It can be denoted by

$$MaxAE = \max_i\left\{\left\|Y(i) - \hat{Y}(i)\right\|\right\} \tag{34}$$

The application of evaluation metrics in research are displayed in

Table 3, from which it can be seen that RMSE and MAE are the two most widely-used metrics. RMSE gives higher weight to larger errors, while MAE assign equal weights to all errors. Different metrics can reflect information included in PHM results from various aspects, so it is suggested that multiple metrics are applied in PHM of Li-ion batteries to give a comprehensive evaluation of proposed methods. To facilitate the comparison study of this field,

Table 3 provides the commonly-used metrics and their indications as well as the applications in the PHM of Li-ion batteries.

6. Conclusions and future works

6.1. Conclusions

Li-ion batteries are gaining more popularities across multiple fields. A safe and reliable operation of Li-ion battery becomes a crucial concern that cannot be overlooked in these applications. Although much attention has been drawn into the research field, PHM of Li-ion battery is still in the early stage of development. In order to gain more insights of this field, this paper provides a comprehensive summary of and a systematical view of the PHM of Li-ion battery based on deep learning. Deep learning-based PHM of Li-ion can be roughly divided into three steps, including data collection, deep learning based PHM and method evaluation. As Li-ion battery health state can be manifested on certain external measurements, these sensitive measurements can be collected for PHM of Li-ion batteries and they are introduced in the paper. Then these data are made a preprocessing or input into the deep networks directly to refine high-representative features and further to determine the health state of battery. In terms of the prediction and actual health state, the performance of these methods are evaluated on specific metrics. Deep learning methods contribute to the PHM development of Li-ion battery. They releases human labors from the design and control of specific feature extraction algorithms and presents the powerful ability of modeling for complex Li-ion battery systems.

6.2. Future works

As the PHM of Li-ion battery is in the early developing stage, many overwhelming challenges are still facing the field. Given the current developments, we provide the future prospects of PHM of Li-ion battery based on deep learning.

1. PHM of Li-ion batteries on small sample of data. With the rapid advance of technology, the quality of battery is achieving continuous improvements. A battery can reach the failure threshold

Table 3
Summary of methods evaluated by different metrics.

Metric	Studies	Indication
AEr	Khumprom et al. [39], Ding et al. [43], Zhang et al. [45], Song et al. [46], Wang et al. [47], Ma et al. [48], Ungurean et al. [51], Li et al. [56], Hong et al. [67], Liu et al. [78]	AEr measures the difference of a predicted value and its true value.
MAPE	Ding et al. [43], Zhao et al. [54], Li et al. [56], Hong et al. [67], Liu et al. [78], Sun et al. [79], Li et al. [96]	MAPE evaluates the mean percentage of error over the true value. It can reflect the average deviation degree from the ground truth. This can be used for regression analysis, e.g., SoC.
MSE	Ding et al. [21], Zhang et al. [23], Tong et al. [50], Hannan et al. [60], De et al. [69], Liu et al.[78], Sun et al. [79], Nguyen et al. [84], Duan et al. [85]	MSE can measure the average square errors of the predicted value and its true value. As this metric tends to give square weights to errors, it is more sensitive to large errors.
RMSE	Xu et al. [19], Li et al. [20], Chemali et al. [24], Jiao et al. [38], Khumprom et al. [39], Tian et al. [41], Ding et al. [43], Shen et al. [44], Zhang et al. [45], Song et al. [46], Wang et al. [47], Ma et al. [48], Tong et al. [50], Cui et al. [52], Tan and Zhao [53], Zhao et al. [54], Liu et al. [55], Li et al. [56], Qian et al. [58], Hannan et al. [60], Shen et al. [62], Huang et al. [63], Li et al. [65], Vidal et al. [68], Hannan et al. [72], Ma et al. [73], Liu et al. [78], Duan et al. [85], Ren et al. [95], Kim et al. [98]	RMSE is the square root of the MSE. It assigns lower weights to large values than MSE.
MAE	Xu et al. [19], Li et al. [20], Chemali et al. [24], Jiao et al. [38], Khumprom et al. [39], Ding et al. [43], Zhang et al. [45], Song et al. [46], Wang et al. [47], Tong et al. [50], Zhao et al. [54], Liu et al. [55], Li et al. [56], Liu et al. [57], Yang et al. [59], Hannan et al. [60], Huang et al. [63], Bian et al. [64], Li et al. [65], Vidal et al. [68], De et al. [69], Chemali et al. [70], Bhattacharjee et al. [71], Hannan et al. [72], Ma et al. [73], Liu et al. [78], Sun et al. [79], Zhao et al. [91], Ren et al. [95], Kim et al. [98]	–MAE measures the average difference of the predicted value and the corresponding true value. –Compared with MSE, MAE shows better performance on the evaluation of small variation in the PHM of Li-ion battery.
MaxAE	Chemali et al. [24], Shen et al. [44], Liu et al. [55], Bian et al. [64], Li et al. [65], Vidal et al. [68], Chemali et al. [70], Bhattacharjee et al. [71], Sun et al. [79], Ren et al. [95]	MaxAE is the maximum difference among the predicted value and the corresponding true value. To an extent, it can reflect the robustness of a method in the application of Li-ion battery.

within from hundreds of cycles to thousands of cycles [99]; this implies that the amount of data that can be available within the same time period is becoming smaller. Therefore, it is essential to develop effective approaches to establish model on small sample of data. Transfer learning and small size neural network could provide solutions for the problem existing in PHM of Li-ion battery. Some pioneering research, e.g., Ref. [20] and Ref. [100], have achieved remarkable performance in certain application contexts, and further research can be devoted to solve more related problems of different aspects.

2. PHM of Li-ion battery under actual operating conditions. Currently, most of the research are conducted on the experimental data. Though some public datasets were collected under dynamic operating conditions, e.g., MIT and CALCE, data collected from actual operating conditions presents higher complexities and nonlinearities. Exploring methods to resolve PHM of Li-ion battery under real conditions is an urgent problem. However, deep learning method holds great potentials to handle these problems. For example, transfer learning may be able to resolve this problem. PHM model can be established from these experimental data. Then these obtained knowledge are reused and transferred to the PHM of real applications, as these data holds the generic pattern.
3. Interpretability of deep learning method in the PHM of Li-ion battery. Deep learning is a blackbox in many applications. Exploring the underlying meaning of calculated results will help discover more useful information that can reflect the health state of a battery and further enhance the performance in the health assessment and prediction. From the view of filter, the weight matrices can be considered as a series of filters in deep learning, and it is likely that more abundant hidden information that can reflect the physical mechanism of degradation preserved in these filters.
4. PHM using partial segmentations of cycling data. In real applications, batteries are usually not fully discharged/charged before charging/discharging. Extracting reliable information from partial segmentations of collected data for PHM of Li-ion battery can provide more significance to real applications. Deep learning methods show powerful ability on feature extraction or completing missing information for partial signals, e.g., CNN can extract spatial–temporal information from raw data; GAN or other generative models can complete the missing part of data from partial signal before feature extraction.
5. Real PHM data generation. The volume of data is an important factor that influences the performance of deep learning models. However, the sophisticated operation of Li-ion batteries and the long duration of cycling experiments lead to the difficulty in collecting large amount of data for PHM model training. Therefore, it is crucial to develop effective and efficient approaches to generating data that approximate the real operating condition infinitely. This can hopefully save large amounts of experimental efforts and time.
6. PHM of Li-ion batteries with weakly supervised learning. In the step of data collection, it is not always practical to obtain desirable data and label pairs, and the subsequent problems may exist. Only partial data are assigned with labels; only course-grained labels can be offered for data; inaccurate labels are given to PHM data. These problems can inevitably obstacle the deep learning model construction [101]. With weakly supervised learning introduced to PHM of Li-ion batteries, these problems could be handled effectively.
7. Development of light-weighted models to the PHM of Li-ion batteries. Deep learning methods achieve high performance in PHM of Li-ion batteries. However, the existing methods tend to involve substantial parameters. This negatively affects the deployment of algorithm on mobile devices and prevents fast identifications of Li-ion battery health state. Developing light-weighted models could provide a promising solution to the problem. These models can enhance the computation efficiency by decreasing the number of parameters, but without sacrificing the model performance considerably. However, little attention has been paid to the related research in PHM of Li-ion batteries currently.

Declaration of competing interest

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

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