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Review article

A critical review of improved deep learning methods for the remaining useful life prediction of lithium-ion batteries

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ABSTRACT

As widely used for secondary energy storage, lithium-ion batteries have become the core component of the power supply system and accurate remaining useful life prediction is the key to ensure its reliability. Because of the complex working characteristics of lithium-ion batteries as well as the model parameter changing along with the aging process, the accuracy of the online remaining useful life prediction is difficult but urgent to be improved for the reliable power supply application. The deep learning algorithm improves the accuracy of the remaining useful life prediction, which also reduces the characteristic testing time requirement, providing the possibility to improve the power profitability of predictive energy management. This article analyzes, reviews, classifies, and compares different adaptive mathematical models on deep learning algorithms for the remaining useful life prediction. The features are identified for the modeling ability, according to which the adaptive prediction methods are classified. The specific criteria are defined to evaluate different modeling accuracy in the deep learning calculation procedure. The key features of effective life prediction are used to draw relevant conclusions and suggestions are provided, in which the high-accuracy deep convolutional neural network — extreme learning machine algorithm is chosen to be utilized for the stable remaining useful life prediction of lithium-ion batteries.

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Contents

1. Introduction

As energy and environmental problems become more and more serious and integrated hybrid energy storage increased autonomy significantly (Al-Ghussain et al., 2021a), lithium-ion batteries have become the first choice of power sources for high

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energy density, high specific energy, low pollution, and low self-consumption advantages. With a high discharge current rate and no memory effect, lithium-ion batteries have become a research hotspot. The remaining useful life (RUL) prediction has been the focus and difficulty in this field, in which aging is the major factor hindering the reliable multi-faceted renewable energy (RE) assessment framework (Al-Ghussain et al., 2021b). The performance degradation process includes calendar and cyclic aging procedures, which threatens the competitiveness with other energy systems. Through the prediction model establishment, the battery degradation degree can be predicted, obtaining the remaining useful life value effectively. It is also one of the key parameters in the charge–discharge control and power optimization management, which has an important impact on the battery life extension. Besides, the remaining useful life prediction improves the power supply performance, which is essential for the optimized battery management system design and the calibration protecting throughout the life. Therefore, the effective RUL prediction model reduces the system investment and improves the application profitability, which is useful for the energy management strategy optimization and battery life extension.

Combining the complexity, accuracy, and representative unevenness of the battery reaction process, various RUL prediction methods have been proposed for lithium-ion batteries. The electrochemical model provides an effective mathematical representation of the internal parameters, thereby improving the RUL prediction accuracy. Due to the complexity and computational complexity increase, the modeling process faces a challenging stage. The vehicle-mounted measurable variables are suitable for the realization adaptive to complex application conditions, which can be introduced into the battery modeling process. The empirical model uses the experimental testing methods, while the semi-empirical model adds physical and chemical support in the curve fitting data. Capturing the relationship between the state of health (SOH) and internal resistance is a typical semi-empirical model, according to which the RUL value can be predicted effectively and also benefits the state of charge (SOC), state of power (SOP), and state of energy (SOE) prediction. As extensive laboratory testing is necessary to develop accurate predictive models, the RUL prediction is achieved by conducting experimental tests adaptive to various working conditions along with the influencing factor analysis. High-performance batteries have long service life characteristics, so there is an increasing demand for predictive extraction with sufficient experimental data.

By evaluating different prediction methods related to deep learning in the references, the high-accuracy prediction method based on deep learning algorithms is considered to be the most suitable strategy compared with the traditional filtering and data-driven methods, so improved RUL prediction models based on deep learning are constructed for lithium-ion batteries. Different modeling methods are compared with key evaluation points and the main advantages of each model are highlighted by introducing specific evaluation criteria, thereby realizing the accurate RUL prediction. A detailed mathematical analysis of the deep learning algorithm is carried out for the RUL prediction, in which an effective evaluation criterion is built to evaluate different methods and strategies. Also, the changing process of the lifetime characteristics is analyzed, which provides a reference to the realization technology of the RUL prediction. The prediction effects of different deep learning algorithms are compared and analyzed with the evaluation criteria of RMSE (%), MaxE (%), speed, and accuracy, according to which the high-accuracy deep convolutional neural network — extreme learning machine algorithm is chosen for the further realization and verification process.

2. Various RUL prediction method analysis

By using the k-nearest neighbor regression and differential optimization strategies, the accurate RUL prediction is carried out for lithium-ion batteries (Zhou et al., 2020a), in which the amount of experimental data should be measured for all the internal-connected cells in the battery pack. Considering the health status monitoring, the robust RUL prediction can be realized by using the time convolutional network (Lin et al., 2020a) and the improved unscented Kalman filtering (UKF) (Wang et al., 2020a,b,c). The RUL prediction and effect evaluation theories are also analyzed for lithium-ion batteries with multiple uncertainties (Zhu et al., 2019), and the non-linear prediction (Zhao et al., 2019a; Zhang et al., 2019b) is conducted to estimate the RUL value considering the recovery phenomenon.

The RUL prediction of aircraft lithium-ion batteries (Liu et al., 2021) is conducted by F-distributed particle filtering (PF) (Zhang et al., 2019a,b,c,d,e) and kernel smoothing (Chen et al., 2020a,b). Multiple hidden variables are used in the prediction process to perform nonlinear drift fractional Brownian motion (Zhang et al., 2020a). The RUL prediction is performed by using the optimal time-series health index (Zheng et al., 2020), which can also be realized by using the adaptive UKF algorithm (Li et al., 2021a,b,c) and optimized support vector regression (SVR) algorithms (Xu et al., 2021a,b). This can be also achieved by using the improved PF algorithm (Xiong et al., 2020a,b) by combining the Wiener process (Shang et al., 2020) and unscented PF processing. The RUL prediction is investigated by using the fractional Brownian motion algorithm (Tian et al., 2020). Also, the cognition and prediction of degradation dynamics are taken into consideration by comprehensive treatment to reduce distance anxiety (Yin et al., 2019). The user-specific driving patterns (UDP) (Zhang et al., 2019a) and capacity recovery effects (CRE) (Ma et al., 2019b) are combined to predict the degradation dynamics, even if part of the experimental data is available for a single battery cell.

Considering the dynamic characteristics, the RUL prediction is realized by fusing the failure time data and the field degradation data onto random effects (Yin et al., 2019) together with the improved cuckoo searching PF method (Qiu et al., 2020a). Besides, an adaptive data-driven feature-enhancement optimization method is proposed to realize the accurate RUL prediction of lithium-ion batteries (Yang et al., 2019). The hybrid prediction method can be also used to optimize the cycle life test of different formulations (Ma et al., 2020a). Multi-parameter optimization is conducted to realize the effective RUL prediction (Zhou et al., 2020a), which uses the electrochemical model as the battery framework (Farmann and Sauer, 2018). Different modeling techniques are used to evaluate the battery calendar aging prediction effects (Liu et al., 2020a), in which the RUL value can be predicted through the time series modeling treatment. Using the mutated long-short term memory (LSTM) algorithm and the neural network (NN) model (Liu et al., 2020a), the RUL prediction can be realized with high accuracy combined with multiple linear regression and recurrent neural network (RNN) methods (Zhao et al., 2019a,b; Zhang et al., 2018a), which thereby reflects the degradation information effectively.

A Takagi–Sugeno observer is designed for the RUL prediction of lithium-ion battery systems adaptive to the fault conditions (Zhao et al., 2019b). The battery life prediction can be also implemented through the Gaussian process regression and indirect health indicators (Pan et al., 2020; Hu et al., 2020). The rank correlation coefficient prediction method is also proposed to obtain the RUL value of lithium-ion batteries (Sun et al., 2021). The RUL prediction model is established by considering the resting time characteristic (Cui et al., 2020), and an improved odorless particle filtration method is proposed to predict the capacity

decline (Jiang et al., 2019). The RUL prediction is also achieved by using the second-order central PF algorithm (Li et al., 2018). Also, a gray modeling method is introduced to construct a new prediction framework (Tian et al., 2019), which is improved by using a novel indicator combined with score processing. A new fusion selection method is introduced to estimate the RUL value (Tang et al., 2019a), in which the Gaussian process regression is combined with the weighted average operator.

The RUL factor is also used to describe the autocorrelation aging mechanism, including capacity loss and Box–Cox transformation. Based on the fractional Brownian motion (Liu et al., 2017a), the long-term dependence is predicted in the multi-mode degradation process (Zhang et al., 2019a). Besides, the degradation modeling and life prediction are also investigated for lithium-ion batteries adaptive to dynamic working environments (Tang et al., 2019a). Data-driven prediction is conducted to achieve the accurate cycle life prediction before the battery capacity is reduced (Severson et al., 2019), which can be also realized by using the Gauss–Helmet-PF algorithm. The prediction effect of the improved Gaussian processing regression model is analyzed for the cycle capacity of lithium-ion batteries (Liu et al., 2019). Besides, it can be also achieved by using health indicators (Cong et al., 2020) and Gaussian process regression modeling (Wang and Mamo, 2018) methods.

The cycle life prediction is introduced into the hybrid energy storage systems (Liu et al., 2019a), which can be also achieved by the hybrid modeling that combines the LSTM and Elman NN algorithms (Xiong et al., 2018). Then, a robust hybrid filtering method is proposed to realize the accurate RUL prediction (Jiang et al., 2018) by taking ENN as an indirect prediction strategy for the vibration stress of lithium-ion batteries (Xiong et al., 2020a,b). The intelligent data-driven prediction algorithms (Zhang et al., 2020a; Qiu et al., 2020b; Ma et al., 2020c; Li et al., 2020b) are also introduced into the real-time RUL prediction until the end of the UAV emission that is filled with uncertainty quantification (Eleftheroglou et al., 2019a). The overall structure of the RUL prediction algorithms is shown in Fig. 1.

In Fig. 1, the relationship between deep learning and other algorithms are expressed in detail, which are used for the RUL prediction. The online RUL prediction is realized by comparing the similarity between the measured battery charging curve segment and the support vector machine (SVM) algorithm. According to the influencing factors reflecting the similarity in the charging process, the RUL value can be estimated online by introducing LSTM and RNN algorithms into the prediction process. As for the accurate RUL prediction, the hybrid model based on SVR and differential evolution can be established, and the optimal multi-stage genetic calculation is investigated. The different RUL prediction types are reviewed to compare the estimation effects, including challenges and recommendations (Lipu et al., 2018). Therefore, the online RUL prediction can be achieved and the mathematical modeling can be performed accordingly (Tian et al., 2021). The specific table presented the state of art is shown in Table 1.

As can be known from the state of art shown in Table 1, the improved deep learning algorithms have been introduced into the RUL prediction of lithium-ion batteries with effective accuracy and speed, including the deep convolutional neural networks, deep reinforcement learning, long short term memory, and recurrent neural network.

3. Deep learning for RUL prediction

In this section, the main RUL prediction features are analyzed for the deep learning algorithms, introducing the main specific indicators of evaluating the modeling accuracy and calculation cost characteristics to evaluate the prediction effect.

3.1. Mathematical modeling of deep learning

Extensive extreme machine learning methods are adopted to realize the cycle life prediction of lithium-ion batteries. The extreme learning machine (ELM) has a single hidden layer compared with the feedforward neural network (FNN) (Guha and Patra, 2018a), which has fast learning speed and effective generalization performance (Ma et al., 2020a), introducing a generalized learning (BL) idea (Yin et al., 2020). An improved ELM model is constructed by data-driven non-parametric aging analysis, which realizes the storage operation and cyclic operation from the operating data (Du et al., 2019). Conducting the improved Gaussian regression and nonlinear regression (Li et al., 2020a,b,c,d), a multi-time scale framework is constructed to predict the battery health status. A cooperative Gaussian processing regression model is established for the transfer learning of capacity trends between the battery cells (Chehade and Hussein, 2020). An improved deep learning method is proposed to describe the online capacity changes (Wei et al., 2020), in which a deep convolutional neural network (DCNN) is built to estimate the battery power portion (Li, (Zhou et al., 2020a) based on the voltage, current, and temperature measurement in the charging process. An intelligent hybrid wavelet-adversarial deep model is built for accurate solar power generation prediction (Meng et al., 2021). Reinforcement learning and unscented transform are also introduced for the stochastic multi-carrier energy management in the smart islands (Zou et al., 2021). An advanced machine learning model-based energy management of renewable microgrids is built by considering the charging demand of hybrid electric vehicles (HEVs) (Lan et al., 2021). A high-precision detection method based on the improved RetinaNet is proposed for the defect recognition of transmission lines (Liu et al., 2020).

The data-driven prediction is conducted by deep learning, in which the deep neural network (DNN) is used to predict the battery RUL value by conducting the preliminary data-driven treatment. The machine learning (ML) algorithm includes SVM, k-nearest neighbor (k-NN), artificial neural network (ANN), and linear regression (LR) methods (Hafiz et al., 2020; Wu et al., 2019; Shin et al., 2019; Eleftheroglou et al., 2019b; Lipu et al., 2018), which can be used to extract the degradative mode recognition of lithium-ion batteries by using the impedance spectrum (Zhang et al., 2020a,b,c,d). To achieve the adaptive time-series prediction and online verification (Ma et al., 2021b), deep learning is realized, which combines the effective variables of RNN (Lui et al., 2021a) and LSTM with variable input sizes and other labeled samples. The iterative DNN structure (Zhou et al., 2020b) is built for the battery RUL prediction, in which two LSTM layers are constructed for the feature extraction, named LSTM1 and LSTM2. In each layer, the battery parameters are the same as each other (Zhang et al., 2020a,b,c,d), so this structure has strong scalability for different network input sizes. The overall structure of the deep learning prediction model is shown in Fig. 2.

In Fig. 2, depending on the prediction form, a different number of data segments are prepared for each sampling process. When these samples are inputted into the network (Xue et al., 2020a), the data segment is the input of each LSTM unit, so the network structure will change adaptive to different input sampling types (Tagade et al., 2020b). When using n=3 as the processing input sampling number, the LSTM1 units with the same parameters are connected to the first layer (Lee et al., 2021), and the second layer LSTM2 follows a similar pattern. When processing different segments (Qiu et al., 2020c), the structure of the LSTM unit changes accordingly. Since one label can obtain multiple samples, the available training data set can be expanded effectively (Ma et al., 2020b). According to the instant verification result of the measurement data, the prediction model structure can be adjusted

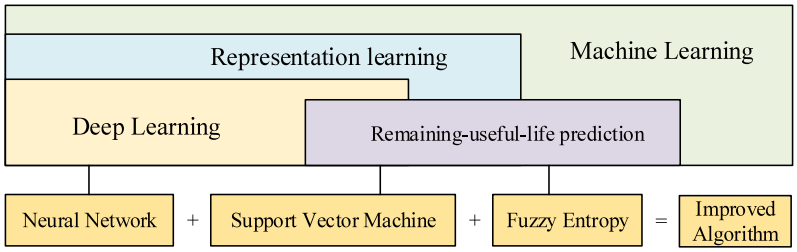


Fig. 1. The relationship between deep learning and other algorithms.

Table 1
The specific table presented the state of art.

Authors	Year	Common criteria
Afrasiabi, M., M. Mohammadi, M. Rastegar, and A. Kargarian	2019	Deep learning forecaster
Al-Ghussain, L., A. Darwish Ahmad, A. M. Abubaker, and M. A. Mohamed	2021	Demand-supply matching
Bi, Y., Y. Yin, and S.-Y. Choe	2020	particle filtering
Chehade, A. A. and A. A. Hussein	2020	Gaussian processregression
Chen, L., J. An, H. Wang, M. Zhang, and H. Pan	2020	Sliding-window gray model
Chen, L., J. Chen, H. M. Wang, Y. J. Wang, J. J. An, R. Yang, and H. H. Pan	2020	Fractional gray model
Chen, L., H. M. Wang, B. H. Liu, Y. J. Wang, Y. H. Ding, and H. H. Pan	2021	Metabolic extreme learning machine
Dong, G., F. Yang, Z. Wei, J. Wei, and K.-L. Tsui	2020	Adaptive Brownian motion model
Farmann, A. and D. U. Sauer	2018	Reduced-order equivalent circuit models
Han, X. F., H. W. He, J. D. Wu, J. K. Peng, and Y. C. Li	2019	Reinforcement learning with deep Q-learning
Hong, J., D. Lee, E.-R. Jeong, and Y. Yi	2020	End-to-end deep learning
Hong, J. C., Z. P. Wang, W. Chen, and Y. T. Yao	2019	Long short-term memory networks
Jiao, R., K. Peng, and J. Dong	2020	Variational autoencoder particle filter
Li, H. P., Z. Q. Wan, and H. B. He	2020	Deep reinforcement learning
Li, P., Z. Zhang, Q. Xiong, B. Ding, J. Hou, D. Luo, Y. Rong, and S. Li	2020	Long short term memory neural network
Li, W. H., N. Sengupta, P. Dechent, D. Howey, A. Annaswamy, and D. U. Sauer	2021	Deep long short-term memory networks
Li, Y., K. Li, X. Liu, Y. Wang, and L. Zhang	2021	Pruned convolutional neural network
Liu, K. L., X. S. Hu, Z. B. Wei, Y. Li, and Y. Jiang	2019	Modified Gaussian process regression
Lu, R. Z., Y. C. Li, Y. T. Li, J. H. Jiang, and Y. M. Ding	2020	Multi-agent deep reinforcement learning
Ma, G., Y. Zhang, C. Cheng, B. Zhou, P. Hu, and Y. Yuan	2019	False nearest neighbors
Ma, Y., Y. Chen, X. Zhou, and H. Chen	2019	Gauss–Hermite particle filter
Ma, Y., L. Wu, Y. Guan, and Z. Peng	2020	Extreme learning machine
Ng, M. F., J. Zhao, Q. Y. Yan, G. J. Conduit, and Z. W. Seh	2020	Data-driven machine learning
Qiu, X., W. Wu, and S. Wang	2020	Cuckoo search particle filter
Shen, S., M. Sadoughi, M. Li, Z. Wang, and C. Hu	2020	Deep convolutional neural networks
Tagade, P., K. S. Hariharan, S. Ramachandran, A. Khandelwal, A. Naha, S. M. Kolake, and S. H. Han	2020	Deep Gaussian process regression
Tan, H. C., H. L. Zhang, J. K. Peng, Z. X. Jiang, and Y. K. Wu	2019	Deep reinforcement learning
Tang, X. P., K. L. Liu, X. Wang, F. R. Gao, J. Macro, and W. D. Widanage	2020	Model migration neural network
Wei, J., G. Dong, and Z. Chen	2018	Support vector regression
Xue, Z. W., Y. Zhang, C. Cheng, and G. J. Ma	2020	Optimized support vector regression
Yang, F., D. Wang, F. Xu, Z. Huang, and K.-L. Tsui	2020	Gradient boosting regression tree model
Yang, R., R. Xiong, S. Ma, and X. Lin	2020	Artificial neural networks
Zhang, Y., R. Xiong, H. He, and M. G. Pecht	2018	Long short term memory recurrent neural network
Zhao, R. X., P. J. Kollmeyer, R. D. Lorenz, and T. M. Jahns	2019	Recurrent neural network
Zhou, Y. P., M. H. Huang, and M. Pecht	2020	K-nearest neighbor regression

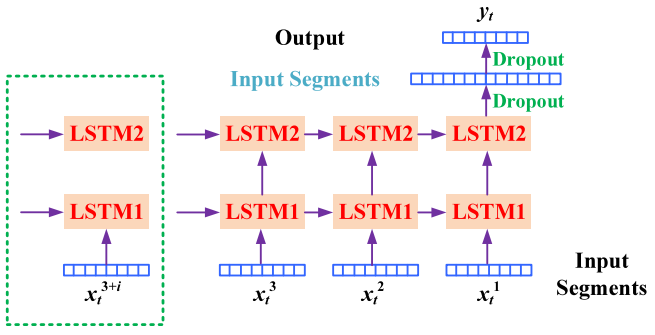


Fig. 2. The whole structure of the deep learning prediction process.

to obtain better performance. After the feature extraction of two LSTM layers, the output of the last LSTM2 unit can be used for the further RUL prediction, which contains the information extracted from the entire input matrix. After that, a full-connected layer is used with neurons on top of the future prediction network. This expression can be described by the mathematical function, as shown in Eq. (1).

$$\hat{\boldsymbol{Y}}_t^n = \left\{\hat{S}_{t+k}\right\}, k = 1, 2, \ldots, n_p \tag{1}$$

In Eq. (1), $\hat{\boldsymbol{Y}}_t^n$ is the predicted factor matrix for the time point of t with the particle number of n, which is formed by the state parameters of $\hat{S}_{t+k}$ for the time point of t and offset of k varying from 1 to n_p. A comprehensive review of the RUL prediction methods is conducted for the advanced battery management systems (BMS) (Xu et al., 2021a,b) as well as the mathematical and experimental analysis (Wang, (Tian et al., 2020,?). The deep Gaussian regression is used to predict the health degradation patterns of lithium-ion batteries (Tagade et al., 2020a). An improved DCNN model is built in combination with the integrated and transfer learning of lithium-ion batteries (Shen et al., 2020a). For the first time, the 10-year daily-cycle data onto 8 implantable lithium-ion battery cells are used as the data source set (Lin et al., 2020), according to which 8 DCNN sub-models are pre-trained. The overall structure of the DCNN prediction process is shown in Fig. 3.

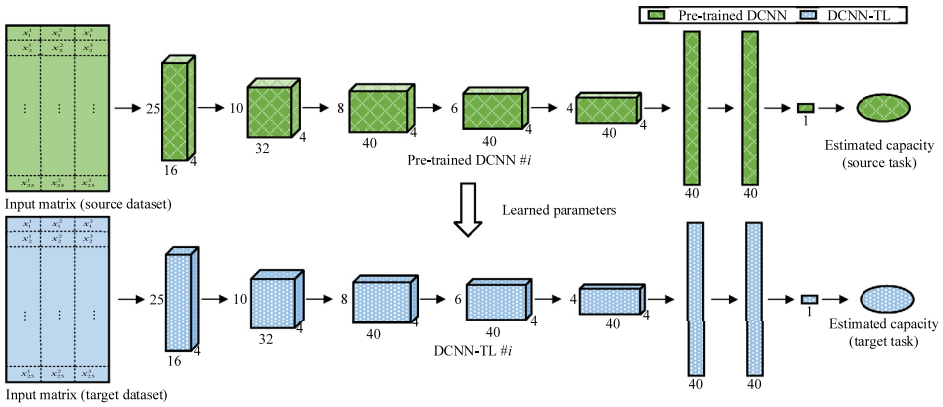


Fig. 3. The overall structure of the DCNN prediction process.

In Fig. 3, five data-driven DCNN-TL submodels are utilized and comprehensive calculation strategies are used to realize the RUL prediction (Ng et al., 2020), in which the pre-trained DCNN modeling construction plays an important role in the iterative calculation process. The accurate RUL prediction depends greatly on the dynamic battery characterization degree by the equivalent modeling (Jiao et al., 2020; Ma et al., 2021a). The equivalent circuit model (ECM) uses the circuit response to simulate the internal reaction against the lithium-ion batteries (Gou et al., 2020). The temperature changing impact on the model structure is analyzed by combining electrochemistry (Corno and Pozzato, 2020) and ECM (Li et al., 2021a,b,c) with a high-precision feature description. On this basis, the distributed feature modeling can be conducted to describe the battery life cycle behavior (Li et al., 2021a,b,c), the performance of which lays a foundation for the state–space equation. On the premise of the mathematical testing result description, the equivalent model can be constructed for the full-life-cycle battery working conditions (Chen et al., 2021), which provides a theoretical basis for the wide-temperature-range state–space expression. Through many experimental tests, the relevant changing law analysis can be carried out for the key factors (Masaud and El-Saadany, 2020), so that the established model can simulate the battery characteristics effectively.

The battery characterization and RUL prediction can be realized effectively through the iterative application of terminal voltage and current. Based on the experimental test of various working conditions, the changing law of each parameter is obtained (Zhang et al., 2019b) and an improved framework is established for the RUL prediction by combining the mathematical state–space description and model parameter identification (Mejdoubi et al., 2019). Time-varying parameters are affected by various temperature conditions and other environmental factors (Ma et al., 2019a), so the model contains resistance–capacitance components (Anseán et al., 2019). Since the time-varying battery state contains stimulus factors, the online parameter recognition generates a stress response to the external factors based on the measured data onto the voltage and current, which can reflect the dynamic battery characteristics effectively.

3.2. DCNN-based calculation flowcharts

The DCNN processing is to collect data samples and adjust the weight-position coefficients of the particles, according to which the measured results are used to correct the previous empirical distribution (Yang et al., 2020a,b,c,d). Under the condition of ensuring the same RUL prediction accuracy, the number of particle samples can be reduced, thereby reducing the calculation amount. The transfer of learning into knowledge learning is conducted (Shen et al., 2020b) from the data source set and encoded as the parameters of n single DCNN sub-models, as shown in Eq. (2).

$$\theta^S = \left\{\theta_1^S, \theta_2^S, \ldots, \theta_n^S\right\} \tag{2}$$

In Eq. (2), the whole structure of DCNN modeling particle–matrix θ^S can be formed by n single DCNN sub-modeling factors of θ_n^S, in which n is the number of single DCNN sub-models. Then, the pre-trained DCNN model is transformed into a DCNN-TL model (Yang et al., 2018), and each step processing includes 5 convolutional layers and 3 full-connected layers. This type is also used to achieve the effective capacity prediction performance of internally connected battery cells (Ma et al., 2020b). The transfer learning method is used to adjust the pre-trained DCNN model through the data set in the source task (Xu et al., 2018). As the long-term cyclic experimental test is feasible (Hong et al., 2020a), short-term cyclic experimental tests are performed to make the model perform well in the target task. In this way, a small data set can be used to achieve effective knowledge transformation, which thereby reduces the data collection requirements with stable prediction accuracy (Finegan et al., 2020). After completing the transfer learning step, n DCNN-TL sub-models can be established according to the learning parameters of the DCNN model. Then, a whole-structure DCNN-ETL model is obtained through integrated learning (Chen et al., 2020a,b), including n DCNN-TL sub-models, one full-connected layer, and one regression layer. Therefore, the entire structure can be constructed for the DCNN-ETL algorithm (Wei et al., 2018). The workflow of transfer learning is shown in Fig. 4.

In Fig. 4, the architecture of the single DCNN-TL model is constructed from the DCNN-ETL modeling process. First, the input matrix X should be fed into each sub-model. And then, the convolution layer uses k kernels of the convolution operation $C(X, K)$ to correct the input matrix X. The filter moves along with X variation in both the horizontal and vertical directions, and a similar calculation treatment should be performed for each data point (Shen et al., 2020a). The i_{th} row and j_{th} column of k_{th} output can be obtained for the convolutional layer, as shown in Eq. (3).

$$\begin{cases} Z_{i,j,k}^{lconv} = C\left(X, K\right)_{i,j,k} = \sum_{r=1}^{k_h} \sum_{s=1}^{k_w} \sum_{t=1}^{k_c} x_{i',j',t'} k_{r,s,t',k} + b_k \\ i' = (i-1)\, S_h + r \\ j' = (j-1)\, S_w + s \end{cases} \tag{3}$$

In Eq. (3), $k_{r,s,t',k}$ and b_k represent the weight and deviation of the k kernel respectively in the convolutional layer. The established state–space model of lithium-ion batteries can be used to predict the RUL value of lithium-ion batteries (Voronov et al., 2018). When the state–space equation is constructed for each

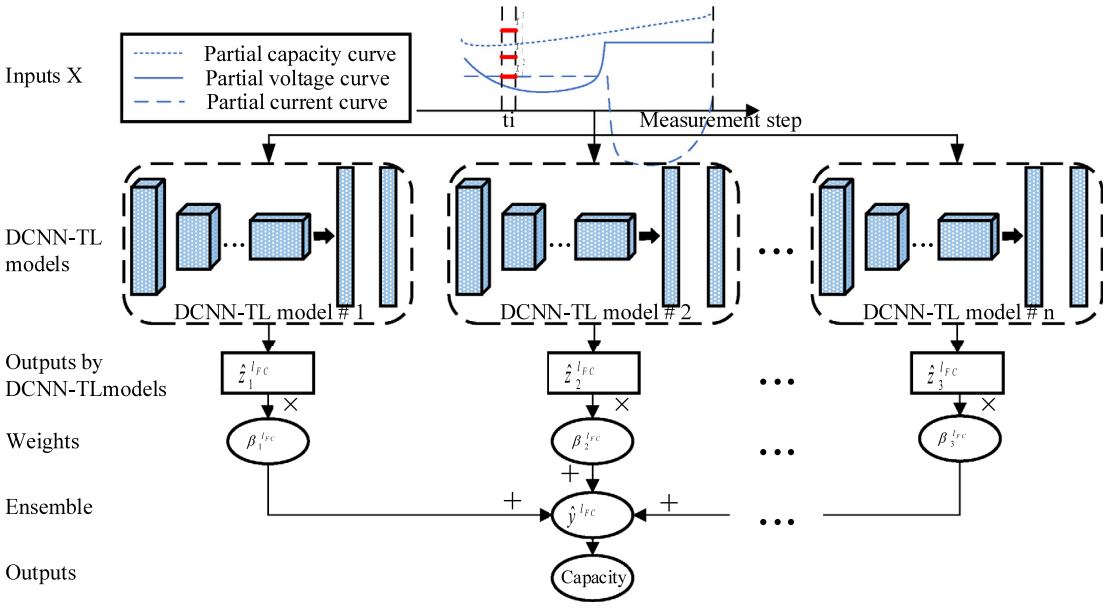


Fig. 4. The iterative residual RUL prediction process using deep learning strategies.

particle, a new data set can be generated. And then, the matched particles are extracted to generate a new data set (Jafari et al., 2018). When the system obtains the updated observation value, the state–space equation will generate a new set of particles (Guha and Patra, 2018b). Consequently, the predicted value is obtained through the observation equation, according to which the error between the observed and predicted values can be calculated for each particle. The one-step iterative calculation structure of n DCNN-TL sub-models can be described, as shown in Fig. 5.

In Fig. 5, a significant feature of the DCNN algorithm is to realize the calculation process without strict data length requirements. Subsequently, it can estimate the time-varying dynamic parameters with high accuracy (Guha and Patra, 2018a), which can extract the discrete random samples accurately. These particles use possible density functions to complete the mean value prediction and data sampling process (Zhang et al., 2017), thereby realizing effective time-varying model parameter prediction (Zhang et al., 2018b). Therefore, it is suitable for complex environmental impacts. The implementation steps of the resampling algorithm are realized and the weight coefficient of each particle is calculated according to Eq. (4).

$$q(\chi_k|x_{0:k}(i), y_{1:k}) = p(x_k|\chi_{k-1}(i)) \tag{4}$$

In Eq. (4), combining theoretical analysis, simulation, and experimental verification, an improved model is established adaptive to complex and wide temperature range conditions, in which only several effective particles are required for iterative calculation that is combined with the set threshold. If the number of effective particles is smaller than the set threshold, it needs to be re-established (You et al., 2017). After sampling, the corrected particles are reselected, so a new particle set can be formed by using these selected particles (Liu et al., 2017b). Subsequently, the posterior prediction of the system is conducted before resampling (Li et al., 2020a,b,c,d,e,f,g), and the calculation process can be realized according to the posterior prediction effect, as shown in Eq. (5).

$$w_t{}^{(i)} = (w_{t-1}{}^{(i)})^{\alpha} \frac{p(z_t|x_t{}^{(i)})p(x_t{}^{(i)}|x_{t-1}{}^{(i)})}{q(x_t{}^{(i)}|x_{t-1}{}^{(i)}, z_{1:t})} \tag{5}$$

In Eq. (5), α is the annealing parameter of the genetic algorithm, which is used to control the weighting factor influence, thereby reducing the sample consumption. According to the RUL prediction requirement, the modeling effect is evaluated by considering the representation accuracy and the computational complexity comprehensively (Liu et al., 2017). Therefore, the modeling process has strong applicability by using the real-time measured experimental data (Li et al., 2017). Also, the equilibrium parameters are introduced to characterize the capacity difference between the internal-connected battery cells. The modeling improvement is conducted respectively by combining the advantages of various construction methods so that the iterative calculation can be performed on the functional relationship and mathematical state–space expression. In the experimental test, the feasibility can be verified by adjusting the discharge capacity and time by changing the number of resistors added in the main circuit.

3.3. Application analysis from literature

The migration neural network (MNN) is constructed to predict the battery aging trajectory (Tang et al., 2020), which can be adaptive to the pulse current working conditions. The artificial neural network (ANN) (Zhao et al., 2021) is used to predict the RUL value of lithium-ion batteries, and the prediction process can be also achieved through empirical mode decomposition (Wu et al., 2020). The RUL prediction is achieved by using the improved extreme learning machine (ELM) algorithm (Liu et al., 2020a), which can be also realized by using the deep neural network (DNN) (Lin et al., 2020a). The capacity and cycle life prediction of lithium-ion batteries are also achieved by using the extensive ELM method (Ma et al., 2020a). A life prediction method is proposed by using the fusion model and attention mechanism (Zhao et al., 2020), which uses linear regression, support vector machine, adaptive non-attention mechanism LSTM, and attention mechanism ALSTM as well as the experimental verification.

As for the microgrid application, grid battery life management can improve the performance of vehicles (Yang et al., 2020a). The hybrid RUL prediction is conducted to realize the cycle life optimization of different lithium-ion battery formulations (Ma et al., 2020a), and the case-based transfer learning is conducted to design the RUL prediction model for different battery formulations (Ma et al., 2020c). Average Euclidean distance (AED) (Li et al., 2020c) and stacked denoising autoencoder (SDA) (Li

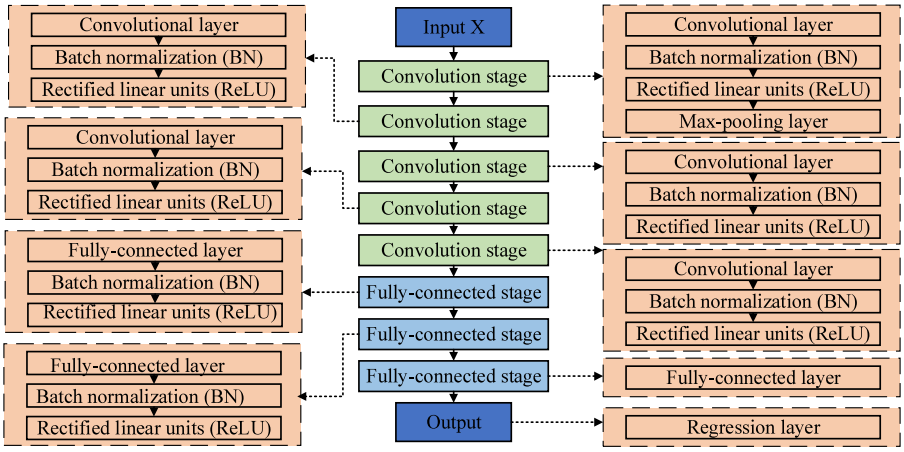


Fig. 5. The one-step architecture of the DCNN-TL sub-models.

et al., 2020b) algorithms are used as powerful deep learning calculation methods. Using a non-uniform sampling of power data and DNN, a non-invasive load monitoring algorithm is proposed (Hong et al., 2020b). The schematic and structure of the LSTM-based prediction network (Hong et al., 2019a,b) can be described as shown in Fig. 6.

The convolutional neural network (CNN) is used to identify the parameters of the electrochemical lithium-ion battery model with high calculation accuracy (Li et al., 2019). A new machine learning method is proposed to realize battery health management (Shen et al., 2021) and an integrated data mining framework is constructed for the battery characteristic expression and prediction (Seruga et al., 2021). The deep learning algorithms perform feature extraction in an effective automated manner by using minimal domain knowledge and manpower (Hong et al., 2020b). These algorithms can be realized with hierarchical data representation architecture, according to which the advanced functions can be extracted from the last layer of the network (Lui et al., 2021b). At the same time, low-level features can be extracted from the bottom layer. These types are inspired by the artificial intelligence (AI) originally (Bi et al., 2020), which has achieved great success in many fields and become one of the most popular research directions in the machine learning society (Zhang et al., 2018b). An overview of deep learning can be obtained from different perspectives, including history, challenges, opportunities, algorithms, frameworks, applications, parallel and distributed computing technologies (Zhang et al., 2020b; Song et al., 2020; Khaleghi Rahimian et al., 2020; Dong et al., 2020). Therefore, the deep learning algorithm is introduced into the RUL prediction process, the overall structure of which is shown in Fig. 7.

In Fig. 7, the DP-based methods are considered to be a huge research field, and the biggest challenge is to train the existing large data sets. As the data sets are becoming large, diverse, and complex, the DP algorithm has become a key tool for big data analysis. Challenges and opportunities arise in key areas (Khodadadi Sadabadi et al., 2021), which should be prioritized, including parallelism, scalability, functionality, and optimization. To solve this problem, different deep learning networks are introduced into different application fields, such as RNN, CNN, TensorFlow, and torch algorithms (Yang et al., 2020a,b,c,d; Wang et al., 2020a,b,c; Qiu et al., 2020b).

3.4. Deep-learning for parameterization

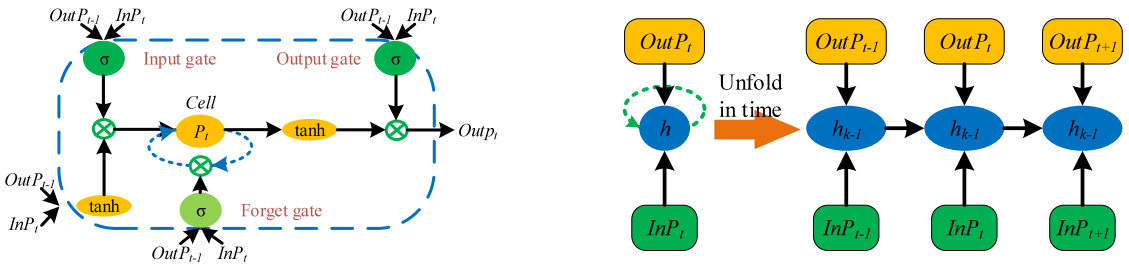
Based on the Gaussian processing regression and deep recursive kernel function, the RUL prediction is conducted for lithium-ion batteries (Ma et al., 2020c), which introduces a gated recursive unit (GRU) (Ma et al., 2020b) to deal with the long-term dependence. Moreover, LSTM and RNN algorithms are also used to realize the lithium-ion battery capacity prediction and verification (Liu et al., 2020b). The Ind-RNN model is built to evaluate the health status of lithium-ion batteries under variable load conditions (Yang et al., 2020b). It is also carried out by considering the energy-saving strategies of the traffic information and electric vehicle path planning (Lin et al., 2020b). The RUL prediction is conducted for the lithium-ion batteries based on the RNN algorithm of recursive units (Li et al., 2020b). Then, the RNN treatment of the convolutional recursive unit is introduced into the RUL prediction process of lithium-ion batteries (Li et al., 2020a). Using comprehensive neuropsychological evaluation data (Xue et al., 2020a,b), the high-precision diagnosis framework is constructed by the deep learning treatment.

The DNN and DCNN algorithms are also used to estimate the RUL value of lithium-ion batteries (Hong et al., 2020a). To avoid the over-fitting phenomenon of the training data, the packet loss technique is also introduced into the network by 0.5, which is an effective regularization method (Chu et al., 2020). The full-connected layer uses the rectified linear unit (ReLU) activated functions to avoid gradient disappearance or diffusion (Atalay et al., 2020). The root-mean-square error (RMSE) and normalized root mean square error (NRMSE) (Shen et al., 2020b) are used to evaluate the loss function of the network training process, and their definitions are expressed, as shown in Eq. (6).

$$\begin{cases} \mathrm{RMSE} = \sqrt{\dfrac{1}{N_s}\sum_{i=1}^{N_s}\left\|\boldsymbol{Y}(i)-\hat{\boldsymbol{Y}}(i)\right\|_2^2} \\ \mathrm{NRMSE} = \dfrac{\sqrt{\frac{1}{N_s}\sum_{i=1}^{N_s}\left\|\boldsymbol{Y}(i)-\hat{\boldsymbol{Y}}(i)\right\|_2^2}}{(\boldsymbol{Y}_{max}-\boldsymbol{Y}_{\min})} \end{cases} \tag{6}$$

In Eq. (6), N_s denotes the number of data samples. $\boldsymbol{Y}(i)$ represents the label vector of the i_{th} sample. $\hat{\boldsymbol{Y}}(i)$ is the corresponding sample prediction result by using the proposed method. In addition to RMSE, two other matrices are also used to evaluate the modeling performance. These models are defined by using the mean absolute error (MAE), max absolute error (MAX), and mean absolute percentage error (MAPE), which are shown in Eq. (7).

$$\begin{cases} MAE = \dfrac{1}{N_s}\sum_{i=1}^{N_s}\left\|Y(i)-\hat{Y}(i)\right\|_2 \\ MAX = Max\left\{Y(i)-\hat{Y}(i)\right\} \\ MAPE = \dfrac{1}{N_s}\sum_{i=1}^{N_s}\dfrac{\left\|Y(i)-\hat{Y}(i)\right\|_2}{\|Y(i)\|_2} \end{cases} \tag{7}$$



(a) LSTM prediction schematic network (b) The unfolded LSTM-RNN architecture

Fig. 6. The schematic and structure of the LSTM-based prediction network.

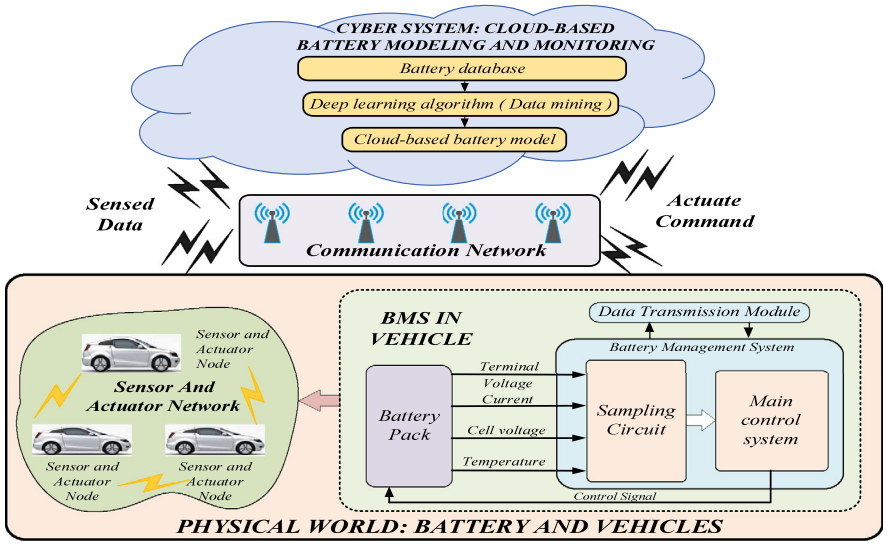


Fig. 7. Deep learning and related method application for the RUL prediction.

In Eq. (7), the SOH values for the next step of n_p can be estimated directly by the historical measurement, which is conducted at the time point of t based on the problem formulation. Therefore, the trained model can perform the multi-step prediction easily. Besides, when the battery is degrading at the time point of t, the development of long-term RUL prediction is very important to be realized online. The RUL value can be predicted accurately and determined as the remaining period before the predicted SOH value exceeds a predetermined failure threshold (Zhang et al., 2019b). Then, the moving time window scheme can be constructed for the remote health evaluation, as illustrated in Fig. 8.

In Fig. 8, the size of the time window is $n_t * n_s$, in which n_t denotes the number of data segments prepared by the test samples that are obtained at the time point of t. First, the direct multi-step advanced RUL prediction is realized at the time point of t, and $Y_t = S(t+k)$ can be obtained at the time point of $k = 1, 2, \ldots, n_p$, which indicates that the future values are estimated from step $t+1$ to $t+n_p$ Next, the prediction stride is selected according to the prognostic scheme. Subsequently, the first p_t estimated points are merged into the time window (Ma et al., 2019), and the same number of data points are discarded at the beginning of the time window, in which the multi-steps are repeated to realize the long-term RUL prediction.

The dual deep learning coordinated control of the hybrid ESS is carried out for the microgrid (Liu et al., 2019b). As for the energy management of the discrete battery systems, the demanding response problem is overcome by multi-agent deep reinforcement learning (Lu et al., 2020). Using the deep learning network, the optimal peak drift of the household load is connected to the public grid (Ma et al., 2020c). An optimized energy storage method based on deep learning is proposed to realize adaptive dynamic programming (Hong et al., 2020b). Meanwhile, the artificial intelligence (AI) and ML algorithms are applied to the target ESS solution (Zhang et al., 2018b). The reliable power dispatches are carried out for the emission-free ships (Li et al., 2020a,b,c,d,e,f,g), so the constrained charging can be realized by using the multi-objective deep reinforcement learning (DRL) model.

The real-time stochastic ESS optimization is achieved through the DP-based prediction (Kwak et al., 2021), residential photovoltaic power generation (RPV), and improved battery energy storage (BES). To solve the lithium-ion battery scheduling problem, a multi-agent reinforcement learning framework is constructed (Zhang et al., 2020a,b,c,d). The energy management strategies based on the DRL modeling are transferred to the hybrid tracked vehicles (Yang et al., 2020c). The deep reinforcement learning (DRL) and transfer learning (TL) can be combined with EMS training, according to which the specific deep deterministic gradient algorithm is executed at different speed intervals (Eleftheroglou et al., 2019b). The energy management based on reinforcement learning and dual deep Q learning is performed on hybrid EVs (Han et al., 2019), according to which a dual learning structure is constructed. The LSTM network is used to predict the multiple parameters of the EV battery system (Hong et al., 2019a,b), in which the developed pre-loss technology is introduced to prevent the overfitting phenomenon. The microgrid energy management is realized by using a deep learning predictor

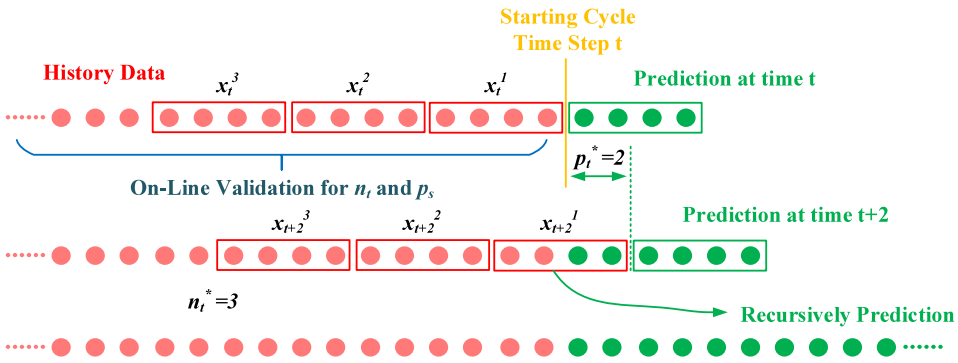


Fig. 8. Moving time window scheme for RUL prediction.

(Afrasiabi et al., 2019), in which a multi-agent framework is constructed for the early dispatch.

Based on the deep Q-learning and Bayesian optimization (Qiu et al., 2020a), the energy management strategies are extracted for EVs. The fault prediction of the battery system is accurate by using the LSTM algorithm (Hong et al., 2019a,b). The energy management of the hybrid buses is realized by deep reinforcement learning in the continuous state–space expression (Tan et al., 2019), while the detection of blister defects uses the CNN strategy (Yang et al., 2020d). A review of reinforcement learning is conducted for the demanding response (Vazquez-Canteli and Nagy, 2019), which considers reinforcement learning to coordinate the multi-agent systems that can participate in the demanding response procedures. In the case that the observation data is not available, the random variable is estimated according to the prior distribution. And then, the data is obtained, thereby optimizing the prior probability of the random variables. Consequently, the data is introduced to obtain the posterior distribution of the random variable x. The state and observation equations are known as well as the initial value of the probability density.

Through the observing point prediction, the mathematical function can be obtained for the next time point (Feng and Dong, 2020). The observed RUL value at the time point of k is used to correct the predicted probability density function, obtaining the posterior probability density function. The initial equation of the probability density and the posterior value can be obtained for the iterative calculation (Wang et al., 2019), according to which the previous equation can be converted by the probability density formula. The observation factors are independent, which leads to the recursive and updating process of the posterior filtering and probability-density function. As it is difficult to obtain the posterior filtering probability density, the observing point prediction method needs to be combined with other algorithms to obtain the posterior probability density.

4. Comparison of the RUL prediction effect

In this part, the critical criteria are introduced to compare different models in the literature, intending to find the best method for the battery RUL prediction. Then, the research direction of the battery life prediction is discussed. The modeling performance and results of different prediction methods are compared, and the internal structure is also related to the battery life prediction. The parameterized model is realized by changing the parameters, which are regarded as functional formal constants. As for the online learning process, it may limit the adaptability of the prediction process. Therefore, the accurate prediction ability depends on the reliability of the initial model. Since the ANN model also has a fixed number of weighting coefficients, it has been regarded as a parametric modeling type (Tang et al., 2019a,b). And then, various prediction effects can be displayed in different deep learning algorithms. The prediction results and effects are obtained and compared by taking RMSE, MaxE, Speed, and Accuracy as evaluation criteria, as shown in Table 2.

In Table 2, it can be known from the comparative analysis that the DP method is very effective for the RUL prediction of lithium-ion batteries. Among them, the DCNN and LSTM strategies are mainly used for accurate RUL prediction. By comparing the parameter influence on the prediction results of the literature, the maximum likelihood method is used to evaluate the prediction results, the implementation process of which is effective when performing the random sampling. Therefore, it is necessary to use a random variable that follows the corresponding distribution type, which can be then introduced into the DCNN-ETL to realize the accurate RUL prediction that is being verified by experimental tests n. The whole-life-cycle experimental tests have been already finished by more than 1-year experimental tests that are , including https://www.researchgate.net/project/Battery-life-test, https://www.researchgate.net/project/Whole-Life-Cycle-Test.

5. Conclusions

The accurate remaining useful life prediction is the key point of lithium-ion battery condition monitoring with high difficulty, and the deep learning method improves the prediction accuracy and robustness. This paper makes a rigorous review of the deep learning modeling method for accurate remaining useful life prediction. A specific criterion is defined to evaluate the accuracy and computational cost of the different modeling types. The experimental results show that the deep learning algorithm has non-parametric characteristics, probabilistic capabilities, and powerful computational advantages, which is suitable for the accurate prediction effect. The constructed mathematical functions are particularly convenient for the accurate remaining useful life prediction purposes, providing an effective solution choice. The latest development of modeling methods requires further research and development. By providing a convenient method to develop an adaptive prediction model, the latest technology is proposed, compared, and analyzed. The tentative and adaptive prediction strategies based on deep learning can improve the promotion and application of lithium-ion batteries. By comparing various improved deep learning methods, the high-accuracy deep convolutional neural network — extreme learning machine algorithm will be realized and verified with the near future research to realize the accurate remaining useful life prediction by shortening test time, increasing the prediction accuracy, and improving modeling adaptability.

Table 2
The prediction effect comparison result for different deep learning algorithms.

Algorithms	RMSE (%)	MaxE (%)	Speed	Accuracy
Extreme Learning Machine (ELM)	/	/	/	94.20% (Zhang et al., 2018a)
Deep Convolutional Neural Network (DCNN)	1.986 (Shen et al., 2020a)	6.838 (Shen et al., 2020a)	14.138 for Trial 1 (Shen et al., 2020a)	/
Deep Neural Network (DNN)	1.59 (Cong et al., 2020)	7.14 (Cong et al., 2020)	/	/
Recurrent Neural Network (RNN)	6.87	37.92	/	/
Long Short-Term Memory (LSTM)	MRE < 5% (Hong et al., 2019a,b), RMSE=0.25425 and NRMSE=0.1424 (Afrasiabi et al., 2019)	MAPE=14.785 (Afrasiabi et al., 2019)	/	/
DCNN - Ensemble Transfer Learning (DCNN-ETL)	1.114 (Shen et al., 2020a)	5.487 (Shen et al., 2020a)	133.924 for Trial 1 (Shen et al., 2020a)	/
DCNN with Ensemble Learning (DCNN-EL)	3.539 (Shen et al., 2020a)	16.798 (Shen et al., 2020a)	144.583 for Trial 1 (Shen et al., 2020a)	/
DCNN with Transfer Learning (DCNN-TL)	1.361 (Shen et al., 2020a)	2.452 (Shen et al., 2020a)	12.294 for Trial 1 (Shen et al., 2020a)	/
Adaptive LSTM (ALSTM)	/	/	8 min 46.847 s (Liu et al., 2017b)	93.12% (Liu et al., 2017b)
ALSTM with an attention mechanism	/	/	9 min 26.701 s (Zhang et al., 2017)	97.22% (Zhang et al., 2017)
Average Euclidean distance - Stacked Denoising Autoencoder (AED-SDA)	/	/	/	92.40% for A1 (Ma et al., 2020a)
Gated Recurrent Unit kernel - Gaussian Process Regression (GRU-GPR)	0.79 (Lipu et al., 2018)	7.92 (Lipu et al., 2018)	/	/

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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