

Article

Online Prediction of Remaining Useful Life for Li-Ion Batteries Based on Discharge Voltage Data

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Abstract: The state of health and remaining useful life of lithium-ion batteries are key indicators for the normal operation of electrical devices. To address the problem of the capacity of lithium-ion batteries being difficult to measure online, in this paper, we propose an online method based on particle swarm optimization and support vector regression to estimate the state of health and remaining useful life. First, a novel health indicator is extracted from the discharge voltage to characterize the capacity of lithium-ion batteries. Then, based on the capacity degradation characteristics, support vector regression is used to predict the remaining useful life of these batteries, and particle swarm optimization is selected to optimize the parameters of the support vector regression, which effectively enhances the predictive performance of the model. Validated for the NASA battery aging dataset, when training with the first 40% of the dataset, the maximum error of the predicted remaining useful life was four cycles, and when training with the first 50% of the dataset, the maximum error of the predicted remaining useful life was only one cycle. When comparing to a deep neural network, support vector regression, long short-term memory algorithms and existing similar methods in the literature, the particle swarm optimization and support vector regression method can obtain more accurate prediction results.

Keywords: Li-ion battery; remaining useful life; health indicator; support vector regression; particle swarm optimization



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1. Introduction

With environmental degradation, energy crises, and other problems becoming more prominent, traditional fuel vehicles no longer meet the requirements of energy saving and environmental protection, and emerging electric vehicles are becoming the main transportation of the future. Lithium-ion (Li-ion) batteries have become the main energy source for electric vehicles because of their high energy density, long service life and pollution-free characteristics [1–7]. The state of health (SOH) and remaining useful life (RUL) are two important monitoring parameters in a battery management system [8]. There are many definitions of SOH, but there is no unified definition yet. From a capacity perspective, this paper defines SOH as the ratio of the battery's maximum capacity in the current cycle to its initial rated capacity; when the ratio drops to 0.7~0.8, the battery is considered to reach its end of life (EoL) [9], and continued use may lead to serious safety accidents. In actual use, the accurate prediction of SOH and RUL is conducive to the active maintenance of the battery, for avoiding safety accidents, and for providing a guarantee for stable battery operation [10].

In recent years, there has been a lot of research on predicting the SOH and RUL of Li-ion batteries. According to the different prediction methods, these research works can

be divided into three categories: statistical filtering methods, data-driven methods, and model fusion methods [11].

Statistical filtering-based methods are mainly mathematical models constructed by the data characteristics of Li-ion batteries, including the Kalman filter and its extension methods and the particle filter and its extension methods. Fang et al. [12] proposed a joint state of charge (SOC) and SOH estimation method based on the dual extended Kalman filter algorithm, in turn based on the relationship between ohmic internal resistance and SOH. Zeng et al. [13] established an improved second-order equivalent circuit model, and used the Bayesian method for online parameter identification, took the ohmic resistance as the characteristic parameter of the SOH, and adopted the fuzzy unscented Kalman filter algorithm for the joint estimation of the SOC and SOH. Hu et al. [14] considered the problem of particle impoverishment in the particle filter and combined kernel smoothing with the particle filter to achieve RUL prediction with a higher accuracy than the conventional particle filter. Zhang et al. [15] introduced the Markov chain Monte Carlo method to solve the sample impoverishment problem of the unscented particle filter, in order to achieve the prediction of RUL. This type of method is easy to implement and has the advantage of a high accuracy, but it is easily affected by external factors.

Model fusion-based methods mainly combine statistical filtering and data-driven methods, which overcome the limitations of a single method. Wei et al. [16] developed a battery SOH state space model based on support vector regression (SVR) and introduced the particle filter to optimize the impedance attenuation parameters to suppress measurement noise and achieve an accurate prediction of the SOH and RUL. Song et al. [17] proposed a joint state estimation method for Li-ion batteries based on data-driven least squares support vector machines and the model-based unscented particle filter. Chang et al. [18] proposed a method for RUL prediction based on the idea of error correction by combining the unscented Kalman filter, complete ensemble empirical mode decomposition, and the relevance vector machine. However, this type of method currently has difficulties in overhead modeling and computing.

In recent years, data-driven research methods, which do not require much expertise in the field of electrochemistry and only need the historical data of battery operation to achieve SOH and RUL predictions, have received a lot of attention from scholars. The main data-driven methods include neural networks [19–22], support vector machines [23,24], moving average models [25,26], Gaussian process regression [4,27], and ensemble learning [28]. Wang et al. [29] used the ant lion optimization algorithm to optimize the parameters of SVR to achieve an accurate prediction of the SOH and RUL. Phattara et al. [30] used a deep neural network (DNN) to predict the SOH and RUL of Li-ion batteries and compared it to other algorithms to highlight the superiority of DNNs. Li et al. [31] used a recurrent neural network with a gated recurrent unit and a convolutional neural network, using voltage, current, and temperature to achieve the simultaneous estimation of the SOC and SOH. Qu et al. [32] considered the existence of noise in the Li-ion battery capacity sequence, and first performed the empirical modal decomposition of the sequence, then built a long short-term memory (LSTM) network based on particle swarm optimization (PSO) for the prediction of the SOH and RUL, supplemented with an incremental learning and attention mechanism to improve the performance of the model. Similarly, Hu et al. [33] divided the decomposed components into principal component data and fluctuation data according to correlation analysis, and used a deep belief network and an LSTM network to predict them, respectively, which also obtained accurate RUL prediction results. Yang et al. [34] used a hybrid pulse power characterization test for direct parameter extraction to identify the parameters of the equivalent circuit model, and the extracted parameters were used to train the back propagation neural network. Finally, the accuracy of back propagation neural network prediction was verified by static and dynamic current profiling tests.

In addition to the research on algorithms, there have been many studies on health indicators (HIs) that characterize the SOH of Li-ion batteries in recent years [35]. There are two main types of HIs—direct and indirect health indicators. Capacity and internal resistance

are usually used as direct health indicators to characterize the SOH of Li-ion batteries, but they typically need to be obtained offline by intrusive methods under laboratory conditions, making them subject to many restrictions in practical application scenarios. Indirect health indicators need to be able to indirectly characterize the SOH of Li-ion batteries and can be measured online [36]. In [37], the discharging voltage difference of equal time intervals was chosen as an indirect health indicator to characterize the SOH, while in [38,39], the time interval of equal discharging voltage difference was chosen as an indirect health indicator to characterize the SOH. Zhou et al. [40] extracted the mean voltage fall from the discharge process of the battery as an indirect health indicator, and Yang et al. [41] chose to use discharge temperature change rate as an indirect health indicator, and Gao Dong et al. [35] extracted the average charge current drop from the charging process as an indirect health indicator considering the instability of the discharging conditions. These indirect HIs make it more convenient to predict the SOH online.

Addressing the problem that the SOH and RUL of Li-ion batteries are difficult to predict online, a new indirect HI was extracted from the discharge voltage as the input of the SVR. In order to improve the prediction accuracy, the PSO was introduced to optimize the SVR parameters, and finally, to achieve the accurate online prediction of the SOH and RUL.

The remainder of this paper is arranged as follows: Section 2 introduces the relevant algorithms and the PSO–SVR algorithm; Section 3 focuses on the Li-ion battery dataset and the extraction of indirect HIs in this paper; Section 4 introduces the relevant model evaluation metrics and shows the prediction results of the PSO–SVR model using the dataset; finally, relevant conclusions are drawn in Section 5.

2. Related Algorithms

2.1. SVR

Support vector regression [42], as a branch of support vector machines, is often used to solve small-sample, nonlinear regression problems. For nonlinear regression problems, assume that the given sample set is $D = \{(x_1, y_1), (x_2, y_2), \dots, (x_n, y_n)\}$, ($x_i \in R^n, y_i \in R$), where x_i is the feature vector of sample i ; correspondingly, y_i is the target value of sample i , and n denotes the total number of samples. It is desirable to obtain a regression model, $f(x) = w \cdot \varphi(x) + b$, such that the difference between $f(x)$ and y is as small as possible, where w, b are the parameters to be determined, w denotes the weight, x denotes the input data, φ is the mapping function, and b denotes the intercept.

Thus, the SVR problem can be transformed as follows:

$$\min L(w, b) = \frac{1}{2} \|w\|^2 + C \sum_{i=1}^n l(f(x_i) - y_i) \quad (1)$$

where C denotes the penalty factor and l denotes the loss function.

Introducing the slack variables, ξ_i and $\hat{\xi}_i$, the SVR problem can be transformed into Equations (2) and (3):

$$\min L(w, b, \xi_i, \hat{\xi}_i) = \frac{1}{2} \|w\|^2 + C \sum_{i=1}^n (\xi_i + \hat{\xi}_i) \quad (2)$$

$$\text{st} \begin{cases} f(x_i) - y_i \leq \varepsilon + \xi_i \\ y_i - f(x_i) \leq \varepsilon + \hat{\xi}_i \\ \xi_i \geq 0, \hat{\xi}_i \leq 0, i = 1, 2, \dots, n \end{cases} \quad (3)$$

where ε denotes the maximum deviation that the regression model can tolerate between $f(x)$ and the target value y . Next, Lagrange multipliers are introduced, and then partial

derivatives of $w, b, \xi_i, \hat{\xi}_i$ are taken to make them zero, respectively, which can be converted into Equations (4) and (5):

$$\max(\alpha, \hat{\alpha}) = \sum_{i=1}^n y_i(\hat{\alpha}_i - \alpha_i) - \varepsilon(\hat{\alpha}_i + \alpha_i) - \frac{1}{2} \sum_{i=1}^n \sum_{j=1}^n (\hat{\alpha}_i - \alpha_i)(\hat{\alpha}_j - \alpha_j) \varphi(x_i)^T \varphi(x_j) \quad (4)$$

$$st \begin{cases} \sum_{i=1}^n (\hat{\alpha}_i - \alpha_i) = 0 \\ 0 \leq \alpha_i, \hat{\alpha}_i \leq C \end{cases} \quad (5)$$

where α_i and $\hat{\alpha}_i$ are the introduced Lagrangian multipliers; therefore, we can obtain:

$$w = \sum_{i=1}^n (\hat{\alpha}_i - \alpha_i) \varphi(x_i) \quad (6)$$

That is, the regression model can be expressed as Equation (7):

$$f(x) = \sum_{i=1}^n (\hat{\alpha}_i - \alpha_i) K(x_i, x_j) + b \quad (7)$$

where $K(x_i, x_j) = \varphi(x_i)^T \varphi(x_j)$ is the kernel function, i.e., the selection and construction of the kernel function needed to satisfy Mercer's theorem. In this paper, the radial basis function (RBF) was selected, and its expression is as per Equation (8):

$$K(x_i, x_j) = \exp\left(-\frac{1}{2\sigma^2} \|x_i - x_j\|^2\right) \quad (8)$$

where σ is the parameter of kernel function, which denotes the width coefficient of the RBF.

2.2. Particle Swarm Optimization

The PSO [43] is a global random search algorithm that simulates the foraging behavior of birds. Assuming that particles fly in a D-dimensional solution set space, each particle has two attributes: position and velocity. The position of particle i at the current time t is $X_i^t = [x_{i1}^t, x_{i2}^t, \dots, x_{iD}^t]$, which represents a solution in the D-dimensional solution set space, and the velocity $V_i^t = [v_{i1}^t, v_{i2}^t, \dots, v_{iD}^t]$ represents the direction and distance of the next flight of the particle; $Pbest_i = [p_{i1}, p_{i2}, \dots, p_{iD}]^T$ is the optimal position experienced by particle i , and $Gbest = [g_1, g_2, \dots, g_D]^T$ is the optimal position experienced by the particle population. Each particle updates the individual optimal position and the global optimal position according to the velocity update (Equation (9)) and the position update (Equation (10)):

$$V_i^{t+1} = \omega V_i^t + c_1 r_1 (Pbest_i - X_i^t) + c_2 r_2 (Gbest - X_i^t) \quad (9)$$

$$X_i^{t+1} = X_i^t + V_i^{t+1} \quad (10)$$

where ω is the inertia constant, which is usually in the range of 0.8–1.2; c_1 and c_2 are learning factors, which adjust the step size of the particle flying in the direction of the individual optimal position, as well as the direction of the global optimal position; and r_1 and r_2 are constants, which are usually random numbers between 0 and 1.

Usually, in experimental studies, when ω takes a large value, the algorithm converges with difficulty, and when ω takes a small value, the algorithm tends to fall into local extremum [44]. Thus, in this paper, adaptive ω values were adopted so that ω decreased linearly; ω takes a larger value in the early stage of the algorithm to improve the search ability and a smaller value in the later stage of the algorithm to ensure that the algorithm can search carefully around the optimal extremum, converging to the global optimal extremum. At the same time, in order to avoid the algorithm falling into local optimization and to

increase the diversity of particles, we added adaptive mutation to the PSO; after the fitness of each generation of particles is calculated, the particles with low fitness value undergo a random mutation within the specified range.

2.3. The PSO–SVR Method

More and more optimization algorithms are used for parameter identification, including particle swarm optimization [32], genetic algorithm [45], bird mating optimization algorithm [46], grey wolf optimizer [47], atom search optimizer [48], selective hybrid stochastic strategy [49] and so on. In the SVR algorithm, the penalty factor C , as well as the kernel parameter γ , directly determine the accuracy of the algorithm. At present, there is no clear guideline scheme for the selection of parameters; thus, the PSO was selected here to find the appropriate parameters of the SVR.

The specific execution flow of PSO–SVR is shown in Figure 1, which mainly contains the following steps:

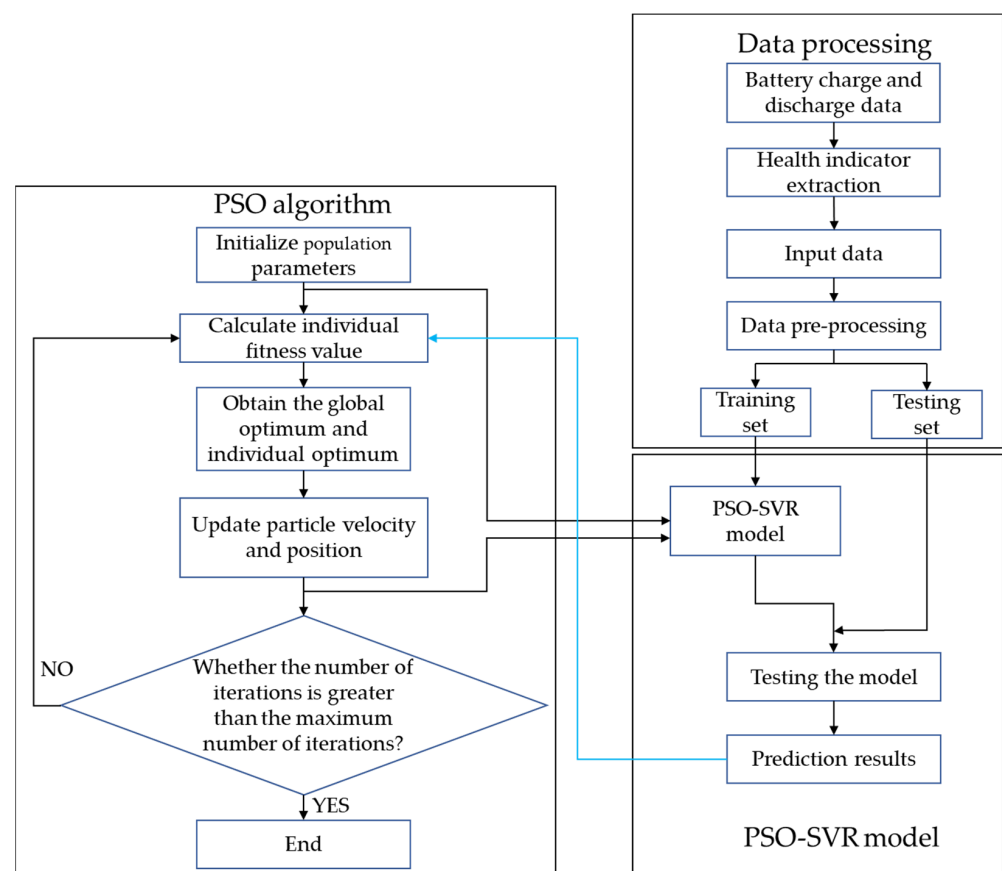


Figure 1. Flowchart of the PSO–SVR method.

Step 1. Indirect health indicator extraction and data processing: First, the battery discharge voltage needs to be processed to extract the indirect HI characterizing the battery capacity degradation. Then, the extracted indirect HI of the k th cycle and the number of cycles k are used as the input features of the model to predict the capacity value of cycle $k + 1$, and the data are divided into a training set and a testing set.

Step 2. Parameter initialization of the PSO algorithm: In PSO, the number of particles is 40, the number of iterations is 200, the maximum value of the penalty factor C , the parameter γ is 200, and the minimum value is 0.0001.

Step 3. Set the fitness function: In this paper, the mean square error (MSE) was selected as the fitness function to evaluate the accuracy of the model prediction:

$$MSE = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2 \quad (11)$$

where y_i and $\hat{y}_i$ denote the actual capacity and the predicted capacity of cycle i , respectively, and n denotes the number of predicted samples.

Step 4. The PSO algorithm performs a parameter optimization: (1) The initialized parameters of each particle are introduced into the SVR model for training and prediction, and the prediction results are introduced into Equation (11) to calculate the fitness value of each particle. (2) The global optimal position and individual optimal position of the particles are recorded. (3) Then, the position of each particle is updated according to Equations (9) and (10). (4) Repeat (1)–(3) until the cutoff condition is reached.

Step 5. SOH and RUL prediction: The global optimal parameters optimized by the PSO algorithm are introduced into the SVR model to predict the SOH and RUL of Li-ion batteries.

3. Extraction of an Indirect Health Indicator

3.1. Dataset

The charge and discharge data of the B0005 (B5), B0006 (B6), B0007 (B7), and B0018 (B18) batteries of the NASA Prognostics Center of Excellence were selected for this study [50]. The batteries all had an initial capacity of 2Ah and were specified to reach EoL when the capacity decayed to 70% of the initial capacity during the charge/discharge cycle.

Each battery was experimented on with the three different modes of charging, discharging, and impedance. As shown in Table 1, the charging process started with a constant current charge of 1.5 A, and when the voltage reached 4.2 V, a constant voltage charge was carried out until the current dropped to 20 mA. In the discharge mode, a constant current discharge was carried out at a current of 2 A until the voltages dropped to their respective cutoff voltages.

Table 1. Experimental conditions for the battery dataset.

No.	Temperature (°C)	Constant Current Charging Current (A)	Charge Cut-Off Voltage (V)	Constant Discharge Current (A)	Discharge Cut-Off Voltage (V)	Capacity (Ah)
5	24	1.5	4.2	2.0	2.7	2.0
6	24	1.5	4.2	2.0	2.5	2.0
7	24	1.5	4.2	2.0	2.2	2.0
18	24	1.5	4.2	2.0	2.5	2.0

Figure 2 shows the change process of the current and voltage in the first cycle of the B5 battery. Figure 3 shows the capacity degradation trend and the battery failure threshold. Overall, the battery capacity decreased as the number of cycles increased, but the capacity regeneration phenomenon after battery resting led to a local rebound of the battery capacity. It can also be seen that the B7 battery did not reach the failure threshold during the whole life cycle; therefore, this paper took 72% of the initial capacity as the failure threshold for the B7 battery to reach the EoL.

3.2. Extraction of a Novel Indirect Health Indicator

Figure 4 shows the change of the discharge voltage with time under different discharge cycles. Starting with the constant current discharge stage, the voltage gradually dropped from 4.2 V to the cutoff voltage, followed by a regeneration of the battery capacity, causing the discharge voltage to rise back up. From the figure, we can see that as the battery aged, it took a shorter time for the voltage to drop to the cutoff voltage. Therefore, from the start of discharge to the cutoff voltage, we took the integral of the voltage over time (IVT) as a

new HI, as shown in the pink area of the figure below, to characterize the energy that the battery could release. We found that the area decreased as the number of cycles increased, and the pink area can be expressed as Equation (12):

$$S_i = \int_{t_0}^{t_{cutoff}} u_i dt \quad (12)$$

where S_i is the area at cycle i , t_0 is the time to start discharging, t_{cutoff} represents the time taken to reach the cutoff voltage, and u_i is the real-time value of the discharging voltage in cycle i .

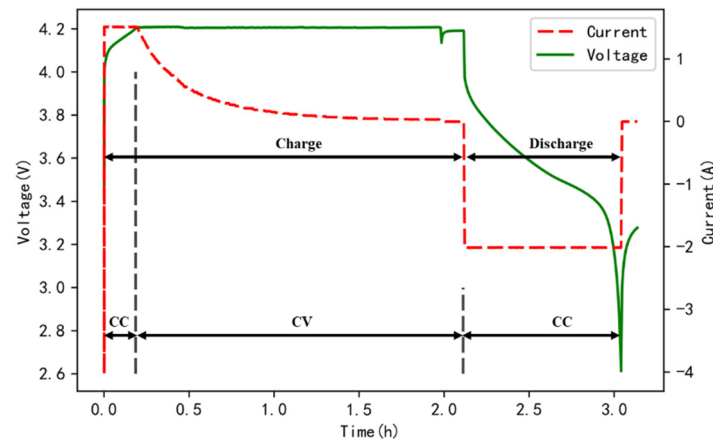


Figure 2. Charge and discharge process in the first cycle of the B5 battery.

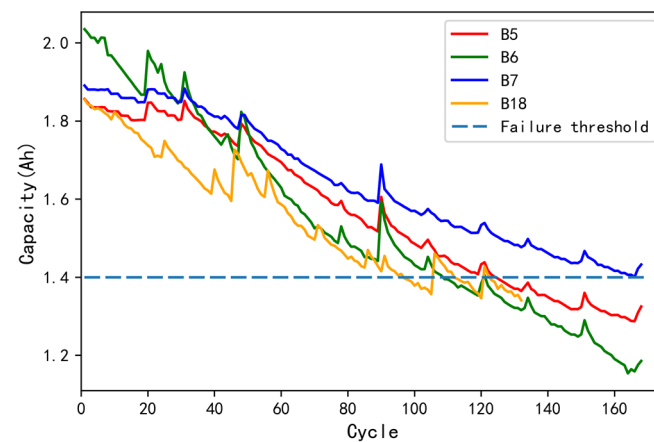


Figure 3. Battery capacity degradation curve.

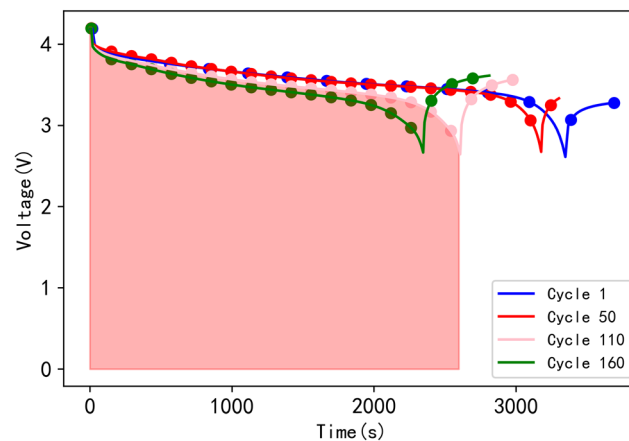


Figure 4. Discharge voltage change curves in different cycles of the B5 battery.

The extraction process of IVT has the following three main steps.

Step 1. Extraction of the discharge voltage and time data for each discharge cycle;

Step 2. Performing a polynomial fit to the discharge voltage and time data;

Step 3. Calculating the IVT according to Equation (12).

Based on the above extraction process, the IVTs of the above four batteries were extracted, respectively, which is shown in Figure 5.

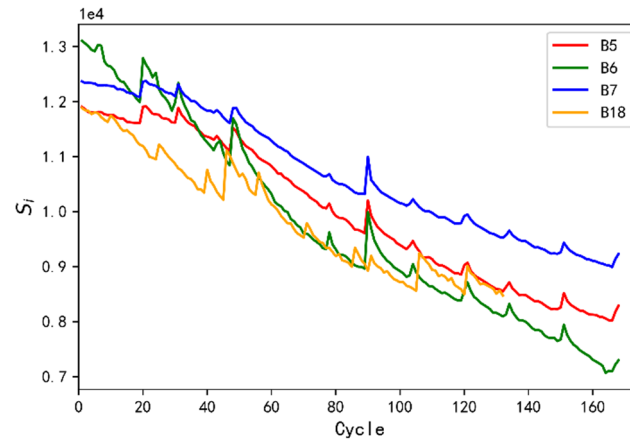


Figure 5. Change curves of the IVTs.

3.3. Pearson's Correlation Analysis

Pearson's correlation analysis is commonly used to measure the degree of correlation between two sets of variables. Assuming that the two sets of variables are $U = \{U_1, U_2, U_3, \dots, U_n\}$ and $V = \{V_1, V_2, V_3, \dots, V_n\}$, their Pearson's correlation coefficients can be expressed as Equation (13):

$$r = \frac{\sum_{i=1}^n (U_i - \bar{U})(V_i - \bar{V})}{\sqrt{\sum_{i=1}^n (U_i - \bar{U})^2} \sqrt{\sum_{i=1}^n (V_i - \bar{V})^2}} \quad (13)$$

where the value range of r is -1 to 1 . When $r = \pm 1$, a strict linear correlation between the two sets of variables is indicated; when $r = 0$, a linear independence between the two sets of variables is suggested; and when r is within $(-1, 0)$ or $(0, 1)$, it means that there is a correlation between the two sets of variables, and the correlation is proportional to the absolute value of r .

Table 2 shows the Pearson's correlation coefficients between the capacity and IVTs of the four batteries, and the absolute values are above 0.999. This shows the validity of the IVTs; that is, IVTs can be used as the input features of the SVR to achieve the online prediction of the SOH and RUL of Li-ion batteries.

Table 2. Results of the correlation analysis between the IVTs and battery capacity.

No.	Pearson's Correlation Coefficient
5	0.99995
6	0.99980
7	0.99987
18	0.99977

4. Battery SOH and RUL Prediction

4.1. Evaluation Criteria

To evaluate the effectiveness of the proposed prediction method, the mean absolute error (MAE), the root mean square error (RMSE), the R^2 score, and the error were selected as the evaluation criteria:

MAE:

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i| \quad (14)$$

RMSE:

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (15)$$

R^2 :

$$R^2 = 1 - \frac{\sum_{i=1}^n (\hat{y}_i - y_i)^2}{\sum_{i=1}^n (\bar{y} - y_i)^2} \quad (16)$$

Error:

$$Error = |\widehat{RUL} - RUL| \quad (17)$$

where y_i and $\hat{y}_i$ denote the actual capacity and the predicted capacity of cycle i , respectively, $\bar{y}$ denotes the average of the true capacity values, n denotes the total number of samples, and $\widehat{RUL}$ and RUL denote the predicted and true values of the RUL, respectively.

4.2. Prediction Results

This paper selected the first 40% and 50% of the sample data in the battery life cycle as the training set, and used the last 60% and 50% of the sample data as the testing set.

Table 3 shows the results of PSO for optimizing the SVR parameters. We compared the PSO–SVR method to DNN, LSTM (see Appendix A for more details), and SVR ($C = 100$, $\gamma = 0.01$) at the same prediction start point. Figures 6 and 7 and Table 4 show the results of the PSO–SVR method compared to the different algorithms (where “-” indicates that the prediction capacity value is not reduced to the failure threshold). We can find that the prediction results of the PSO–SVR are significantly better than those of the other algorithms, except for the MAE of PSO–SVR, which is 0.0001 higher than that of SVR on the B18 battery when the first 40% of the dataset was used as the training set. In general, the prediction results of the model are essentially consistent with the decreasing trend in the actual capacity, at the same time, the model can also feedback the fluctuation data generated by capacity regeneration or other noise in time.

Table 3. The results of PSO for optimizing the SVR parameters.

No.	Start Point	C	γ
5	69	78.17	0.04017
	85	14.56	0.09385
6	69	32.10	0.06572
	85	7.92	0.06847
7	69	34.88	0.05593
	85	44.26	0.02135
18	54	96.50	0.01042
	67	115.41	0.57710

When the first 40% of the dataset is used as the training set, the maximum error, the maximum MAE and the maximum RMSE of PSO–SVR are 4, 0.0194 and 0.0269, respectively. Taking B5 as an example, the MAE of PSO–SVR is 0.0083, while the MAEs of the DNN, LSTM, and SVR are 0.1175, 0.0282, and 0.0312, respectively; similarly, the RMSE of PSO–SVR is 0.0137, while the RMSEs of DNN, LSTM, and SVR are 0.1313, 0.0330, and 0.0325, respectively. In terms of R^2 , the larger the R^2 value, the better the prediction effect, and the R^2 value of PSO–SVR is 0.9816, which is significantly larger than that of the other methods.

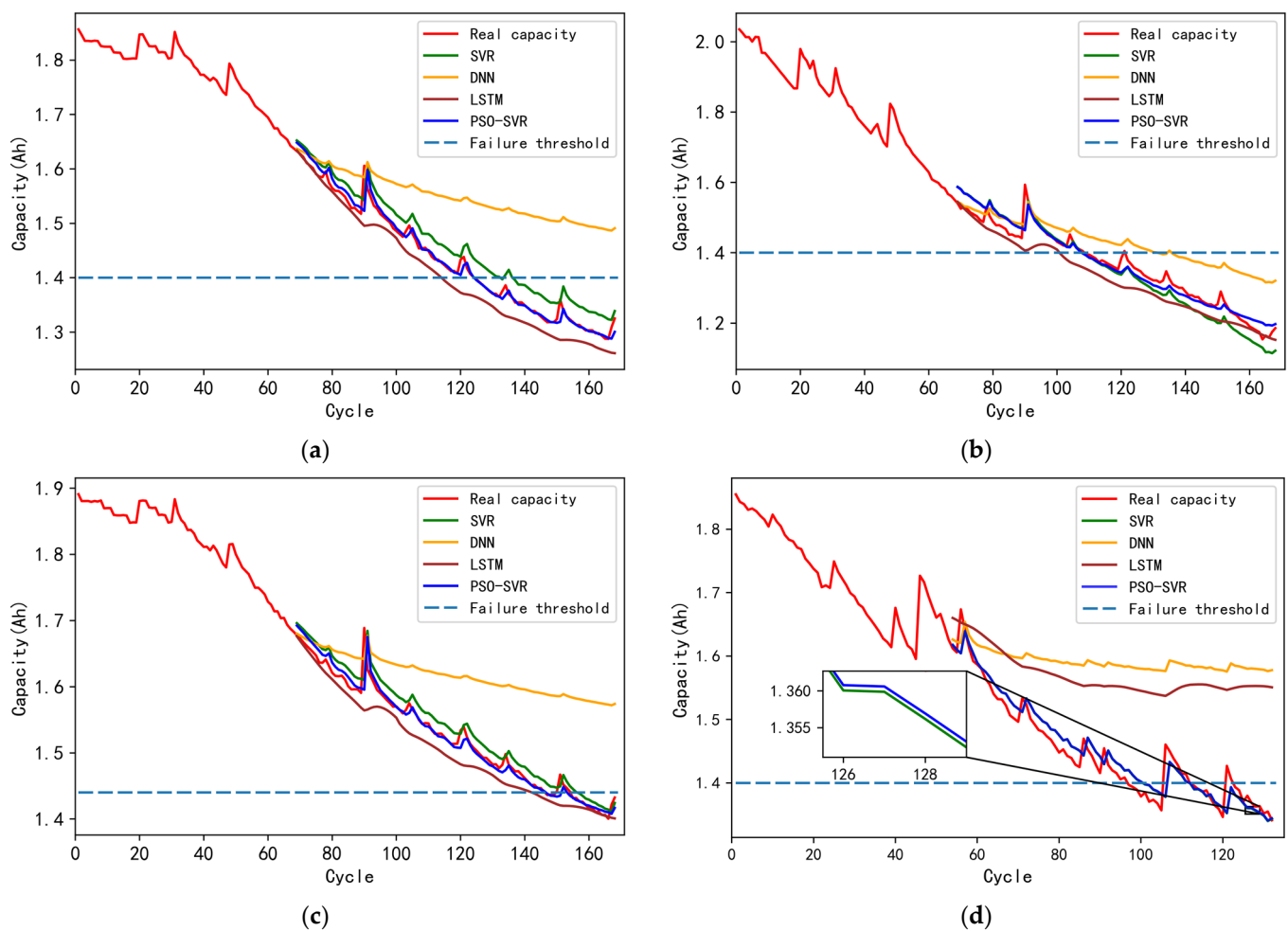


Figure 6. Prediction results based on SVR, DNN, LSTM and PSO-SVR using the first 40% of the total cycle data for training: (a) B5; (b) B6; (c) B7; (d) B18.

When the first 50% of the dataset is used as the training set, the maximum error, the maximum MAE and the maximum RMSE of PSO-SVR are 1, 0.0177 and 0.0230, respectively. Additionally, taking B5 as an example, the MAE of PSO-SVR is 0.0076, while the MAEs of DNN, LSTM and SVR are 0.0852, 0.0125, and 0.0157, respectively; similarly, the RMSE of PSO-SVR is 0.0133, while the RMSEs of the DNN, LSTM, and SVR are 0.0957, 0.0185, and 0.0183, respectively. In terms of R^2 , the R^2 value of the PSO-SVR is 0.9726, which is also significantly larger than that of the other methods.

When predicting the B18 battery and using the first 40% of the dataset as the training set, and when predicting the B7 battery and using the first 50% of the dataset as the training set, the prediction results of PSO-SVR and SVR are almost the same, which shows that when we initialize the SVR parameters, we select the appropriate parameters.

Overall, the prediction results of PSO-SVR highly fitted the actual capacity values, which proves that the PSO-SVR method can realize the accurate online prediction of Li-ion batteries' SOH and RUL and provide the necessary information for the maintenance and replacement of Li-ion batteries.

Figures 8 and 9, respectively, show the absolute error (AE) and MAE between the true value and the predicted value obtained by different prediction algorithms when the first 40% and 50% of the dataset were used as the training set. We can find that the AE of PSO-SVR is significantly smaller than that of the DNN, LSTM, and SVR, and the AE of PSO-SVR almost remained within 0.02. In terms of the MAE, the PSO-SVR method retained it within 0.02, and the MAE of the PSO-SVR method is less than 0.01 for the B5 battery and when the first 40% of the B7 battery dataset was used as the training set.

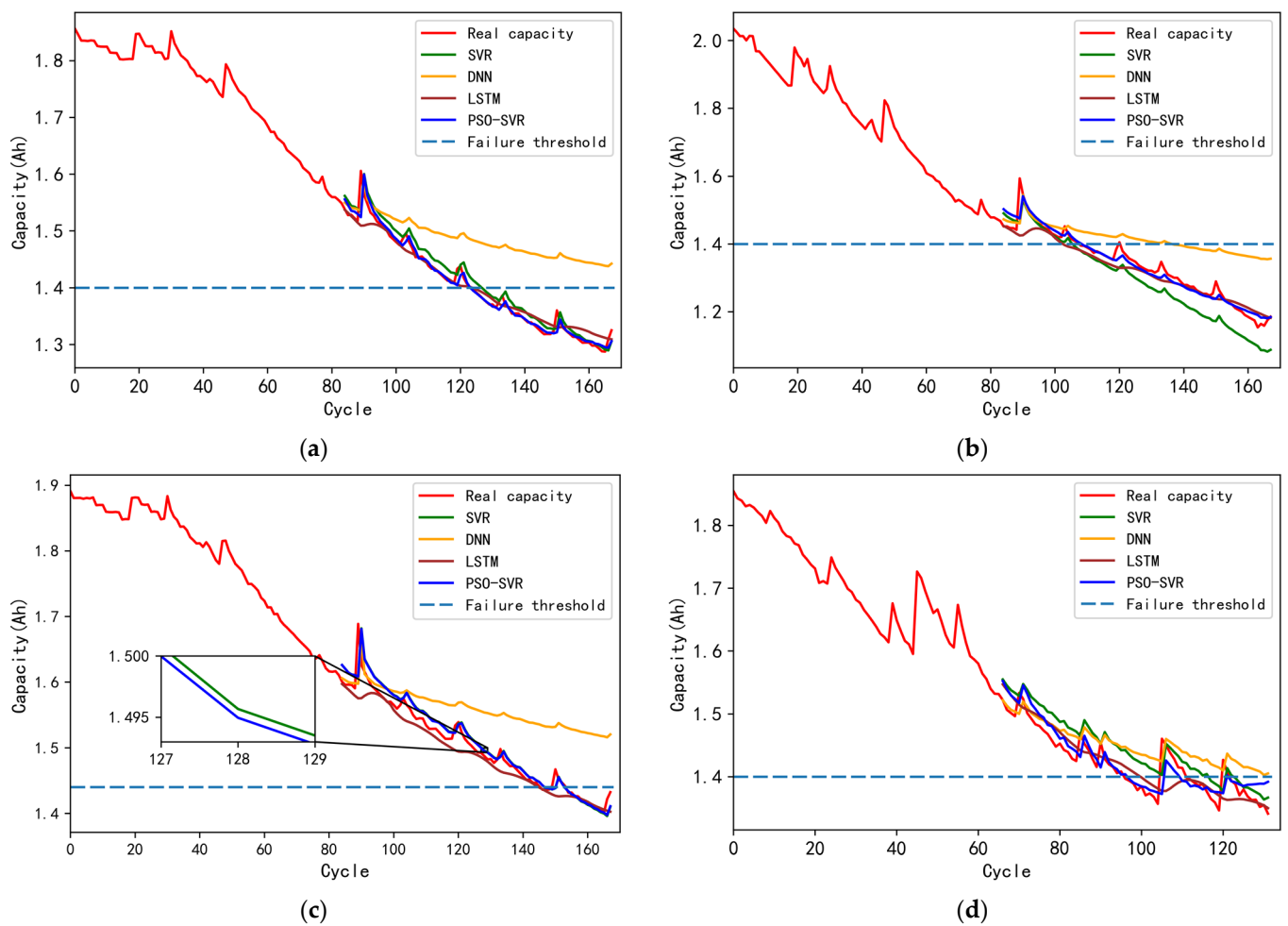


Figure 7. Prediction results based on SVR, DNN, LSTM and PSO-SVR using the first 50% of the total cycle data for training: (a) B5; (b) B6; (c) B7; (d) B18.

Table 4. Comparison of the results of the different prediction methods.

No.	Start Point	Method	Actual RUL	Predicted RUL	Error	MAE	RMSE	R^2
5	69	DNN	56	-	-	0.1175	0.1313	-0.6972
		LSTM		46	10	0.0282	0.0330	0.8924
		SVR		64	8	0.0312	0.0325	0.8961
		PSO-SVR		56	0	0.0083	0.0137	0.9816
	85	DNN	40	-	-	0.0852	0.0957	-0.4212
		LSTM		40	0	0.0125	0.0185	0.9470
		SVR		43	3	0.0157	0.0183	0.9479
		PSO-SVR		40	0	0.0076	0.0133	0.9726
6	69	DNN	40	63	23	0.0675	0.0802	0.4622
		LSTM		32	8	0.0403	0.0492	0.7977
		SVR		39	1	0.0306	0.0369	0.8865
		PSO-SVR		39	1	0.0194	0.0269	0.9397
	85	DNN	24	53	29	0.0815	0.0996	-0.0090
		LSTM		19	5	0.0233	0.0344	0.08798
		SVR		22	2	0.0467	0.0545	0.6975
		PSO-SVR		25	1	0.0141	0.0219	0.9510

Table 4. Cont.

No.	Start Point	Method	Actual RUL	Predicted RUL	Error	MAE	RMSE	R^2
7	69	DNN	78	-	-	0.0932	0.1046	-0.7833
		LSTM		74	4	0.0213	0.0268	0.8833
		SVR		88	10	0.0176	0.0198	0.9362
		PSO-SVR		78	0	0.0080	0.0139	0.9687
	85	DNN	62	-	-	0.0588	0.0679	-0.1013
		LSTM		61	1	0.0130	0.0202	0.9021
		SVR		63	1	0.0123	0.0168	0.9329
		PSO-SVR		63	1	0.0118	0.0164	0.9360
18	54	DNN	43	-	-	0.1454	0.1577	-3.0975
		LSTM		-	-	0.1232	0.1322	-1.8809
		SVR		47	4	0.0168	0.0219	0.9211
		PSO-SVR		47	4	0.0169	0.0219	0.9211
	67	DNN	30	-	-	0.0348	0.0391	0.3564
		LSTM		34	4	0.0195	0.0251	0.7340
		SVR		51	21	0.0301	0.0335	0.5282
		PSO-SVR		31	1	0.0177	0.0230	0.7774

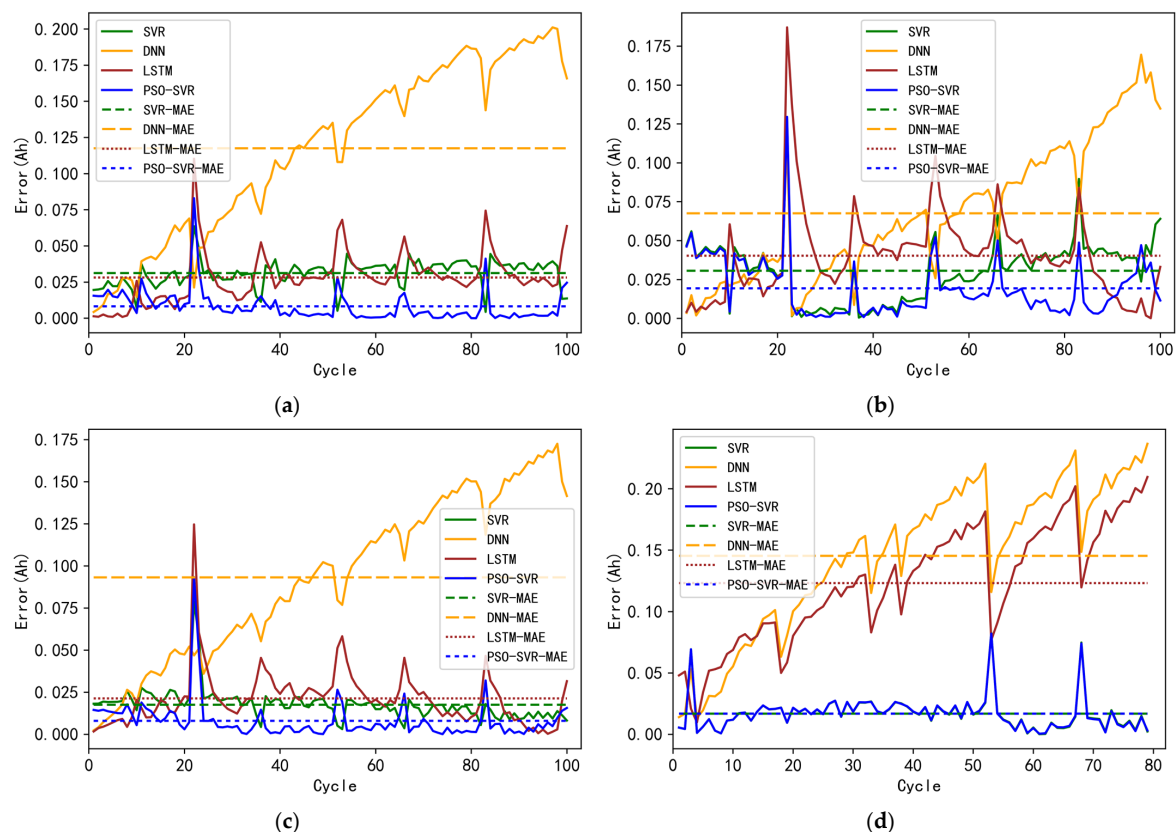


Figure 8. Absolute error and mean absolute error based on SVR, DNN, LSTM and PSO-SVR using the first 40% of the total cycle data for training: (a) B5; (b) B6; (c) B7; (d) B18.

In addition, a comparison was made to similar studies in the literature, in which the failure threshold was uniformly set to 1.44 Ah, and the results are shown in Table 5. We can find that only for the B5 battery, when the prediction start point was 68, the error value of PSO-SVR was one value larger than that of the method used in the literature [29]; meanwhile, when the prediction start point was 84, the error value of PSO-SVR was the same as that of the method in the literature [29]. For the B18 battery, when the prediction start point was 53, the error value of PSO-SVR was the same as the method in the litera-

ture [29]; meanwhile, when the prediction start point was 66, the error value of PSO-SVR was 0, which was better than that of the method in the literature [29]. For the B6 and B7 batteries, the error value of PSO-SVR was significantly smaller than that of the method in the literature [29]. When the prediction start point was 68, the error value of PSO-SVR for both was 0, and when the prediction start point was 84, the error value of PSO-SVR was 1/4 and 1/12 of that of the method in the literature [29], respectively.

Table 5. Comparison of the results of PSO-SVR to that of other prediction methods.

No.	Start Point	Method	Actual RUL	Predicted RUL	Error
5	68	ALO-SVR [29]	43	43	0
		PSO-SVR	43	44	1
	84	ALO-SVR [29]	27	27	0
		PSO-SVR	27	27	0
6	68	ALO-SVR [29]	31	35	4
		PSO-SVR	32	32	0
	84	ALO-SVR [29]	15	19	4
		PSO-SVR	16	17	1
7	68	ALO-SVR [29]	78	97	19
		PSO-SVR	79	79	0
	84	ALO-SVR [29]	62	74	12
		PSO-SVR	63	64	1
18	53	ALO-SVR [29]	30	38	8
		PSO-SVR	30	38	8
	66	ALO-SVR [29]	17	19	2
		PSO-SVR	17	17	0

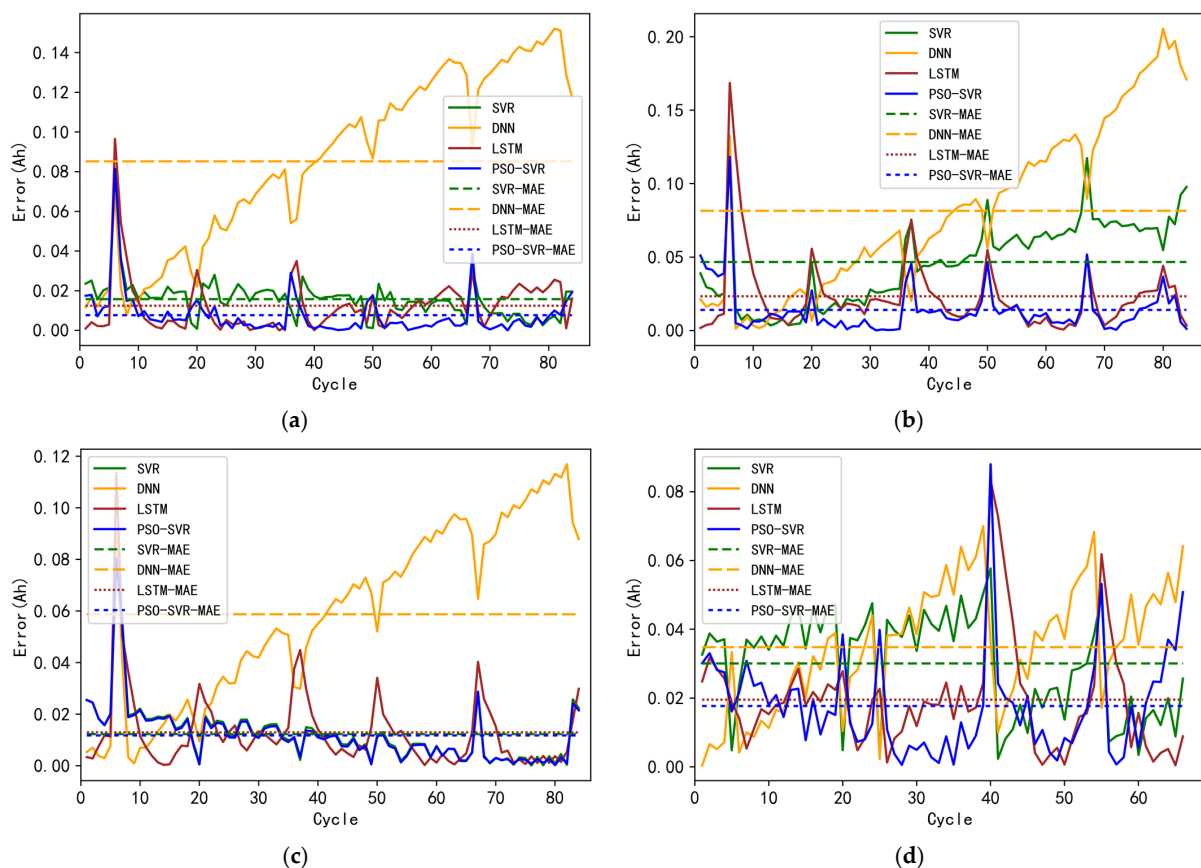


Figure 9. Absolute error and mean absolute error based on SVR, DNN, LSTM and PSO-SVR using the first 50% of the total cycle data for training: (a) B5; (b) B6; (c) B7; (d) B18.

5. Conclusions

For the problem of the SOH and RUL prediction of Li-ion batteries, the IVT based on discharge voltage and an online prediction method of PSO–SVR were proposed in this paper.

Firstly, the IVT used to characterize the capacity of the battery was extracted from the discharge voltage. Secondly, the SVR model was selected to predict the SOH and RUL for the characteristics of NASA battery aging data, and then the IVT and cycle number were taken as the input features of the model to achieve online prediction of the SOH and RUL, and the PSO–SVR model was constructed for the problem of parameter selection for the SVR, and the optimal parameters of the SVR were obtained by using the PSO algorithm. Finally, the prediction results showed the feasibility of this scheme and also demonstrated the superiority of this scheme when compared to other algorithms and similar studies in the literature.

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Abbreviations

SOH	State of health
RUL	Remaining useful life
EoL	End of life
SOC	State of charge
SVR	Support vector regression
DNN	Deep neural network
LSTM	Long short-term memory
PSO	Particle swarm optimization
HI	Health indicator
IVT	Integral of the voltage over time

Appendix A

The details of the DNN and the LSTM networks used in this paper are shown in Table A1. In order to prevent overfitting, we have added the early stopping method to the DNN and the LSTM.

Table A1. The details of the DNN and LSTM networks.

Algorithm	Layer Type	Nodes	Activation	Others
DNN	Dense	100	Relu	Optimizer = Adam Loss = mean absolute error Batchsize = 16 Epoch = 200 Monitor = val_loss Patience = 50
	Dense	100	Relu	
	Dropout	100 (rate = 0.25)	None	
	Dense	1	None	

Table A1. Cont.

Algorithm	Layer Type	Nodes	Activation	Others
LSTM	LSTM	100	Tanh	Optimizer = Adam
	Dropout	100 (rate = 0.3)	None	Loss = mean absolute error
	Dense	1	None	Batchsize = 16 Epoch = 200 Monitor = val_loss Patience = 10

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