Improved Whale Optimization Algorithm and Support Vector Machine for Remaining Useful Life Prediction of Lithium-ion Batteries

Y. Z. Wang[1], Y. L. Ni[1,*], Y. Z. Zhang[2], Z. L. Shen[3], S. D. Zhang[1] and J. G. Wang[1]

[1]*Jilin Province International Research Center of Precision Drive and Intelligent Control, Northeast Electric Power University, Jilin 132012, China*

[2]*Zhang Jiakou Wind, Photovoltaic and Energy Storage Demonstration Station Co., Ltd. State Grid Xinyuan Company, Zhang Jiakou 075000, China*

[3]*Dalian Power Plant, Huaneng Power International Inc., Dalian 116100, China*

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Abstract: Prediction of remaining useful life (RUL) of Lithium-ion batteries (LIBs) is a key component of the prognostics and health management (PHM). A method based on improved whale optimization algorithm and support vector machine (IWOA-SVM) is proposed, which can improve the prediction accuracy for RUL of LIBs and timely maintain and replace the battery to ensure the safety and stability of the energy storage system. With the number of iterations increase, the WOA algorithm inevitably falls into local optimal solution. Therefore, the adaptive weights are introduced to improve the global search ability of the WOA algorithm. To verify the performance of the proposed method, the five test functions are utilized to compare with WOA algorithm. Experimental data simulations were performed using NASA Ames Prognostics Center of Excellence (PCoE) datasets to verify the proposed method. Compared with the SVM and WOA-SVM methods, the results show that the proposed method can accurately ensure RUL prediction accuracy.

1 INTRODUCTION

Lithium-ion batteries (LIBs) have been widely used in electric vehicles (EVs) and energy storage systems (ESS) due to their high energy densities, low self-discharge rate, and long lifetime (Xiong R, Tian J, Mu H and Wang C, 2017). With the service of LIBs, the safety problems caused by the degradation of LIBs have attracted much attention. Remaining useful life (RUL) is the number of times from the current time to the failure threshold under a certain condition, and it is an indicator for evaluating the state of health for LIBs (Wang Y, Ni Y, Lu S, Wang J and Zhang X, 2019). The battery performance is rapidly degraded when the capacity of LIB is reduced by 70%-80% of the rated capacity (Duong P L T and Raghavan N, 2018). Accurately predicting the remaining useful life (RUL) of LIBs is of great significance to battery maintenance and prevention of dangerous accidents.

There are mainly two methods in predicting the RUL of LIBs, one is the model-based methods such as the particle filter (PF) (Lyu C, Lai Q, Ge T, Yu H, Wang L and Ma N, 2017), the other one is the data-driven approaches such as the artificial neural networks (ANN) (You G W, Park S and Oh D, 2017) and support vector machine (SVM) (Patil M, Tagade P, Hariharan K, Kolake S, Song T, Yeo T and Doo S, 2015). The model-based methods analyse the operating mechanism of the battery from the perspective of the electrochemical mechanism for LIBs and are difficult to model due to the complexity of capacity degradation trajectory for LIBs (Zhang Y, Xiong R, He H and Pecht M G, 2019). Guha et al. (Guha A and Patra A, 2018) proposes a fractional-order equivalent circuit model (FOECM), which the parameters are determined via recursive least-squares method and a fractional-order state variable filter and estimate the electrochemical impedance spectrum (EIS), then combine with PF method to predict RUL of LIBs. The data-driven approaches do not require consideration of electrochemical mechanisms, which mine the hidden information from the historical degradation data. Qin et al. (Qin T, Zeng S and Guo

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J, 2015) utilized particle swarm optimization (PSO) to optimize the support vector regression (SVR) kernel parameter and can obtain accurate prediction results. Li et al. (Li L, Liu Z, Tseng M and Chiu A, 2019) proposed the improved bird swarm algorithm to optimize least squares SVM (IBSA-LSSVM) and improve the prediction accuracy of battery RUL. Gao et al. (Gao D and Huang M, J., 2017) employed the PSO algorithm to search the kernel parameters of the multi-kernel SVM (MSVM) model to improve the RUL prediction accuracy. Li et al. (Li S and Fang H, 2017) proposed the WOA algorithm to select the parameter of SVR. Although the SVM method can predict RUL of LIBs, there is still problem in how to select the optimal parameters and provide high accuracy.

The main contribution of this work is to establish the IWOA-SVM method to improve the prediction accuracy of RUL for LIBs. The WOA-SVM method cannot ensure the prediction accuracy due to the WOA algorithm easily falls into the local optimal solution, therefore, the adaptive weights are introduced to solve this shortcoming. The performance of the IWOA algorithm is verified via five test functions. Besides, compared with the SVM and WOA-SVM methods, the results show that the IWOA-SVM method can provide higher prediction accuracy of RUL for LIBs.

The remainder of this work is organized as follows: Section 2 reviews the related method and the detailed implementation of the proposed method is presented. The experimental results by comparing with SVM and WOA-SVM methods are presented in Section 3. Section 4 presents the conclusions.

2 MODEL ESTABLISHMENT

2.1 SVM Method

When the support vector machine (SVM) (Wei J, Dong G and Chen Z, 2018) is utilized for regression prediction, according to given simple set $D = \{(x_i, y_i) \mid i = 1,2,...,m\}$, ($x_i \in R^m$, $y_i \in R$), where x_i is the i-th input value, $y_i \in R$ denotes the i-th output value, and m represents the total number of samples. Therefore, the regression of SVM can be denoted as:

$$f(x) = w^T \cdot \phi(x) + b \tag{1}$$

where w is a weight, ϕ represents a nonlinear mapping, and b denotes the intercept. The dual problem of SVM can be obtained by introducing the Lagrangian multipliers:

$$\min_{\alpha_i,\hat{\alpha}_i}\left(-\frac{1}{2}\sum_{i,j}^{m}(\hat{a}_i - a_i)(\hat{a}_j - a_j)K(x_i,x_j) - \sum_i^m a_i(y_i+\varepsilon) + \sum_i^m \hat{a}_i(y_i-\varepsilon)\right) \tag{2}$$

$$s.t.\begin{cases}\sum_i^m (a_i - \hat{a}_i) = 0, \\ 0 \le a_i, \hat{a}_i \le C, \qquad i = 1,2,..m\end{cases} \tag{3}$$

where a_i, $\hat{a}_i$, a_j, and $\hat{a}_j$ are the Lagrangian multipliers, $K(x_i, x_j)$ is the kernel function, and the radial basis function $K_{RBF}(x_i,x_j) = \exp(-\| x_i - x_j \|^2 / (2\sigma^2))$ is chose in the SVR. Where σ is the parameter of kernel function. Therefore, the regression function of the SVM can be presented:

$$f(x) = \sum_i^n (a_i - \hat{a}_i) K_{RBF}(x_i, x_j) + b \tag{4}$$

2.2 Whale Optimization Algorithm and Improved Whale Optimization Algorithm

2.2.1 Whale Optimization Algorithm

The WOA (Mirjalili S and Lewis A, 2016) is a meta-heuristic optimization algorithm that mainly simulates the humpback whale hunting behavior, namely the bubble-net hunting method.

1) Encircling the prey: The humpback whales can quickly encircle the prey after noticing the prey, and constantly update its position, which can be denoted as

$$\vec{D} = |\vec{C} \cdot \vec{X}^*(t) - \vec{X}(t)| \tag{5}$$

$$\vec{X}(t+1) = \vec{X}^*(t) - \vec{A} \cdot \vec{D} \tag{6}$$

where t is the current iteration, X^* denotes the position of the current optimal solution, and X indicates the position of the whale. $\vec{A}$ and $\vec{C}$ are the coefficient vector.

2) Bubble net attacking: Two approaches of shrinking encircling mechanism and the location is updated by spiral are presented to model the whale hunting behavior, which the mathematical model can be expressed as follows:

$$\vec{X}(t+1) = \begin{cases}\vec{X}^*(t) - \vec{A} \cdot \vec{D} & if\ p < 0.5 \\ \vec{D}' \cdot e^{bl} \cdot \cos(2\pi l) + \vec{X}^*(t) & if\ p \ge 0.5\end{cases} \tag{7}$$

where $\vec{D}'$ represents the distance between the i-th whale and the current optimal position, b is a the constant coefficient utilized to define the logarithmic spiral form, l denotes the random number between -

1 and 1, and p denotes the random number between 0 and 1.

3) Search for prey: When $|A| \geq 1$, the humpback whales are randomly selected to force them away from a reference whale to find a better prey in order to enhance the global search ability of the algorithm. The mathematical model is expressed as follows:

$$\vec{X}(t+1) = \vec{X}_{rand} - \vec{A} \cdot \vec{D} \quad (8)$$

where $\vec{D} = |\vec{C} \cdot \vec{X}_{rand} - \vec{X}|$ and $\vec{X}_{rand}$ denotes the position vector of the whale randomly selected.

2.2.2 Improved Whale Optimization Algorithm

The introduction of adaptive inertia weight in the WOA algorithm (IWOA) makes the algorithm adaptively update the position of the WOA algorithm to improve the optimization accuracy. The model can be expressed as follows:

$$\vec{X}(t+1) = \begin{cases} w_1 \cdot \vec{X}^*(t) - w_2 \cdot \vec{A} \cdot \vec{D} & if\ p < 0.5 \\ \vec{D}' \cdot e^{bl} \cdot \cos(2\pi l) + w_1 \cdot \vec{X}^*(t) & if\ p \geq 0.5 \end{cases} \quad (9)$$

where $w_1 = -0.5 * [\cos(0.5\pi * (t/T)) - 0.5]$ is the adaptive coefficient of the current optimal position and $w_2 = 0.5 * [\cos(0.5\pi * (t/T)) + 0.5]$ represents the adaptive coefficient of the encircling step.

To test the search ability of the IWOA algorithm, compared with WOA algorithm through five test functions. The five test functions are presented in table 1. The number of population (NP) is 40 and the number of maximum iteration (Max_iter) is 100 for two algorithms. Each function calculates 10 times for each algorithm in 2 dimensions (D) and 30 D, and the test results are shown in table 2.

Table 1: The five test functions.

Test functions	Range	The optimal value
$f_1 = \sum_{i=1}^{n} x_i^2$	[-100,100]	0
$f_2 = \sum_{i=1}^{n} i x_i^2$	[-10,10]	0
$f_3 = \sum_{i=1}^{n} \lvert x_i \rvert + \prod_{i=1}^{n} \lvert x_i \rvert$	[-10,10]	0
$f_4 = \sum_{i=1}^{n} [x_i^2 - 10\cos(2\pi x_i) + 10]$	[-5.12,5.12]	0
$f_5 = \frac{1}{4000}\sum_{i=1}^{n} x_i^2 - \prod_{i=1}^{n} \cos(\frac{x_i}{\sqrt{i}}) + 1$	[-600,600]	0

Table 2: The test results for the methods.

Function	Algorithm	The best value 2 D/30 D	The worth value 2 D/30 D	Mean value 2 D/30 D
f_1	WOA	8.26e-40/3.42e-16	1.13e-28/3.25e-11	1.29e-29/3.39e-12
	IWOA	5.21e-161/2.14e-156	4.67e-138/1.91e-116	4.74e-139/1.91e-117
f_2	WOA	1.18e-41/9.22e-16	3.14e-28/1.53e-12	3.40e-29/1.58e-13
	IWOA	2.95e-180/3.09e-169	4.00e-139/3.83e-130	4.00e-140/3.83e-131
f_3	WOA	4.91e-21/1.41e-10	6.51e-18/1.20e-08	9.00e-19/2.12e-09
	IWOA	4.01e-86/2.64e-80	8.23e-72/6.98e-69	8.87e-73/8.25e-70
f_4	WOA	0/2.27e-13	7.11e-15/11.49	1.78e-15/1.15
	IWOA	0/0	0/0	0/0
f_5	WOA	0/6.66e-16	5.92e-02/3.05e-12	1.13e-02/7.69e-13
	IWOA	0/0	0/0	0/0

By the comparison results in table 2, the IWOA algorithm obtain the optimal value of the five functions better than the WOA algorithm. For example, when the test function is f_5 in 2 D, the mean value of the WOA algorithm is 1.13e-02, whereas the IWOA algorithm is 0, which indicates the IWOA algorithm can obtain the optimal value. By the comparison results in table 2, the IWOA algorithm obtain the optimal value of the f_4 and f_5 two test functions. Besides, with the dimensions increase, the convergence accuracy of the WOA algorithm cannot be provided, whereas the IWOA algorithm can be guaranteed. It can be concluded that the search stability of the proposed method better than the WOA algorithm.

2.3 The Parameters of SVM Method Optimized by the IWOA Algorithm

The problem of getting into the local optimal solution can be solved via the IWOA algorithm and the better parameters of SVM method can be obtained. The framework of RUL prediction for LIBs by the IWOA-SVM model is shown in figure 1.

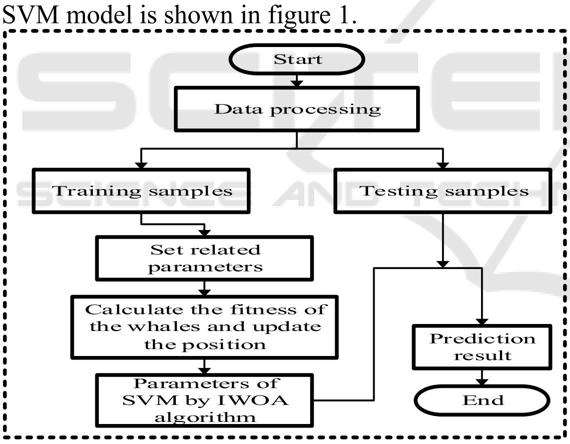


Figure 1: The framework of RUL prediction for LIBs based on IWOA-SVM method.

The special steps of IWOA-SVM can be described as follows:

Step 1. Data processing: Divided the data into the training samples and the testing samples.

Step 2. Set related parameters: NP is 20, the lower boundary is lb =0.01, the upper boundary is ub =100, and Max_iter is 100.

Step 3. Calculate the fitness of the whales and update the position.

Step 4. The parameters of SVM can be obtained via IWOA algorithm.

Step 5. Predict the RUL of LIBs: Verify the proposed method by the testing samples and predict RUL of LIBs.

3 RUL PREDICTION OF LIBs BASED ON IWOA-SVM METHOD

3.1 Capacity Datasets for LIBs

The datasets of LIBs are obtained from the NASA Prognostics Center of Excellence (PCoE) (Goebel K, Saha B, Saxena A, Celaya J R and Christophersen J P, 2008). The commercial available 18650 LIBs with the nominal capacity of 2Ah are utilized to test at room temperature of 25°C. Firstly, the LIBs were in constant current (CC) charge model at 1.5 A until the voltage achieved 4.2 V, then kept on a constant voltage (CV) model until the charge current dropped to 20 mA. The discharge process was in CC model at 2 A until the voltage fell to the cutoff voltage. The LIBs B0005 (B5) and B0007 (B7) of NASA are utilized to experiment and the failure threshold is taken as 72% of the nominal capacity. The degradation trend of two batteries are presented in figure 2.

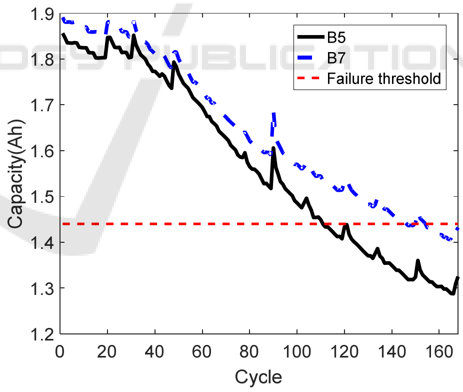


Figure 2: The capacity degradation trajectory of two batteries.

3.2 Performance Evaluation Criterion

The mean absolute error (MAE) and the root mean square error (RMSE) are utilized to measure the accuracy of forecasting,

$$MAE = \frac{1}{n}\sum_{i}^{n} | \hat{y} - y | \tag{10}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i}^{n}(\hat{y}-y)^2} \qquad (11)$$

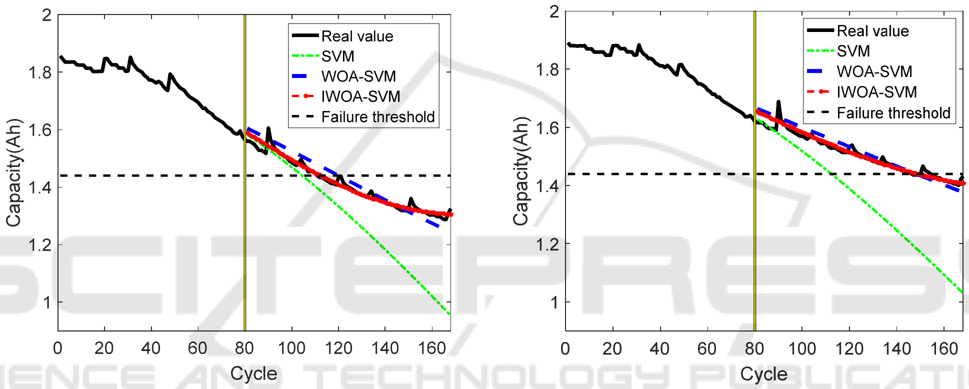
where $\hat{y}$ is the predicted capacity value, and y denotes the true capacity value.

3.2.1 RUL Estimation of LIBs

To verify the prediction performance of the proposed method, the capacity datasets of batteries B5 and B7 are utilized to test and compared with SVM and WOA-SVM methods. The detailed parameter settings are shown in table 3. The RUL prediction of LIBs is carried at the starting point (SP) is cycle 80 and the prediction results of three methods are shown in figure 3. The absolute values of the error are presented between the real and predicted values of the two batteries in figure 4. Besides, the results of the RUL prediction are represented in table 4. In table 4, the RUL value is the real RUL value and the PRUL denotes the predicted RUL value.

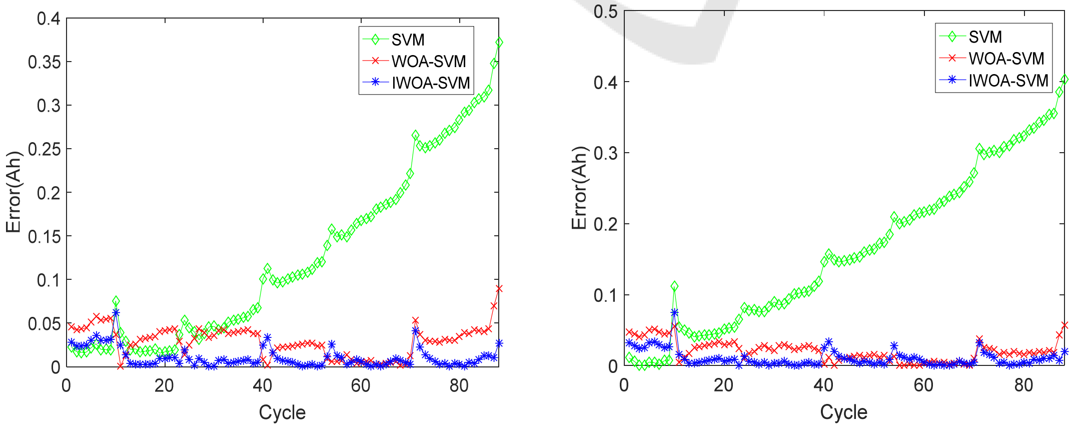
Table 3: The parameter settings for three methods.

Algorithm	Parameter settings
SVM	$NP=20$, $Max\_iter=100$, $C=10$, $g=0.01$
WOA-SVM	$NP=20$, $Max\_iter=100$, $C=[0.01,100]$, $g=[0.01,100]$
IWOA-SVM	$NP=20$, $Max\_iter=100$, $C=[0.01,100]$, $g=[0.01,100]$



(a) B5 (b)B7

Figure 3: The curves of RUL prediction for three methods:(a) B5; (b)B7.



(a) B5 (b) B7

Figure 4: The absolute values of the error for three methods: (a) B5; (b)B7.

Table 4: The results of the RUL prediction based on three methods.

No.	SP	RUL	SVM				WOA-SVM				IWOA-SVM			
			PRUL	AE	MAE	RMSE	PRUL	AE	MAE	RMSE	PRUL	AE	MAE	RMSE
B5	80	31	25	6	0.125	0.161	40	9	0.028	0.032	32	1	0.010	0.015
B7		66	33	33	0.162	0.196	68	2	0.021	0.025	67	1	0.011	0.016

From the table 4, the AE (It should be noted that the AE is absolute error between the RUL value and the PRUL value) values of SVM and WOA-SVM methods are 6 and 9 based on the battery B5, respectively. Whereas the IWOA-SVM is six times smaller than that of the SVM method and nine times smaller than that of the WOA-SVM method. For battery B7, the MAE value of SVM is 0.162, whereas the proposed method is fourteen times smaller than that of the SVM method, besides, the RMSE value of the proposed method is twelve times smaller than that of the SVM method. It can be concluded that the proposed method can provide higher accuracy than other two methods.

To further verify the effectiveness of the proposed method, compared with other up-to-date methods, the results as shown in table 5. An integrated quantum PSO and SVR (QPSO-SVR) method established in Ref. (Wang Z, Zeng S, Guo J and Qin T, 2018) was compared with PSO-SVR method. As shown in table 5, the AE values of PSO-SVR and QPSO-SVR methods are 7 and 5, respectively, whereas the proposed method is 1. Therefore, it can be concluded that the proposed method can provide higher accuracy for predicting the RUL of LIBs.

Table 5: The comparison results of the proposed method with other methods.

No.	Method	Threshold (Ah)	SP	RUL	PRUL	AE (cycle)	RMSE
B5	PSO-SVR[16]	1.4	80	44	51	7	0.04
	QPSO-SVR[16]	1.4	80	44	49	5	0.02
	IWOA-SVM	1.4	80	44	44	1	0.01

4 CONCLUSIONS

A method is proposed based on improved whale optimization algorithm and SVM for predicting RUL of LIBs. To avoid the WOA algorithm falls into the local solution, the adaptive weights are introduced to solve this shortcoming. Compared with the WOA algorithm via the five test functions in 2 dimensions and 30 dimensions, respectively, the optimal value of the IWOA algorithm can be obtained better than that of the WOA algorithm, which indicates that the IWOA algorithm can obtain higher convergence accuracy. Besides, the datasets of NASA are utilized to validate the performance of the proposed method. Compared with SVM and WOA-SVM methods, it can be concluded that the RMSE value of the proposed method is less than 0.02 for all test batteries. Therefore, the proposed method can provide higher prediction accuracy for the RUL of LIBs. In the future, the further work is to utilize the IWOA algorithm to optimize the parameters of multi-kernel SVM (MSVM) model for providing more prediction accuracy of battery RUL.

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