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State of Charge Prediction Algorithm of Lithium-Ion Battery Based on PSO-SVR Cross Validation

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ABSTRACT Lithium-ion battery refers to a complex nonlinear system. Real-time diagnosis and accurate prediction of battery state of charge(SOC) parameters are hotspots and critical issues in battery research. To reduce the dependence of state of charge prediction on battery model accuracy and speed, and achieve real-time online estimation, a SOC prediction model of lithium-ion battery system is developed based on the model of support vector machine (SVM). SVM parameter is optimized using an algorithm of particle swarm optimization, and the performance of prediction model is assessed using cross-validation. The obtained experimental data is simulated, involving the comparison with the support vector machine model, and the prediction simulation of the battery in the state of fault. The results reveal that this model with a better performance than that of the support vector machine exhibits high accuracy and generalization ability.

INDEX TERMS State prediction, particle swarm optimization, Lithium-ion power battery, nonlinear data diagnosis, support vector machine.

I. INTRODUCTION

Lithium-ion battery is a sophisticated nonlinear system. The state of charge of the battery is affected by multiple parameters (e.g., the application environment and usage tasks), which cannot be directly ascertained. How to extract critical information from considerable nonlinear raw data and accurately carry out SOC prediction arouses huge attention from battery researchers. Accurate SOC evaluation tends to directly impact the efficiency, service life and vehicle stability of li-ion battery [1]–[3]. The working condition of lithium-ion power battery, a complex chemical system susceptible to factors (e.g., working environment and self-aging) exhibits nonlinearity and time-varying characteristics for its output; it gets more complicated particularly under extreme working conditions [4]. Accordingly, it is extremely difficult to predict SOC [5].

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A range of existing SOC prediction methods with different advantages and disadvantages are applied under different working conditions. In most battery applications, to estimate SOC, battery management system (BMS) adopts the most intuitive, fast and less computational methods, namely, open-circuit voltage measurement method and ampere-hour integral method. However, the mentioned methods are not accurate and cannot avoid accumulated errors or satisfy the online requirements [6]. Despite considering battery nonlinear factors and showing high prediction accuracy, Kalman filter and the battery equivalent model method rely primarily on the selection of battery model parameters. With the variation in working environment and battery aging, the constantly changing parameters will lead to the down-regulation of SOC prediction accuracy. To address mentioned problem, a ''black box'' model using data-driven method is proposed for SOC prediction. For instance, the neural network-based SOC prediction model only considers the mathematical relationship between input and output irrespective of internal reaction

mechanism of the battery [7]. Currently, neural network lacks definite theoretical basis when selecting the network structure, weights, and thresholds; it usually falls into locally optimal solution during the training process, and requires numerous data for training. SOC prediction of battery can be considered a regression issue, allowing SVR (Support Vector Regression) with good regression fitting ability to deal with small samples and nonlinear problems [8]. In literature [9], SOC fitting ranging 35% to 90% was well completed under the open-circuit voltage of the battery and SVR, and state of charge prediction of lithium iron phosphate battery was implemented based on the maximum absolute prediction error of 4%. In literature [10], the idea of fuzzy information granulation (FIG) was introduced based on the prediction of SOC using SVR. With electrical current, voltage and granulation time as inputs, SOC prediction model was built to predict SOC. In literature [11], a dual filter comprising standard Kalman filter and unscented Kalman filter was developed for the first time to incorporate with SVR for predicting SOC. Prediction of SOC using SVR in above methods achieved effective fitting and improved prediction accuracy. Nevertheless, SVR parameter selection and optimization were not involved, and the training speed of the model required further improvement.

In the present study, the algorithm of particle swarm optimization is corporate with SVR progressively to predict battery SOC, optimize SVR parameters using particle swarm optimization algorithm. The SOC prediction accuracy is enhanced, and the model training speed is accelerated. In the meantime, given the difficulty in obtaining data of vehicle lithium-ion battery under some extreme conditions, the generalization ability of SVR model under PSO constraint is impacted by the difficulty to ensure sufficient sample size. Whether with good generalization ability or not is a critical indicator to measure the performance of support vector regression [12], [13]. In this study, the performances of the model are evaluated and compared by introducing cross-validation method; thus, the model can exhibit good generalization ability [14]–[16]. Generalization ability refers to the good or bad performance of the trained model when facing novel data. Thus, a method for SOC prediction of lithium battery is proposed based on particle swarm support vector regression. Such method is suitable for the prediction of working conditions under the battery failure, which is also the innovation of the algorithm proposed in this study.

II. ESTABLISHMENT OF BATTERY SOC PREDICTION MODEL

A. PRINCIPLE OF SUPPORT VECTOR REGRESSION ALGORITHM

Support Vector Machine (SVM) which combines VC dimension (for Vapnik Chervonenkis dimension) theory and structural risk minimization theory shows supreme advantages in solving small sample, nonlinear and high-dimensional mode recognition. In this study, SVM is applied to the SOC prediction of lithium ion battery, with three external characteristic

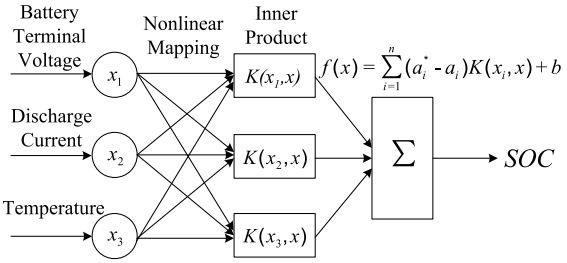


FIGURE 1. Support vector machine SOC simulation model.

parameters of battery, namely, terminal voltage, discharge current and battery temperature as inputs, battery SOC as the output, to build a support vector machine model. Also, the SOC prediction problem is transformed to a non-linear regression problem.

For nonlinear regression problems, it is necessary to transform the nonlinear problems into linear problems in high-dimensional space by mapping. Assuming that elements in the training sample set as (x_1, y_1), (x_2, y_2) to (x_n, y_n), where, variable $x_i \in R^d$ represents the D-dimensional vector describing the sample characteristic. the input x_i and the output y_i in the training set. Required fitting accuracy $f(x) = \omega\varphi(x) + b$ is used to fit and train the relationship between the input x_i and output y_i. The fitting accuracy ε must comply with equation 1 [17].

$$|f(x_i) - y_i| \leq \varepsilon \tag{1}$$

After introducing slack variables ξ_i and ξ_i^*, this regression problem can be converted into a convex quadratic programming problem available to obtain the globally optimal solution as expressed in Equation 2 and Equation 3.

$$\begin{cases} \omega \cdot \phi(x_i) + b - y_i \leq \varepsilon + \xi_i \\ y_i - \omega \cdot \phi(x_i) - b \leq \varepsilon + \xi_i^* \\ \xi_i \geq 0 \\ \xi_i^* \geq 0 \\ i = 1, 2, \cdots n \end{cases} \tag{2}$$

$$st.\min\left\{\frac{1}{2}\|\omega\|^2 + C\sum_{i=1}^{n}\left(\xi_i + \xi_i^*\right)\right\} \tag{3}$$

To facilitate calculation and reduce calculation difficulty, the following can be obtained by introducing Lagrangian function:

$$f(x) = \omega \cdot \phi(x) + b = \sum_{i=1}^{n}\left(\alpha_i^* - \alpha_i\right)K(x_i, x) + b \tag{4}$$

A support vector machine SOC prediction model as shown in Figure 1 can be built with battery terminal voltage, discharge current, and battery temperature as inputs, as well as the battery SOC as an output.

In the figure, x_i is the target support vector. $K(x_i, x)$is the kernel function. Kernel function can input low-dimensional data into high-dimensional space. By selecting a suitable kernel function, the ability of the model to solve nonlinear

problems can be significantly enhanced. This study adopts a radial basis kernel function.

$$K(x_i, x_j) = \exp(\frac{-\|x_i - x_j\|^2}{2\sigma^2}) \quad (5)$$

where: variable σ is the parameter of the kernel function. The expression $x - x_i$ is used for the input variable in the radial basis kernel function, which exhibits simple processing, good analyticity, good radial symmetry and smoothness. Thus, it is suitable for small sample analysis.

It can be known that the accuracy and performance of SVM algorithms depend largely on two parameters, that is, the penalty factor γ and kernel width σ. The penalty factor γ can balance the confidence coefficient and empirical risk of the SVM. The smaller the γ , the larger the fitting error and higher empirical risk will be, but its generalization ability is enhanced. The larger the γ, the smaller the fitting error will be, but its generalization ability is weakened. Small kernel width will cause local optimization and result in overtraining of SVR. But if it is too large, it will cause undertraining. So, selecting appropriate parameters can help maximize the balance between the ability of SVR to fit known training samples and to predict unknown test samples. Particle swarm optimization is simple, efficient and easy to implement, it exhibits a faster processing speed than normal optimization algorithms, immune to falling into the locally optimal solution. Thus, it is used to implement the optimization calculation of SVR model parameter γ and parameter σ.

B. SVR PARAMETER OPTIMIZATION

Particle Swarm Optimization based on swarm intelligence is one of the widely used methods in support vector machine parameter optimization calculation, it requires no gradient information in the iterative process and fewer parameters, thus reducing operating difficulty. With strong generalization ability and adaptability, profound intelligent background, it is highly practical in research and engineering fields [18]. Each optimization problem can be considered a particle, and all particles are searched in a d-dimensional space. Each particle has a fitness function able to calculate fitness value to determine whether the current position is good or not, endowing memory function to any particle to reserve the best position searched. Each particle has a velocity to determine the flying distance and direction. According to the flying experience of the particle itself and other particles, dynamic adjustment is made. The flow diagram of particle swarm algorithm is presented in Figure 2.

m particles exist in D-dimensional space. The position of the particle i is expressed in equation 6, and the velocity of particle i is expressed in equation 7.

$$x_i = (x_1, x_2, \ldots, x_D), 1 \le i \le m, 1 \le d \le D \quad (6)$$

$$V_i = (V_1, V_2, \ldots, V_D), 1 \le i \le m, 1 \le d \le D \quad (7)$$

The best position in the past that particle i has experienced is:

$$p_i = (p_{i1}, p_{i2}, \ldots p_{iD}) \quad (8)$$

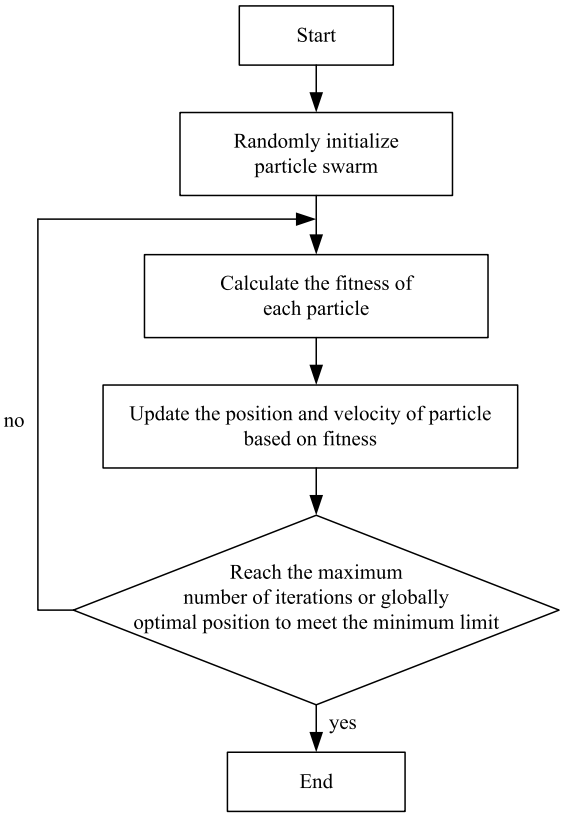


FIGURE 2. The flow diagram of PSO.

The best position that m particles have experienced in the past is:

$$p_g = (p_{g1}, p_{g2}, \ldots p_{gD}) \quad (9)$$

In general, continuous real numbers are chosen in the calculation of the position and velocity of particles. The iterative process of the algorithm is the constant position of the particle and iteration of the velocity [19], as expressed below:

$$V_{iD}^{k+1} = V_{iD}^{k} + c_1 r_1 (p_{iD}^{k} - x_{iD}^{k}) + c_2 r_2 (p_{gD}^{k} - x_{iD}^{k}) \quad (10)$$

$$x_{iD}^{k+1} = x_{iD}^{k} + V_{iD}^{k+1} \quad (11)$$

c_1 and c_2 represent learning factor or acceleration factor being usually positive number of 2. r_1 and r_2 represent pseudo-random number uniformly distributed within the interval within the range of. Set the maximum value that the particle velocity can reach as V_{max}. If the particle swarm is k, first of all, initializing the state of the particle, and the search range of the particle is set to x_i. If exceeding the set range during the search, the position is reinitialized and the search is continued. When the particle exceeds the set search range, indicating that the particle moves too fast, you can set the speed of particle to $V_{max}/2$. When all particle searches are completed, the center points of the two types of data can be obtained, expressed as equation 12 and equation 13:

$$x_m^{(1)} = \frac{\sum_{i=1}^{n(1)} x_i^{(1)}}{n_{(1)}} \quad (12)$$

$$x_m^{(-1)} = \frac{\sum_{i=1}^{n(-1)} x_i^{(-1)}}{n_{(-1)}} \tag{13}$$

In equation 12 and equation 13, $n(1)$ and $n(-1)$ respectively represent the number of samples belonging to their respective categories, and $x_m^{(1)}$ represents the sample center point of class 1, and $x_m^{(-1)}$ represents the sample center point of class -1.

The particle's speed and position are constantly updated, so the particle has the memory capability to complete the global search. The D-dimension velocity update formula of particle i can be expressed as equation 14 and the D-dimension position update formula can be expressed as equation 15. Where, ω represents the inertia weight, which is able to adjust the ability of particles to search the solution space.

$$V_{id}^{k+1} = \omega V_{id}^{k} + c_1 r_1 (p_{id}^{k} - x_{id}^{k}) + c_2 r_2 (p_{gd}^{k} - x_{id}^{k}) \tag{14}$$

$$x_{id}^{k+1} = x_{id}^{k} + V_{id}^{k+1} \tag{15}$$

III. PSO-SVR MODEL BASED ON CROSS VALIDATION

A. SELECTION OF PSO-SVR MODEL BASED ON CROSS VALIDATION

Through PSO-SVR [20], data characteristics can be searched from data samples to build a mathematical model by finding statistical laws in the data. Finally, the analysis and prediction of new data samples are achieved. If adequate sample size is available for training, a model with excellent performance can be obtained [21]. However, the sample size is seldom adequate in practical applications. Therefore, there is no guarantee to obtain a model with good performance, or to evaluate and compare the performance of the model obtained by training [22]. Accordingly, this study introduces cross-validation to solve above problems [23].

According to the basic idea of cross-validation method, raw data is divided into groups, each used as a training set and a validation set, respectively. The validation set is used to verify the performance of the trained model for evaluating the model. Hold-Out Method [24], K-fold Cross Validation [25], and Leave-One-Out Cross Validation are common cross-validation methods [26]–[28]. In this study, K-fold cross-validation is selected, the basic idea of which is to divide the data set into K groups (usually divided equally). The validation set takes data from each subset, and the rest of the subset is used as the training set. K models will be obtained after validation. For each model, the mean of the accuracy of the validation set using K models acts as the performance index of the model under this cross-validation. Cross validation is repeated K times, each subsample is verified once, and the results are verified immediately. The result is averaged K times, other combination is then used, and finally a single estimate is obtained [29]–[31].

This method can effectively prevent over-learning and under-learning from happening; it and can also guarantee the model to perform well under the new data set. Its flow diagram is presented in Figure 3.

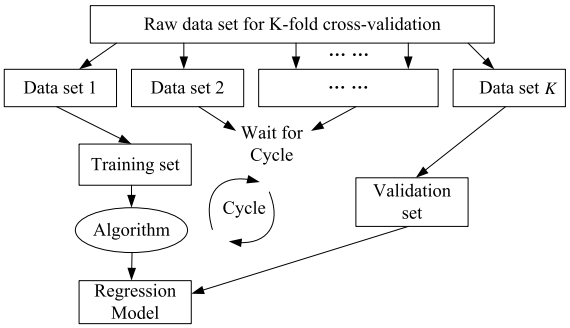


FIGURE 3. K-fold cross validation flow diagram.

B. K-FOLD CROSS VALIDATION PROCESS

In order to ensure the accuracy of regression, LOOCV algorithm has high computational cost. However, the difference between k-fold cross-validation and LOOCV is that each test set will no longer contain only one data, but multiple data, which not only guarantees the prediction accuracy but also the low calculation cost; thus, the optimal division of the test set is ensured. The steps of the k-fold cross-validation process are presented below.

Step 1: Divide the raw data set for K-fold cross-validation into K sets.

Step 2: All data of each model are used as training sets for training, and training parameters are obtained. The training parameters are tested on its data to obtain the test error.

Step 3: Though the second step, we get K models and K test errors. Subsequently, average the K errors, the estimated generalization error are obtained.

Step 4: The model with the smallest estimated generalization error is the optimal model.

Step 5: The optimal model is used to train all the data again, and the obtained model parameters are the cross-validation training results.

IV. IMPLEMENTATION OF BATTERY SOC PREDICTION MODEL

Firstly, a certain number of batteries are selected for cyclic charge and discharge experiments (e.g., including battery normal charge and discharging [32], overcharging and discharging [33], real-time collection of battery voltage, current, temperature, and SOC data [34]). Given huge influence of differences in above four battery parameter dimensions on the learning rate, regression precision and generalization ability of SVM, Z-score standardization processing is performed on each data. Standardized data showed standard normal distribution. This method shows good performance when measuring similarity with distance and solving regression problems [35]. In equation 16, μ denotes the mean value of the sample, and σ represents the standard deviation of the sample.

$$x^* = \frac{x - \mu}{\sigma} \tag{16}$$

Data after standardization processing can be used for model training. The total process of training is illustrated

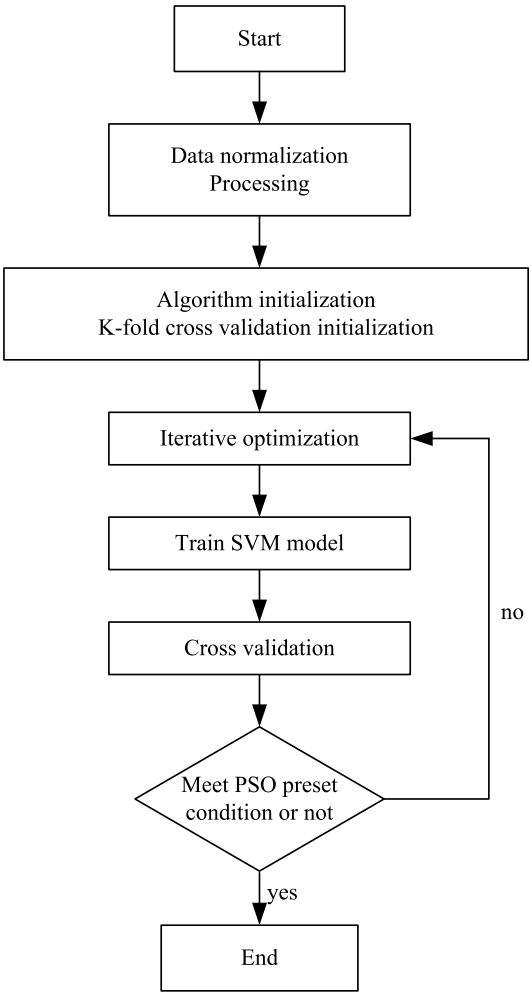


FIGURE 4. The total process of model training.

in Figure 4. PSO-SVR based lithium battery SOC prediction model can be obtained according to the training process. Besides, it is available to perform further simulation and verification.

V. SIMULATION AND ANALYSIS OF EXPERIMENTAL RESULTS

Firstly, Panasonic NCR18650B and 3300mAh lithium iron phosphate batteries are selected as objects for charge and discharge experiments (e.g., overcharging and over discharge tests). The process of experiment is shown in Table 1.

To verify the performance of SOC prediction of the model under different battery conditions, totally 2500 groups of data, namely, 500 groups of batteries under over-high voltage, voltage below level, excess temperature, high internal resistance, and normal state, are taken as a training set to perform simulation in MATLAB using LIBSVM toolbox. The experimental platform and the sample battery are presented in Figure 5, and part of the test process data of the sample battery is shown in Figure 6. In Figure 5, the red dotted line on the left is the Arbin instrument "LBT-5V30A" selected

TABLE 1. The choice of options.

Step	Rule	End condition
1	1A discharge	Voltage reaches 3.0V
2	Standing for 10min	
3	500mA charge to constant voltage when voltage reaches 3.65V	Electric current reaches 0.05A
4	Static standing for 10min	
5	1A discharge	Voltage reaches 3.0V
6	End	

FIGURE 5. Experimental platform.

as the battery charge and discharge test equipment, the blue dotted line on the right represent battery samples, the yellow dotted line is the software database for test data, and the green dotted line represent the connecting wire and the fixture of sample batteries.

SVM sorting and regression can be supported by LIBSVM toolbox and different parameters can be modified based on providing many default parameters to achieve better results.

A. ANALYSIS OF PARTICLE SWARM OPTIMIZATION PROCESS

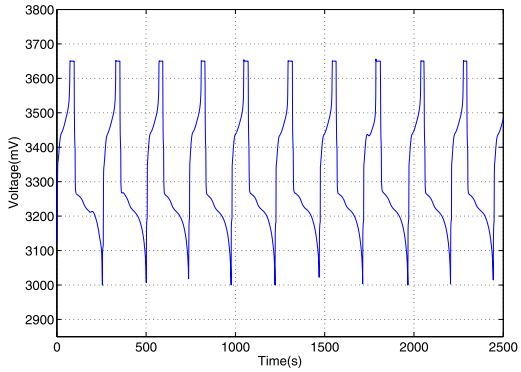
Generally, the particle swarm algorithm inertia weight ω is initially set as 0.9 and set as 0.4 at the end with the optimal performance. However, as it is based on experience, ω should be updated usually by following ways as expressed in equation 17 to equation 20. Four updating rules are tested using data obtained. From figure 7 and figure 8, it can been seen that the particle with faster search speed can achieve convergence more quickly in accordance with the updating rule of equation 20. Convergence can be realized at the time of iteration around 500 times, while convergence function stops changing and reaches its peak of 0.952. At the same time, $\sigma = 1.18$ and $\gamma = 1.41$ can be obtained.

$$\omega(n) = \omega_{start} - (\omega_{start} - \omega_{end})(t_{\max} - n)/t_{\max} \quad (17)$$

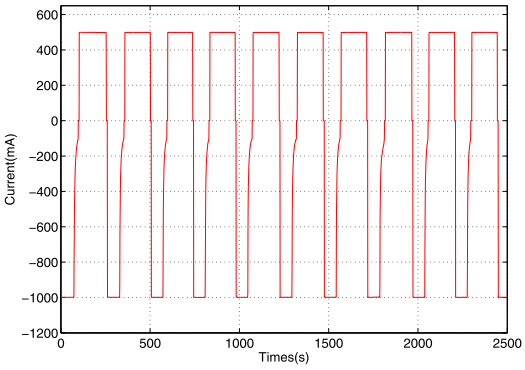
$$\omega(n) = \omega_{start} - (\omega_{start} - \omega_{end})(n/t_{\max})^2 \quad (18)$$

$$\omega(n) = \omega_{start} + (\omega_{start} - \omega_{end})(2n/t_{\max} - (k/t_{\max})^2) \quad (19)$$

$$\omega(n) = \omega_{start} + (\omega_{start}/\omega_{end})^{1/(1+en/t_{\max})} \quad (20)$$



(a) Testing Voltage



(b) Testing Current

FIGURE 6. Parts of the test data.

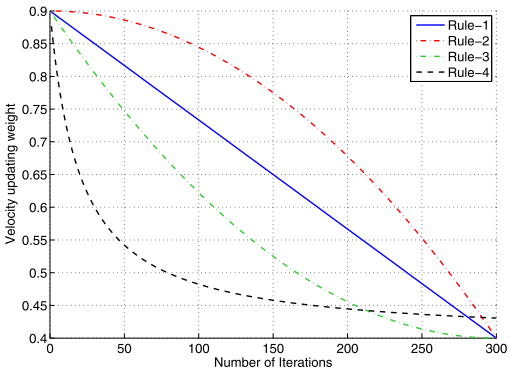
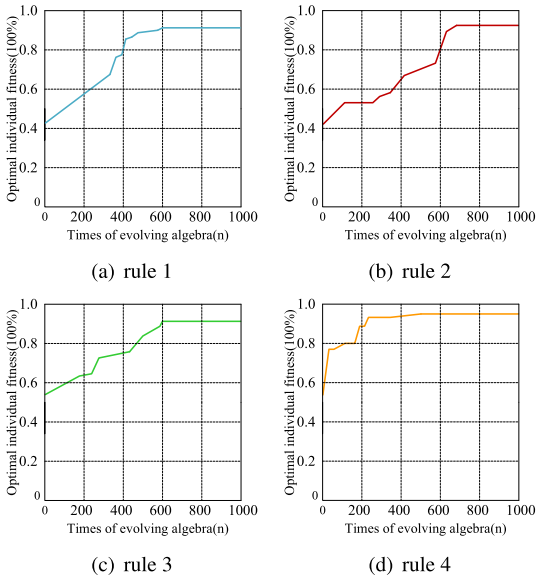


FIGURE 7. The comparation figure of four kinds weight updating rules.

B. RESULTS OF CROSS VALIDATION

To verify the effectiveness of cross validation, Figure 9 shows the accuracy contour map of particle trajectory without cross validation. Over-fitting significantly elevated (Error rate decreases in the training set, but on the validation set, error rate increases after decreases). The accuracy of cross-validation is shown in figure 9, reaching up to 98.7%. It can be found through observation that the cross-validation particle swarm algorithm can achieve convergence quickly, without fully exploring the entire spatial pair. Besides, over-fitting is effectively reduced, and the accuracy of parameter combination is compared as many as possible by using limited data sets to complete parameter optimization. In addition, it is available to visually evaluate the performance of the model, and it is suitable for model selection.



(a) rule 1 (b) rule 2

(c) rule 3 (d) rule 4

FIGURE 8. The comparation figure of four kinds updating rules results.

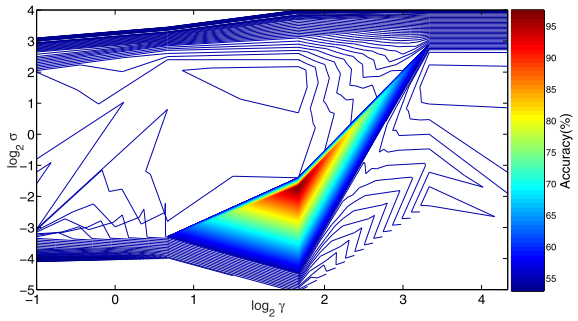


FIGURE 9. The cross-validation accuracy contour map.

C. ANALYSIS OF PSO-SVM MODEL SIMULATION RESULTS

To verify the generalization ability of PSO-SVM model obtained, 100 groups of data in continuous time are tested separately. The final test results suggest that the maximum value of the absolute error is 1.5%, the minimum value is 0.8%, and the average value is 1.2%. Compared with SVM, the maximum value of the absolute error is 2.01%, the minimum value reaches 0.6%, the average value is 1.5%, and the stability of estimation error is noticeably improved. All errors are higher than those for PSO-SVM. The result is shown in figure 10.

To verify PSO-SVM model in the state of lithium ion battery fault, 50 groups of data of batteries under over-high voltage, voltage below level, excess temperature, high internal resistance, and normal state, are taken to perform simulation test, respectively. The model shows the data error in these five states within the acceptable range. The results

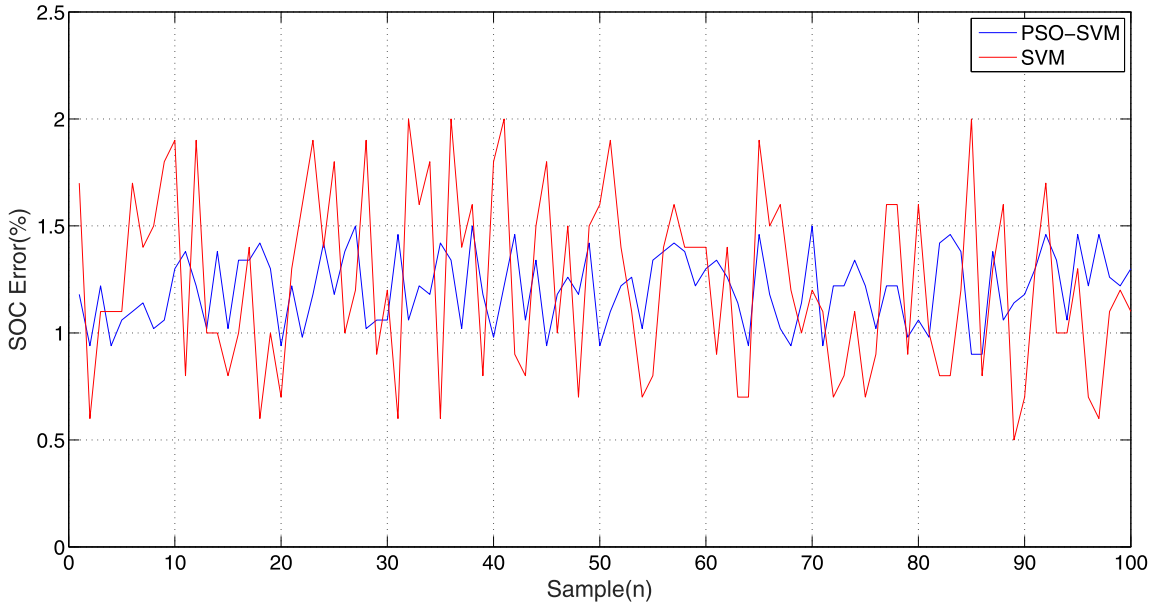


FIGURE 10. Prediction result error diagram.

TABLE 2. Prediction results on battery different fault conditions.

Battery status	Maximum error(%)	Minimum error(%)	Average error(%)
High Voltage	3.1	0.7	1.90
Low Voltage	2.7	0.6	1.65
Over Temp.	3.5	0.7	2.10
High Res.	4.1	0.4	2.50
Normal state	1.5	0.8	1.2

are listed in Table 2. It can be found that the average error in the four fault states is higher than that in the normal state. This reveals that battery performance fluctuates significantly in the fault state, which noticeably impacts the overall performance.

D. THE COMPARISON BETWEEN PSO-SVR CROSS VALIDATION AND TRADITIONAL PREDICTION ALGORITHM

Support vector machine is a learning technique based on the structural risk minimization principle as well as a new regression method with good generalization ability. To verify the effectiveness of the algorithm proposed in this study, typical references in the research direction of battery SOC prediction are introduced, as shown in Table 3. The cross-validation PSO-SVR algorithm adopted in this study is compared with other classical algorithms. The estimated error data listed in the table and the cites are originate the existing research results of our research team.

According to the comparison in Table 3, electrochemical impedance spectroscopy, classical kalman filter algorithm, BP neural network and improved BP neural network algorithm are common algorithms in the study of battery SOC prediction technology. The average error of these algorithms is greater than that of the algorithm proposed in this study.

TABLE 3. The comparison of prediction algorithms.

Prediction model	Average estimation error(%)	Sample size(n)
Impedance spectroscopy [36]	2.2	150
Classical Kalman filter [37]	1.8	100
BP neural network [38]	1.9	100
PSO-BP neural network [39]	2.0	789
PSO-SVR	1.5	100

It is noteworthy mentioning that the PSO-SVR method is also especially suitable for the prediction of working conditions under the condition of battery failure, which is also the innovation of the algorithm proposed in this manuscript.

VI. CONCLUSION

In accordance with statistical theory, support vector machine theory following risk minimization efficiently solves nonlinear regression problems and achieves prediction results of unknown samples that approximate actual values. With SVM, this study introduces particle swarm optimization and cross-validation to optimize SVM parameters, thereby noticeably enhancing the performance of SVM. SOC is predicted by exploiting actual lithium battery voltage, current and temperature data. As suggested from the simulation results, the maximum and minimum estimation errors of the PSO-SVR model algorithm under normal conditions reach 1.5% and 0.8%, respectively, and the average error of the algorithm is 1.2%, which is optimized from 1.5% error of the classical SVM algorithm without PSO. Compared with other conventional SOC estimation algorithms, the proposed method exhibits

faster training speed, higher accuracy and stronger generalization ability. In particular, under the battery failure, the battery parameters will vary rapidly. The prediction error of the algorithm ranges from 1.65% to 2.5%, and the prediction results are confined into an acceptable range. The PSO-SVR model adopted in this study is capable of effectively solving the SOC prediction problem of lithium batteries and achieving accurate prediction, which is of certain implication to its engineering application.

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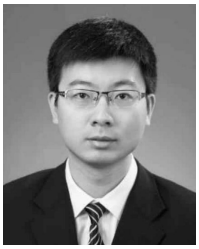

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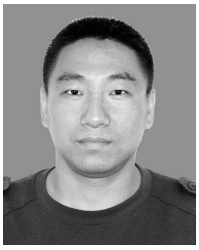

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