Toward Group Applications of Zinc-Silver Battery: A Classification Strategy Based on PSO-LSSVM

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ABSTRACT To solve problem of the reliability and consistency of silver-zinc batteries after being sorted into groups, a proposed classification strategy of zinc-silver battery based on least squares support vector machine with PSO (PSO-LSSVM) was proposed in this paper. Sample data was extracted from the charging curve of silver-zinc batteries to pre-sort training samples using FCM clustering. The least squares support vector machine model parameters were optimized and improved using particle swarm optimization algorithm. The method breaks the limitation of building battery classification model based on prior knowledge, reduces the dependence on parameter selection, and enhances model training speed and accuracy. In the end, experimental data was used for battery classification model training and testing. Test results show that the battery pack obtained by the group strategy has good dynamic consistency, the rate of capacity decay is significantly reduced. The rate of capacity decay is no more than 10% after 30 cycles of life test. The silver-zinc battery group classification strategy proposed to this paper improves the consistency and reliability of the battery and the life of battery packs.

INDEX TERMS Classification strategy, least squares support vector machine, rate of capacity decay, silver-zinc battery, particle swarm optimization.

I. INTRODUCTION

Silver-zinc battery as a new-type chemical power source emerging from the early 1940s, characterized by high energy, high density, stable platform of discharge voltage, high reliability and high safety characteristic than lithium ion batteries. Silver-zinc battery is widely used in underwater and surface equipment, aerospace fields [1]–[3]. Silver-zinc battery electrolyte is mainly composed of potassium hydroxide solution, which is a non-combustible liquid. Therefore, the safety of silver-zinc battery is superior to that of other batteries. A large amount of silver-zinc battery in groups must be serial or parallel connected to meet the demand for high capacity and high voltage applications. In case of inconsistent performance of the single battery in the pack, the difference in single battery will be amplified due to continuous charge and discharge cycle, which not only affects correctly judging the state of health(SOH) or the state of charge(SOC) of the battery pack, but also evoke the capacity attenuation and lifetime decay of the battery pack, and even leads to safety and reliability issues [4], [5]. Therefore, an optimal battery group strategy is particularly necessary [6].

There are several major battery sorting strategies at present including battery parameter sorting method, electro-chemical impedance spectrum sorting method and battery dynamic characteristic sorting method, et. al. Parameter sorting method which just selects single characteristic parameter as battery classification basis is an easy method to implement, but achieves poor effect after grouping. The battery performance can be comprehensively evaluated by multi-parameter group method together with several static parameters [7]. The static characteristics of the battery can be fully reflected, but
may not guarantee the consistency of the dynamic characteristics [8]. By analyzing the differences between the charge and discharge curves at the same rate, using batteries of highly similar degree of charge and discharge curve in groups, dynamic characteristic curve method can comprehensively manifest the overall characteristics of the battery and have a satisfactory classification effect.

In literature [9]–[12], charge capacity grading curve and standard characteristic parameters on discharge voltage platform were extracted as the input of the battery group strategy. Despite it improved the effect compared with the traditional method, the strategy is more difficult to implement as it is difficult to determine the standard characteristic parameters. In addition, the model is simple with poor generalization and applicability. With the development of machine learning, it has also been widely used in battery group strategies. In literature [13], six performance parameters of a 100-cell lithium-powered battery were studied using unsupervised clustering method. It was found that batteries selected by random forest data method showed high consistency. In literature [14]–[16], factor analysis module was used for optimization based on battery discharge curve. System clustering module was used to extract the main factor and total factor of the battery, respectively. Fuzzy C-means clustering algorithm was implemented by programming to establish the battery group strategy. As above literature algorithm sorted battery samples based on experience, there exist certain error. It also required to manually adjust parameters which wasted a large amount of time and had certain influence on battery performance.

SVM and LS-SVM algorithms are widely used in engineering fields for studying and solving sorting problems. In literature [17], LS-SVM algorithm was used to sort the wear degree of brakes. Brakes and provide quantitative evaluation after parameter adjustment for several times. In literature [18]–[20], the fault of motor was sorted using LS-SVM algorithm. It can be seen that the LS-SVM algorithm has a promising application prospect in the industrial field.

A battery classification strategy based on least squares support vector machine with PSO was proposed in this paper, which centers on exploring intrinsic law of the dynamic characteristics of single cells. Particle swarm optimization algorithm was used simultaneously to autonomously search the optimal parameters of the least squares support vector machine, saving time for parameter adjustment and allowing battery sorting without manual sorting [21], [22]. This method breaks the limitation of building battery classification model based on prior knowledge, reduces the dependence on parameter selection, improve the dynamic consistency of battery packs and enhances the rate of capacity decay after sorting silver-zinc batteries in groups.

II. PRINCIPLE OF BATTERY GROUP ALGORITHM

A. LS-SVM PRINCIPLE

The least squares support vector machine (LS-SVM) is an improved SVM with structure parameters which change the inequality constraints in traditional SVM to equality constraints, sets the quadratic sum of errors and loss function as the empirical loss of the training set. It can reduce computation complexity with faster solution speed and better robustness, and can provide effective solution to nonlinear system estimation. At the same time, LS-SVM algorithm is available to implement multi-sorting combined with the binary tree theory, thus greatly expanding its range of application. Give a training sample set as follows:

\( \{(x_i, y_i) | x_i \in R^d, y_i \in R = [-1, +1], i = 1, 2, \ldots, n\} \)

where \( x_i \) is \( n \) dimension input vector, \( y_i \) is the output data of LS-SVM model. Considering battery data model linearly inseparable, it requires to map data samples from low-dimensional space to high-dimensional space through nonlinear function \( \varphi(x) \). Thus, low-dimensional space algorithm will not be taken into consideration when constructing the optimal classification hyper plane of SVM model in high-dimensional characteristic space. Instead, training sample point in high-dimensional characteristic space was used for operation to build the kernel function and the decision function.

\[
K(x_i, x_j) = \varphi(x_i) \times \varphi(x_j)
\]

\[
y = \omega^T \varphi(x) + b
\]

where: \( \omega \) and \( b \) are parameters of LS-SVM regression model. \( \omega \) represents weight vector and \( b \) represents paranoid value. According to the principle of structural risk minimization, after adding slack variable \( e_i \) to LS-SVM regression model, obtain its optimization conditions as follows:

\[
J(\omega, e)_{\text{min}} = \frac{1}{2} (\omega^T \omega + \gamma \sum_{i=1}^{n} e_i^2)
\]

\[
s.t. \quad y_i = \omega^T \varphi(x_i) + b + e_i, \quad i = 1, 2, \ldots, n
\]

where: \( y \) is the penalty factor, and \( e_i \) is the error. After introducing Lagrangian multiplier, equation 2 can be converted to:

\[
L(\omega, b, e, \alpha) = \frac{1}{2} \|\omega\|^2 + \gamma \sum_{i=1}^{n} e_i^2 - \sum_{i=1}^{n} \alpha_i (\omega^T \varphi(x_i) + b + e_i - y_i)
\]

where: \( \alpha = [\alpha_1, \alpha_2, \ldots, \alpha_n]^T \) is Lagrangian multiplier. The optimal \( b \) and can be obtained through KKT condition.

\[
\begin{align*}
\frac{\partial L}{\partial \omega} &= 0 \quad \Rightarrow \quad \omega = \sum_{i=1}^{n} a_i \varphi(x_i) \\
\frac{\partial L}{\partial b} &= 0 \quad \Rightarrow \quad \sum_{i=1}^{n} a_i = 0 \\
\frac{\partial L}{\partial e_i} &= 0 \quad \Rightarrow \quad a_i = \gamma e_i \\
\frac{\partial L}{\partial a_i} &= 0 \quad \Rightarrow \quad \omega^T \varphi(x_i) = b = e_i - y_i = 0
\end{align*}
\]
The optimization problem can be solved by solving the following linear system of equations:

$$
\begin{bmatrix}
0 & 1 \\
1 & \Omega + \gamma^{-1}E
\end{bmatrix}
\begin{bmatrix}
b \\
a
\end{bmatrix}
= 
\begin{bmatrix}
0 \\
y
\end{bmatrix}
$$

where: $\Omega_{ij} = K(x_i, x_j)$ is called the kernel function.

The discrimination function of LS-SVM sorting model can be obtained from above equation and expressed as:

$$
y(x) = \sum_{i=1}^{n} [a_i K(x_i, x) + b]
$$

The 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 greatly improved. This paper selected a radial basis kernel function:

$$
K(x, x_i) = \exp\left(\frac{-|x - x_i|^2}{2\sigma^2}\right)
$$

where: $\sigma$ is the parameter of kernel function. The expression $x - x_i$ was used as input variable in the radial basis kernel function. With simple processing, good analyticity, good radial symmetry and smoothness, it is suitable for analyzing small-size samples.

Introduce radial basis kernel function into equation 9 to obtain the specific expression of the discrimination function:

$$
f(x) = \text{sign}\left(\sum_{i \in SV} \left[ a_i y_i \left(\frac{-|x - x_i|^2}{2\sigma^2}\right) + b\right]\right)
$$

**B. PARTICLE SWARM PARAMETER OPTIMIZATION**

Particle swarm optimization is a kind of algorithm with advanced evolutionary. Compared with other optimization algorithms, the particle swarm algorithm with fewer parameters and clear optimization ideas can implement encoding process easily. Therefore, it is widely applied in a lot of fields.

It can be known from algorithm principle that the performance of SVM algorithm largely depends on two parameters, that is, the penalty factor $\gamma$ and kernel width $\sigma^2$. The penalty factor $\gamma$ can balance the confidence coefficient and empirical risk of the SVM. The smaller $\gamma$, the larger fitting error and higher empirical risk, but its generalization ability is enhanced. The larger $\gamma$, the smaller fitting error, but its generalization ability is weakened. Small kernel width will cause local optimization, and result in overtraining of SVM. But if it is too large, it will cause undertraining. So, selecting appropriate parameters can help to maximize the balance between the ability of SVM to fit known training samples and to predict unknown test samples. Particle swarm optimization is simple, efficient and easy to implement, with 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 SVM model parameter $\gamma$ and parameter $\sigma^2$.

During the optimization process of particle swarm optimization algorithm, each possible solution can be denoted by the position of the point in the solution space. If distributing particles randomly to the solution space, each particle can be evaluated by a fitness function of iteration to locally optimal solution and globally optimal solution. In each iteration, the particle tracked its historical optimal solution, the global historical optimal solution to the entire particle swarm, and the velocity vector of the last iteration of the particle so as to update the position of the particle. The iterative process is shown in Figure 1.

![FIGURE 1. PSO particle iterative process.](image-url)

According to particle swarm optimization algorithm, firstly assume that there is a community comprising $V$ particles in a $D$-dimensional target search space, and the $i$-th particle is denoted as a $D$-dimensional vector as follows:

$$
x_i = (x_{i1}, x_{i2}, \ldots, x_{iD}), \quad i = 1, 2, \ldots, N
$$

The “flying” velocity of the $i$-th particle is denoted as a $D$-dimensional vector:

$$
V_i = (v_{i1}, v_{i2}, \ldots, v_{iD}), \quad i = 1, 2, \ldots, N
$$

The optimal position currently searched for by the $i$-th particle is called the individual extreme value:

$$
P_{best} = (p_{i1}, p_{i2}, \ldots, p_{iD}), \quad i = 1, 2, \ldots, N
$$

The optimal position searched so far by the whole particle swarm is the global extreme value, denoted as:

$$
g_{best} = (p_{g1}, p_{g2}, \ldots, p_{gD})
$$

Through iterative optimization, particles update their position and velocity information according to equation 16 and equation 17 as follows:

$$
v_{id} = \omega v_{id} + c_1 \cdot rand_1() \cdot (p_{id} - x_{id}) + c_2 \cdot rand_2() \cdot (p_{gd} - x_{id})
$$

$$
x_{id} = x_{id} + v_{id}
$$

where: $c_1$ and $c_2$ are learning factors or acceleration constants. $\omega$ is the inertia factor, $rand_1$ and $rand_2$ are independent random numbers in the range 0 to 1. The right side
of equation 16 is represented as a sum of three parts, they are the inertia part, the cognitive part and the social part, respectively, the motion inertia of the particle that tends to maintain its previous velocity, the memory of the particle's historical experience that tends to approach its historical optimal position, and knowledge sharing between particles, and indicating that particles tend to approach the historical optimal option of the group or neighborhood. \( v \) represents the velocity of the particle, \( v_{id} \in [-v_{max}, v_{max}] \), \( v_{max} \) is a constant.

### C. MODEL BUILDING

To avoid damage to the battery service life when leaving the factory, only a simple charge and discharge experiment is performed, thus obtaining relatively small battery tests data. However, LS-SVM algorithm can achieve good sorting effect with low-dimensional samples data as input. To build an accurate LS-SVM battery classification model, it is necessary to pre-process training samples and optimize parameters. Modeling steps are as follows:

1. **Step 1:** Determine the battery training sample set of LS-SVM model \( \{(x_i, y_i)|x_i \in R^d, y_i \in R = [-1, +1], i = 1, 2, \ldots, n\} \) and pre-process data class.
2. **Step 2:** Determine the range of model parameters \( \gamma \) and \( \sigma^2 \), set the particle dimension of the particle swarm as 2, and randomly generate the initial position and velocity of the particle.
3. **Step 3:** Set each particle as the parameter of least squares support vector machine, train the prediction model, and output the prediction result.
4. **Step 4:** Introduce the output results into the fitness evaluation function to obtain globally optimal solution or reach the maximum number of iterations, then skip to step 6, otherwise perform step 5.
5. **Step 5:** Update the position of particle using the above iterative equations based on the fitness of each particle obtained.
6. **Step 6:** Introduce the searched optimal solution into least squares support vector machine and build a battery classification model.

### III. IMPLEMENTATION OF SILVER-ZINC BATTERY CLASSIFICATION MODEL

#### A. SAMPLE DATA ANALYSIS AND SELECTION

The charge voltage curve of silver-zinc battery changed obviously at different stages, conductive to the selection of the characteristic points of the least squares support vector machine model. In this paper, 110 silver-zinc batteries of the same production batch of 75Ah from a battery manufacturer of China were selected as the object of study. The experimental platform and the sample battery are shown in Figure 2, the red dotted line on the left is the Arbin instrument “LBT-5V30A” which was selected as the battery charge and discharge test equipment, the yellow dotted line on the right are battery samples, the blue dotted line is the software database for test data.

![Experimental platform.](image)

The sample data was marked as 1~110. 1~50 was used as the training object, 51~100 were used as the testing object, and 101~110 were not processed at all. The charge voltage curve of 1~50 silver-zinc batteries was collected and shown in Figure 3.

It can be observed from Figure 3 that the charge curve can be divided into multiple stages. The stage turning points not only showed significant change in amplitude, but also showed great difference in time, which will lead to batteries in different charging states after sorting in groups. In that case, some of the batteries are not fully charged while individual battery is overcharged, which greatly affects the state of charge and health of the battery after sorting in groups. Therefore, to guarantee the consistency of batteries after sorting in groups, the turning time points of the charge curve of the silver-zinc batteries were selected as training samples. The sampling points of batteries 1~50 are shown in Table 1.

| Sampling point 1 | Sampling point 2 | Sampling point 3 |
|------------------|------------------|------------------|
| Sample 1         | 12340.07         | 57695.09         | 23991.07         |
| Sample 2         | 12340.07         | 57600.09         | 23305.07         |
| Sample 3         | 11889.07         | 53999.02         | 21735.07         |
| Sample 4         | 11079.07         | 53768.02         | 21159.07         |
| Sample 5         | 14244.07         | 52061.02         | 23940.07         |
C. LS-SVM MODEL PARAMETER OPTIMIZATION BASED ON PARTICLE SWARM

According to the parameter requirements of the least squares support vector machine, the spatial range of the particle swarm solution was set as $\gamma \in [0.1, 10000]$, $\sigma^2 \in [0.001, 10]$. Considering the relatively large search space, the total number of particles of PSO were set as 100, and the maximum number of iterations were set as 200. PSO optimization path and accuracy is shown in Figure 5.

When the particle reaches the local optimal solution, it does not stop updating. The numbers in Figure 5 represent the accuracy of LS-SVM algorithm in model training under the current parameters. It can be known from the figure that in particle swarm model, it can be deemed to reach globally optimal solution in case that the iterative process value almost remained unchanged after 114 iterations. Thus, $\gamma = 486.3$, $\sigma^2 = 9.327$ could be obtained. It can also be seen from the figure that simultaneous iteration of multiple particles with no need of optimization on the whole solution plane can obtain faster rate of convergence while guaranteeing solution accuracy and avoid falling into locally optimal solution. Under the same condition, comparison between PSO and traditional parameter optimization algorithms is shown in Table 3.

It can be seen from Table 3 that compared with the other two parameter optimization algorithms, the least squares support vector machine model for particle swarm optimization has higher accuracy and the fastest convergence rate.

D. MODEL TRAINING

LS-SVM was popularized to the third class using binary tree support vector machine and the parameters obtained by particle swarm optimization algorithm was set as the
It could be seen from the figure that the trained LS-SVM sorter had distinct boundaries and clear class, suggesting that battery classification model built by binary tree initial parameters of LS-SVM [31]–[33]. Battery samples 1–50 were trained, and the projection of the trained LS-SVM on two-dimensional plane is shown in Figure 6.

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support vector machine can easily implement battery sorting and guarantee consistency after sorting batteries in groups [34], [35].

IV. ANALYSIS OF EXPERIMENTAL RESULTS

To verify the sorting effect of LS-SVM model, the test battery samples 51∼100 were sorted. The sorting results are shown in Figure 7. The battery mark numbers are shown in Table 4.

Capacity decays experiment was performed on single sorted cell in battery packs. 10 batteries were selected from each of the three classes of 1∼50 batteries to form battery pack1 to battery pack 3, and 10 batteries were selected from each of the three classes of 51∼100 batteries to form battery pack 4 to battery pack 6. The unsorted 10 batteries (No. 101∼110) were used to individually form battery pack 7. The capacity decay test was performed on the battery packs 1 to 7 with the same charge and discharge test process. The test results are shown in Figure 8. Considering normal silver-zinc battery pack with a cycle life of 30 times, the figure only provides results of the first 30 capacity cycle tests.

It can be seen from the Figure 8 that after 30 times of cycle life tests, the capacity retention rate of battery pack 1 and 4 is about 90%, the capacity of battery pack 2, 3, 5 and 6 drops from 75Ah to 60∼63Ah, with the capacity retention rate of about 85%, the capacity of battery pack 7 is down to 73%, moreover, battery pack 7 has failed when cycle time reached to 25. The unsorted battery pack 7 showed the fastest rate of capacity decay, while battery pack 1 to 6 had little difference in the rate of capacity decay, suggesting the consistency of batteries sorted by the battery classification model improved significantly. It could be seen obviously that the rate of capacity decay of battery pack 1 and battery pack 4 was the smallest, suggesting that the first class of battery with good dynamic consistency and capacity retention ability is suitable to be used in military, aerospace and other fields. The other two classes of batteries which own better dynamic consistency and capacity retention ability are applicable in industrial and civil use fields.

V. CONCLUSION

To solve problem of the reliability and consistency of silver-zinc batteries after being sorted into groups, a proposed classification strategy of zinc-silver battery based on least squares support vector machine with PSO was proposed in this paper. With the time turning points of charging curve of silver-zinc batteries as sample data, a silver-zinc battery classification model was built. Clustering of training samples were performed using FCM algorithm. The clustering results were used for LS-SVM model training and particle swarm optimization algorithm was used to implement LS-SVM parameter optimization. In the end, silver-zinc batteries were well sorted in groups using the trained model. Experimental results show that the battery pack obtained by the group strategy has good dynamic consistency and low rate of capacity decay. The optimal sorting result of the capacity still remained at 92.94% after 30 cycles of life tests. This classification strategy is easy for implementation with high sorting rate and high accuracy rate, suitable for sorting with non-linear battery test data, and it enhances the efficiency of sorting large quantity battery in groups.

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