Least squares support vector machine for state of charge estimation of lithium-ion battery using gray wolf optimizer

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Abstract. An accurate SOC estimation can ensure the effective and normal operation of the battery. To this end, a method for estimating the SOC of lithium-ion battery based on least squares support vector machine (LSSVM) is proposed, and the gray wolf optimizer (GWO) algorithm is used to further optimize the model parameters to overcome the non-linearity and unevenness of the actual working condition. Influence of interference factors, and then obtain accurate SOC estimation results. The optimized LSSVM is verified by collected data at different temperatures, the results shows the proposed optimization model is greatly improved compared to before optimization, the model accuracy is improved by about 35%.

Nomenclature

| abbrevation | description |
|-------------|-------------|
| BMS | battery management system |
| SOC | state of charge |
| OCV | open circuit voltage |
| EVs | electric vehicles |
| ECM | equivalent circuit model |
| BTMS | Battery thermal management system |
| LSSVM | least squares support vector machine |
| GWO | gray wolf optimizer |
| $\omega$ | weight vector |
| $b$ | bias |
| $\alpha$ | Lagrangian multiplier |
| $K(x,x')$ | kernel function |
| $t$ | current iterations |
| $\hat{A}$ | coefficient vector |
| $\hat{C}$ | coefficient vector |
| $\hat{X}_p(t)$ | position vector of prey |
| $\hat{X}$ | position vector of wolf |
1. Introduction
Lithium-ion batteries have the advantages of high energy density, fast discharging rates, and large cycles; fast discharging rates mean the battery can produce more power per unit of time. Reliable BMS is a prerequisite for the normal operation of lithium-ion battery [1]. As a most important technology of BMS, SOC is defined as the ratio of the current remaining available energy to the current total capacity, and is a prerequisite for effective management of battery energy utilization and prevention of battery overcharging. The complex chemical reactions inside the battery make it difficult to model. At the same time, due to the complex external interference conditions during the driving of the vehicle, the actual data collected by the battery exhibits strong coupling and nonlinear characteristics, which makes the actual SOC value is difficult to estimation [2]. Therefore, a reasonable for SOC estimation is well needed.

Lithium ion battery SOC estimation algorithms are mainly divided into four categories [3]: coulomb counting method, open circuit voltage method, equivalent circuit model method and data-based method. The ampere-hour integration method is to accumulate the current of charging and discharging during the vehicle driving, and there is a noise error caused by the SOC estimation drift during current measurement, which will produce an error accumulation effect. The open circuit voltage method is generally used in laboratory conditions because the result of the OCV takes a very long time. The physical model method mainly includes electrochemical model, equivalent circuit model and fractional-order model [4-7]. Limited to the current application conditions, the model is generally simplified to approximate the actual model, so the accuracy of the model is limited. The data-based method is an artificial method based on complex mathematical formulas, which is performed like a brain of human, so that it can learn the internal structure of the battery independently without understanding of the complex structure of the battery structure. LSSVM is a modeling method based on machine learning, which has better performance than support vector machines. However, when the model is trained, the model parameters are the results of the machine's self-learning training data, which has a certain degree of randomness, manual parameter adjustment is inefficient and wastes a lot of time and manpower. Therefore, the gray wolf optimization algorithm is used to optimize LSSVM parameters to optimize the performance of LSSVM in SOC estimation [8, 9]. GWO can effectively avoid the phenomenon of local optimality and make the model reach the optimality under different conditions. Compared with LSSVM, GWO-LSSVM shows a better estimation performance.

2. Least squares support vector machine
Least squares support vector machine is an improved algorithm of support vector machine. By converting inequality constraints into equality constraints, and replacing quadratic programming with a least squares linear system as the loss function, it effectively improves the calculation efficiency and avoids the increase of training samples. The structure of LSSVM is shown in Figure 1. For a given training sample set \( S=\{(x_1,y_1),(x_2,y_2),\ldots,(x_n,y_n)\} \), and non-linear mapping \( \varphi(\cdot) \), suppose the LSSVM model is:

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

where \( \omega \) represents weight vector and \( b \) represents bias.

According to the principle of risk minimization and put the Lagrangian multiplier \( \alpha \) in, and according to the KKT condition, differential \( \omega, b, \alpha_i \) separately, Formula (2) can be obtained:

\[
\sum_{k=1}^{n} (\alpha_k \cdot K(x_i, x_k)) + b + \frac{\gamma}{\gamma} = y_i, \quad i = 1, 2, \cdots, n
\]

(2)
Finally, the LSSVM regression function can be created:

$$y = f(x) = \sum_{i=1}^{n} \alpha_i K(x_i, x) + b$$  \hspace{1cm} (3)$$

where $K(x_i, x)$ represents kernel function and $K(x_i, x) = \varphi(x)^T \cdot \varphi(x_i)$.

In this paper, the radial basis function with good generalization ability and wide convergence domain is selected as the kernel function of the LSSVM regression model, and the learning and generalization ability of LSSVM model is greatly affected by $\gamma$ and $\alpha$.

3. Gray wolf optimizer

The gray wolf algorithm divides the solutions into four categories according to the actual social hierarchy of gray wolf populations, namely: the optimal solution $\alpha$, the second optimal solution $\beta$, the third optimal solution $\delta$ and the remaining other solutions $\omega$. Gray wolves will surround their prey when preying. This behavior is expressed by the following formula:

$$D = \left| \bar{C} \cdot \bar{X}_p(t) - \bar{X}(t) \right|$$  \hspace{1cm} (4)$$

$$\bar{X}(t+1) = \bar{X}_p(t) - \bar{A} \cdot \bar{D}$$  \hspace{1cm} (5)$$

where $t$ represents the current iterations, $\bar{A}$ and $\bar{C}$ represents coefficient vector, $\bar{X}_p(t)$ is the position vector of prey and $\bar{X}$ is the position vector of wolf.

When wolves surround their prey, they begin to hunt. Based on the currently obtained range, the three optimal solutions are determined and the other search agents are forced to update their location based on the location of the best search agent. In this regard, the following formula is proposed:

$$\bar{X}_1 = \bar{X}_\alpha - \bar{A}_1 \cdot (\bar{D}_\alpha)$$

$$\bar{X}_2 = \bar{X}_\beta - \bar{A}_2 \cdot (\bar{D}_\beta)$$

$$\bar{X}_3 = \bar{X}_\delta - \bar{A}_3 \cdot (\bar{D}_\delta)$$  \hspace{1cm} (6)$$

To perform the mathematical transformation of proximity to prey, the value of $\bar{a}$ needs to be continuously reduced, and the range of $\bar{A}$ will be reduced accordingly. When $\bar{A} \in [-1, 1]$, the next location for the search agent can be any location between the current agent location and the prey.
location. When $|A| > 1$, the gray Wolf leaves the prey and looks for a more suitable prey. The value range of $C$ is $[0,2]$, which provides random weights for prey and is conducive to algorithm exploration and avoiding local optimality. The flowchart of modeling process is shown in Figure 2 and the battery data used in this paper come from University of Maryland.

**Figure 2.** Flow chart of proposed model.

### 4. Results and discussion

#### 4.1. Optimal parameters

Using the gray wolf optimization algorithm, 30 population sizes are selected and 100 iterations are used to optimize the parameters of the LSSVM model. The optimization curve is shown in Figure 3. At 0°C, parameter 1 after model optimization is 87.7906, parameter 2 is 23.1807; at 25°C, parameter 1 after model optimization is 54.8171, parameter 2 is 21.616; at 45°C, parameter 1 after model optimization is 15.004, parameter 2 is 1.3522.
4.2. SOC estimation

Under FUDS driving cycles, the 3000 sets of the battery data is collected. And 90% percentage of the collected data are selected as model training samples to train the model, and the remaining 10% percentage are used for model testing. The SOC is estimated based on the proposed method, and the estimation result is compared with LSSVM. The results are shown in Figures 4, 5, 6 and 7:
Figure 6. Result of proposed model and LSSVM at 45°C (a) SOC, (b) error.

Figure 7. Error of proposed model and LSSVM at (a) 0°C, (b) 25°C, (c) 45°C.

5. Conclusions
The main contribution of this paper is the development of a SOC estimation model using LSSVM and GWO that shows a better estimation performance in SOC estimation under different temperatures. The GWO algorithm was used to search for the optimal model parameters globally to optimize the model. The experimental results show that the minimum estimation accuracy RMSE of the LSSVM model optimized by GWO is 0.89%, and the model accuracy is improved by about 35%.

In the future, we will focus on the effect of battery aging on SOC estimation and reduce the calculation burden.

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