The State of Charge Estimation of Power Lithium Battery Based on RBF Neural Network Optimized by Particle Swarm Optimization

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Abstract

In order to ensure the safe and stable operation of electric vehicles (EV), it is necessary to accurately estimate the state of charge (SOC) of power lithium battery for electric vehicle. Because of the nonlinear relationship between SOC and its influencing factors, RBF neural network has obvious advantages in solving nonlinear problems, so in this paper, an SOC estimation method of power battery based on RBF neural network is proposed. In order to improve the accuracy of SOC estimation, we use particle swarm optimization (PSO) to optimize the RBF neural network model and identify the value of RBF network center vector and the weights through global optimal searching ability of PSO algorithm. The results simulation show that the SOC model based on PSO-RBF neural network has good estimation accuracy.

Key Words: Electric Vehicle, State-of-charge Estimation, Radial Basis Function Neural Network, Particle Swarm Optimization Algorithm

1. Introduction

Power battery is the power source of electric vehicles, and the remaining power of battery directly affects the driving range and driving performance of electric vehicles [1]. State of charge (SOC) is an important parameter reflecting the remaining power of the battery, SOC estimation is a basic function of the power battery management system [2], the accuracy of SOC estimation also reflects the performance of the battery management system.

The existing methods of SOC estimation are as follows: discharge experiment method, current time integral method, open circuit voltage (OCV) measurement, resistance method, linear model method, Kalman filtering method [3], neural network method and so on. The discharge experiment method and open circuit voltage method can’t realize the SOC real-time measurement, which is not appropriate to the estimation of electric vehicle battery SOC; resistance method’s shortcomings is difficult to measure battery single body resistance accurately; current time integral method depends on the accuracy of the battery SOC initial value, which has large accumulated error; linear model method is only applicable to the condition of low current and SOC graded [4]; Kalman filter algorithm needs to establish an accurate battery equivalent model. Neural network method is especially fit for the SOC prediction of power battery to deal with complicated nonlinear characteristics. The prediction of battery SOC does not need to consider the internal complex nonlinear characteristics of the battery, but only to consider the external characteristics of the battery system. It can estimate the different environment of battery SOC state through a large number of sample data and also has high prediction accuracy and good robustness [5].

In this paper, the neural network model for electric vehicle lithium-ion power battery SOC estimation is pro-
posed. Firstly, the structure of RBF neural network model for SOC estimation is designed. Secondly, the center vector and the weights of the RBF neural network are optimized and trained using particle swarm optimization algorithm. Finally, the battery data is obtained by the electric vehicle simulation software, and we use it to train and test the well-designed models.

2. SOC Estimation Based on RBF

2.1 RBF Neural Network Structure

The structure of RBF neural network is shown in Figure 1. It is divided into three layers: the input layer, the hidden layer, and the output layer. The number of input data is equal to the dimension of sample data. The amount of hidden layers can be selected as needed. The output layer is the result of the input data.

Where $C_i$ is the radial basis function center of RBF Network; $||x - C_i||$ is the distance between the input and the center; $h$ is the neurons number of hidden layer; $W$ is the connection weight of hidden layer to the output layer. The essence of RBF neural network is to transform the input data into another space. The distance between the input vector and the radial basis function center vector can be seen as an independent variable. Because the distance radially isotropic, the function that fluctuates with the independent variable is called radial basis function [6]. Radial basis functions generally take the Gauss function, function is as follows.

$$\varphi_i(x) = \exp\left(\frac{||x - C_i||^2}{2\sigma_i^2}\right)$$  \hspace{1cm} (1)

$\sigma_i$ is the width of the radial basis function.

2.2 RBF Neural Network Learning Algorithm

There are three parameters need to be solved in the learning algorithm of RBF neural network: radial basis function center, variance, and hidden layer to output layer weights. RBF network has a variety of learning algorithms according to the selection method of radial basis function center, such as random center method, gradient training method, supervised selection center method and the orthogonal least squares, etc [7].

In this paper, the gradient method is used, defining the objective function as:

$$E(k) = \frac{1}{2} (y(k) - y_m(k))^2$$  \hspace{1cm} (2)

where $y(k)$ is true SOC value, $y_m(k)$ is RBF network output.

According to the gradient descent method, the iterative algorithm of the connection weight, width vector and center vector of RBF network are shown as follows [8]:

$$\Delta w_j(k) = -\eta \frac{\partial E(k)}{\partial w_j} = \eta (y(k) - y_m(k)) h_j$$  \hspace{1cm} (3)

$$w_j(k) = w_j(k-1) + \eta (y(k) - y_m(k)) h_j$$  \hspace{1cm} (4)

$$\Delta \sigma = -\eta \frac{\partial E(k)}{\partial \sigma_j} = (y(k) - y_m(k)) h_j \frac{||x - C_i||}{\sigma_j}$$  \hspace{1cm} (5)

$$\sigma_j(k) = \sigma_j(k-1) + \eta \Delta \sigma_j + \alpha (\sigma_j(k-1) - \sigma_j(k-2))$$  \hspace{1cm} (6)

$$\Delta c_{\mu}(k) = -\eta \frac{\partial E(k)}{\partial c_{\mu}} = (y(k) - y_m(k)) h_j \frac{x_i - c_{\mu}}{b_j^2}$$  \hspace{1cm} (7)

$$c_{\mu}(k) = c_{\mu}(k-1) + \eta \Delta c_{\mu} + \alpha (c_{\mu}(k-1) - c_{\mu}(k-2))$$  \hspace{1cm} (8)

where, $\eta$ is learning rate, $\alpha$ is momentum factor. $\eta \in [0, 1], \alpha \in [0, 1]$.

2.3 RBF Neural Network Structure Designed for SOC Estimation

In RBF neural network, the number of nodes in the input layer depends on the number of influencing factors. The selection of influencing factors directly decides...
the accuracy of the estimation of lithium ion battery SOC. The main influencing factors of battery SOC are the battery charge and discharge rate, battery temperature, ambient temperature, self-discharge and aging degree, etc. In this paper, the change mechanism and external performance has been studied, and the input vector of RBF neural network is synthetically determined based on the various estimation methods and calculation formulas of SOC.

1) SOC is estimated by using improved current time integral method, the formula is as follows [9]:

\[
SOC_k = \gamma \beta SOC_{k-1} - \frac{1}{\delta C} \int_{t_{k-1}}^{t_k} \eta_{k-1} I_{k-1} dt
\]

(9)

where, \( \gamma \) is the correction factor of self-discharge; \( \beta \) is the correction factor of cell aging degree; \( SOC_{k-1} \) is the battery SOC at time k-1; \( C \) is capacity of the battery; \( \delta \) is correction factor of battery capacity, which is closely related to aging of the battery; \( I_{k-1} \) is battery charge and discharge current at time k-1 (discharge is positive and charge is negative); \( \eta_{k-1} \) is battery efficiency coefficient at time k-1, which is closely related to battery charge and discharge current.

The essence of current time integral method is to put the battery as a special capacitor, the calculation amount of charge depends on the battery charge and discharge current. Battery SOC change at time K depends on the charge import to the battery at time K, which is as follows:

\[
\begin{align*}
\Delta Q_k &= I_{k-1} \Delta t \\
\Delta SOC_k &= f_1(\Delta Q_k) \\
SOC_k &= SOC_{k-1} + \Delta SOC_k
\end{align*}
\]

(10)

(2) According to the open circuit voltage method, the open circuit voltage and the SOC of the battery have a relatively fixed function under certain temperature conditions, which is the OCV-SOC curve [10]. The open circuit voltage of the battery can also serve as the external characteristic of battery SOC. SOC expression can be written as:

\[
SOC(k) = f_2(U_{acc}(k), T_k)
\]

(11)

In above formula, \( T_k \) can be regarded as battery temperature at time K.

(3) The PNGV model can reflect power battery transient response process and has high estimation accuracy. It is suitable for battery modeling in urban condition [11]. The extended Kalman filter (EKF) method was used to estimate the battery SOC based on PNGV (Partnership for a New Generation of Vehicle) model. The relationships between battery voltage, battery internal resistance, open circuit voltage and current are given by:

\[
U_k = U_{acc} - IR_0 - U_p
\]

(12)

where \( U_k \) is battery terminal voltage; \( U_{acc} \) is battery open circuit voltage; \( R_0 \) is battery ohmic resistance; \( U_p \) is polarization voltage of the battery, it is related to battery polarization internal resistance.

Due to the internal resistance of the battery in charge and discharge process, the terminal voltage lags behind battery open circuit voltage relatively, when using the open circuit voltage method, the SOC of battery at time k-1 can be written as follows:

\[
\begin{align*}
U_{acc} &= U_k + IR_0 + U_p \\
R &= f_3(I_k, U_{acc}, U_k) \\
SOC_k &= f_4(U_{acc}(k), T_k)
\end{align*}
\]

(13)

(4) The charge and discharge process of the battery, the battery temperature \( T \) changes relevant to charge and discharge current and internal resistance, the calculation of battery heat \( \Delta Q_k \) can be expressed as follows:

\[
\begin{align*}
\Delta T &= T_k - T_{k-1} \\
\Delta T &= f_5(\Delta Q_k) \\
\Delta Q_k &= I_{k-1}^2 R_{k-1} \\
R_{k-1} &= f_6(I_{k-1}, T_k, T_{k-1})
\end{align*}
\]

(14)

where \( T(k) \) is battery temperature at moment k-1; \( T(k - 1) \) is battery temperature at moment k-1.

(5) According to [12], Shi Wei et al. proposed the SOC
estimation of LiFePO4 battery by $\Delta Q/\Delta V$ curve. Substitutes Eq. (9), the following relations can be obtained simply.

\[
\begin{align*}
\Delta Q_k &= I_{k-1} \Delta t \\
\Delta U_k &= U_k - U_{k-1} \\
SOC_k &= f_k(\Delta Q_k / \Delta U_k) \\
SOC_k &= f_k(U_{k-1}, U_{k-1}, U_k)
\end{align*}
\]  \hspace{1cm} (15)

Combining with Eqs. (1)−(5) and considering the relationship between the various factors, SOC calculating can use the following comprehensive physical quantities, the expression can be written as follows:

\[
SOC_k = f_k(U_{k-1}, U_{k-1}, T_{k-1}, T_k)
\]  \hspace{1cm} (16)

From the mechanism changes of battery SOC, we can well understand the SOC comprehensive calculation expression above. Because the battery can be seen as a special capacitor, the charge and discharge of the battery is the main reason for the change of the SOC. The changes of the terminal voltage and the temperature are the external characterizations of SOC.

Because lithium batteries have low self-discharge rate and short hours in an open period and the cell aging degree is difficult to directly measure. Besides, the existing vehicle heat management system makes the battery ambient temperature constant relatively, so the effect of self-discharge, aging factors and battery ambient temperature will not be considered in the SOC estimation process. So in this paper, $X = (U_{k-1}, U_k, I_{k-1}, I_{k-1}, T_{k-1}, T_k)$ is determined as the input vector of RBF neural network. Meanwhile, these physical quantities are easy to be measured, which is convenient for SOC estimation and avoids the dependence on the initial value of SOC. In addition, the number of nodes in hidden layer is set to 40 after many simulation experiments, so the final structure of the RBF network is shown in Figure 2.

3. SOC Estimation Based on PSO-RBF

3.1 Basic Principles of PSO Algorithm

In an N-dimensional target search space, there are M particles in the group, in which each particle is represented as an N-dimensional vector $x_i = (x_{i1}, x_{i2}, \ldots, x_{iN})$. Substitutes $x_i$ into an objective function, then the value of the solution can be adapted according to the quality analysis of adaptation degree value. The velocity of particle $i$ is a vector of N dimensions, denoted as $v_i$. The best location to search for the particle $i$ is $p_i = (p_{i1}, p_{i2}, \ldots, p_{iN})$. The best location to search for the whole particle swarm is $p_g = (p_{g1}, p_{g2}, \ldots, p_{gN})$. The particle velocity and position update formulas are denoted as [13]:

\[
v_n(t+1) = w \ast v_n(t) + c_1 \ast r_1(p_n(t) - x_n(t)) + c_2 \ast r_2(p_g(t) - x_n(t))
\]  \hspace{1cm} (17)

\[
x_n(t+1) = x_n(t) + w \ast v_n(t+1)
\]  \hspace{1cm} (18)

where $i = (1, 2, \ldots, M)$, $n = (1, 2, \ldots, N)$, $t = (1, 2, 3, \ldots, T)$ is expressed as population iteration; the second part is the influence of particle’s current search individual best position $p_i(n)$, it can be understood as “self-cognition behavior” of particles, expressing the self-thinking of particles. The third part shows the influence of the optimal position of the whole particle swarm $p_g(n)$, which can be understood as the “social behavior” of particles, and represent the information sharing and cooperation among individuals in the particle swarm [14].

In the search process, $w$, $C_1$, $C_2$ are used to control the search weight of speed, best location of the individual and the best location of population, respectively, in order to achieve the balance between region search and local search. $w$ is the inertia weight, which controls the particle’s flying speed. when the inertia weight is larger, the larger search size of the particle will be in the global; when the search size of particle is smaller, the particle tends to the subtle local search. In summary, $C_1$ is used to adjust the size of the impact of individual best position; $C_2$ is used to control the best position of the group’s influence.

![Figure 2. SOC estimation RBF network structure.](image-url)
r1 and r2 are random numbers on [0~1], $v_{\text{max}}$ is a constant that is used to limit the range of particle velocity. $x_{\text{max}}$ is a constant that limits the search range of the particle swarm [15].

3.2 The Basic Flows of PSO Algorithm

Optimization RBF Network

In this paper, the RBF neural network hidden layer nodes are set to 40, the parameters need to be optimized for the RBF network center vector and weight vector, so the particle dimension in the PSO optimization algorithm is $6 \times 40 + 40 = 280$. The basic optimizations flows are as follows:

(1) Initialize population. The population size of the particle swarm is 40; the particle correlation parameters are set to $c_1 = 2.05$, $c_2 = 2.05$, and the maximum number of iterations is $T = 1000$.

(2) Calculate the fitness of particles based on objective function. In this paper, the objective function is set as the sum of training samples error.

$$f_i = 100\sum_{i=1}^{n}|SOC_p - SOC_t|$$ (19)

where $SOC_p$ is the RBF neural network estimated value, $SOC_t$ is the true value; $n$ is the number of training samples.

(3) Update the best location and the best location of particle swarm.

(4) Update particle velocity and position.

(5) Calculate the fitness of particles based on objective function.

(6) Update the particle best location and the best location of particle swarm. To determine whether to reach the maximum number of iterations, output the optimal solution when reaching the end of the conditions. Otherwise go (3).

(7) End. The process is shown in Figure 3.

4. Power Battery Data Extraction and Pretreatment

Most research of EV battery SOC estimation is based on power battery unit. However, pure electric vehicle performance is the true reflection of battery characteristics. Therefore, the accuracy of electric vehicle power battery SOC estimation can be reflected only when the battery pack model was loaded in pure electric vehicle platform. So in this paper, the advanced vehicle simulation software ADVISOR (Advanced Vehicle Simulator) was taken as the simulation platform and the battery data of electric vehicle were obtained.

4.1 Battery Data Acquisitions

In the simulation software ADVISOR, parameters of the electric vehicle simulation model are set as Table 1.

Most of the existing methods estimating lithium ion battery SOC based on constant current discharge conditions. But the operating conditions of the electric vehicle power battery was taken as the simulation platform and the battery data of electric vehicle were obtained.

![Figure 3. Particle swarm optimization process.](image)

<table>
<thead>
<tr>
<th>Table 1. Parameters of electric vehicle</th>
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<tbody>
<tr>
<td>Curb weight (kg)</td>
</tr>
<tr>
<td>Load weight (kg)</td>
</tr>
<tr>
<td>Wheelbase (mm)</td>
</tr>
<tr>
<td>Center of gravity height (m)</td>
</tr>
<tr>
<td>Wheel radius (mm)</td>
</tr>
<tr>
<td>Windward area (m²)</td>
</tr>
<tr>
<td>Drive motor type</td>
</tr>
<tr>
<td>Transmission type</td>
</tr>
<tr>
<td>Battery model</td>
</tr>
<tr>
<td>Battery module type</td>
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<tr>
<td>Number of battery module</td>
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</table>
power lithium ion battery are different from that of the ordinary battery. The impact of road conditions, driving behavior, and inconsistent motor power demand lead to battery discharge current drastic changes.

Urban Dynamometer Driving Schedule (UDDS) is simulation operating condition based on the characteristics of urban road vehicle driving after the statistics of the proportion of the driving conditions of the city. The pure electric vehicle generally run in urban conditions because of the limits of the driving mileage UDDS operating conditions can better reflect the dynamic performance and economic performance of pure electric vehicle [16]. Therefore, in this paper, the power battery SOC estimation simulation based on the UDDS operating conditions was investigated. The electric vehicle simulation results under UDDS condition are shown in Figure 4.

The cycle time of UDDS is 1369s, the sampling period of ADVISOR is 1s, and the data are 1370 groups. In general, the more training samples of neural networks, the higher the reliability of the model trained and the better the robustness of the model is, but the training time of the model will be the longer. In this paper, 400 groups of them were randomly selected as the training data of the neural network, and the 100 groups of them were used as test data.

4.2 Data Pretreatment

Before the use of a neural network model to calculate the multi parameter analysis, the neural network training data set must be normalized firstly, and the normalized data are helpful to accelerate the convergence speed of the training network. Therefore, before the use of the neural network model to estimate the power lithium battery SOC, the battery data set has been normalized, the normalized formula is given by:

\[
x'_i = \frac{x_{\text{max}} - x_i}{x_{\text{max}} - x_{\text{min}}}
\]

After normalizing the battery data, the data of battery SOC, battery terminal voltage and battery discharge current are distributed in the range of 0 to 1.

5. Simulation Results Analysis

5.1 SOC Estimation Model Training

In order to speed up the convergence speed of particle swarm optimization algorithm, adaptive inertia weight is adopted in the optimization process of PSO algorithm, and the update formula is as follows, the iteration process is shown in Figure 5.

\[
w(t) = w_i - (w_i - w_j) \cdot \left( \frac{\log(t+1)}{\log(T+1)} \right)
\]

5.2 Verification and Testing of SOC Estimation Model

In the above context, the center vector, and network weights of the RBF neural network are obtained using particle swarm optimization algorithm, then tested the RBF neural network model is tested and verified with
100 battery test data, and comparison with the conventional RBF neural network model is done. The estimation results of two SOC estimation models are shown in Figure 6.

The estimated percentage error of the two models is shown in Figure 7, Figure 8.

As can be seen from Figures 7~8, the electric vehicle lithium battery SOC was estimated using the conventional RBF neural network, the maximum estimation error is up to 8%, estimation error is large, and so it cannot reach the purpose of estimating the SOC value accurately. Then, SOC estimated using PSO-RBF neural network. The maximum estimated error is 1.2%, which is smaller and of high accuracy, good performance and satisfactory results. The mean absolute error (MAE), root mean square error (RMSE) and training time of the two SOC estimation models are shown in Table 2.

6. Conclusions

A SOC estimation method for power lithium battery of electric vehicle based on PSO-RBF neural network is proposed in this paper. Compared with the traditional RBF neural network algorithm, the global optimal searching ability of PSO-RBF neural network algorithm for center vector and weights is better, so the PSO-RBF neural network model is more accurate in the electric vehicle lithium battery SOC estimation. The method can accurately estimate the SOC with estimation error within range of 1.2% and with training time about 2.54s, MAE is 0.0036 and RMSE is 0.6039. At the same time, it avoids the dependence on SOC initial value, which makes the method have good robustness. The practical results show that PSO-RBF neural network method can be applied for SOC estimation in electric vehicle power lithium battery.

**Table 2.** Comparison of model estimation errors

<table>
<thead>
<tr>
<th>Estimation model</th>
<th>RBFNN</th>
<th>PSO-RBFNN</th>
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<tbody>
<tr>
<td>Training time (s)</td>
<td>1.98</td>
<td>2.54</td>
</tr>
<tr>
<td>MAE (%)</td>
<td>0.0867</td>
<td>0.0036</td>
</tr>
<tr>
<td>RMSE (%)</td>
<td>2.9453</td>
<td>0.6039</td>
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</table>
References


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