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SOC estimation of lithium-ion power battery for HEV based on advanced wavelet neural network

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Abstract: In order to improve the estimation accuracy of the battery's state of charge (SOC) for the hybrid electric vehicle (HEV), the SOC estimation algorithm based on advanced wavelet neural network (WNN) is presented. Based on advanced WNN, the SOC estimation model of a lithium-ion power battery for the HEV is first established. Then, the convergence of the advanced WNN algorithm is proved by mathematical deduction. Finally, using an adequate data sample of various charging and discharging of HEV batteries, the neural network is trained. The simulation results indicate that the proposed algorithm can effectively decrease the estimation errors of the lithium-ion power battery SOC from the range of $\pm 8\%$ to $\pm 1.5\%$, compared with the traditional SOC estimation methods.
Key words: wavelet neural network; state of charge (SOC); hybrid electric vehicle; lithium-ion power battery
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The battery management system (BMS) is important in the control system of the hybrid electric vehicle (HEV), which mainly guarantees that the performance of the battery pack is in a reasonable range of its parameters[1]. The BMS can protect the safety, extend the life and estimate the state of charge (SOC) of batteries.

The SOC is a very important parameter in the BMS[2], which cannot be measured directly because of the inaccurate mathematical model[3]. In fact, it is influenced by many factors, such as different charging/discharging currents, temperature, self-discharge, aging and so on. So it can be only estimated by means of the battery's external characteristics, such as voltage, current and temperature. Presently, the accurate estimation of the remaining capacity of the lithium-ion power battery is still a difficult problem in the field of HEV design.

There are many traditional SOC estimation methods, such as the resistance measurement method (RM method), the zero load model method (ZLM method), the current integral method (CI method), the electrochemical analysis (EA method), and the voltage measurement method (VM method). Some new SOC estimation methods including the Kalman filter method (KF method), the fuzzy inference method (FI method), and the artificial neural network method (ANN method) are presented.

So far, the CI method and the KF method have been implemented in practical applications. The SOC estimation using an adaptive extended Kalman filter was reported in Ref. [4]. A merged fuzzy neural network and its applications in battery SOC estimation was investigated by Li et al[5]. The ANN method can be found in Ref. [6].

The FI method and the ANN method have attracted a great deal of attention in the last few years[7-8]. In this paper, some concepts about lithium-ion power batteries are first introduced. Furthermore, the advanced wavelet neural network (WNN) architecture is approximately designed. Then, in order to choose additional momentum WNN inputs, the correlation analysis of a few different variables is proposed. Training data sets are selected and the Levenberg-Marquardt training algorithm is adopted. Other data sets are used to verify the advanced WNN model. Finally, an example is given to illustrate the effectiveness of the proposed method.

1 SOC Estimation Model Based on WNN

1.1 Data of lithium-ion battery pack

The HEV simulation software platform ADVISOR collects the data which are used by estimation processes, such as battery current, voltage, demand power and the value of the SOC. The data of the battery in the ADVISOR is obtained through the actual testing results of the researchers in the United States Energy Department Renewable Energy Laboratory. The SOC relationship with the resistance, voltage, current and instantaneous power is shown in Fig. 1, where C represents the multiple of the battery's rated capacity.

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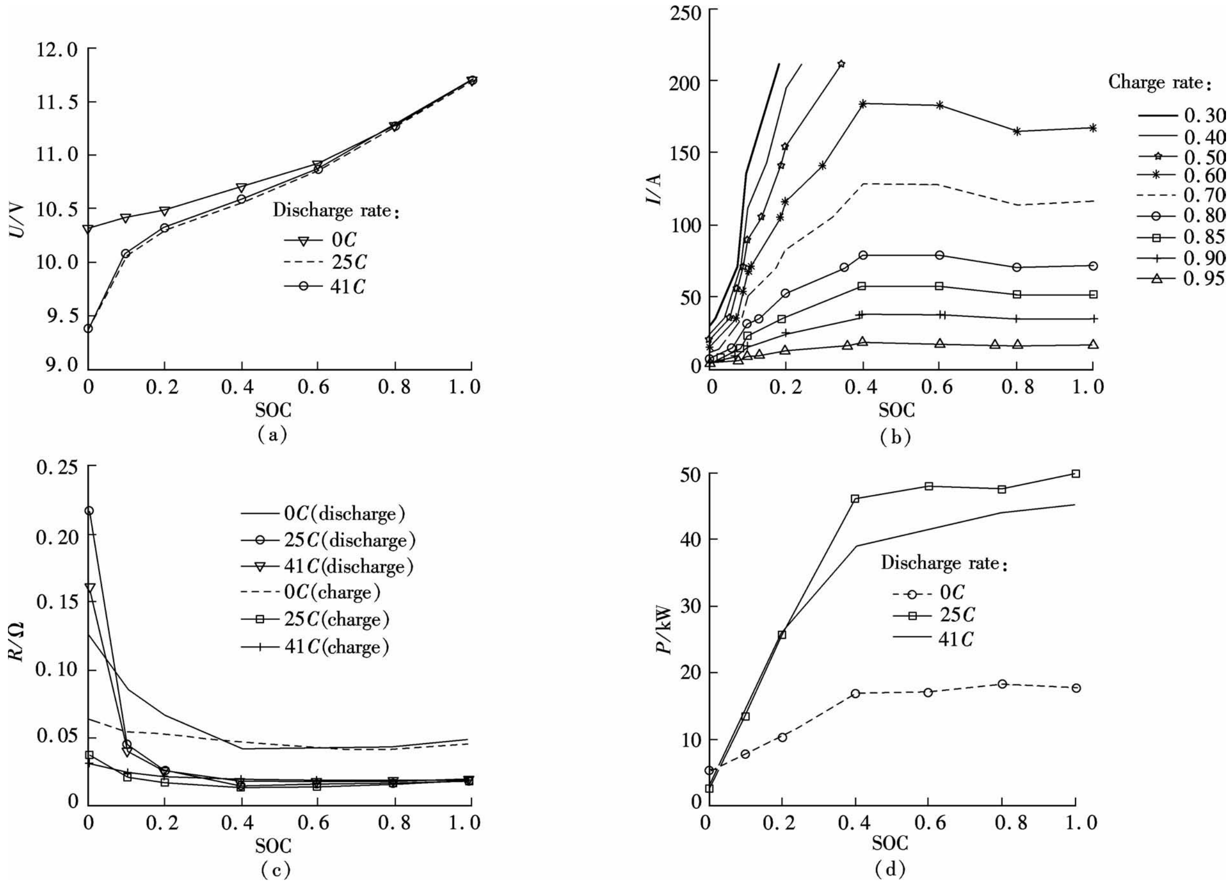

Fig. 1 Relationship between SOC and various parameters. (a) Voltage; (b) Current; (c) Resistance; (d) Instantaneous power

1.2 SOC estimation model based on advanced WNN

The structure model and the algorithms of the WNN are designed, combining the advantages of both wavelet transform and ANN. The three-layer advanced WNN to estimate and predict the SOC of lithium-ion power battery is described in Fig. 2, which can be used as a general function approximator. The main goal is to estimate the SOC of the battery when driving a vehicle in Manhattan drive cycle. Besides, the starting advanced WNN SOC estimation of the lithium-ion power battery is originally unknown whether the SOC is 100% or not.

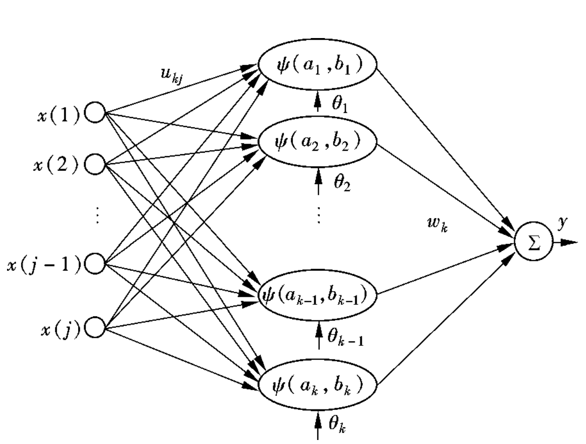

Fig. 2 BP network structure of three layers

$\psi(x)$ is a generating function in mother wavelet function[9]. The possible adjustable parameters are composed of weights w_k, u_{kj} and θ_k. Wavelet translation parameter b_k and wavelet dilation parameter a_k are shown in Fig. 2.

$$\psi_{a,b}(x)=\frac{1}{\sqrt{a}}\psi\left(\frac{x-b}{a}\right)\qquad a>0,\ b\in\mathbf{R}\tag{1}$$

The Morlet wavelet function is given in Refs. [10 − 11]. The Morlet wavelet translation parameter b and the wavelet dilation parameter a are given in Ref. [12]. The derivation process of the Morlet wavelet function is as follows:

$$\psi(x)=\cos(1.75x)\exp(-0.5x^2)\tag{2}$$

$$\psi\left(\frac{x-b}{a}\right)=\cos\left(1.75\,\frac{x-b}{a}\right)\exp\left[-0.5\left(\frac{x-b}{a}\right)^2\right]\tag{3}$$

where $\psi(a_k, b_k)$ is a generating function in the Morlet wavelet function finally as

$$\psi(a_k,b_k)=\cos\left(1.75\,\frac{x_k-b_k}{a_k}\right)\exp\left[-0.5\left(\frac{x_k-b_k}{a_k}\right)^2\right]\tag{4}$$

1.3 Learning algorithm of wavelet neural network

Since the learning algorithm of the WNN uses the steepest descent method, the wavelet base function is $\psi(x)$ and the input is x.

The real output of WNN can be given as

$$\hat{y} = \sum_{k=1}^{L}\left(w_k\psi_k\left(\frac{\sum_{j=1}^{m}u_{kj}x_j - b_k}{a_k}\right)+\theta_k\right) \tag{5}$$

And the output error of the WNN is

$$E = \frac{1}{2}\left(y - \sum_{k=1}^{L}\left(w_k\psi_k\left(\frac{\sum_{j=1}^{m}u_{kj}x_j - b_k}{a_k}\right)+\theta_k\right)\right)^2 \tag{6}$$

Grads value and direction are calculated by finite differences with the first order local deviation. The derivation process of the output error for the WNN with the first order local deviation can be shown as follows:

$$\frac{\partial E}{\partial w_k} = -\left(y - \sum_{k=1}^{L}\left(w_k\psi_k\left(\frac{\sum_{j=1}^{m}u_{kj}x_j - b_k}{a_k}\right)+\theta_k\right)\right)\cdot \psi_k\left(\frac{\sum_{j=1}^{m}u_{kj}x_j - b_k}{a_k}\right) \tag{7}$$

$$\frac{\partial E}{\partial u_{kj}} = -\left(y - \sum_{k=1}^{L}\left(w_k\psi_k\left(\frac{\sum_{j=1}^{m}u_{kj}x_j - b_k}{a_k}\right)+\theta_k\right)\right)\cdot \psi'_k\left(\frac{\sum_{j=1}^{m}u_{kj}x_j - b_k}{a_k}\right)\frac{x_j}{a_k} \tag{8}$$

$$\frac{\partial E}{\partial b_k} = \left(y - \sum_{k=1}^{L}\left(w_k\psi_k\left(\frac{\sum_{j=1}^{m}u_{kj}x_j - b_k}{a_k}\right)+\theta_k\right)\right)\cdot \psi'_k\left(\frac{\sum_{j=1}^{m}u_{kj}x_j - b_k}{a_k}\right)\frac{1}{a_k} \tag{9}$$

$$\frac{\partial E}{\partial a_k} = \left(y - \sum_{k=1}^{L}\left(w_k\psi_k\left(\frac{\sum_{j=1}^{m}u_{kj}x_j - b_k}{a_k}\right)+\theta_k\right)\right)\cdot \psi'_k\left(\frac{\sum_{j=1}^{m}u_{kj}x_j - b_k}{a_k}\right)\frac{\sum_{j=1}^{m}u_{kj}x_j - b_k}{a_k^2} \tag{10}$$

$$\frac{\partial E}{\partial \theta_k} = \left(y - \sum_{k=1}^{L}\left(w_k\psi_k\left(\frac{\sum_{j=1}^{m}u_{kj}x_j - b_k}{a_k}\right)+\theta_k\right)\right) \tag{11}$$

where the Morlet wavelet function $\psi(a_k, b_k)$ is the WNN activation function or an orthonormal matrix as follows:

$$\left.\begin{aligned} &a_{k+1} = a_k - \xi\frac{\partial E}{\partial a_k}, \quad b_{k+1} = b_k - \xi\frac{\partial E}{\partial b_k} \\ &\theta_{k+1} = \theta_k - \xi\frac{\partial E}{\partial \theta_k}, \quad w_{k+1} = w_k - \xi\frac{\partial E}{\partial w_k} \\ &u_{kj+1} = u_{kj} - \xi\frac{\partial E}{\partial u_{kj}} \end{aligned}\right\} \tag{12}$$

where ξ is the learning rate of weights in the Morlet WNN.

$$\left.\begin{aligned} &\boldsymbol{x} = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_m \end{bmatrix}, \boldsymbol{w} = \begin{bmatrix} w_1 \\ w_2 \\ \vdots \\ w_k \end{bmatrix}, \boldsymbol{a} = \begin{bmatrix} a_1 \\ a_2 \\ \vdots \\ a_k \end{bmatrix}, \boldsymbol{b} = \begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ b_k \end{bmatrix} \\ &\boldsymbol{\theta} = \begin{bmatrix} \theta_1 \\ \theta_2 \\ \vdots \\ \theta_k \end{bmatrix}, \boldsymbol{u} = \begin{bmatrix} u_{11} & u_{12} & \dots & u_{1k} \\ u_{21} & u_{22} & \dots & u_{2k} \\ \vdots & \vdots & & \vdots \\ u_{j1} & u_{j2} & \dots & u_{jk} \end{bmatrix} \end{aligned}\right\} \tag{13}$$

The WNN parameters including w_k, u_{kj} and θ_k need to be trained.

An improved gradient descent method is proposed. The proposed WNN with additional momentum items is applied to the WNN. The momentum of the additions such as Δa_k, Δb_k, $\Delta\theta_k$, Δw_k etc. are described as

$$\left.\begin{aligned} &a_{k+1} = a_k - \xi\frac{\partial E}{\partial a_k} + \alpha\Delta a_k, \quad b_{k+1} = b_k - \xi\frac{\partial E}{\partial b_k} + \alpha\Delta b_k \\ &\theta_{k+1} = \theta_k - \xi\frac{\partial E}{\partial \theta_k} + \alpha\Delta\theta_k, \quad w_{k+1} = w_k - \xi\frac{\partial E}{\partial w_k} + \alpha\Delta w_k \\ &u_{kj+1} = u_{kj} - \xi\frac{\partial E}{\partial u_{kj}} + \alpha\Delta u_{kj} \end{aligned}\right\} \tag{14}$$

2 Convergence of Advanced WNN

The weights vector of the WNN $\boldsymbol{W} = \{a_k, b_k, \theta_k, w_k, u_{kj}\}^{\mathrm{T}}$. The weights value revision formula is put forward with the improved gradient descent method as follows:

$$W(n+1) = W(n) + \Delta W(n) + \boldsymbol{\eta}\left(-\frac{\partial E}{\partial \boldsymbol{W}}\right) \tag{15}$$

where $\boldsymbol{\eta} = \mathrm{diag}\{\eta_a, \eta_b, \eta_\theta, \eta_w, \eta_u\}$, $e = y - \hat{y}$, $\frac{\partial E}{\partial \boldsymbol{W}} = -e\frac{\partial y}{\partial \boldsymbol{W}}$.

Theorem 1 Given $\boldsymbol{C}_{\max} = \{C_{1\max}, C_{2\max}, C_{3\max}, C_{4\max}, C_{5\max}\}^{\mathrm{T}} = \left[\max_k\left\|\frac{\partial y(k)}{\partial \boldsymbol{a}}\right\|, \max_k\left\|\frac{\partial y(k)}{\partial \boldsymbol{b}}\right\|, \max_k\left\|\frac{\partial y(k)}{\partial \boldsymbol{\theta}}\right\|, \max_k\left\|\frac{\partial y(k)}{\partial \boldsymbol{w}}\right\|, \max_k\left\|\frac{\partial y(k)}{\partial \boldsymbol{u}}\right\|\right]^{\mathrm{T}}$. The estimation algorithm based on the advanced WNN is convergent, that is

$$E(k+1) - E(k) \leqslant 0 \qquad k = 1, 2, \dots$$

if there exist η_i, $i = 1, 2, 3, 4, 5$ which satisfy

$$0 < \eta_i < \frac{1}{(1+\alpha)^2 C_{i\max}} \tag{16}$$

where $\boldsymbol{\eta}$ is the learning rate of weights in the advanced WNN, $\boldsymbol{\eta} = \mathrm{diag}\{\eta_a, \eta_b, \eta_\theta, \eta_w, \eta_u\} = \mathrm{diag}\{\eta_1, \eta_2, \eta_3, \eta_4, \eta_5\}$; $\|\cdot\|$ is the Euclidean norm.

Proof Consider the discrete Lyapunov function of SOC estimation based on the advanced WNN:

$$V(k) = \| E(k) \| = \frac{(y-\hat{y})^2}{2} \tag{17}$$

Then similar to the proof in Ref. [13], we have

$$\begin{aligned}\Delta V(k) &= E(k+1) - E(k) = E(W^{k+1}) - E(W^k) \leqslant \\ &- \eta_i \left(\left\| \frac{\partial E(W_i^k)}{\partial W_i(k)} \right\|^2 + \sum_{i=1}^{5} \left\| \frac{\partial E(W_i^k)}{\partial W_i(k)} \right\|^2 \right) + \\ &C_{\max}\eta_i^2(1+\alpha^2)\left(\left\| \frac{\partial E(W_i^k)}{\partial W_i(k)} \right\|^2 + \sum_{i=1}^{5} \left\| \frac{\partial E(W_i^k)}{\partial W_i(k)} \right\|^2 \right) \leqslant \\ &- [\eta_i - C_{max}\eta_i^2(1+\alpha)^2] \left[\left\| \frac{\partial E(W_i^k)}{\partial W_i(k)} \right\|^2 + \right. \\ &\left. \sum_{i=1}^{5} \left\| \frac{\partial E(W_i^k)}{\partial W_i(k)} \right\|^2 \right]\end{aligned}$$

Denote $\beta_k = \eta_i - C_{\max}\eta_i^2(1+\alpha)^2$, then

$$E(W^{k+1}) \leqslant E(W^k) - \beta_k \left(\left\| \frac{\partial E(W_i^k)}{\partial W_i(k)} \right\|^2 + \sum_{i=1}^{5} \left\| \frac{\partial E(W_i^k)}{\partial W_i(k)} \right\|^2 \right) \tag{18}$$

If (16) is true, then we have

$$\beta_k = \eta_i - C_{\max}\eta_i^2(1+\alpha)^2 > 0 \tag{19}$$

From (18) and (19), we obtain

$$E(W^{k+1}) \leqslant E(W^k) \qquad k = 1, 2, \ldots \tag{20}$$

Thus, the estimation algorithm based on the advanced WNN is convergent. The proof is completed.

3 Data Training and Simulation Results

3.1 Data for training

We consider a single lithium battery, whose capacity is 6 AH. The training data is from HEV under Manhattan drive cycle after simulation. The training data of the SOC based on the advanced WNN takes the range from 50% to 70% as an example. Figs. 3(a) to (f) show the input of the WNN model for SOC estimation, which includes the current, voltage, temperature, charging efficiency, discharging efficiency, and target SOC.

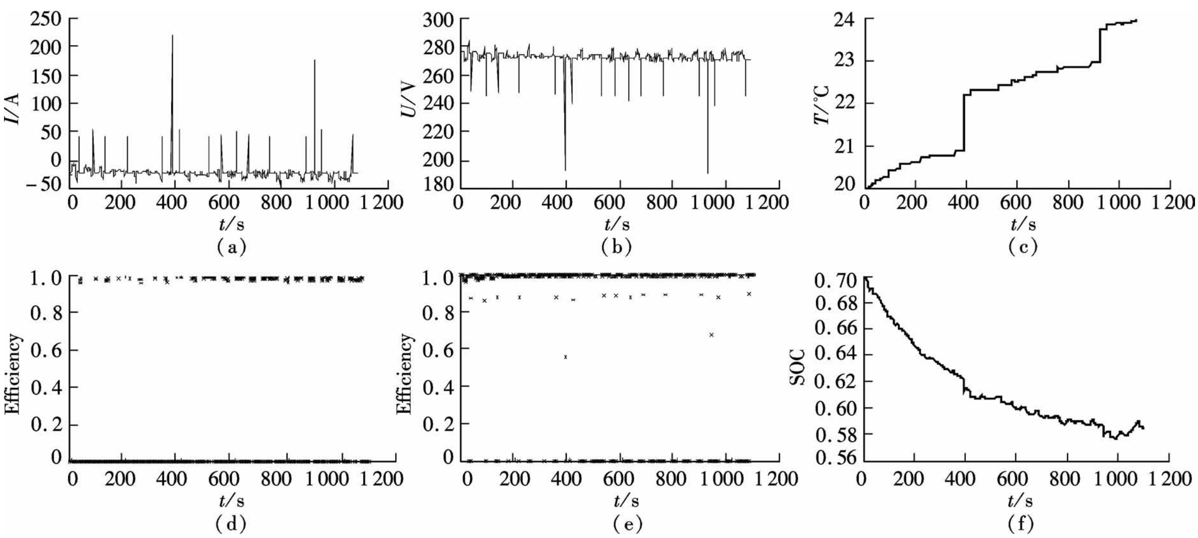

Fig. 3 Training data of wavelet neural network in battery packs. (a) Current; (b) Voltage; (c) Temperature; (d) Charging efficiency; (e) Discharging efficiency; (f) Target SOC

3.2 Training method and training results

The advanced WNN is a learning system with supervisor. We select the TRAINLM training function and the TRAINGDM adaption learning function. Fig. 4 shows the results of the estimated SOC and the true SOC in the ANN algorithm, the BPNN algorithm, the WNN algorithm and the advanced WNN algorithm under Manhattan drive cycle, respectively.

The current, voltage, temperature, charging efficiency and discharging efficiency are added to the ANN model, the BPNN model, the WNN model and the advanced WNN model of the SOC estimation. The accuracy of the WNN and the advanced wavelet neural network is verified by comparing the SOC value output from the model with the true value of the SOC. The simulation results are shown in Fig. 4.

3.3 Errors in WNN algorithm and advanced WNN algorithm

The simulation errors are shown in Fig. 5. We conclude that the absolute error in the ANN algorithm can be controlled in the range of ±8%; the absolute error in the BPNN algorithm can be controlled in the range of ±6%;

the absolute error in the WNN algorithm can be controlled in the range of ±3%, which meet the demands of practical work. Error in the advanced WNN algorithm is less, in the range of ±1.5%. Besides, according to the method of the forecast precision, the advanced WNN model is better than the WNN model, which can meet the SOC estimation requirement of HEV.

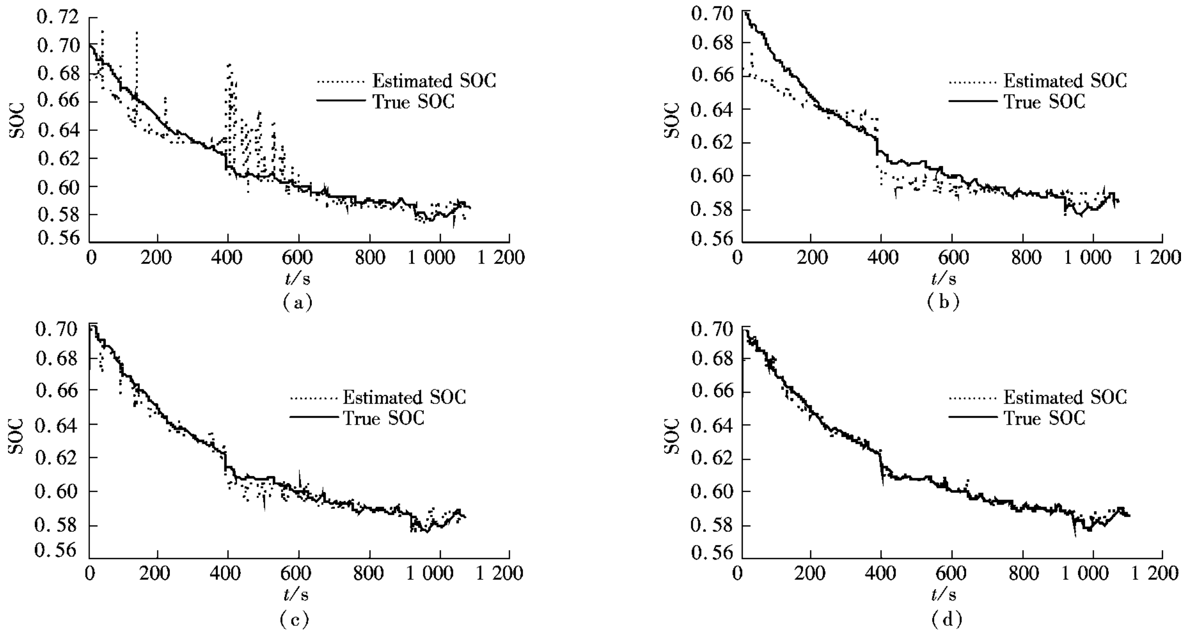

Fig. 4 Estimate SOC and true SOC in different algorithms. (a) ANN algorithm; (b) BPNN algorithm; (c) WNN algorithm; (d) Advanced WNN algorithm

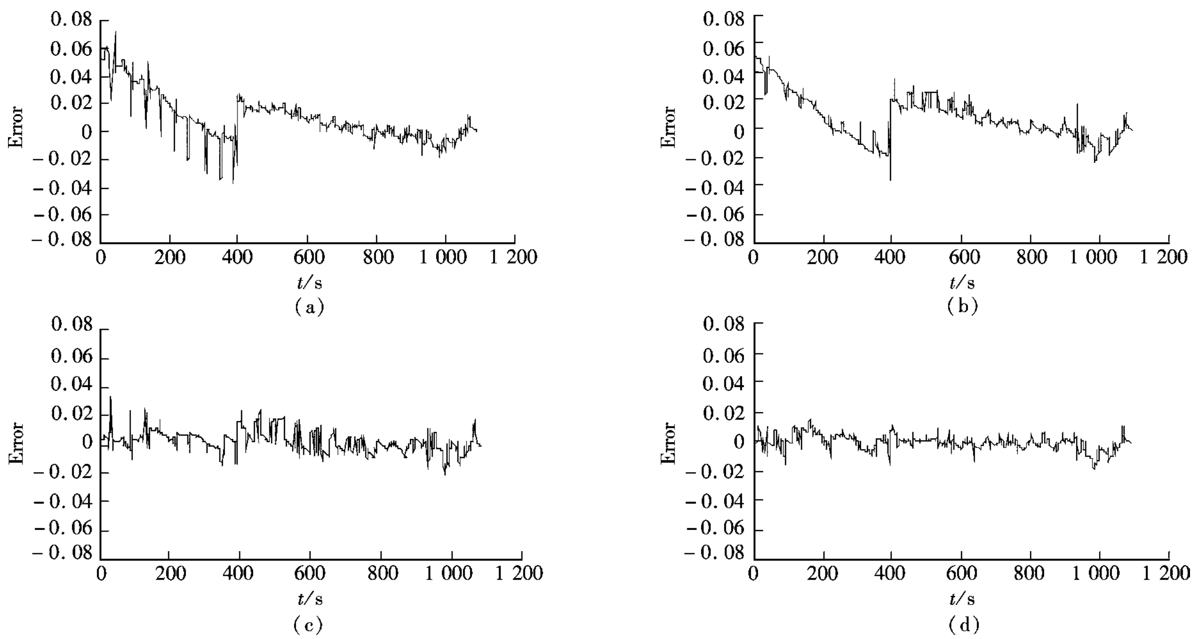

Fig. 5 Errors in different algorithms. (a) ANN algorithm; (b) BPNN algorithm; (c) WNN algorithm; (d) Advanced WNN algorithm

4 Conclusions

1) The simulation results show that the SOC estimation algorithm based on the advanced WNN is an effective method to estimate the SOC of the lithium-ion power battery with high performance.

2) The convergence of the advanced WNN algorithm can be proved by mathematical deduction.

3) The nonlinear estimation accuracy in a certain range of the SOC and the local minimum problem of the advanced WNN are improved by training quality and speed. The SOC estimation error is in the range of ±1.5%, which is better than other traditional algorithms.

In the future work, we will add modified particle swarm optimization (MPSO) to optimize the additional momentum wavelet neural network.

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基于先进小波神经网络的 HEV 动力锂离子电池 SOC 估计

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摘要: 为了提高混合动力汽车(HEV)电池荷电状态(SOC) 的估计精度,提出了一种基于先进小波神经网络的 HEV 动力电池 SOC 估计算法. 首先,建立了基于先进小波神经网络的电池 SOC 估计模型. 然后,通过数学推导证明了先进小波神经网络的收敛性. 最后,利用大量 HEV 动力电池在行驶过程中充放电的数据样本,对神经网络进行网络训练. 仿真结果表明,所提出的估计算法与传统 SOC 估计算法相比,提高了电池 SOC 的估计精度,有效地将估计误差从 ±8% 减小到 ±1.5%.

关键词: 小波神经网络;荷电状态;混合动力汽车;动力锂离子电池

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