Battery SOC Prediction for HEV based on Extreme Learning Machine

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Abstract. The extreme learning machine (ELM) is proposed based on the prediction of the battery’s state of charge (SOC) of the hybrid electric vehicles (HEV). The HEV simulation system is developed under the environment of advanced vehicle simulator (ADVISOR). Considering the influence of working condition to SOC, the Urban Dynamometer Driving Schedule (UDDS) is adopted as the working condition. At the same time, the energy feedback is also taken into consideration when HEV under regenerative braking mode is working. The working voltages, currents and surface temperature of battery are employed to predict the real-time value of SOC, and the results indicate that the prediction model possesses higher predicted accuracy.

1. Introduction

The battery is one of the energy sources of a hybrid vehicle. To ensure good battery performance, extend battery life, and improve the fuel economy of a hybrid vehicle, the battery must be managed and controlled reasonably and efficiently, provided that it can be accurately and reliably obtain the existing capacity parameters of the battery [1]. Just like the oil gauge of a normal car fuel tank, the battery also needs to know the capacity of its power supply. The state of charge (SOC) is an important parameter reflecting the battery capacity. The SOC cannot be directly measured as the internal characteristics of the battery, but it only can be predicted by externally measured parameters such as voltage, current, temperature, etc. [2-3].

The commonly used battery SOC prediction methods can be summarized into three categories. The first type is to directly predict the SOC according to the voltage, current or internal resistance of the battery. The main methods are open circuit voltage method [4], Ensue measurement method [5] and internal resistance characteristics method [6]. Though it is relatively easy to operate under these methods, there still comes along with defects with low prediction accuracy due to the unstable relationship among battery voltage, current or internal resistance and SOC; the second type is based on Kalman filter recursive algorithm. In the prediction method, the Kalman filter method regards the battery as a dynamic system, and the SOC is a state quantity inside the system. The prediction accuracy of this method is relatively higher than the first one, but the description equation of the
dynamic system method needs to be selected. The recursive process also involves complex matrix
inversion operations. At the same time, the Kalman filter is a recursive algorithm, which is very
sensitive to the selection of initial values. The error of the initial value will lead to the deterioration of
the prediction results [7]; the third type is based on the RBF kernel function neural network [8] and
least square support vector machines [9] prediction method. In fact, the least square support vector
machines (LS-SVM) is actually a kind of neural network, which applies the principle of structural risk
minimization [10] to neural networks, and is widely used currently. Its main problem is the slow
training speed, for it is easy to fall into local minimum points and very sensitive to the choice of
learning rate.

In order to overcome the shortcomings of the above methods, and at the same time to take into
account of the large variation of the voltage and current of the HEV battery, the Extreme Learning
Machine (ELM) provides an effective solution. ELM is a single hidden layer forward neural network
learning machine [11]. It has a simple network structure, fast learning speed and good generalization
performance. Moore-Penrose generalized inverse solution network weight can be used to randomly
generate between input layer and hidden layer. The connection weight and the threshold of the hidden
layer neurons do not need to be iteratively adjusted. Only by setting the number of hidden layer
neurons, can the unique optimal solution be obtained.

In this paper, the HEV simulation model is developed based on ADVISOR so as to obtain various
performance parameters of the battery, and select the extreme learning machine method to predict
the battery SOC. In order to bring the extreme learning machine into a full play, it compares and analyses
the performance between ELM and LS-SVM.

2. Basic principle of ELM
The extreme learning machine belongs to the single hidden layer forward neural network as is shown
in Figure 1.

Given a collection of N different samples
\[ N = \{(x_i, y_i) \mid i = 1,2,\cdots,N; x_i \in \mathbb{R}^n; y_i \in \mathbb{R}^m\}, \]
the ELM output with hidden layer neurons can be expressed as
\[ f(x_i) = \sum_{j=1}^{L} \beta_j g(a_j \cdot x_i + b_j), \quad i = 1,2,\cdots,N \quad (1) \]
among them: \( a_j = [a_{j1}, a_{j2}, \cdots, a_{jn}] \), represents an input weight vector connecting the jth hidden layer
node; \( b_j \) is the threshold of the jth hidden layer neuron; \( \beta_j = [\beta_{j1}, \beta_{j2}, \cdots, \beta_{jm}]^T \), is the output weight
vector connecting the jth hidden layer node; \( a_j \cdot x_i \) represents the inner product of \( a_j \) and \( x_i \); \( g(x) \) is the
activation function of hidden layer neurons [12].

According to equation (1), a system of linear equations with N equations can be obtained:
\[ H \beta = Y \quad (2) \]
In equation (2), implicit layer output matrix

\[
H = \begin{bmatrix}
g(a_1 \mathbf{x}_1 + b_1) & \cdots & g(a_1 \mathbf{x}_L + b_1) \\
\vdots & \ddots & \vdots \\
g(a_N \mathbf{x}_1 + b_1) & \cdots & g(a_N \mathbf{x}_L + b_1)
\end{bmatrix}
\]

\[
\beta = [\beta_1, \beta_2, \cdots, \beta_L]^T, \quad Y = [y_1, y_2, \cdots, y_N]^T.
\]

For the hidden layer output matrix \( H \), if \( L \leq N \), then \( H \) is ranked full by probability 1. At the same time, for most problems, there is \( L \leq N \).

Therefore, the output layer parameters \( \beta \) can be solved by the minimum 2-norm least square of equation (2).

\[
\beta = H^+ Y
\]

In the formula (4), \( H^+ \) is a Moore-Penrose generalized inverse of \( H \).

The ELM algorithm is actually a kind of "regression" expression. When dealing with classification problems, ELM uses multi-output regression algorithm to achieve [13].

Suppose that for a classification problem of an \( S \) class, the sample set can be expressed as

\[
N = \{(x_i, y_i)\}_{i=1}^N
\]

Among them, \( x_i \in \mathbb{R}^d, y_i \in \{1, 2, \cdots, S\} \).

Define a new multidimensional target vector

\[
c_i = \left( c_{i1}, c_{i2}, \cdots, c_{is} \right)
\]

In equation (6),

\[
c_y = \begin{cases} 1, & y_i = j \\ -1, & \text{others} \end{cases}
\]

For the new sample set \( X \) produced \( \{(x_i, c_i)\}_{i=1}^N \), the ELM model training is completed by using equations (1) to (4), and the final prediction result of the classification is given by equation (7).

\[
\hat{y}_i = \max_i \left( c_i \right)
\]

In equation (7), \( \hat{c}_i \) is the prediction vector of \( c_i \); \( \max(\cdot) \) represents the largest element in the vector "\( \cdot \)".

3. Development of HEV

ADVISOR is an Advanced Vehicle Simulator developed by the Natural Renewable Energy Library, which provides modules for the various components of an electric vehicle. With these modules, a virtual hybrid vehicle experimental platform can be built. The software also provides a simulated driving program that uses a standard test path to obtain various parameters of the vehicle while driving [14].

It should be noted that ADVISOR uses a hybrid simulation method combining a unique forward simulation method and a backward simulation method. The backward simulation method calculates the various components of the vehicle on the premise that the vehicle satisfies the requested travel trajectory of the road cycle. The performance of the forward simulation method is suitable for the development of various hardware loop systems and corresponding control systems. Therefore, ADVISOR is a hybrid simulation method that is mainly based on the simulation method and supplemented by the forward simulation method. This method bears a small amount of calculation and ensures the accuracy of the simulation results. In addition, ADVISOR is still a joint simulation, which requires joint development of each function module M file and the corresponding SIMULINK device.

In this paper, the HEV is a standard small car using lead-acid batteries. The vehicle parameters are shown in Table 1. The test conditions used in the simulated driving program select the US Urban
Dynamic Cycle Drive Case (UDDS). As shown in Figure 2, UDDS is widely used in HEV performance testing and is highly representative. The simulation results of the HEV battery performance after development are shown in Figure 3. Since the regenerative braking process of the HEV will give energy feedback to the battery, the SOC curve of the battery will continue to increase slightly in Figure 3.

Table 1. The parameters of HEV

| Parameter                  | Value         |
|----------------------------|---------------|
| Vehicle quality (full load)| 891(1191)kg   |
| Windward area              | 2.0 m²        |
| Air resistance coefficient | 0.335         |
| Rolling resistance coefficient | 0.009       |
| Rolling radius             | 0.28 m        |
| Maximum motor power        | 30 kW         |
| Batteries’ voltage         | 360 V         |
| Batteries’ capacity        | 100 AH        |
| Batteries’ initial SOC     | 0.9           |

Figure 2. The working condition of UDDS

Figure 3. The simulation results of the HEV battery performance after development.
4. Design of HEV battery SOC predictor based on ELM

The ELM is used for the prediction of the SOC of the HEV battery, taking the operating voltage, current and surface temperature of the battery as the input of the ELM, and the output is the SOC value of the battery.

4.1. Sample data acquisition

Combined with the content of the second section, the performance parameters of the developed HEV battery are sampled. Here, we have executed the simulation test condition twice, and the hybrid vehicle has driven a total of 2740s. During the course of the simulation driving, the battery parameters were recorded via the sampling speed of frequency 1. The collected values include the battery voltage value, current value and temperature value and the corresponding SOC value, and a total of 2740 groups and 10960 data were obtained. In order to fully verify the validity of the prediction model, the sample data obtained by the loop execution is arranged, the odd-numbered items in the first cycle execution sample are used for training, and the second-cycle execution of the even-numbered items in the sample is tested.

4.2. Sample data pre-processing

For multi-parameter analysis calculations, the basic unit of measurement for the parameters must first be unified. This view also can be applied to ELM. The data set used in training should be firstly normalized before model training. At the same time, normalized data is also helpful to speed up the convergence of the training network. The normalization method used in this paper is to process the raw data into new data with a mean of 0 and a variance of 1 [15].

4.3. ELM-based SOC prediction step

1) Determining the input and output variables as required for battery SOC prediction modelling;
2) Collecting the input and output sample data are collected, and after normalization, an input and output sample set for training and testing the ELM model is established;
3) Utilizing the ELM model with the training sample set to obtain the optimal parameters;

Figure 3. The results of battery performance
4) Adopting the trained ELM model to predict the test sample set in one or more steps and output the best prediction results;
5) Inversely normalizing the prediction results and calculating the prediction error.

5. Simulation research
In order to fully explain the superiority of ELM, a comparative study is conducted with LS-SVM, which gains more studies currently studied more. The number of hidden layer neurons in ELM is set to 30. Considering that the selection of LS-SVM regularization coefficient and kernel parameters will have a greater impact on the prediction results, the Bayesian evidence framework (BEF) is used. The algorithm optimizes LS-SVM, and the optimization path of BEF adopts the simplex method.

5.1. Predictive model results comparison
The prediction results of BEF-LS-SVM and ELM are shown in Figure 4 and Figure 5 respectively. It can be seen from Figure 4 and Figure 5 that the prediction effect of ELM is obviously better than that of BEF-LS-SVM, and the predicted value is more closely matched with the actual value. In addition, despite the energy feedback of the battery, the ELM prediction model still has high tracking performance.

![Figure 4. The prediction result based on BEF-LS-SVM](image1)

![Figure 5. The prediction result based on ELM](image2)
5.2. Predictive model evaluation

In order to further illustrate the advantages and disadvantages of the prediction models built by ELM and BEF-LS-SVM, the running time, predicted value and actual value of the model, Mean Squared Error (MSE) and Absolute Error (AE). And Relative Error (RE) is used as indexes to evaluate the model. The mean square error mainly evaluates the overall performance of the prediction model, while the absolute error and relative error mainly measure the local performance of the prediction model. MSE, AE, and RE are defined as

\[
MSE = \frac{1}{l} \sum_{i=1}^{l} (y_i - \hat{y}_i)^2
\]

(8)

\[
AE = |y_i - \hat{y}_i|
\]

(9)

\[
RE = \frac{|y_i - \hat{y}_i|}{y_i}
\]

(10)

Table 2 shows the MSE values and running times of the two prediction models. As shown in Table 2, although both of the MSE values are small, the MSE value of BEF-LS-SVM is about 100 times the MSE value of ELM. It fully manifests that the overall performance of the ELM-based SOC prediction model is very good. In addition, from the perspective of running time, the running time of the ELM is about 1/3 of that of the BEF-LS-SVM, and the response speed is fast.

| Prediction models | MSE   | Run time/s |
|-------------------|-------|------------|
| BEF-LS-SVM        | 0.0051| 8.7541     |
| ELM               | 4.12e-005 | 3.0055     |

Table 2. The MSE values and run time of two prediction models

Figure 6 and Figure 7 show error diagrams of the BEF-LS-SVM and ELM prediction models respectively. It can be found from Figure 6 and Figure 7 that the error of the ELM prediction model is about 1/2 of that of the BEF-LS-SVM prediction model, regardless of the absolute error or the relative error, so the local performance of the ELM prediction model is superior.

![Figure 6. The prediction errors based on BEF-LS-SVM](image-url)

1: The relative error based on BEF-LS-SVM

2: The absolute error based on BEF-LS-SVM

Figure 6. The prediction errors based on BEF-LS-SVM
6. Conclusions
In this paper, the HEV simulation model based on ADVISOR is developed. The predictive model of battery SOC for HEV is constructed by using the extreme learning machine method. The simulation model of the built prediction model is carried out under UDDS conditions, and the following conclusions are obtained:

1) Using ELM to establish a prediction model for HEV battery SOC is feasible, and the model performance is good;
2) Considering the energy feedback of the battery, the established prediction model still has higher prediction accuracy;
3) The overall performance of ELM’s SOC prediction model is better than that of the BEF-LS-SVM prediction model.

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