Research on a Soft Measurement Method for SOC of Electric Vehicle Battery

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Abstract. Aiming at the problem that the State of charge (SOC) can not be directly measured, the SOC soft sensing method based on subtractive clustering and adaptive fuzzy neural network is introduced. Firstly, the structure of AFNN was decided by SC; Secondly, by adopting the back-propagation algorithm and least square method respectively, the front and back parameters of AFNN were optimized, and the study efficiency of the parameters was raised. Finally, the fuzzy membership functions and rules which generated automatically by AFNN are applied to the soft measurement of battery SOC for HEV. Under the CYC-HWFET working conditions, the working voltages, currents and surface temperature of battery are used to predict the value of SOC, and the results indicate that the prediction model possesses higher predicted accuracy, and the errors between the real value and the soft measurement value are small.

1. Introduction

Under the international background of oil shortage and serious environmental pollution, electric vehicle has become one of the most promising new energy vehicles with its advantages of energy saving and environmental protection \cite{1}. Batteries are the main energy components of electric vehicles. Therefore, it is of great significance to manage and control them in a reasonable and effective manner. In the battery energy management system, the prerequisite is to accurately detect the remaining electricity, that is to say, to understand the State of charge (SOC) value. SOC, as the internal characteristic of batteries, cannot be obtained by direct measurement method, but can only be predicted by soft measurement method through the external characteristic parameters such as voltage, current and temperature which can be measured directly \cite{2}.

Commonly used SOC soft measurement method for electric vehicle batteries include open-circuit voltage method \cite{3}, Safe-time metrology \cite{4}, internal resistance characteristic method \cite{5}, Kalman filter method \cite{6} and neural network method \cite{7} etc. These methods have their own advantages and disadvantages, such as open-circuit voltage method and ampere-time measurement method, which are easy to operate, but the measurement accuracy is not high. The measurement accuracy of Kalman filtering method is higher than that of the previous method, but the description equation of dynamic system needs to be determined. The matrix inversion operation involved in the recurrence process is more complex, and it is sensitive to the selection of initial values. The wrong initial values will lead to the deterioration of the prediction results. Neural network method has higher accuracy and faster speed in soft measurement, but the training speed is slow, and it is easy to fall into the local minimum point without getting the optimal point, and it is too sensitive to the choice of learning rate.

In order to overcome the shortcomings of the above-mentioned soft measurement method, we propose a method that is based on the subtractive clustering and adaptive fuzzy neural network. The
structure of the adaptive fuzzy neural network is determined by subtractive clustering, which combines the rich artificial control experience of the fuzzy logic algorithm with the advantages of the self-learning and self-adapting of the neural network, giving full play to the advantages of both. The simulation model of electric vehicle is established in ADVISOR, and the performance parameters of battery are obtained under CYC-HWFET operating conditions. The research of subtraction clustering and adaptive fuzzy neural network soft measurement for battery SOC of electric vehicle is carried out.

2. Basic Principles of Subtraction Clustering
Subtractive clustering algorithm is a single-order algorithm for estimating the number and location of clusters in data automatically [8]. In this algorithm, the candidate set of clustering center is the sample data points, and the calculation amount is linear with the data points, and is independent of the number of bits considered.

The idea of subtractive clustering algorithm is as follows: In M-dimensional space, n data points \( (x_1, x_2, \cdots, x_n) \) are assumed to have been normalized to a hypercube. Since each data point is a candidate for clustering center, the density index \( D_i \) of the data point \( x_i \) can be defined as

\[
D_i = \sum_{j=1}^{n} \exp \left[ -\frac{\|x_i - x_j\|^2}{(\gamma_a / 2)^2} \right]
\]

In Formula (1): The radius \( \gamma_a \) is a positive number. Obviously, if a data point has several adjacent data points, the data point has a high-density index value. A neighborhood of Point \( x_i \) has been defined by \( \gamma_a \), and data points other than \( \gamma_a \) that contribute little to the density index of the point[9].

The first cluster center is the data point with the largest density index value. Let it be \( x_{c1} \), and the corresponding density index is \( D_{c1} \). The density performance index of each data point is recalculated according to formula (2):

\[
D_i = D_i - D_{c1} \cdot \exp \left[ -\frac{\|x_i - x_{c1}\|^2}{(\gamma_b / 2)^2} \right]
\]

In Formula (2), \( \gamma_b = k\gamma_a \) (k is a positive number, which normally is \( k = 1.5 \) ) is the adjacent range of the first clustering center \( x_{c1} \). At that time when \( D_i < 0 \), the density index value corresponding to this data point was set to 0, which excluded the possibility of using this data point as the clustering center, and continued to search the clustering center from the remaining data points using the above method until the density index of the remaining data points were less than a certain threshold [10].

After finding the clustering center of sample data set by subtractive clustering algorithm, the number of fuzzy rules and membership functions of each input variable can be determined according to the number of clustering centers, and the location of membership functions in the universe can also be defined.

3. Self-adaptive Fuzzy Neural Network
The self-adaptive fuzzy neural network combines the fuzzy system with the neural network, fully considering the complementarity of the two. It integrates logic reasoning, language calculation and non-linear dynamics, with the abilities of learning, association, recognition, self-adaptation and fuzzy information processing. In the fuzzy neural network, the input and output nodes of the neural network are used to represent the input and output signals of the fuzzy system, the hidden nodes of the neural network are used to represent the membership function and the fuzzy rules, and the reasoning ability of
the fuzzy system is greatly improved by using the parallel processing ability of the neural network, which can effectively solve the modelling and control problems of the non-linear system.

In order to understand more easily the adaptive fuzzy neural network based on subtractive clustering, we present a first-order Sugeno fuzzy neural network model, considering two inputs $x_1$ and $x_2$, and one output $y$. The general rule is only two if-then fuzzy rules, which are in the following specific form.

Figure 1 Represents the structure of an adaptive fuzzy neural network based on subtractive clustering.

Rule 1: if is $C_1$ then $y = p_1x_1 + q_1x_2 + c_{13}$

Rule 2: if is $C_2$ then $y = p_2x_1 + q_2x_2 + c_{23}$

Here $p_i$ and $q_i$ represent the conclusion parameters; $c_{ij}$ is the clustering centre, $(i=1,2, j=i+1)$.

![An adaptive fuzzy neural network structure based on Subtractive Clustering](image)

In Figure 1, the structure of the adaptive fuzzy neural network based on subtractive clustering is shown. First layer: The fuzzification layer is used to calculate the membership degree of clustering centre $C_i$ corresponding to input vectors $X = (x_1, x_2)$.

$$Q'_i = \mu_{C_i}(X), \quad i = 1, 2$$

(3)

The second layer: Rule inference layer (computational rule strength layer), where the rule strength is the membership degree of the clustering centre $C_i$ corresponding to the input vector $X$.

$$Q'_2 = Q'_1, \quad i = 1, 2$$

(4)

The third level: Normalization of incentive intensity as connection weight $w_i$.

$$Q'_3 = w'_i = \frac{w_i}{w_1 + w_2}, \quad i = 1, 2$$

(5)

The fourth level: Each node in this layer is an adaptive node whose output is: $i = 1, 2$

$$Q'_4 = w'_i \left(p_ix_1 + q_ix_2 + c_{ij}\right), \quad i = 1, 2$$

(6)

The fifth level: Calculate the total output of all input signals.

$$Q'_5 = \sum_i w'_iy_i, \quad i = 1, 2$$

(7)

4. Learning Method of Adaptive Fuzzy Neural Network

The adaptive fuzzy neural network identifies the control model and adjusts the membership function by modifying the connection weight. Back propagation (BP) algorithm with gradient descent is used to adjust the parameters, but in order to improve the speed and quality of learning, we choose the combination of BP algorithm and least squares to realize the self-learning of the network.

In the hybrid algorithm, the parameters of membership function (conditional parameters) adopt BP algorithm, while the three unknown parameters of the neural network are: the centre, width and connection weights are adjusted by least squares algorithm. Under the given condition parameters, the global optimum of the conclusion parameters can be obtained. The hybrid algorithm can not only reduce
the dimension of the search space in the gradient method, but also improve the convergence speed of the parameters. When learning the adaptive fuzzy neural network, the learning error is calculated according to the actual output value and the target learning value of the system, and then the conditional parameters of the system are adjusted by BP algorithm. The conditional parameters of the system include the parameters of the membership function of each fuzzy node in the fuzzification layer (i.e. the centre \(d_{ij}\) and width \(\sigma_{ij}\) of the Gauss membership function).) and the connection weight \(w_{ij}\) between Layer 4 and Layer 5.

The back-propagation process of the error signal in the control system is as follows:

\[
E = \frac{1}{2} (y_k - y_{dk})^2 
\]  \hspace{1cm} (8)

In Formula (8), \(y_k\) and \(y_{dk}\) are the expected value and output value of the output layer node \(k\) respectively. During the learning process, the centre \(d_{ij}\), width \(\sigma_{ij}\) and connection weight \(w_{ij}\) are adjusted to:

\[
d_{ij}(n+1) = d_{ij}(n) - \eta \frac{\partial E}{\partial d_{ij}} = d_{ij}(n) - \eta \lambda 
\]  \hspace{1cm} (9)

\[
\sigma_{ij}(n+1) = \sigma_{ij}(n) - \eta \frac{\partial E}{\partial \sigma_{ij}} = \sigma_{ij}(n) - \eta \lambda Q_{ij} \left[ x_i - d_{ij}(n) \right] / \sigma_{ij} 
\]  \hspace{1cm} (10)

\[
w_{ij}(n+1) = w_{ij}(n) - \eta Q_{ij} \left[ y_{dk} - y_{ik} \right] / S 
\]  \hspace{1cm} (11)

Among them, \(n\) is the number of iterations; Learning factor \(\eta \in (0,1)\) affects the speed of convergence.

\[
\lambda = \left[ (y_{dk} - y_k) / S \right] \cdot Q_{ij} \left\{ \frac{1}{2} \left[ x_i - d_{ij}(n) \right] / \sigma_{ij}^2(n) \right\} ; \quad S = \sum_i w_i \quad i = 1, 2 
\]  \hspace{1cm} (12)

5. Establishment of SOC soft measurement Model for Electric Vehicle Battery

5.1 Variable Selection of soft measurement Model
SOC represents the remaining capacity of the battery, and its value can be expressed as the remaining capacity in ratio to the total capacity of the battery when its discharge ends at the cut-off voltage. However, SOC as the internal characteristics of batteries cannot be directly measured. It can only be obtained by soft measurement of some external characteristics such as voltage, current and temperature of batteries which can be directly measured. In this paper, the voltage, current and temperature are the input variables of the soft measurement model, while the output variables are the SOC values.

5.2 Data Acquisition and Processing of Soft Measurement Model
The simulation model of electric vehicle is established in ADVISOR, and the CYC-HWFET working condition is selected as the test condition, as shown in Figure 1. The battery data collected are shown in Figure 2. The simulated test conditions were cycled twice, and the hybrid electric vehicle traveled for 1532 seconds. In the course of simulating driving, the battery parameters including battery voltage, current, temperature and corresponding SOC values were recorded at the sampling speed of frequency 1. A total of 1532 sets and 6128 data were obtained. In order to fully verify the validity of the soft measurement model, the sample data obtained by circular execution are arranged, the odd data in the first circular execution sample is used for training, and the even data in the second circular execution sample is tested.
In addition, before training for the model, the training data set should be normalized first. The normalization method used in this paper is to process the original data as a new data with a mean value of 0 and a variance of 1. The normalized data is helpful to accelerate the convergence speed of the training network.

5.3 Soft Measurement Model Establishment

In this paper, subtractive clustering (SC) and adaptive fuzzy neurology network (AFNN) are used to realize the soft measurement of battery SOC of electric vehicles. SC is used to divide input space. Effective input space division can reduce the number of rules, while AFNN training method is used to optimize the premise and conclusion parameters of rules. The input sample is battery voltage, current and temperature, and the output sample is battery SOC value.

The acceptance rate of SC algorithm is 0.5, the rejection rate is 0.15, the training number of modelling data is 1500, and the convergence accuracy is 0.001. The training sample error is shown in Figure 3. The longitudinal coordinate is the error and the abscissa the sample number. The training error is very small, stable at about 0.089. Fig. 5 is the structure of the adaptive fuzzy neural network. From Fig. 4,
we can easily find that the input variables in the first layer are 3, so the number of neurons is 3. In the second layer, the number of neurons is 45, and the linguistic variables should be 45. The third layer is the rule layer, which is designed automatically by the neural network. The logical method used is "and", which has 15 rules. Therefore, the number of neurons in this layer is 15. The fourth layer represents the conclusion of the fuzzy rule, and the number of neurons is 15. The fifth layer is the output layer and the output is SOC, so the number of neurons is 1.

6. Simulation Research
In order to fully illustrate the methodological advantages of subtractive clustering (SC) and adaptive fuzzy neural network (AFNN), and compared with the soft measurement methods for electric vehicles SOC based on grid partition (GP) battery and adaptive fuzzy neural network. The simulation results are shown in the figure6. From Figure 6, it is not difficult to find that GP-AFNN method shows poor effect of soft measurement for battery SOC at the beginning and the end stage, and there is a big deviation between the real value and the soft measurement value. In the intermediate process GP-AFNN method performs well. While in SC-AFNN method, whether in the beginning, the end or the middle process, the soft-sensing value changes with the change of the real value, and the deviation between them is small. The SC-AFNN overall soft measurement effect is better.

Figure 6. Comparison of simulation results of two methods
Figure 7. shows the absolute and relative error values of the two methods. In SC-AFNN method, both absolute error and relative error are less than that in the GP-AFNN Method; in SC-AFNN, the maximum error under the method is only 0.003, while in GP-AFNN the maximum error under the method is 0.02, which is about 7 times of difference. Obviously, what is proposed in this paper is SC-AFNN method has high accuracy.
7. Conclusion
This paper presents a soft measurement method for battery SOC of electric vehicle based on subtractive clustering and adaptive fuzzy neural network. This method is briefly introduced, and a soft measurement model is established. The verification by simulation is carried out under CYC-HWFET working condition. The results show that the soft measurement model based on subtractive clustering and adaptive fuzzy neural network is correct. It can realize the accurate soft measurement of battery SOC of electric vehicle with small error.

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