State of charge estimation of Li-ion batteries in an electric vehicle based on a radial-basis-function neural network*

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The on-line estimation of the state of charge (SOC) of the batteries is important for the reliable running of the pure electric vehicle in practice. Because a nonlinear feature exists in the batteries and the radial-basis-function neural network (RBF NN) has good characteristics to solve the nonlinear problem, a practical method for the SOC estimation of batteries based on the RBF NN with a small number of input variables and a simplified structure is proposed. Firstly, in this paper, the model of on-line SOC estimation with the RBF NN is set. Secondly, four important factors for estimating the SOC are confirmed based on the contribution analysis method, which simplifies the input variables of the RBF NN and enhances the real-time performance of estimation. Finally, the pure electric buses with $LiFePO_4$ Li-ion batteries running during the period of the 2010 Shanghai World Expo are considered as the experimental object. The performance of the SOC estimation is validated and evaluated by the battery data from the electric vehicle.

Keywords: state of charge estimation, battery, electric vehicle, radial-basis-function neural network

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1. Introduction

Many countries are increasingly concerned with energy conservation and environmental protection. The power source of the pure electric vehicle is batteries instead of fuel oil, so the electric vehicle has the advantages of zero gas emissions, less environmental pollution, and energy savings. Electric vehicles with Li-ion batteries are being widely researched. The state of charge (SOC) of the batteries is their current capacity usually expressed as a percentage of their full capacity. The SOC estimation is important for ensuring the reliable running of the vehicle, improving the battery efficiency, and increasing the battery service life. Therefore it is crucial to estimate the SOC when the electric vehicle is in operation.

Much research work has been done to estimate the SOC. Conventional methods for SOC estimation include chemistry-dependent methods, electrochemical modeling,[1] circuit models,[2] open-circuit voltage (OCV) measurements,[3] and impedance spectroscopy.[4] Usually, these methods require special concrete models, and most of them are suitable for the offline estimation of the SOC in the laboratory. In Ref. [5], the battery was considered as a linear system, based on which the Kalman filter algorithm was researched to estimate the SOC. In fact, the battery is a nonlinear system, so it is difficult to set an analytical mathematic model for the battery. Comparatively, the artificial neural network has the advantage of describing nonlinear features, so the neural network can be utilized for estimating the SOC of a battery system without the knowledge of the cell internal structure.[6−10] In Ref. [6], the radial-basis-function neural network (RBF NN) was discussed to estimate the SOC of the lead acid battery with experimental data in the laboratory.

In this paper, by employing the RBF NN, we propose an on-line practical method for the estimation of the SOC of lithium batteries in the electric vehicle. Differently from previous research, in order to simplify the RBF NN structure to decrease the computation time among many factors of the batteries related to the SOC estimation, such as terminal voltage, work-

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ing current, and temperature, the important factors for estimating the SOC are determined by using the contribution analysis method. On the other hand, the Li-ion batteries in the electric bus are the research object, and all experimental data is derived from the practical process of the electric bus in operation instead of the laboratory test.

2. Background of battery data acquisition

During the period of the 2010 Shanghai World Expo exhibition, 120 pure electric buses were granted to carry visitors by the Chinese government. Each bus carried 104 $LiFePO_4$ Li-ion batteries in 10 battery packs in series. In order to ensure the safety of the electric bus in operation, it was necessary to monitor the status of all batteries in the remote monitoring center. The equipment installed in the electric bus could sample the battery data such as voltage, current, and temperature, and transmit the data to the monitoring center using GPRS wireless technology with a transmission period of 20 s. So a large number of battery data from each electric bus in operation are stored in the monitoring center's server computer, which provides the data basis for the research of SOC estimation.

3. Design of SOC estimation based on the RBF neural network

3.1. SOC estimation model based on the RBF neural network

The radial-basis-function neural network is a typical feed-forward neural network, which has many merits, such as nonlinear mapping characteristics, self-organized study ability, training fast, and the capability of converging to global optimization and approaching the function in the best way.[9,10] Simply for its great advantages, we will adopt the RBF NN to estimate the SOC of the batteries.

The structure of the RBF NN is composed of one input layer, one hidden layer, and one output layer, as shown in Fig. 1.

The input vector $\boldsymbol{X} = (x_1, x_2, \ldots, x_n)$ is composed of the input signals x_i, $i = 1, 2, \ldots, n$, where n is the number of input neurons. The output $h_j(\boldsymbol{X})$ of the j-th neuron in the hidden layer is

$$h_j(\boldsymbol{X}) = \varphi(\|\boldsymbol{X} - \boldsymbol{C}_j\|), \tag{1}$$

where $\varphi(\cdot)$ is the radial basis function, $\boldsymbol{C}_j$ ($\boldsymbol{C}_j \in \mathbf{R}^n$) is the center of the j-th hidden neuron, and $\|\cdot\|$ is the Euclidean norm.

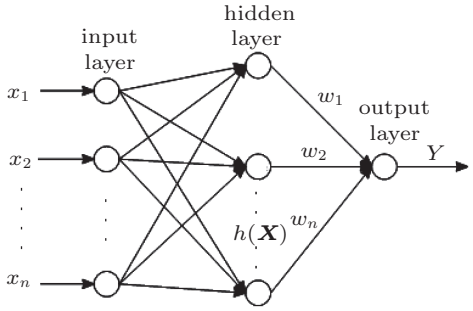


Fig. 1. Structure of the RBF NN for SOC estimation.

The output $Y(\boldsymbol{X})$, which is designed as the SOC estimation, is the linearly combined signal of the outputs $h_j(\boldsymbol{X})$ from the hidden layer with the synaptic weights w_j

$$Y(\boldsymbol{X}) = \sum_{j=1}^{m} w_j h_j(\boldsymbol{X}), \tag{2}$$

where m is the number of hidden neurons.

If $\varphi(\cdot)$ is adopted to be the Gaussian function, $h_j(\boldsymbol{X})$ is described by

$$h_j(\boldsymbol{X}) = \exp\left(-\frac{\left\|\boldsymbol{X} - \boldsymbol{C}_j\right\|^2}{2\sigma_j^2}\right), \tag{3}$$

where σ_j is the spread of the j-th neuron for the i-th input signal.

3.2. Input variables determined by the contribution analysis method

It is very important to select the proper input variables for a neural network. On one hand, as the number of the input variables increases, the NN architecture will be larger, and the computing time will be longer. On the other hand, the irrelevant or mutually correlated input variables are not useful for improving the prediction accuracy. Therefore, how to select a few but sufficient input variables is a key issue.

It is known that not only factors such as the voltage, current, and temperature at the current time are related to the degree of degradation of the battery packs, but also the past values of voltage, current, and SOC as additional factors should be considered.

So the network input variables may be derived from a set with 10 factors as follows: $\boldsymbol{X}$= (LatSoc, TotalV, TotalI, MinV, MaxV, MaxT, MinT, AvgT, DifV, DifSoc), where LatSoc is the SOC of all battery packs in series at the last time, TotalV is the total terminal voltage of all battery packs in series at the current time, TotalI is the total current of all battery packs in series at the current time, MinV is the minimum terminal voltage of the cell at the current time, MaxV is the maximum terminal voltage of the cell at the current time, MaxT is the maximum temperature of all battery packs at the current time, MinT is the minimum temperature of all battery packs at the current time, AvgT is the average temperature of all battery packs at the current time, DifV is the difference of total terminal voltage between the current time and the last time, and DifSoc is the difference of SOC between the current time and the last time.

The contribution analysis method is used to determine the important input variables according to the contribution factor of each input variable to the output variable of the RBF network. Since each input variable affects the output variable through the connected hidden layer nodes, the contribution factor of each input variable to the output variable can be mapped through the contribution factor of the input nodes to the hidden layer nodes and the contribution factor of the hidden layer nodes to the output layer node. The input variables of the RBF NN are determined as follows.

Define

$$p_i = \|\boldsymbol{X} - \boldsymbol{C}_i\|, \quad (i = 1, \ldots, m). \tag{4}$$

According to Eq. (1), the output of the j-th neuron in the hidden layer is

$$h_j = \varphi(p_i). \tag{5}$$

Define S_j to be the contribution factor of the j-th input node variable to the output variable and is expressed as

$$S_j = \sum_{i=1}^{m} R_{ij} T_i, \quad (i = 1, \ldots, m;\ j = 1, \ldots, 10), \tag{6}$$

where R_{ij} represents the contribution factor of the j-th node variable in the input layer to the i-th node variable in the hidden layer, and T_i represents the contribution factor of the i-th node variable in the hidden layer to the output variable in the output layer. The R_{ij} and T_i are expressed respectively as

$$R_{ij} = \frac{\mathrm{Cov}(p_i, x_j)\, c_{ij}}{\mathrm{Var}(p_i)\, \mathrm{Var}(x_j)}, \quad (i = 1, \ldots, m;\ j = 1, \ldots, 10), \tag{7}$$

$$T_i = \frac{\mathrm{Cov}(h_i, Y)\, w_i}{\mathrm{Var}(h_i)\, \mathrm{Var}(Y)}, \quad (i = 1, \ldots, m). \tag{8}$$

The larger the contribution factor of the input variable, the more important the input variable is. Sort S_j according to the descending order and define Z_q as

$$\mathrm{Z}_q = \sum_{j=1}^{q} |S_j|. \tag{9}$$

When $Z_q/Z_{10} \geq 0.85$ is confirmed, the total number of q corresponding variables are considered to be the input variables of the RBF NN.

4. Experimental validation

4.1. Parameters identification of the RBF neural network

According to Section 3, the RBF NN only has one output representing the SOC estimation. In general, more neurons can improve the accuracy of the estimation, but more neurons will make the network more complex and the computation time will be longer. After a lot of experiments with different numbers of neurons, finally the hidden layer is designed to own 30 neurons. Because the input variables are related with 10 factors, the input layer of the RBF is initially composed of 10 neurons. The output layer of the RBF is designed to own 1 neuron representing the SOC estimation. The 4300 battery data sampled from the No. 1 pure electric bus running during the period of 10th to 20th July 2010 are used to train the RBF NN. The K-mean clustering learning algorithm is applied to determine the center and the spread of each neuron in the hidden layer. The weights between the hidden layer and the output layer are adjusted by the least square method. The target error of the network training is given by the mean square error (MSE), which is expressed as

$$\mathrm{MSE} = \sqrt{\frac{\sum_{i=1}^{t} (Y_i - \hat{Y}_i)^2}{t}}, \tag{10}$$

where Y_i is the true value, $\hat{Y}_i$ is the estimation of the RBF NN, and t is the number of training times. When MSE is bellow 0.001, the network training is completed.

4.2. Input variable determination

According to Eq. (6), the contribution factor of each variable is computed, as shown in Table 1. According to Eqs. (6)–(9), the sum of the contribution factors from six variables TotalV, LastSoc, TotalI, AvgT, MaxT, and MinT is 88.55%, so these six variables are important to the SOC estimation. Furthermore, because variables AvgT, MaxT, and MinT are related to the temperature parameter of the batteries, and in order to simplify the input structure of the RBF NN, variables MaxT and MinT are discarded. Finally, the input layer of the RBF NN is designed to have only 4 variables, i.e., TotalV, LastSoc, TotalI, and AvgT. The hidden layer is still composed of 30 neurons, and the output layer still has only one neuron representing the SOC estimation. According to Section 4.1, the parameters of the RBF NN are identified by the K-mean clustering learning algorithm and the least square method.

Table 1. Contribution factor of each input variable.

Input variable	TotalV	LatSoc	TotalI	AvgT	MaxT	MinT	MaxV	MinV	DifV	DifSoc
Contribution	0.199	0.178	0.152	0.130	0.105	0.083	0.055	0.029	0.023	0.002
Percent	20.8	18.62	15.92	13.55	10.96	8.7	5.76	3.08	2.41	0.21

4.3. Experimental results and analysis

The batteries data from the No. 1 pure electric bus running on 7th and 27th August 2010 are used to verify the SOC estimation of the RBF NN. The estimation results are shown in Figs. 2–5.

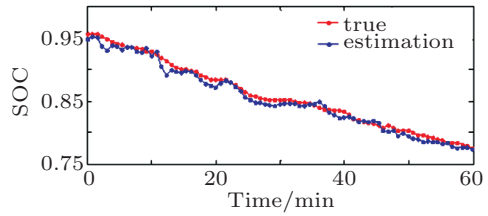


Fig. 2. (colour online) SOC estimation of batteries on 7th August 2010.

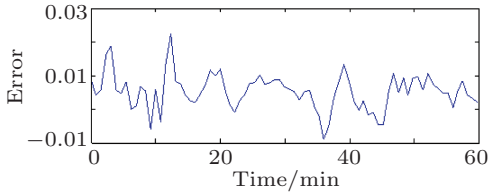


Fig. 3. (colour online) Error of SOC estimation on 7th August 2010.

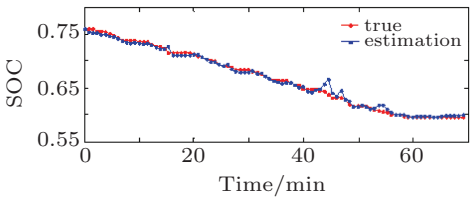


Fig. 4. (colour online) SOC estimation of batteries on 27th August 2010.

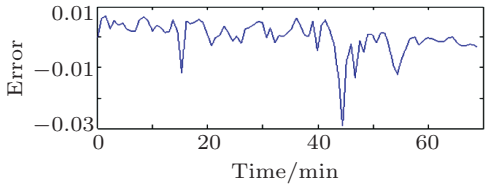


Fig. 5. (colour online) Error of SOC estimation on 27th August 2010.

The error of SOC estimation is below 0.03, which shows that the design scheme has good SOC estimation performance.

5. Conclusion

By employing the RBF NN to model the Li-ion batteries, we try to estimate the SOC of the batteries in the electric bus with reliable precision whilst online. Although many factors of batteries are related to the SOC estimation in theory, by introducing the contribution analysis method, four important factors, i.e., the total terminal voltage and the total current of all battery packs in series at the current time, the SOC of all battery packs in series at the last time, and the average temperature of all battery packs at the current time, as the input variables in the RBF NN are enough for estimating the SOC with good precision. The network training and SOC estimation are conducted using the data of the $LiFePO_4$ Li-ion batteries in the electric bus in operation during the period of 2010 Shanghai World Expo. The practical results show the validity of the method for the SOC estimation.

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