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The Comparison of SOC Estimation Performance with Different Input Parameters Using Neural Network

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ABSTRACT: The battery is a high nonlinear system and the neural network model (NNM) has been proposed to estimate the battery's State-Of-Charge (SOC) recently. To determine different input parameters' impact on NNM's estimation performance, the paper firstly identifies the battery's external parameters affecting the value of SOC and puts forwards three different NNMs for estimation performance comparison. And then a variety of discharging processes are experimented on 6Ah Lithium-ion battery to collect the training and testing data samples. Lastly, based on the data samples, the SOC estimations using NNM are conducted and estimation performances for three models are contrasted. The results show that the battery's temperature and internal resistance both could improve NNM's estimation precision and robustness against the measuring noise. But the temperature is more suited to estimate SOC in practice for its easy implement in practice.

KEYWORDS: Electric vehicle; State-of-charge; Neural network; Measuring noise; Robustness.

INTRODUCTION

As an inner character-state parameter of the battery, State-of-Charge (SOC) can help the battery management system in electric vehicle predict the battery's remaining energy and determine effective management strategy to avoid over-charging and over-discharging [1]. However, the battery is a high nonlinear system and it is difficult to predict its SOC accurately. The neural network method has been applied to estimate SOC for its easy implement and good nonlinearity and got rapid development in recent years [2-4].

For the neural network model, the appropriate selection of input parameters is very important and it directly determines the precision of SOC estimation. Early researchers usually selected the terminal voltage and the current of the battery as the model's input parameters [5, 6]. Current researchers begin to add the battery's temperature to improve the SOC estimation accuracy [7, 8]. The paper firstly identifies the external character-state parameters which affect the value of SOC and puts forwards three NNMs for estimation performance comparison. Then a variety of discharging processes are also experimented on 6Ah Lithium-ion battery to collect the training and testing sample. Lastly, Based on the sample collected, the SOC estimations using NNM are conducted and estimation performances for these three models are contrasted.

THE MODEL USING RBFNN

The Equation of SOC

According to the definition of SOC, when the battery with discharges with the current I, the SOC at the time t can be described as:

$$SOC_t = SOC_0 - \frac{\eta_1}{\eta_2 C}\int_0^t I dt \tag{1}$$

η_1 and η_2 are Coulomb efficiency and Battery discharging efficiency, and C is Total charging volume.

As known from the battery electrochemical kinetics, the battery discharging efficiency is closely related to the internal resistance and the battery open-circuit voltage can be substituted by the terminal voltage in practice. So the battery discharging efficiency can be expressed as:

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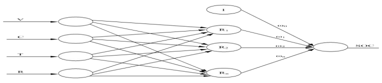
$$\eta_2 = 0.99\frac{V - IR}{V} \tag{2}$$

V and R is terminal voltage and internal resistance. After plugging Equation (2) into Equation (1), it will draw that:



(3)

Known from Equation (3), the value of SOC relates to V, I and R. However, the battery's temperature has an impact on the total charging volume [9]. So, the four external parameters above are identified as the external parameters affecting the value of SOC.

The Structure of RBF-NNM

Figure 1 shows that the NNM includes input layer, hidden layer and output layer. Input layer is the input parameters transferring data to the hidden layer. To realize the nonlinear transformation from the input layer to the hidden layer, a series of the Radial Basis Functions constitute the hidden layer.

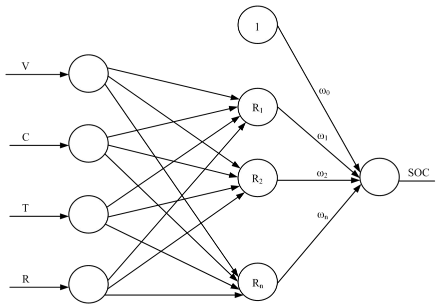


Figure 1. Topology structure of RBF-NNM.

The Gaussian function (Radbas) is the transfer function of radial basis function (RBF) neurons, The Gaussian radial basis function is defined as:

$$R_k(x_i) = \text{Radbas}(\| w_k - x_i \| / \sigma_k) = e^{-(\|w_k - x_i\|^2 / \sigma_k^2)} \tag{4}$$

Where $R_k(x)$ is the radial basis function of kth neurons in hidden layer. x_i is the input of RBF network. w_k is the centre of the kth hidden neuron. σ_k are the width of the kth hidden neuron, adjusting the sensitivity of the RBF neurons. As can be seen in the Gaussian radial basis function expression, the closer input vector is in proximity to function centre, the bigger hidden nodes output value is.

As the terminal port of NNM, output layer is the estimated SOC. Three kinds of NNMs in the paper are built to analyse input parameters' impact on SOC estimation performance. These models are VC (inputs are terminal voltage and current), VCT (inputs are terminal voltage, current and temperature) and VCTR (inputs are terminal voltage, current, temperature and internal resistance).

RBF neural network output layer is linear neurons, and network output is the linear superposition of the hidden layer output:

$$SOC_e(x_i) = \omega_0 + \sum_{k=1}^{K} \omega_k \cdot e^{-(\|w_k - x_i\|^2 / \sigma_k^2)} \tag{5}$$

Where SOC_e is the network prediction SOC, ω_k is the weight connecting the kth hidden neuron to the output neuron. ω_0 is the network deviation, which is chosen as: $\omega_0 = 1$.

EXPERIMENTS AND SIMULATIONS

Data Acquisition and Normalization

For acquiring training and testing samples, a variable of discharging processes for the 6Ah Lithium-ion battery are experimented on the battery platform [10-13]. The battery platform is consisted of programmable electronic load module, data acquisition module, charger and discharger module and safety-protection module. Data acquisition module could measure the discharging current, terminal voltage, instantaneous temperature and the internal resistance. The experiment is in that order:

Step 1: Take the power values of vehicle under the hybrid drive cycles of UDDS and US06 through the ADVISOR, and then scale the power values down in equal proportion to the range of the Lithium-ion battery power;

Step 2: Utilize the programmable electronic load module to set the discharging process for the full-charge Lithium-ion battery and simulate the power sequence above. Simultaneously, set the discharge cut-off voltage to prevent over-discharging;

Step 3: Set the sampling rate of data acquisition module at 1HZ to collect enough data automatically. Stop discharging and save data when the Lithium-ion battery reaches the cut-off voltage.

Huge differences exist in the value ranges of the four original data. If training data samples are selected directly from the original data, the rectifications of network parameters will be impacted seriously during the model's training process. The negative influence can be eliminated by normalizing the original data. According to the current integral method, the actual SOC is calculated after the whole discharging process and the total capacity can be obtained by integrating the discharging current of the whole process.

Model Simulation

20 percent of the post-processing data are selected to train the three models respectively, and the trained models are tested with the remainder post-processing data to compare their SOC estimation performances.

In practice the measuring noise always exists in the original data and it is significant to explore model's robustness against the measuring noise. So the paper adds white noise to the total original data artificially and analyses three models' SOC estimation performances again. The total steps follow that:

Group 1: The post-processing data are used to train three models and the rest of posting-processing data are for the test of trained models;

Group 2: Contrast the real SOC with the estimated SOC and compare the SOC estimation performances;

Group 3: Add the white noise whose average value is 0 and standard deviation is 0.1 to the original data and normalize the new data to estimate SOC with the three models again;

Group 4: Contrast the real SOC with the estimated SOC and compare three models' robustness against the measuring noise.

RESULTS

The SOC Estimation Precision

Without the measuring noise added artificially, the SOC estimation results of VC, VCT and VCTR can be seen from Figures 1 and 2 presents the estimated error between the estimated SOC and the real SOC. The estimation performance comparisons for three models are shown in Table 1, indicating that VCTR has the least SOC estimation error.

We can conclude that the SOC estimation accuracy could be improved effectively when the input parameters of NNM are added with the battery's temperature or temperature and internal resistance. Moreover, adding both temperature and internal resistance to NNM could improve the SOC estimation performance further compared with that for only temperature.

Shown as Figure 1, it's interesting to find that the estimated SOC for both VC and VCT keeps greater than the real SOC during the whole discharging process, mainly because VC and VCT both ignore the effect of the internal resistance on SOC. Based on Equation (3), we find that the estimated value of SOC would become larger when internal resistance is ignored, which leads to the phenomenon above.

Table 1. Characteristic parameters and values of variable used in this analysis.

Algorithm	MAE	MaxAE	RMSE
VC	0.0417	0.1279	0.0457
VCT	0.0264	0.0679	0.0295
VCTR	0.0192	0.0465	0.0213

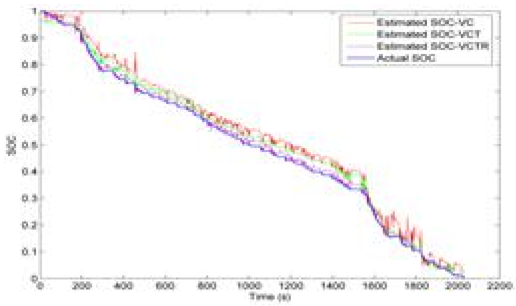


Figure 1. SOC estimation curves for three models without measuring noise added artificially.

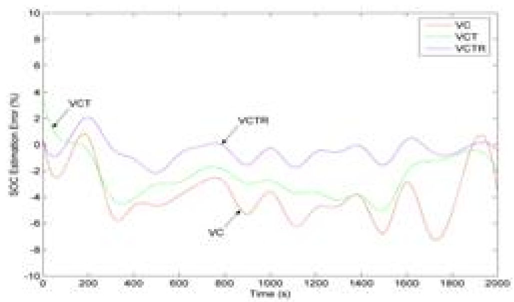


Figure 2. SOC estimation error without measuring noise added artificially.

The Robustness against the Measuring Noise

When the measuring noise is added to the original data artificially, the SOC estimation results of VC, VCT and VCTR can be seen from Figures 3 and 4 presents the estimated error between the estimated SOC and the real SOC. The estimation performance comparisons for three models are shown in Table 2.

Table 2. Performance comparison of three models with measuring noise added artificially.

Algorithm	MAE	MaxAE	RMSE
VC	0.0524	0.1299	0.0572
VCT	0.0273	0.0671	0.0312
VCTR	0.0182	0.0710	0.0215

When the measuring noise is added artificially, the MAE and RMSE of SOC estimation for VC both increase much more markedly than these for VCT and VCTR, which indicates that VCT and VCTR have the better robustness against the measuring noise. Even though VCTR has the better SOC estimation accuracy compared with VCT, the measurement of internal resistance is not easy to implement in the real driving condition. So the ideal input parameters for NNM should be the terminal voltage, the current and the temperature.

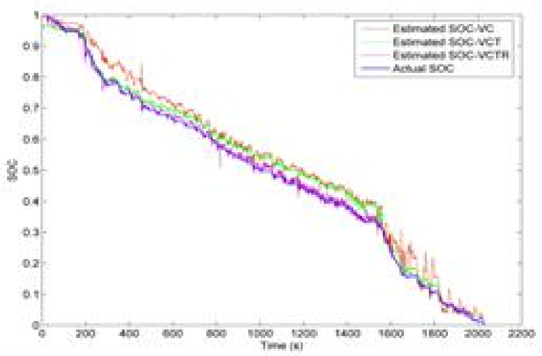


Figure 3. SOC estimation curves for three models with measuring noise added artificially.

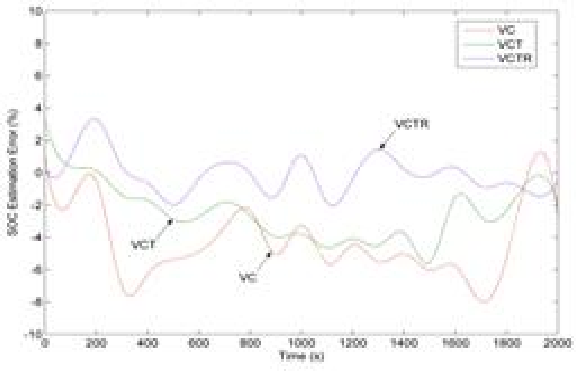


Figure 4. SOC estimation error with measuring noise added artificially.

CONCLUSIONS

The paper builds the qualitative relation between SOC and the battery external character-state parameters. Based on the qualitative relation, three kinds of NNM are put forward for SOC estimation performance comparison. It is worthy to conclude that:

Group 1: SOC is closely related to terminal voltage, current, temperature and internal resistance;

Group 2: VCTR has the highest estimated accuracy and can solve the problem that the estimated SOC keeps greater than the real SOC during the whole discharging process effectively;

Group 3: When estimating SOC using NNM with different input parameters, VCT and VCTR have better robustness against the measuring noise;

Group 4: VCT is more suited to estimate SOC in practice, because it has good estimation performance overall and no measuring difficulty.

In these four model mentioned above, the accuracy of VCRT model is the highest in SOC prediction. But measuring internal resistance of cell is much difficult. So VCT models with higher accuracy measurement should be taken into account. The all inputs of this model are external characteristic parameters of battery. These parameters have been taken in the process of application. Thus this prediction model has great value of practical application

In this paper, the SOC prediction model does not consider the effect of battery service life on the model. For the further improvement in prediction model, in the later work the influence of the battery life on SOC prediction model should be study.

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