Battery State of Charge Estimation for Electric Vehicle Based on Neural Network

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***Abstract*—Prediction of battery's remaining capacity is always a significant issue to which electric vehicle researchers paid close attention. Batteries of different types or the same type batteries of different model varies in prediction model of remaining capacity, the expert's advice obtained from experiment is not so universal that it is significant to build and improve the prediction model of remaining capacity for batteries of different types. This article takes iron phosphate Li-ion battery as the object of study, based on charge-discharge performance test of iron phosphate Li-ion battery, introduces neural network method to build prediction model for remaining capacity of battery and verify the model with test data in the end.**

Keywords-Li-ion battery, state of charge estimation, the method of neural network

Ⅰ. INTRODUCTION

With the increasingly soaring oil price and exacerbating influence of traffic emission on environment, out of the considerations of utilizing resources and energy economically as well as protecting environment, electric vehicles enter into a period of rapid development(1). As the power producer of electrical vehicles, electrical vehicle battery is the key technology that must be worked out during the development of electric vehicles(2). Prediction of battery's remaining capacity is always a significant issue to which electric vehicle researchers paid close attention(3). At present, battery's charging status is widely adopted both at home and abroad to describe status of battery capacity, and various methods are emerging to estimate SOC value, which mainly measure such measurable parameters as current, voltage, temperature, electric resistance, etc. to estimate or modify SOC. But while electric vehicles are moving, the nonlinear relation between these measurable parameters and SOC results in difficulty in traditional mathematical modeling as well as poor reliability(4). In addition, batteries of different types or the same type batteries of different model varies in prediction model of remaining capacity, the expert's advice obtained from experiment is not so universal that it is significant to build and improve the prediction model of remaining capacity for batteries of different types. Presently, iron phosphate Li-ion battery is widely used in electric vehicles and hybrid electric vehicles for its high safety, environmental friendliness, sound charge-discharge platform, better cycle performance, etc(5). This article takes iron phosphate Li-ion battery as the object of study, based on charge-discharge performance test of iron phosphate Li-ion battery, introduces neural network method to build prediction model for remaining capacity of battery and verify the model with test data in the end.

Ⅱ. PROCEDURES AND RESULTS OF CHARGE-DISCHARGE EXPERIMENT

There are various batteries can be used as power source for electric vehicles, commonly, lead battery, nickel-cadmium battery, MH-Ni battery, Li-ion battery, fuel cell, and etc. Iron phosphate Li-ion battery, one type of Li-ion batteries, is widely used in electric vehicles and hybrid electric vehicles for its high safety, environmental friendliness, sound charge-discharge platform, better cycle performance, and etc. This article takes iron phosphate Li-ion battery as the object of study. Experimental equipments mainly consist of some 26650P iron phosphate Li-ion batteries with nominal voltage of 3.2V, a ZEEMOO850 battery detection device, a ZEEMOO3000E internal resistance tester. The detailed test data mainly includes battery voltage measurement, battery current measurement and battery capacity measurement.

■ *A Experiment procedures*

- Charge a single 26650P iron phosphate Li-ion battery to 3.65V, put it aside for 5 hours, and then perform discharge test.
- Use ZEEMOO850 to do discharge test on the battery, use ZEEMOO3000E to measure its internal resistance during which the battery shall be taken down from the detection device and used internal resistance tester to measure the internal resistance under open-circuit voltage.
- Under room temperature, discharge test shall be performed with various constant current values, and the data can be accessed in Excel format from upper computer.

■ *B. perimental results and analysis*

The discharge experiment proves that, during the discharge process of iron phosphate Li-ion battery, discharge voltage and discharge capacity have definite relation with the service conditions, e.g. discharge rate, environment temperature, and etc. When current of different values goes through the battery, voltage descends at different rates, the voltage descends sharply when the battery discharges with current of large value, and the curve moves steeply; With the decrease of discharge current, voltage of the battery descends slower and slower, and as a result it moves smoothly in the curve. Chart 1 is the discharge curve at different discharge rate. We can see from

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the chart that voltage descends faster at higher discharge rate; as a result it discharges less capacity in the same time. Chart 2 is the curve for corresponding discharge voltages and discharge time with different discharge current; and chart 3 is the curve for the corresponding remaining capacity and discharge time. Since there are too much data, here we only draw out the discharge curves with discharge current values of 1A，3A，6A and 9A.

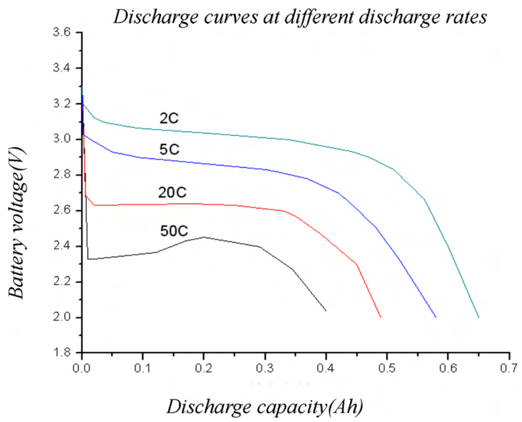

Chart 1 Discharge curves at different discharge rates

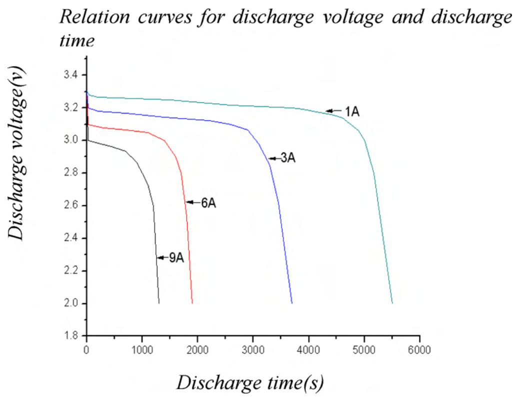

Chart 2 Relation curves for discharge voltage and discharge time

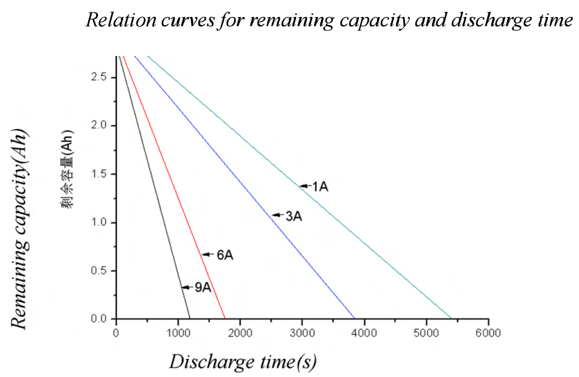

Chart 3 relation curves for remaining capacity and discharge time

III. THEORETICAL ERIVATION FOR REMAINING FOR REMAINING CAPACITY PREDICTION

In terms of practical use, we carry out the derivation of prediction theory for battery's remaining capacity like this: assume at time t, the battery's remaining capacity is C(t), voltage U(t), current I(t), the rated capacity of battery $C_{0,}$ average internal resistance R_0 , internal resistance variation R(t) changing along with time, discharged capacity $C_1(t)$, because $C(t)=C_0-\ C_1(t)$, implicit function of these parameters can be expressed as

$$f_1\big(U(t), I(t), R(t), C_0, R_0, t, C(t)\big) = 0$$

Rated capacity C_0 and average internal resistance R_0 are both different values for batteries of different models and types, while their values are definite for battery of certain type. So, these two parameters do not have big influence on the relation between the parameters and the battery's remaining capacity and can be ignored, the formula can be simplified as:

$$f_2\big(U(t), I(t), R(t), t, C(t)\big) = 0$$

We can see from the previous experimental data of charge-discharge experiment on 26650P iron phosphate Li-ion battery with rated capacity of 3Ah that: internal resistance does not change clearly along with time variation R(t), so when we study the relation between the parameters and battery's remaining capacity, we do not consider internal resistance variation as a major factor, and the formula is simplified as:

$$f_3\big(U(t), I(t), t, C(t)\big) = 0$$

We can see from battery discharge experimental data that discharged capacity C(t) can be figured out when discharge time t is known, but usually discharge time is unknown, neither is discharged capacity C(t), so relation of the parameters is:

$$f_4\big(U(t), I(t), C(t)\big) = 0$$

Remaining capacity of the battery can be expressed as:

$$C(t) = g(I(t), U(t)) = 0$$

After discretization:

$$C(K) = f(U(K), I(K), T)$$

In which T indicates sampling period, which is usually constant; I(k)indicates discharge current, which is also constant under certain discharge condition, as a result, the final function expression of remaining capacity of battery is:

$$C(K) = f(U(K), I, T)$$

We can read from the above theoretical derivation that, BP network should take discharge voltage U(t), discharge current I(t) as input and remaining capacity C(t) as output. And it makes preparation for building prediction model.

Ⅳ. PREDICTION SYSTEM MODELING FOR REMAINING CAPACITY OF BATTERY

This article applies counterpropagation algorithm, that is, BP network, to training the data. The following will use BP neural network which is one of intelligent prediction methods for system modeling and training and learning.

A. System modeling. High-degree nonlinear mapping from input to output can be realized by neural network, Kolrnogorov theorem ensures that any continuous function can be realized via a three-layer feedforward network, later it is found that BP network can realize any continuous function with accuracy of any degree you want. This article applies single hidden layer structure, via changing the number of nodes, finds out that there is poor prediction accuracy for network of less than 10 nodes; as the number of nodes increases, accuracy of network training becomes higher and higher, network training time is faster and faster from 15 hidden nodes to 100 hidden nodes, while consuming more and more RAM. In terms of practical use, take the number of hidden nodes as 11, and the neural network includes 2 inputs and 1 output.

B. This article applies BP neural network to carry out prediction output of experiment data. The network structure is shown in chart 3-1. Input signals transmit from input node, through nodes in each hidden layer, and then to output node, output of each layer only affects that of the next layer. Artificial neural network can perform accurate simulation of future output through "learning and training" samples. Learning process is the process using algorithm to adjust weight value and threshold value; and training process is to propagate learned network, calculate output error and decide whether to go on with learning or not.

C.

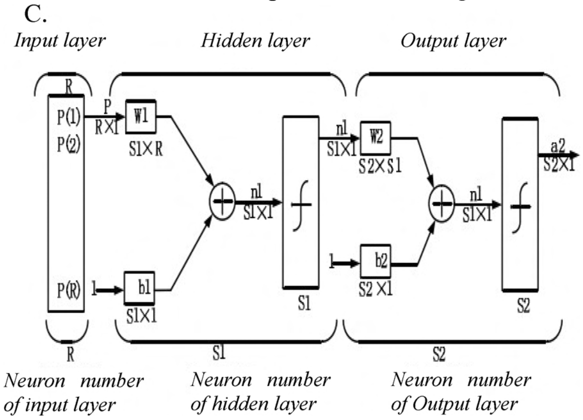

Chart 4 BP network model

Ⅴ. MODEL PREDICTION AND SIMULATION

It proves that the model is available through verifying the model with test data; the following uses the built model to prediction remaining capacity of battery.

Through nntraintool of matlabBP neural network, we can see that training error curve in Chart 5 takes network training time of 22.1324 seconds.

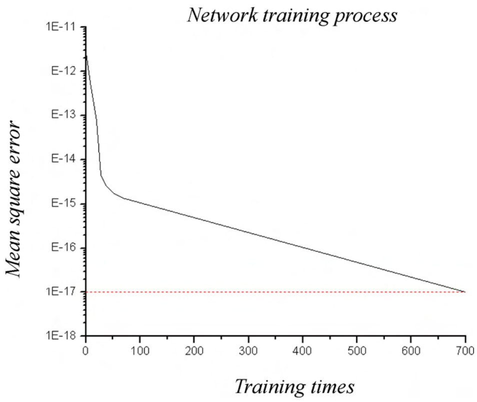

Chart 5 Curve for error during network training process

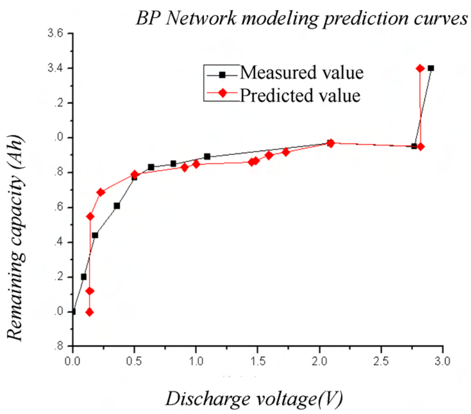

Chart 6 network modeling prediction curves

We can see from Chart 5 that when applying prediction model based on BP neural network to prediction 9A discharge data, prediction results are in better coincidence with the curve of measured value. Chart 6 shows the gap between measured values and predicted values, from which we can see most of the predicted values do not differ too much from the measured data to test network's propagational features. Test results are show in table 1:

Table Ⅰ Related data of test results.

Voltage (V)	*Current (A)*	*Remaining capacity (Ah)*	*Predicted capacity (Ah)*	*Relative error (%)*
3.434	8.9973	2.985	2.8380	4.91
3.284	8.9966	2.084	1.9550	4.32
3.255	8.9966	1.938	1.8300	3.61
3.202	8.9966	0.563	0.6530	3.09

We can see from the comparison in the table that error exists to some extent between the predicted capacity and the actual values, and prediction takes longer time. The results may meet the requirements when accuracy and real time are not strictly required, but if such requirements are higher, the predicted results from BP neural network modeling only will not meet such requirements and need improvement.

Ⅵ. CONCLUSION

A.Charge-discharge experiment of iron phosphate Li-ion battery proves that during discharge process discharge voltage and discharge capacity have definite relations with service conditions, e.g. discharge rate, environment temperature, and etc. The higher the discharge rate is, the faster the voltage descends, and the less capacity it discharges in the same time.

B.Through theoretical derivation of prediction of remaining capacity, BP network should take discharge voltage U(t), discharge current I(t) as input and remaining capacity C(t) as output.

C.After building BP network modeling according to theoretical derivation of prediction of remaining capacity, through simulation, predicted results of remaining capacity have error to some extent with the actual values, and the modeling method is available when accuracy is not highly required, and it shall be improved for requirements of higher accuracy.

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