Acta Technica 62 (2017), No. 5B, 767–774

Establishment and application for SOC model of lithium-ion battery based on ANFIS

Jianping Shi[2,3], Mingfang Liu[2]

Abstract. In this paper, a prediction model of lithium-ion battery residual capacity of adaptive neuro-fuzzy inference system (ANFIS) is established through analyzing experimental data of rebound voltage of lithium-ion battery in high and low temperature. In this prediction model, the rebound voltage and temperature is the input and the residual capacity used is the output. Based on MATLAB, a large amount of experimental data is used to train and test the prediction model of ANFIS and then the prediction model is used to predict and verify the residual capacity of different battery packs. Experimental results demonstrate that the prediction model has good performance and accuracy in predicting the residual capacity of lithium-ion battery.

Key words. Lithium-ion battery, rebound voltage, SOC, ANFIS.

1. Introduction

In recent years, lithium-ion battery has increasingly drawn people's attention and is widely applied to production, common life and other fields. At present, the study on management system of lithium-ion battery has made great progress. But the key technology of lithium-ion battery still exist some shortage, where estimation and prediction of residual capacity become one of the focuses. Nowadays, there are several estimating methods of state of charge (SOC) in estimation and prediction of residual capacity, such as ampere-hour method [1], open circuit voltage method [2], fuzzy control algorithm, neural network algorithm [3], Kalman filtering algorithm [4] and etc. These estimating methods both have shortcomings and their estimating performance is not good. In the estimation and prediction of residual capacity, the timeliness of battery SOC estimation is very important. If the real-time accurate

[1]Acknowledgement - This work is supported by Jiangsu science and technology plan project under Grant No. BY2016031-06, and by Top-notch Academic Programs Project of Jiangsu Higher Education Institutions(TAPP) under Grant No. PPZY2015B129.

[2]Workshop 1 - School of Electrical and Photoelectronic Engineering, Changzhou Institute of Technology , Changzhou, Jiangsu213022, China

[3]Corresponding author: Jianping Shi

prediction of battery SOC can be realized in battery management system, it will promote the development of battery management technology, as well as related industries. In this paper, a lithium-ion battery SOC prediction model is proposed based on rebound voltage according to the timeliness requirement of battery SOC prediction, combined with fuzzy control and theory of neural network.

2. Applicability and influence factors of the SOC estimation by the rebound voltage

2.1. Applicability of rebound voltage

The change in offline voltage of lithium-ion battery is shown in Fig.1. Point A indicates the offline cut off voltage of lithium-ion battery. When the lithium-ion battery is offline, its terminal voltage undergoes a jump from point A to point B. And then, in case of out of load, it slowly recovers in a period of time to a stable voltage - Open Circuit Voltage (OCV). The voltage of point B in the above-mentioned process is called rebound voltage, denoted by Ut.

The detailed analysis in Ref. [5] proves that the voltage value of rebound battery Utdepends on the value of OCV while OCV and residual capacity of the battery have a relatively fixed relationship [6]. As a result, there exists a close relationship between rebound voltage and residual capacity. In view of the fact that voltage value is easy to detect and obtain, rebound voltage shows its obvious effectiveness in SOC prediction.

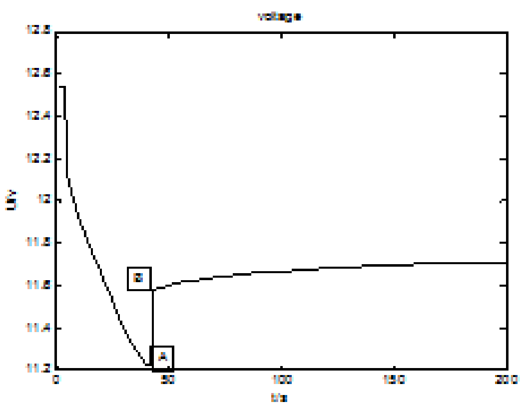

Fig. 1. Change in offline voltage of lithium-ion battery

2.2. Influence factors

The capacity of battery is affected by some factors, such as temperature, charge-discharge rate, cycle life and etc. Therefore, it is necessary to consider the influence of these factors to estimate battery SOC.

1. Influence of temperature

It is well known that battery's capacity is affected by temperature. With the development of battery application, operating temperature of secondary battery is varied in different situations. At low temperature, electrochemical reaction rate decreases, while the residual capacity of secondary battery declines along with it. At high temperature, it will accelerate the chemical reaction rate, releasing more capacity in same condition. The ambient temperature has a certain effect on OCV. The lower the temperature is, the lower the OCV of the same capacity. What's more, the rebound voltage is part of the open-circuit voltage. Therefore, at the same rebound voltage, it will release more SOC in the low temperature than in the high temperature.

2. Influence of charge-discharge rate

When the battery is discharged at a different rate, the discharge capacity will be different. The greater discharge current is, the less capacity will be released relatively. The smaller the discharge current is, the more capacity will be released. As a result, the change of discharge rate will bring some difficulties to the secondary battery SOC prediction. Besides, frequently discharge or charge at a large rate will bring a certain degree of damage on secondary battery [6].

3. Influence of cycle life

Cycle life of lithium-ion battery is affected by some factors, such as battery structure, assembly process, electrode materials, charge-discharge rules, temperature and etc. With reduction of cycle life, actual capacity gradually reduces too, which makes SOC estimation more difficult.

3. Experimental analysis

Considering these above mentioned factors, the experiment on lithium-ion battery SOC estimation is investigated. In experiment, two packs of the battery were used where each battery pack consists of three pieces of INCMP58145155N-I lithium-ion battery in series, which is rated voltage 3.7V and capacity 10Ah. The model BTS-M chmetcnvUnitNameaSourceValue300HasSpaceFalseNegativeFalseNumberType1TCSC0300A/12V battery parameters' automatic testing equipment is utilized to study the experiment.

The experimental process is described as follows. First of all, the two packs were deep discharged from 10% to 70% everyday, with a record of rebound voltages. Then, after 2 hours of voltage recovery, the packs were completely discharged with chmetcn-vUnitNameCSourceValue.2HasSpaceFalseNegativeFalseNumberType1TCSC00.2C. When each settled experimental period of discharge depth had finished, the same experiment was conducted again at a different change-discharge rate. Besides, the two sets of battery were placed in high and low environmental temperatures separately, so as to observe the impact of ambient temperature.

3.1. Analysis of temperature

In this research, the two battery packs are tested in high and low temperatures, respectively. Considering the performance of the two battery packs is different, the experiment under different temperature is proceed using same battery pack. Table 1 shows the residual capacity under different temperatures with discharge of 50%.

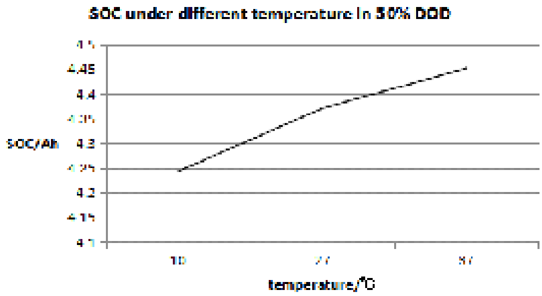

Fig. 2. Schematic diagram of SOC under different temperatures with discharge of 50%.

Fig. 2 shows that the change of temperature has an impact on the residual capacity under the same conditions. From the data, the initial conclusion can be seen that in a certain range of temperature, when temperature increasing, the residual capacity increases too. Therefore, influence of temperature on the SOC prediction cannot be ignored.

3.2. *Analysis of discharge rate*

The discharge rate influences battery capacity c, as described in section 2.2. In order to observe the effect of discharge rate on the residual capacity, several experiments was conducted in same experimental conditions at a different discharge rate. Table 1 shows the experimental data of battery pack 1.

Table 1. Residual capacity after discharge under different temperatures

Depth of Discharge Discharge Rate	30%	40%	50%	60%
0.2C	6.202778	5.2125	4.231111	3.227778
0.5C	6.070556	5.051111	4.015833	3.046111
0.8C	5.782222	4.898056	3.920278	2.903889

It can be seen from Table 1 that the residual capacity is constantly decreasing at same depth of discharge while the discharge rate keeps increasing. Hence, it can be seen that discharge rate does affect capacity of battery. However, since discharge rate might be affected by the load, we found that the average value did not change a lot in the actual operation. Therefore, discharge rate is not considered as the input of the prediction model in actual operation.

In a word, the input of the following modeling has been determined as rebound voltage and ambient temperature.

4. Application of ANFIS in SOC Model Establishment of Lithium-Ion Battery

In this work, an adaptive neural-fuzzy inference system (ANFIS) is presented to build the SOC prediction model of Lithium-ion battery based on the rebound voltage. In fact, ANFIS learning algorithm process and its architecture is integrated with learning methods of feed-forward neural network, along with several supervisory learning functions. Besides, adaptive network is a structure which consists with several nodes and a network to connect them. Furthermore, part or even all of the nodes have the feature of self-adaptability. This means that their outputs depend on the parameters (one or more), which belong to the activation function of the nodes, while the learning rules dictate how these parameters should be changed to minimize the prescribed error. What's more, the basic rules of adaptive networks are based on Gradient Descent and Chain Rule [7]. Because the gradient descent has a slow process rate, and might easily fall into local convergence, ANFIS adopted hybrid rules, which can accelerate its learning process.

Generally, fuzzy inference systems often need large amounts of experienced knowledge as the fuzzy rule base. Owing to the strong subjectivity, it is a fatal flaw for a subject who has not been fully understood yet. However, the neural network, with good learning and adaptive ability, can realize the control of nonlinear systems and conclude the regularity from the data. The combination of the two methods can well make up for their shortcomings. By use of neural network learning method, an objective rule base was generated, which is required by the fuzzy inference system, with adaptive ability. ANFIS is suitable for modeling complex systems that are not well mastered [8].

MATLAB (2013a) provides a graphical interface editor for adaptive neuro-fuzzy inference system, which can be called by typing "anfiseditor" in the main window. This research takes the experimental data as samples for training, calibrating and testing. The network structure and system structure are shown in Fig. 3 and Fig. 4, respectively, and the partial rule view in Fig. 5.

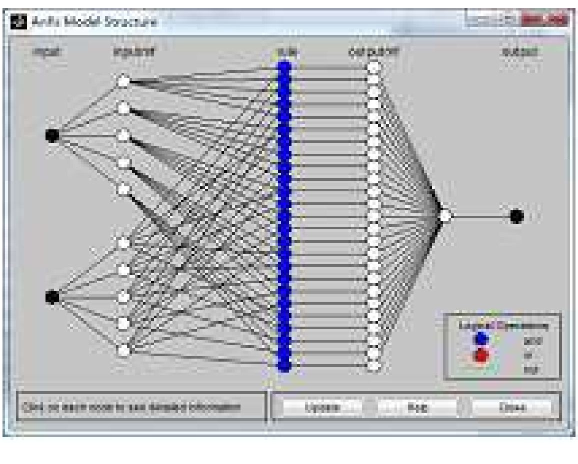

Fig. 3. Network structure.

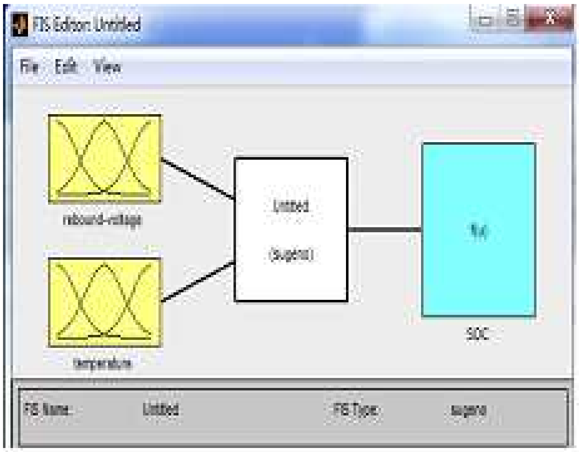

Fig. 4. System structure

Fig. 5. The partial rule view.

5. Simulation check

After the establishment of ANFIS model, the work is simulated in Simulink environment to verify the reliability. The rebound voltage and temperature on the date of 20th experiment day are input into the model and the experiment results can be obtained as shown in Fig. 6. It can be seen from Fig. 5 that the SOC value is 0.6093. The relative error is only 0.0022 between SOC value and experimental value of 0.6071.

The process can be concluded as follows: firstly, simulation was conducted on each experimental date; secondly, the output value was compared with the actual

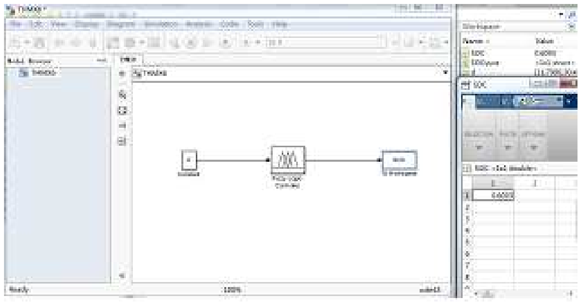

Fig. 6. Simulation of SOC prediction on the 20th experiment date.

experimental data. Fig. 7 shows comparison result of the two kinds of values. Predicted value and actual value of SOC model has a small deviation. In conclusion, the SOC prediction model of lithium-ion battery established in this work is reliable and applicable.

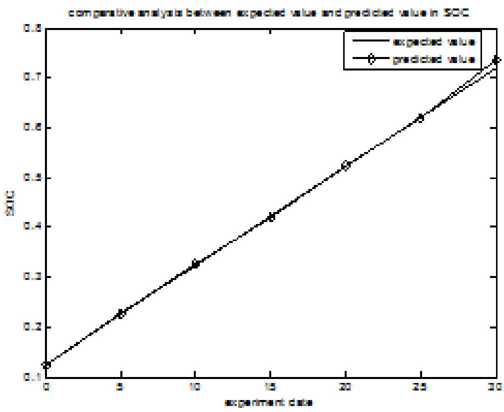

Fig. 7. Comparative analyses between predicted value and expected value in SOC

6. Conclusion

According to the timeliness demand of battery SOC prediction, a prediction model based on rebound voltage is proposed based on rebound voltage in this research considering the influence factors of the prediction. After analyzing the fuzzy control and theory of neural network, this work found the advantage of ANFIS in analyzing unknown complex systems. Then a SOC prediction model for lithium-ion battery is built based on ANFIS. In the end, the performance and reliability of the model are verified by simulation and calibration. Finally, when it comes to influence of the cycle life, this work is not thoroughly finished due to the restriction of the project condition. Therefore, lithium-ion battery recession might have a certain impact on SOC, which needs conducting further in-depth studies.

References

[1] J. S. Tomar, D. C. Gupta, N. C. Jain: *Reliable battery operation a challenge for the battery management system.* Journal of sower sources *15* (1984), No. 2, 211–220.

[2] J. S. Tomar, A. K. Gupta: *Abattery state of charge indicator for electric wheelchairs.* IEEE transactions on industrial electronics *98* (1985), No. 2, 257–262.

[3] R. H. Gutierrez, P. A. A. Laura: *A method for measurement and interpretation of impedance for industrial batteries.* Journal of power sources, *18* (1985), No. 3, 171–180.

[4] R. P. Singh, S. K. Jain: *A comparative study of equivalent circuit models for Li-ion batteries.* Journal of power sources *7* (2004), No. 1, 41–52.

[5] M. N. Gaikwad, K. C. Deshmukh: *Critical review of the methods for monitoring of lithium-ion batteries in electric and hybrid vehicles.* Journal of power sources *29* (2005), No. 9, 797–804.

[6] S. Chakraverty, R. Jindal, V. K. Agarwal: *Electrochemical model-based state of charge estimation for li-ion cells.* IEEE transactions on control systems technology *12* (2005) 521–528.

[7] N. L. Khobragade, K. C. Deshmukh: *Extended kalman filtering for battery management systems of Li PB-based HEV battery packs: Part 1. Background.* Journal of power sources *30* (2005), No. 4, 555–563.

[8] Y. F. Zhou, Z. M. Wang: *New control strategy for shunt power conditioners.* Electric power system research, *316* (2008), Nos. 1–5, 198–210.

Received November 16, 2017