Neural network based SOC estimation during cycle aging using voltage and internal resistance

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Abstract—**The state of charge(SOC) estimation of a Lithium-ion battery is critical and fundamental in managing and using it safely and optimally. The SOC estimation often overlooks the effects of aging and cycling of the battery. This paper presents a model free estimation method based on the Neural network algorithm using the terminal voltage and the internal resistance instead of the capacity. The terminal voltage plays a major role in the SOC estimation of each cycle and the internal resistance adapts it according to the cycle aging effect. After the training of the network for a few intermittent cycle numbers, the SOC estimation error with different cycle numbers for testing results in less than 3%. This method can be used in the lithium-ion battery applications in which the model parameters are not easy to obtain.**

Keywords—SOC; Neural Network; Model free; Battery cycling

I. INTRODUCTION

Lithium-ion batteries are becoming the dominant energy storage systems in many applications such as the portable devices, EVs, and energy backup systems. Specifically, EV batteries have gained much attention recently due to the international efforts to reduce the air pollution caused by the internal combustion engines. Lithium-ion batteries play a crucial role in prevailing the EVs around the world due to their high specific energy and performance. However, lithium-ion batteries require to be managed with great care in the view of safe and optimal usage for most applications.

Two of the most basic and pivotal parameters in managing the lithium-ion batteries are the state of charge(SOC) and state of health(SOH). SOC is an electrical fuel gauge that indicates the remaining charges relative to the capacity in percentage. Challenges obtaining the SOC may be that there is no way to measure it directly and that the capacity deteriorates in the course of aging. SOH is another estimation parameter that shows the percentage of the confidence level of the battery performance relative to the nominal or initial state, reflecting the aging factors such as the capacity and the power degradation. The SOH estimation is generally harder than the SOC because of its slow process compared with the other. Considering the definitions above, however, the capacity is the key parameter that interplays between SOC and SOH. This finding leads us to an inference that an accurate estimation of either of them prompts the other.

In this paper, we primarily focus on the SOC estimation, whose methods have been introduced in many studies. The voltage-based estimation [1, 2, 3] is the most basic and intuitive method that offers a reasonable result in both upper and bottom limits of the charging and discharging modes, respectively. However, it may not be accurate in the middle region due to a rather weak dependency of the voltage on the current flow. The current-based Coulomb-counting(CC) method [4] is a very simple and popular approach for the SOC estimation, where the current is integrated over time. It is quite accurate only if the initial SOC is known and the capacity degradation is taken into consideration. A more robust method is accomplished by incorporating the voltage and the current based approaches to compensate each other. This technique includes the extended Kalman filters(EKFs) [5], the unsented Kalman filters(UKFs) [6, 7]. These methods have proved to improve the estimation performance but the priori knowledge of the battery such as the battery models and the electrical or chemical characteristic parameters needs to be assessed.

Another possible approach is the data-driven method that requires no battery model and operational knowledge. The support vector machine(SVM) [8] and the neural networks(NNs) [3, 9, 10] are the two main representatives. They establish a cost function and train the network with the data to minimize it. The more the data are trained, the more accurate the estimation of the network becomes. However, the amount of data is proportional to the complexity of the analyzing procedure. The network also depends on the choice of the inputs and outputs.

In this paper, we demonstrate a NNs based SOC estimation from a battery cell cycling data. The voltage and the internal resistance were used as inputs and the SOC the output. In order to include the aging effect to the SOC estimation, the internal resistance was used instead of the capacity because it is easier to measure. After the training of five cycle data out of 500, the network could be used for testing all other cycle data by comparing the estimated and the true SOC. This paper is arranged as follows. Section 2 illustrates the cycling experiment of a cell and the resultant data such as the capacity degradation and the increase of the internal resistance. Section 3 shows a brief introduction of the NNs and their training and estimating the SOC from the cycling data. Section 4 gives the conclusions.

II. LITHIUM-ION BATTERY CYCLE TEST

A. Battery cycle life test experiment

A lithium-ion battery cell shown in Fig. 1 was cycled for 500 times to trace the capacity degradation and the internal resistance increase using the Zive SP1 (WonATech Co., Ltd.).

The battery cell was placed inside a home-made chamber with the temperature controlled to be 25ºC. The testing cell has the nominal capacity of 800mAh (14500) and nominal voltage of 3.7V.

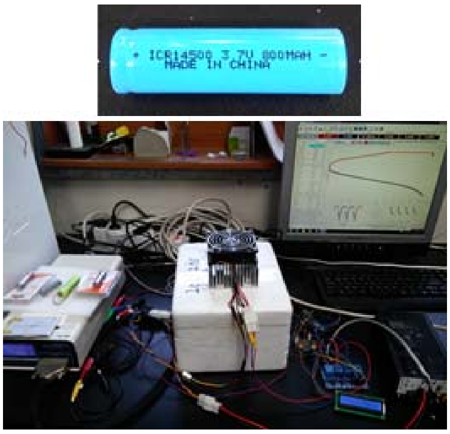

Fig. 1. A lithium-ion battery and the cycle experiment setup

The cycle life test was performed with *constant current and constant voltage mode* for charging and *constant current mode* for discharging. Fig. 2 shows the voltage and current during the charge/discharge for the second cycle where a sudden voltage drop, dV, is denoted when the discharge starts. This voltage drop implies the series internal ohmic resistance which is the ratio of the voltage difference to the current difference.

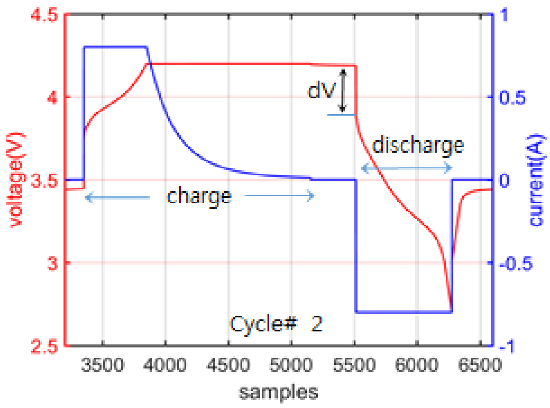

Fig. 2. Voltage and current of the second cycle

B. Capacity degradation for cycle life

The capacity of the cell was monitored by integrating the discharge current. As the cell undergoes the cycling, the capacity degradation is ineluctable due to the losses of lithium ions that contribute to the charge transfer during the electrochemical process inside the cell. The capacity degradation with cycle number was shown in Fig. 3. Initial capacity, 850mAh, is larger than the nominal one, 800mAh. The capacity decreases slowly until 300 cycles but it rapidly declines later on. This capacity reduction for cycle aging should be considered in the SOC estimation. However, it takes time to discharge a battery from the full to the empty state and it is sometimes not convenient to measure the capacity for each and every cycle.

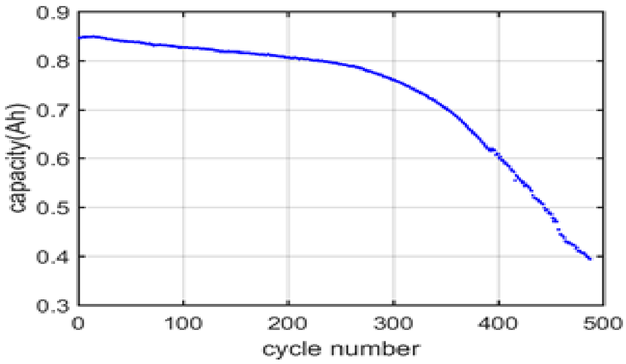

Fig. 3. Capacity degradation with cycle number

The SOC varying from 100% to 0% for discharge can be represented alternatively by the depth of discharge(DOD) which is the complement of SOC. DOD is the ratio of the current integration to the capacity(C) as shown in the equation below. Fig. 4 shows DOD and CC curves for the five cycle data (1, 100, 200, 400, 488) which were selected from the 500 cycle data. The CC curves have the same slope for the five cycle numbers due to the constant discharge current. On the other hand, the slope of the DOD becomes larger for a larger cycle number because the total discharge time gets shorter due to the degradation of the capacity. This difference between CC and DOD makes it difficult to estimate the SOC as the battery experiences the cycle aging.

$$SOC(\%) = 100\% - DOD(\%) = 100\% - \frac{\int I dt}{C} \times 100$$

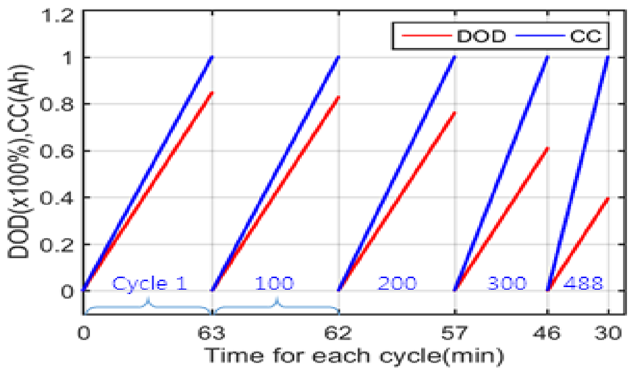

Fig. 4. DOD and CC for five cycle numbers

C. Power degradation for cycle life

Lithium ion batteries can be represented as an equivalent electrical circuit model shown in Fig. 5. The internal ohmic resistance, R_0, is the electrolyte resistance including the electrode resistance. The diffusive resistance, R_1, is the charge transfer resistance at the interface between the electrode and electrolyte solution. The capacitance, C_1, is the electric double layer static capacity formed at the interface between the electrode and electrolyte solution [11]. These parameters should be determined in advance for the battery state estimation. In this paper, however, we evaluated R_0 only from dividing dV by the constant discharge current, 800mA.

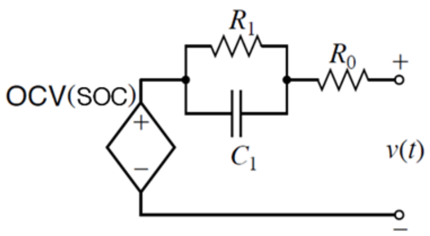

Fig. 5. Equivalent circuit model

The battery power is closely related to the internal resistance, the increase of which curtails the current flow from the battery to the load. The increasing tendency of R_0 is presented in Fig. 6 as a function of the cycle number. Even though the correlation strength between the capacity and the internal resistance is not strong in general, their inverse correlation is seen apparently, observing Fig. 3 and Fig. 6. One favorable aspect of using R_0 is that it can be easily obtained right at the start of the discharge after the full charge. Since this scenario is fairly common in most battery applications, R_0 is a very useful parameter in the SOC estimation.

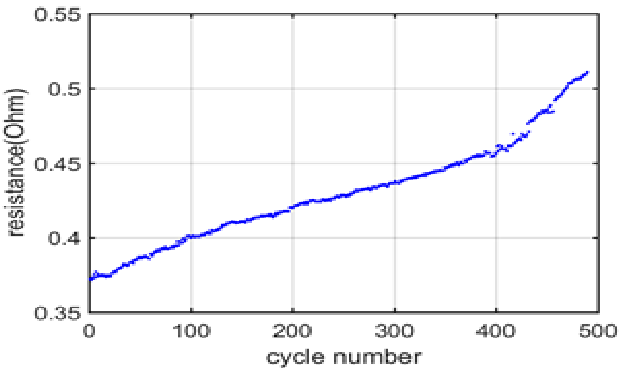

Fig. 6. Internal resistance with cycle number

III. SOC ESTIMATION BASED ON NEURAL NETWORK

Neural networks (NNs) are the data-driven and model-free tools that establish the relation between the inputs and outputs of the data. NNs are very useful especially when dealing with the highly nonlinear systems such as lithium-ion batteries.

A. Neural Network algorithm

A neural network consists of three layers, each of which has one or more nodes that are connected between the two adjacent layers. Fig. 7 illustrates the schematic diagram of a feed-forward neural network that imitates the operation of the battery system. The four possible inputs to the neural network in Fig. 7 are sample points, currents, voltages, capacities and internal resistances and the output is the battery SOC. The hidden layer has 5 nodes that are interconnected with the input and output nodes. Each interconnection has the weight that needs to be updated by training the network with the data. The weight parameters are optimized by the back propagation algorithm where the estimation errors between the true and the estimated outputs propagate backward from the output layer to the input layer through the hidden layers.

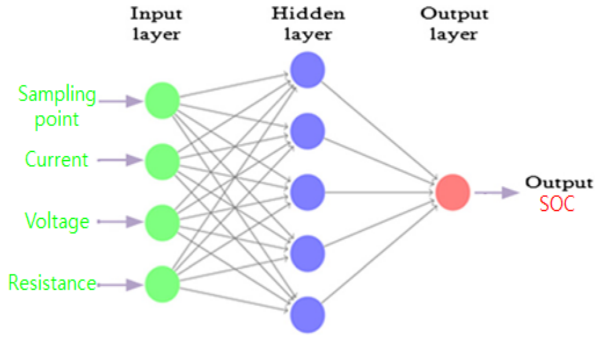

Fig. 7. NNs diagram with 4 inputs and 1 output

B. Training of the network

Most real world applications of the Lithium-ion batteries are very sophisticated and unpredictable to estimate the states of the battery performance. EV batteries, for example, have to undergo fast changes in current and hence voltage, which results in the nonlinear response of SOC. In addition, the aging and cycling effects come into play in estimating the SOC. In order to demonstrate the SOC estimation based on the NNs, the battery cycle data obtained from the experimental setup shown in Fig. 1 were used for training and testing the network.

For the training of the NNs, five cycle data for discharge out of 500 cycle data such as 1, 100, 200, 400, and 488, were used instead of using all cycle data. Two inputs for the NNs are the voltage and the internal resistance excluding the capacity as shown in Fig. 8 and Fig. 9 as a function of the time during which each discharge cycle takes place. The constant discharge current (1C-rate) that gave no contribution to the network was not used for the input value. The voltage curves shown in Fig. 8 demonstrates the gradual changes in shape with the cycle number whereas the ohmic resistances are constant for each cycle but increases as the cycle number gets larger as shown in Fig. 9. The output for the training of the network was the SOC shown in Fig. 10.

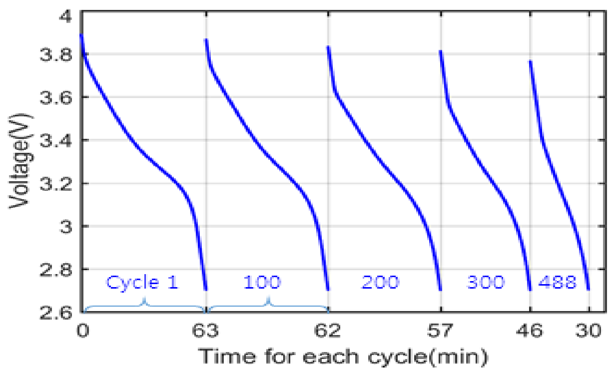

Fig. 8. Voltage with five training cycle numbers

After the training, the NNs were validated by comparing the true SOC and the estimated SOC for the five cycle data as shown in Fig. 11. The estimation error plotted in Fig. 12 is mostly less than 2%, which means the NNs is imitating the battery system properly for all the five training data even though the bigger error was observed at both edges, the start and the end of each cycle.

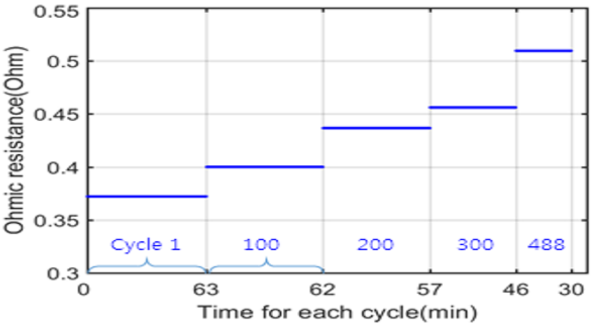

Fig. 9. Internal resistance for five cycle numbers

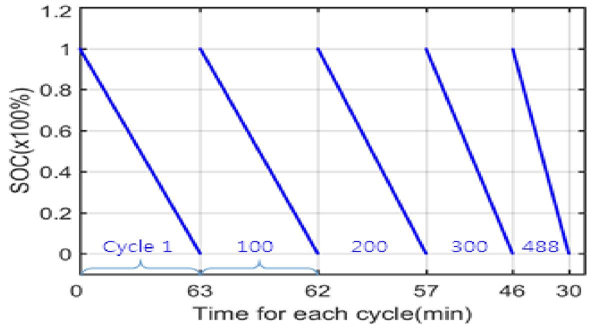

Fig. 10. SOC for five cycle numbers

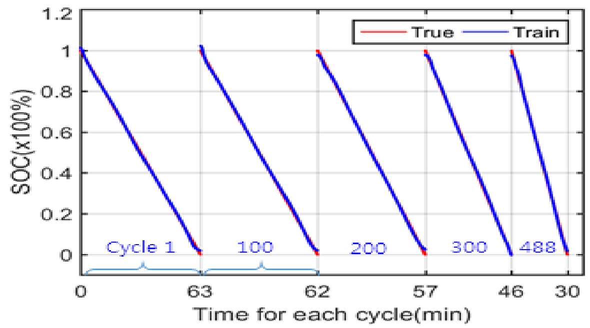

Fig. 11. Estimation of the true and estimated SOC for five training cycle numbers

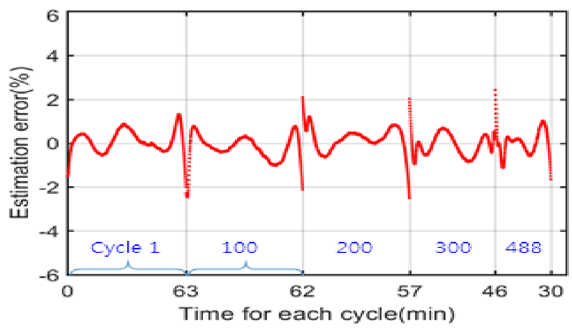

Fig. 12. Estimation error for the training cycle numbers

C. Testing the network for SOC estimation

The trained NNs were tested to estimate the SOC for different cycle numbers, 50, 150, 250, 350, and 450. The voltage and the ohmic resistance for those cycles are shown in Fig. 13 and Fig. 14 as a function of the time that took for each discharge cycle. The true SOC and the estimated SOC are plotted in Fig. 15 showing a reasonable fitting between them. The estimation error was shown in Fig. 16 to be less than 3% for all the testing cycle numbers.

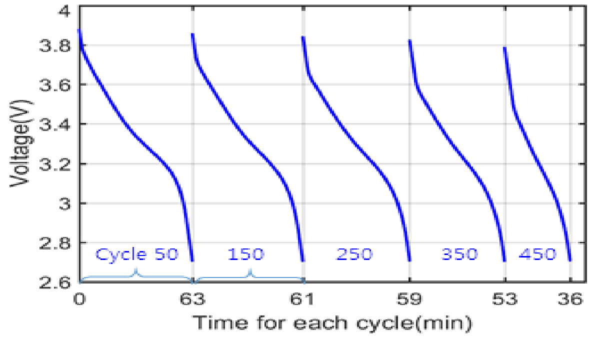

Fig. 13. Voltage profile for five testing cycle numbers

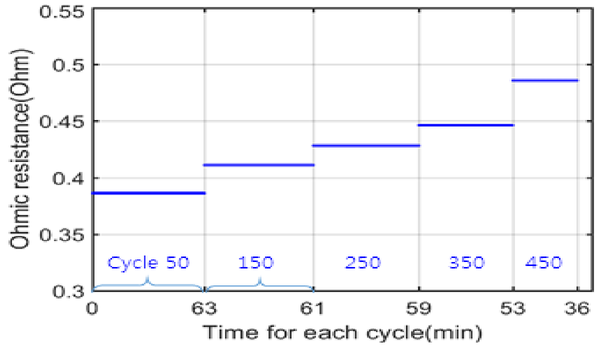

Fig. 14. Internal resistance for five testing cycle numbers

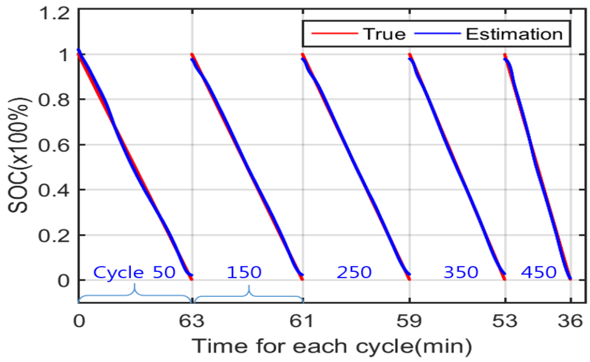

Fig. 15. The true and the estimated SOC comparison

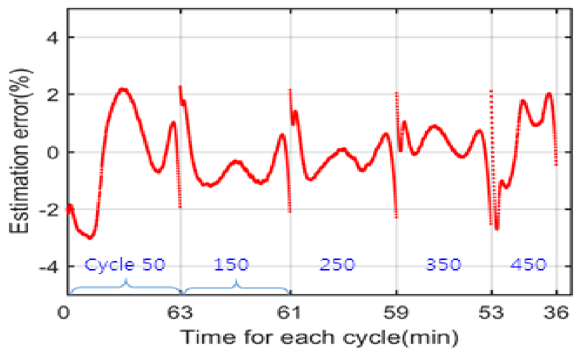

Fig. 16. SOC estimation error between the true and the estimated

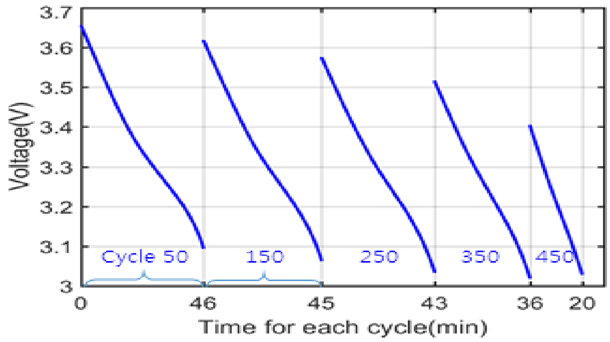

Fig. 17. Voltage profile for five testing cycle numbers with 200 samples reduced

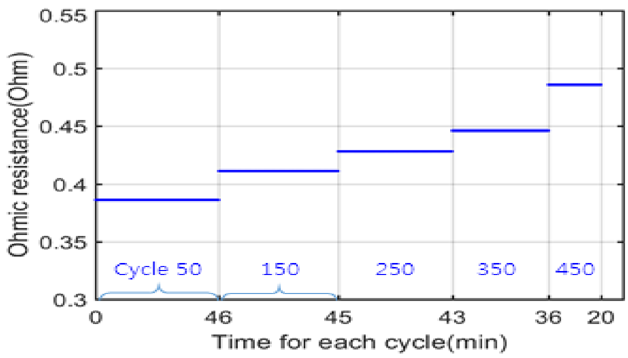

Fig. 18. Internal resistance for five testing cycle numbers with 200 samples reduced

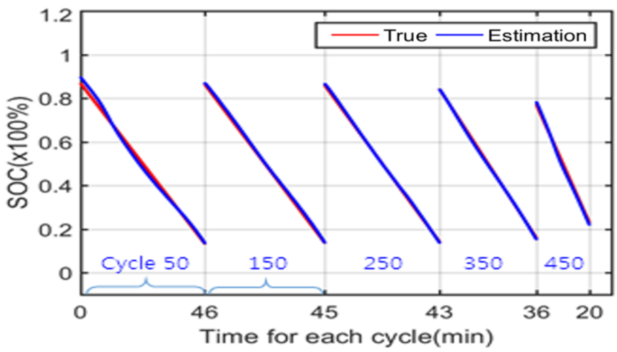

Fig. 19. The true and the estimated SOC comparison for five testing cycle numbers with 200 samples reduced

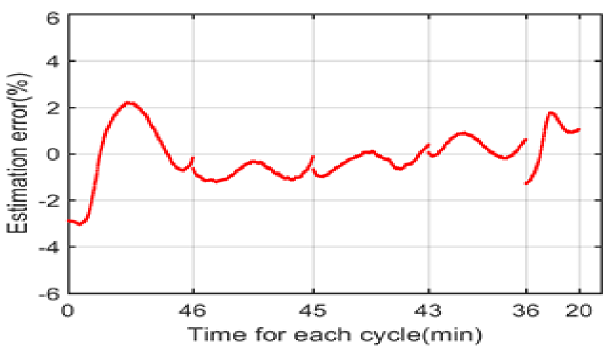

Fig. 20. SOC estimation error between the true and the estimated

The trained NNs were tested to estimate the SOC for the truncated data from the previous ones. In this testing scenario all the testing discharge cycle data were reduced in sample size by 200 samples (1000 seconds), i.e. 100 samples from the start and 100 samples from the end of each cycle data. This implies that the network was tested for different initial values. Fig. 17 and Fig. 18 show the voltage and the ohmic resistance with reduced discharge time. The SOC comparison between the true and the estimated is shown in Fig. 19 with reasonable deviation. The estimation error in Fig. 20 demonstrates to be less than 3% mostly.

IV. CONCLUSIONS

In this paper, we present a neural networks(NNs) based SOC estimation as a cell undergoes the cycle aging. The NNs were trained with the five intermittent cycles out of 500 and tested for different cycle numbers. The two inputs to the network are the voltage and the internal resistance and the SOC the output. The easily measurable internal resistance was preferable to the capacity. Using these two inputs took into account the aging effect to the SOC. The SOC estimation error for different testing scenarios was less than 3% mostly. This method should be tested for the real application data in the future.

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