A Novel SOC Estimation Method for Multiple Number of Lithium Batteries Using Deep Neural Network

딥 뉴럴 네트워크를 이용한 새로운 리튬이온 배터리의 SOC 추정법

Asad Khan*, Young-hwi Ko**, Woojin Choi

Soongsil University,
369 Dongjak-gu Seoul, KOREA

Abstract

For the safe and reliable operation of Lithium-ion batteries in Electric Vehicles (EVs) or Energy Storage Systems (ESSs), it is essential to have accurate information of the battery such as State of Charge (SOC). Many kinds of different techniques to estimate the SOC of the batteries have been developed so far such as the Kalman Filter. However, when it is applied to the multiple number of batteries it is difficult to maintain the accuracy of the estimation over all cells due to the difference in parameter value of each cell. Moreover the difference in the parameter of each cell may become larger as the operation time accumulates due to aging. In this paper a novel Deep Neural Network (DNN) based SOC estimation method for multi cell application is proposed. In the proposed method DNN is implemented to learn non-linear relationship of the voltage and current of the lithium-ion battery at different SOCs and different temperatures. In the training the voltage and current data of the Lithium battery at charge and discharge cycles obtained at different temperatures are used. After the comprehensive training with the data obtained with a cell resulting estimation algorithm is applied to the other cells. The experimental results show that the Mean Absolute Error (MAE) of the estimation is 0.56% at 25°C, and 3.16% at 60°C with the proposed SOC estimation algorithm.

1. Introduction

Lithium ion batteries are the important power source for Electric Vehicles (EVs), Portable Electronics and Energy Storage Systems (ESSs). The Lithium ion batteries have advantages over the other batteries such as high specific energy and high energy density. Due to those advantage a longer drive range, a higher cycle life, a higher columbic efficiency (up to 98%) and lower self-discharge rate can be achieved when it is used for EV applications. For the safe and reliable operation of Lithium-ion batteries in Electric Vehicles (EVs) or Energy Storage Systems (ESSs), it is essential to have accurate information of the battery such as State of Charge (SOC).

The estimating methods for SOC include Coulomb counting (CC), Extended Kalman Filter (EKF), Particle Filter (PF) and Observer. One of the most popular methods in estimating SOC is CC method which calculates the SOC by accumulating the currents over time. However, due to the errors in the measurements, the accurate SOC estimation is difficult as the error is also accumulating over time. Other methods such as EKF, PF and Observer can estimate the SOC with a good enough accuracy since it does not fully rely on the current accumulation. However, these methods need an accurate model of battery for the accurate estimation of SOC.

Machine learning has been used over the long period of time. Machine learning techniques has an advantage that they can learn with raw data and without the need for hand-engineered models. In ref [3], an extreme learning machine is used at a constant ambient temperature of 25°C. Though an SOC estimation error under 1.5% is claimed, this can be only achieved in conjunction with the Kalman filter. Since the extreme learning machine is trained on constant discharge pulses their performance in transient load demand and/or in real world scenarios is unknown. In ref [4], Support Vector Machine (SVM) is used with a moving window to improve the computational efficiency when modeling the battery; a MAE of less than 2% is achieved. However, as is the case for the above works, it can be achieved in conjunction with an EKF. In Ref [5], a load classifying neural network is used on 12 US06 driving cycle, however different kind of neural networks are used for idling, charging and discharging operation. The method achieves an average estimation error of 3.8% or 2.6% when additional filtering is applied. Furthermore, validation is performed on only pulse discharge test hence the performance of the method in real world application is unknown.

In this paper a novel DNN based SOC estimation method for the Lithium batteries is proposed without the help of Kalman Filter or any other method. The voltage and current data obtained at different temperature are mapped to SOC. The DNN is first trained with a data set obtained with a cell and then the resulting algorithm is applied to the other cells of the same kind. The proposed method has following advantages. (1) A single DNN maps inputs signals of battery such as voltage, current and temperature directly to the battery SOC and use of additional filter or other conventional estimation algorithms are not required. (2) The DNN can get its own weights by self-learning algorithm. This is different from other techniques such as lumped parameter models, equivalent circuit model or electrochemical models which require a great amount of time. (3) Only one DNN can be used to estimate SOC at different ambient temperature conditions. It can be regarded as a significant advantage since the traditional estimation techniques uses different models or different look-up tables for the estimation at different ambient temperatures.

2. Deep Neural Network for the SOC Estimation

The feedforward neural networks can model complex non-linear system by mapping the inputs to a desired output. Once training is completed DNN can estimate SOC in a very short period of time. In this paper the Structure of DNN consists of three-layer including an input layer, hidden layer, and output layer. The model is shown in Fig. 1. The equation for single neuron is given in Eq. (1.1).

$$\hat{y} = f\left(W^{T} \times x + b\right) \tag{1.1}$$

Where, x is an input vector, W is weights and b is bias. Each layer consist of multiple neurons which interact each other. And each layer has its own equation and output as given in Eq. (1.2).

$$y_k = f\left(\sum_k \left(W_k . h + b_k\right)\right) \tag{1.2}$$

Where, f represents activation functions and RELU is the best selection for the regression problem. The DNN has more than one hidden layer, Eq. (1.2) can be written for all layers as Eq. (1.3).

$$Y = f\left(\sum_{k}\left(W_k^l.h + b_k^l\right)\right) \tag{1.3}$$

Where, k represents the number of neurons, l represents number of layers and Y is the output SOC value. The mean square error calculated in the preceding feedback process is shown in Eq. (1.4).

$$E = \frac{1}{2}\sum_{k=1}^{n}\left(t_k - y_k\right)^2 \tag{1.4}$$

Where, k = 1, 2, 3…n, E represents the mean square error, t_k represents the expected output and y_k represents the actual output. In the process of error backpropagation, the weight is adjusted by following Eq. (1.5).

$$W_{a+1} = W_s - \eta\frac{\partial E}{\partial W_a} \tag{1.5}$$

Where, W_{a+1} represents the correct weight, w_a represents the current state weight and η represents the learning rate. Through continuous training and adjustment, the DNN can obtain the best training model so that the mean square error can meet the requirements. In this method, RMSprop optimizer is used to optimize weight of the mean square error. The optimizer can effectively improve the convergence speed of DNN and reduce the prediction error.

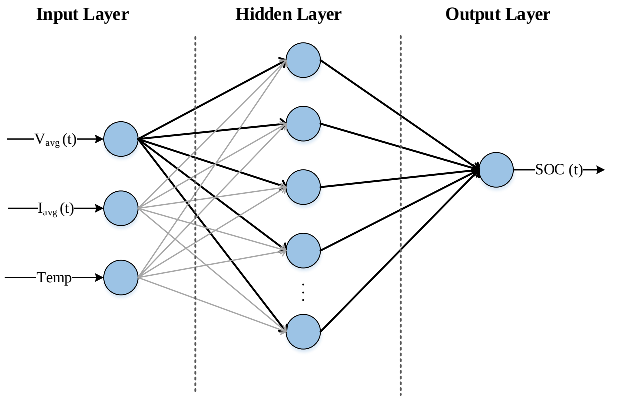

Figure 1. DNN structure

2.1 Data Preparation, Learning and Validation

Three different Dynamometer Driving Cycles (DDCs) with some charging profiles are applied on a battery cell and the measured data are used to train and to validate the DNN. Three DDCs such as UDDS, HWFET and Japanese 10-15 SOC are selected to obtain the range of mean, power from the battery. The UDDS is applied to a battery and the resulting data measured are used for DNN training at different ambient temperatures ranging from -20°C to 60°C. For the testing HWFET and Japanese 10-15 mode drive cycle are used at 0°C, 25°C and 60°C degree temperatures. All the information about DDCs can be found in Table 1.

Table 1

Used DDCs and their characteristics

Test	Use	Power (W)		
		Mean	RMS	Peak
UDDS	Training	3.627	4.987	22.62
HWFET	Validation	3.2	4.45	17.85
J 10-15 mode	Validation	1.48	1.219	13.90

The test procedure to acquire data is as followings: (1) Set thermal chamber temperature to a certain desirable value, (2) Charge the battery fully and (3) Run the DDC profile while acquiring the data. The DDC repeats until the battery voltage reaches 2.5V. This process is repeated for all temperatures and all the DDCs. Figure .2 shows experimental setup for measurement of battery data. National instrument cDAQ-9174 is used to acquire voltages and current signals through custom sensing circuit from the battery module placed in heat chamber. Heat chamber maintains constant temperature through.

Table 2.

Samsung INR18650-29E	
Nominal Voltage	3.65V
Nominal Capacity	2850mAH
Min/Max Voltage	2.5V/4.2V
Max. Charge Current	2750mA
Min. Charging temperature	10°C
Max. discharge current	8250mA (non-continuous)

The Lithium battery cell used in the experiment is Samsung INR18650-29E, Nickel Manganese Cobalt Chemistry Li-ion battery, with a nominal capacity of 2.85Ah. Other specifications are shown in Table 2. The Extended Kalman Filter is used to estimate the SOC while the DDCs are applied to the battery.

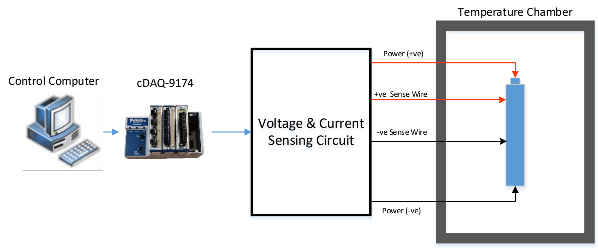

Figure 2. Experimental Setup for the Lithium battery test

In this paper, TensorFlow, a machine learning library in Python, is used. The TensorFlow framework provides an ability to quickly prototype and test different network architectures and it is able to automatically compute the backpropagation. The training took about 5hrs and it depends on the amount of input data.

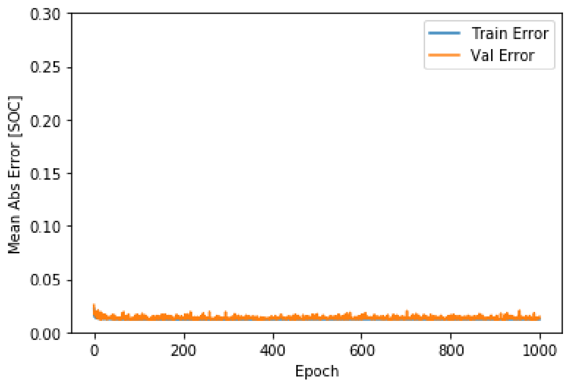

Fig. 3 Training Progress over 1000 OPOCHS.

The DNN is allowed to learn with the data measured through the pretest. Fig. 3 shows the learning progress over 1000 EPOCHS. The MAE Error in training is around 1.4% and the MAX value is around 5%, which proves that the training was done successfully.

After successful learning of DNN it is allowed to validate itself with 20% of data in the same profile to counter check the accuracy of the network trained. It can been seen in the Fig. 3 that the DNN is well trained and validation accuracy is of MAE <1%.

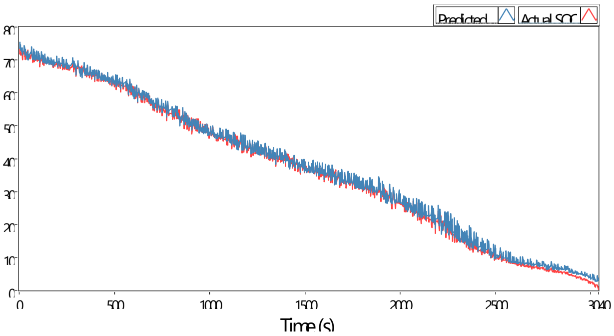

Fig. 4 Training results of DNN.

2.2 State of Charge Estimation Results

As already discussed three different DDCs including UDDS, HWFET and Japan 10-15 modes are applied to a Lithium battery and the data are acquired and stored in a PC. In the experiments, the UDDS profile is used for learning and validation of DNN while HWFET and Japan 10-15 DDCs are used to evaluate the performance of the DNN for SOC estimation. Fig. 5 shows the SOC estimation result by the DNN. By comparing the true SOC values with the values estimated by DNN, the MAE of the SOC estimation is 0.591% and its MAX value is 5.9%.

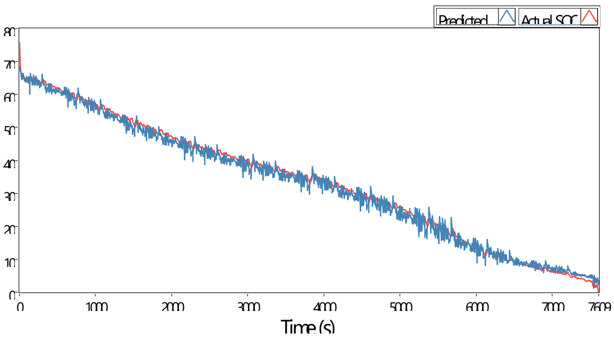

Fig. 5 SOC Estimation with HWFET DDC at 25°C

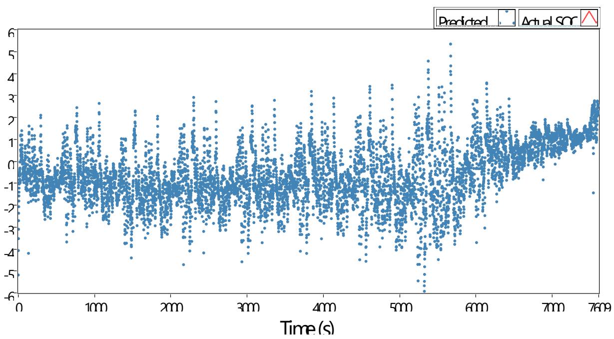

Fig. 6 SOC Estimation prediction error of HWFET at 25°C

The HWFT and J1015 profiles are also run at 0°C, 25°V, and 60°C. The voltage, current and temperature are recorded. The DNN is allowed to estimate SOC at these temperature and the SOC estimation error at 25°C is 0.59% and 0.236% for HWFET and J1015, respectively.

The SOC estimation error is around 3.54%, 3.16% 1.8% and 3.16% for HWFET at 0°C, HWFET at 60°C, J1015 at 0°C, and J1015 at 60°C, respectively, as shown in Fig. 7.

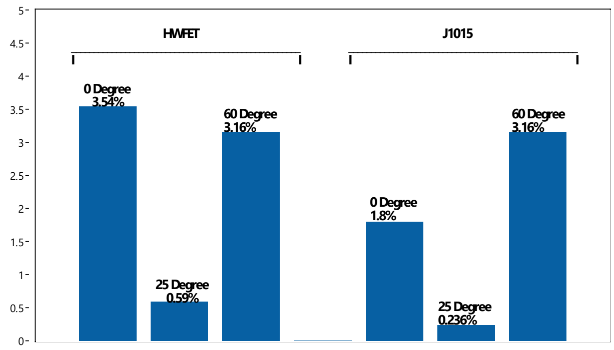

Fig. 7 SOC Estimation errors with J 10-15 DDC at 25°C

3. Conclusion

The main contribution of the paper can be summarized as followings. Firstly, the measured battery voltage, current and temperature are mapped directly to SOC by the DNN and less than 0.5% MAE in SOC estimation has been achieved. Secondly, the DNN self-learned all its weights and eliminated the need to hand-engineer and to parameterize the traditional models. Thirdly, single DNN can be used to map the behavior of a lithium-ion cell at different temperatures. The DNN can be formulated as an equation so that it can be implemented in any kind of microcontroller. The SOC estimation of the large number of batteries can be achieved with relatively lower computational burden if the DNN is developed to learn the behaviors of the battery at different temperatures.

Acknowledgment

This research was supported by the R&D program for new energy industry through Chungnam center for creative economy and innovation (CCCEI) funded by local government of chungchengnamdo.

Reference

[1] Chuan-Wei Zhang, Shang-Rui chen*, Huai-Bin Gao, KeJun Xu and Meng-Yue Yang, "State of Charge Estimation of Power Battery using Improved Back Propagation Neural Network", Batteries,11 December 2018.

[2] Ephrem Chemali*, Phillip J.Kollmeyer, Matthias preindl, Ali Emadi "State-of-charge estimation of li-ion batteries using deep neural networks: A machine learning approach", Journal of Power Sources, 2018.

[3] J. Du, Z. Liu, Y. Wang, State of charge estimation for li-ion battery based on model from extreme learning machine, Contr. Eng. Pract. 26 (2014) 1-19

[4] J. Meng, G. Luo, F. Gao, Lithium polymer battery state-of-charge estimation based on adaptive unscented kalman filter and support vector machine, IEEE Trans. Power Electron. 31 (3) (2016) 2226–2238.

[5] S. Tong, J.H. Lacap, J.W. Park, Battery state of charge estimation using a load classifying neural network, Journal of Energy Storage 7 (Supplement C) (2016) 236–243.