https://doi.org/10.6113/TKPE.2021.26.1.1

딥 뉴럴 네트워크를 이용한 새로운 리튬이온 배터리의 SOC 추정법

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

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Abstract

For the safe and reliable operation of lithium-ion batteries in electric vehicles or energy storage systems, having accurate information of the battery, such as the state of charge (SOC), is essential. Many different techniques of battery SOC estimation have been developed, such as the Kalman filter. However, when this filter is applied to multiple batteries, it has difficulty maintaining the accuracy of the estimation over all cells owing to the difference in parameter values of each cell. The difference in the parameter of each cell may increase 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 determine the nonlinear relationships of the voltage and current at different SOCs and temperatures. In the training, the voltage and current data obtained at different temperatures during charge/discharge cycles are used. After the comprehensive training with the data obtained from the cycle test with a cell, the resulting algorithm is applied to estimate the SOC of other cells. Experimental results show that the mean absolute error of the estimation is 1.213% at 25°C with the proposed DNN-based SOC estimation method.

Key words: SOC estimation, Parameter variation, Artificial intelligence, Deep neural network, Machine learning

1. Introduction

Lithium-ion batteries are the important power source for Electric Vehicles (EVs), Portable Electronics and Energy Storage Systems (ESSs). It has advantages over the other batteries such as high voltage, high specific energy, and high energy density. Therefore, a longer drive range, a higher cycle life, a higher columbic efficiency (up to 98%) and a lower self-discharge rate can be achieved when it is used for EV applications[8],[9]. For the safe and reliable operation of Lithium-ion batteries in EVs or ESSs, it is essential to have accurate information of the battery such as the State of Charge (SOC).

The SOC estimation methods include Coulomb Counting (CC), Extended Kalman Filter (EKF), Particle Filter (PF) and State Observer (SO). One of the most popular methods in estimating SOC is the CC method which calculates 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 SO can estimate the SOC with good enough accuracy since it does not fully rely on the current accumulation. However, these methods need an accurate model of battery with

Paper number: TKPE-2021-26-1-1
Print ISSN: 1229-2214 Online ISSN: 2288-6281
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Manuscript received Jun. 27, 2020; revised Aug. 9, 2020; accepted Sep. 2, 2020
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parameters for the accurate estimation of SOC.

Machine learning has been used to provide solutions to many kinds of different engineering problems over a long period of time. It has an advantage that the complex system can be modeled 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 a SOC estimation error under 1.5% is claimed, it can be achieved only in conjunction with the Kalman Filter.

Since the extreme learning machine is trained with the data obtained by the constant discharge pulses its performance during the transient 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 and an MAE of less than 2% is achieved. However, as is the case for the above works, it can be achieved in conjunction with an Extended Kalman Filter (EKF). In Ref. [5], a load classifying neural network is used to estimate the SOC of the battery with data obtained from twelve US06 driving cycle tests, however a different kinds of neural networks should be used for idling, charging and discharging operation, respectively. The method achieves an average estimation error of 2.6% when the additional filtering is applied. Furthermore, the validation is performed only with a pulse discharge test hence the performance of the method in the practical application is unknown.

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

2. Deep Neural Network for SOC Estimation

The feed-forward neural networks can model complex non-linear systems by mapping the inputs to the desired output. Once training is completed the DNN can estimate the SOC of the battery in a quite short period of time. The DNN is the collection of the software neurons arranged in multiple layers. The DNN used in this paper consists of three layers, an input layer, a hidden layer, and an output layer as shown in Fig. 1. The equation for the single neuron can be represented by Eq. (1).

$$\hat{y} = f(W^T \times x + b) \tag{1}$$

Where x is an input vector, W is weight and b is a bias. Each layer consists multiple neurons that interact with each other. The output of a single layer can be represented by Eq. (2).

$$Y = f(\sum_k (W_k \cdot x + b_k)) \tag{2}$$

Where f represents the activation function. There are several kinds of different activation functions that can be used for DNN. For the SOC estimation of the battery ReLU (Rectified Linear Unit) is the best selection because it rejects negative values and converges fast. The DNN has more than one hidden layer and Eq. (2) can be expanded for all layers by Eq. (3).

$$Y = f(\sum_{k,l=1}^{n} (W_k^l \cdot x + b_k^l) \tag{3}$$

Where k represents the number of neurons, l represents the number of layers and Y is the output SOC value. The MAE calculated in the preceding feedback process can be represented by Eq. (4).

$$E = \frac{1}{2} \sum_{i=1}^{n} \frac{|t_k - y_k|}{n} \tag{4}$$

Where i is an element in a data set, E represents the

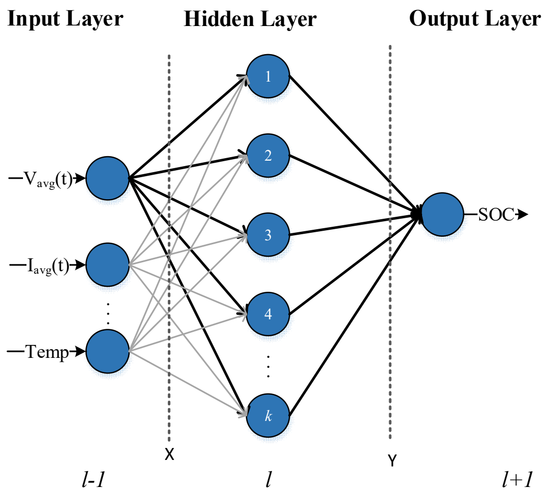


Fig. 1. Structure of DNN.

TABLE I
MAE OF SOC ESTIMATION WITH DIFFERENT COMBINATIONS OF LAYERS AND NEURONS FOR DNN

Number of Layers	Number of Neurons	MAE(%)
2	24	2.6
2	64	1.9
3	64	1.2
4	64	1.9
5	64	1.65
8	4	1.75
8	64	1.8
8	128	2.55

MAE, t_k represents the expected output and y_k represent the actual output. During the process of back propagation, the weight is adjusted by Eq. (5).

$$W_{a+1} = W_s - \alpha \frac{dw}{\sqrt{v_{dw}} + \epsilon} \tag{5}$$

Where, W_{a+1} is the new corrected weight, W_a is the current state weight and α is the learning rate. Through continuous training and adjustment, the DNN can obtain the best model by minimizing the MAE. For this purpose, Root Mean Square Propagation (RMSprop) Optimizer is used to minimize the MAE by adjusting the weights as shown in Eq. (5). The optimizer can effectively improve the convergence speed of DNN and reduce the prediction error.

In order to find the best combination of layers and neurons which gives the lowest MAE for the SOC estimation of the battery, several different combinations of layers and neurons are tested. Table I shows the MAE results with different combinations of layers and neurons. As shown in Table I the best combination of DNN which gives the lowest MAE is the DNN with 3 layers and 64 neurons of which MAE is 1.2%.

TABLE II
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
Japan 10-15	Validation	1.48	1.219	13.90

3. Data Preparation, Learning and Validation

For DNN training a handsome amount of battery data is needed. Three different Dynamometer Driving Cycles (DDCs) such as Urban Dynamometer Driving Schedule (UDDS), Highway Fuel Economy Test (HWFET) and Japan 10-15 are selected.

After applying theses DDCs on a battery cell the measured data, voltage and current of the battery are collected and used to train the DNN. For the training purpose, only UDDS profile data is used. The tests are repeated at different ambient temperatures ranging from 0°C to 60°C. For the testing, HWFET and Japan 10-15 are used at 0°C, 25°C and 60°C. The sampling rate of the data acquired is 1Hz. All the information about the DDCs can be found in Table II.

In order to obtain the current waveform of the battery with UDDS, HWFET and Japan 10-15 the following equations are used. At first, the electrical power required to drive EV is calculated by using Eq. (6).

$$P_e = \left(\frac{1}{\eta_{wheel}} \frac{1+sgn(P_m)}{2} + \frac{1}{\eta_{reg}} \frac{1-sgn(P_m)}{2} \right) P_m \tag{6}$$

Where P_m is the mechanical power required to drive EV with DDC as shown by Eq. (7).

$$P_m = Fv = (F_{rr} + F_{ad} + F_{la} + F_{hc} + F_{wa})v \tag{7}$$

Where F_{rr} is the rolling resistance force, F_{ad} is the aerodynamic drag force, F_{hc} is the hill climbing force, F_{la} is the acceleration force, F_{wa} is the angular acceleration force and fte is the tractive effort. Here,

TABLE Ⅲ
PARAMETERS USED FOR DDCS

Variable	Value	Unit
Mass (m)	1580	Kg
Area (A)	2.6426	m2
Drag Coefficient (Cd)	0.19-0.29	
Rolling Resistance Coefficient (μrr)	0.01-0.015	
Air Density (p)	1.2-1.25	Kg/m3
Gravity (g)	9.81	m/s2
Battery to Wheel Efficiency (Nwheel)	0.7	
Wheel to Battery Efficiency (Nreg)	0.5	

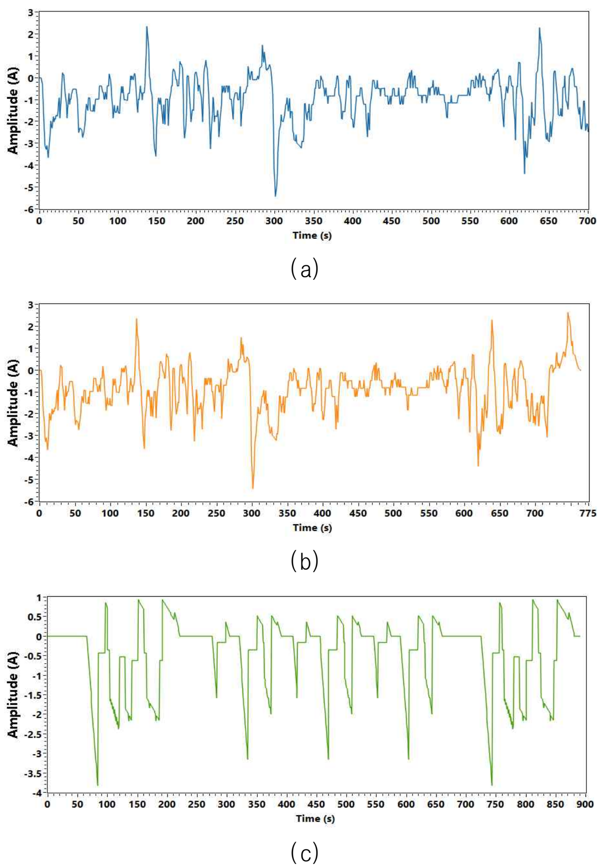


Fig. 2. Battery current profiles obtained with DDCs. (a) UDDS cycle profile, (b) HWFET cycle profile, (c) Japan 10-15 mode cycle.

F_{hc} is 0 because there is no slope and F_{wa} is less than 1% of total power which can be neglected.

Hence, the mechanical power can be represented as shown in Eq. (8).

$$P_m = (\mu_{rr} mg + \frac{1}{2}\rho A C_d v^2 + ma)v \tag{8}$$

The acceleration can be calculated by using Eq. (9).

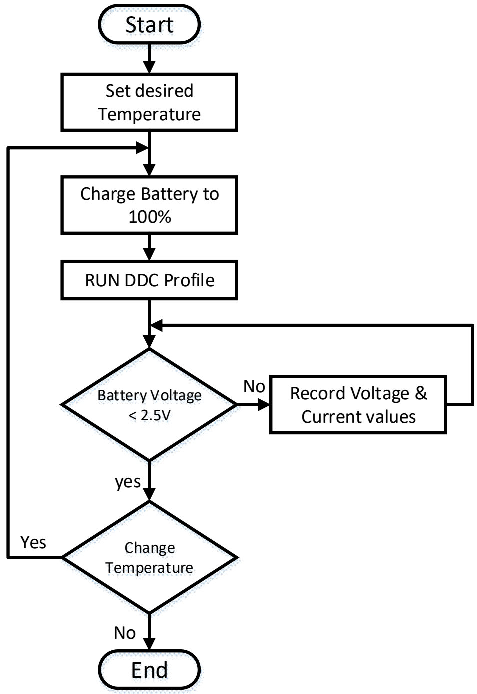


Fig. 3. Flowchart of test procedure for data acquisition.

$$a_k = \frac{v_k - v_{k-1}}{\delta t} \tag{9}$$

The velocity values for HWFET, UDDS and Japan 10-15 can be acquired from ref [6]. By using values in Table. Ⅲ Eq. (6) can be rewritten as Eq. (10). After mixing some charge profiles with the DDCs the measured data are used to train and to validate the SOC estimation performance of DNN.

$$P_m = 154.998v + 0.38318v^3 + 1580av \tag{10}$$

Fig. 2 shows the current waveform of UDDS, HWFET and Japan 10-15 profiles calculated by Eq. (10). The current values are scaled down by a factor of 20 to suit single-cell specification given in Table. Ⅳ.

The test procedure to acquire the data with DDC is as follows: (1) Set thermal chamber temperature to a certain value, (2) Charge the battery fully and (3) Run the DDC profile while acquiring the data as shown in Fig. 3. The DDC repeats until the battery voltage reaches 2.5V. This process is repeated with all the DDCs at each temperature. Fig. 3 and Fig. 4 shows the flowchart of the test procedure and experimental setup for the data acquisition from the battery. A commercially available data acquisition board from National Instrument (cDAQ-9174) is used to acquire the voltage and current waveforms of the battery through the sensing circuit. The temperature

TABLE IV
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)

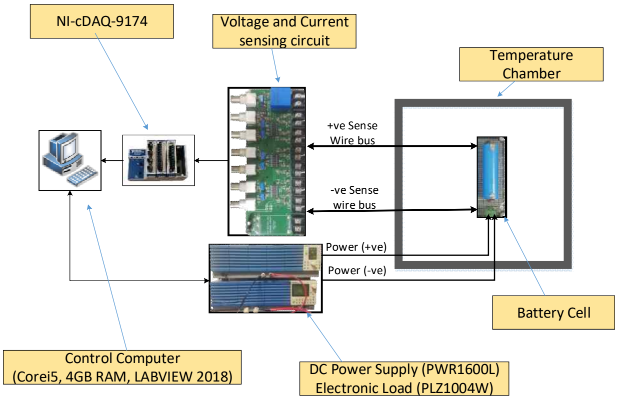


Fig. 4. Experimental setup for DNN training with a battery cell.

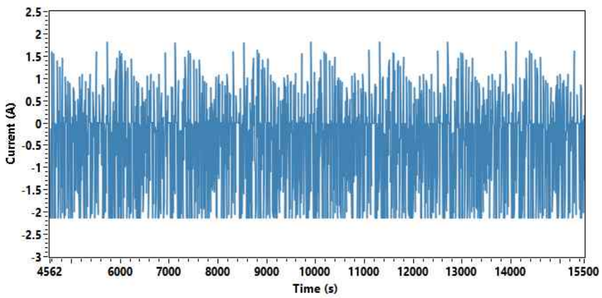
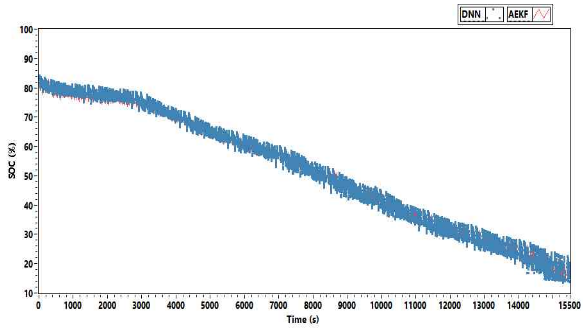


Fig. 5. UDDS test profile cycles used for DNN training.

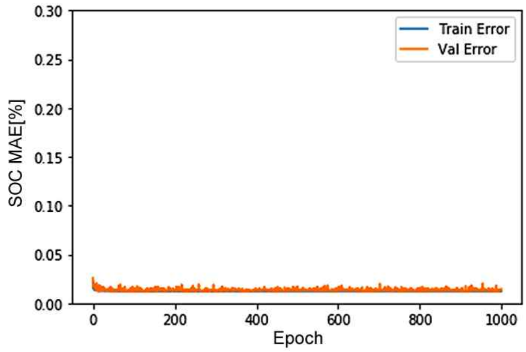
of the chamber is maintained constant during the experiment.

The Lithium-ion cell used in the experiment is Samsung INR18650-29E (Nickel Manganese Cobalt Chemistry) whose nominal capacity is 2850mAh. Other specifications can be found in Table IV. The Adaptive Extended Kalman Filter (AEKF)[10] is used to estimate the SOC while the DDCs are applied to the battery and the data obtained during the test is used for DNN training.

In this paper, TensorFlow, a machine learning library in Python, is used for batch work. The TensorFlow framework provides an ability to quickly prototype and tests different network architectures and it is able to automatically compute the backpropagation. The training time of DNN is proportional to the amount of input data and the number of epochs.



(a)



(b)

Fig. 6. SOC estimation results during DNN training. (a) Comparison between DNN and AKEF results, (b) MAEs over 1000 epochs.

The DNN is trained with the data obtained through the pretests. The UDDS current profile is applied to a battery cell and it is repeated around eight times as shown in Fig. 5. The obtained current, voltage, temperature and SOC calculated by AEKF are used to train DNN.

The obtained data is divided into two parts. 80% of the data is used for the training and 20% of the data is used for the validation. Fig. 6. shows the SOC estimation results during DNN training. Fig. 6 (a) shows the SOC estimation results by both DNN and AKEF and Fig. 6 (b) shows the MAE value at each epoch over 1000 epochs for the training. As shown in Fig. 6 the minimum training error is around 0.02%, which proves that the training is successful.

After the successful training process, the DNN is validated with the rest of 20% data of the same profile to check the accuracy of the trained DNN. During the validation SOC values estimated by the trained DNN are compared with those estimated by AEKF as shown in Fig. 7. The maximum MAE value is 0.2% which proves that the training was successful.

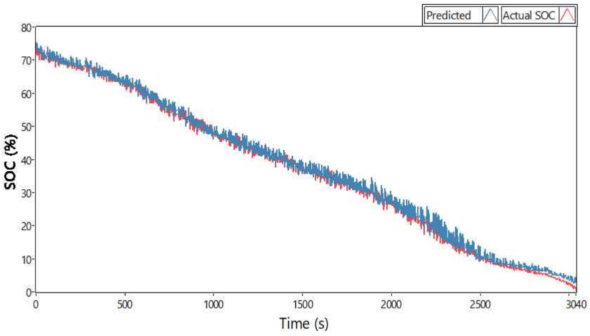


Fig. 7. Validation of trained DNN for SOC estimation.

In order to implement it in a microcontroller the final equation of the trained DNN needs to be built. The trained DNN equation used to predict SOC of the battery with voltage, current and temperature can be represented by Eq. (11).

$$Y = f(W_h^T \times X + b_h) \tag{11}$$

Where Y is the output of hidden layer, f is the activation function, W_h is the weight of the hidden layer, X is the input array and bh is the bias of the hidden layer. The output of the hidden layer will be used as the input of DNN. The output layer can be represented by Eq. (12).

$$SOC = f(W_o^T \times Y + b_o) \tag{12}$$

Where W_o is the weight, Y is the input array to the output layer, b_0 is the bias of the output layer and f is the activation function. The output layer gives SOC as output. The input array X consists of voltage, current and temperature of the battery. Here, ReLU is used as an activation function as shown in Eq. (13).

$$f(x) = Max(0,x) \rightarrow \begin{Bmatrix} 0 \text{ for } x < 0 \\ x \text{ for } x \geq 0 \end{Bmatrix} \tag{13}$$

Eq. (13) shows that ReLU is a function whose output is zero for negative input value and returns the same value for the positive input value.

4. Experimental Results

In order to further validate the performance of the trained DNN two kinds of tests were performed. Here, the trained DNN is applied to estimate the SOCs of different Lithium battery cells which were not used for the training. The trained DNN is implemented in a DSP TMS320F28335 using Eqs. (11)-(13). The weights and biases are extracted by the Python model and saved in the memory of the DSP. Fig. 8 shows the implementation of DNN in a DSP for validation with six battery cells and the laboratory experimental setup is shown in Fig. 9.

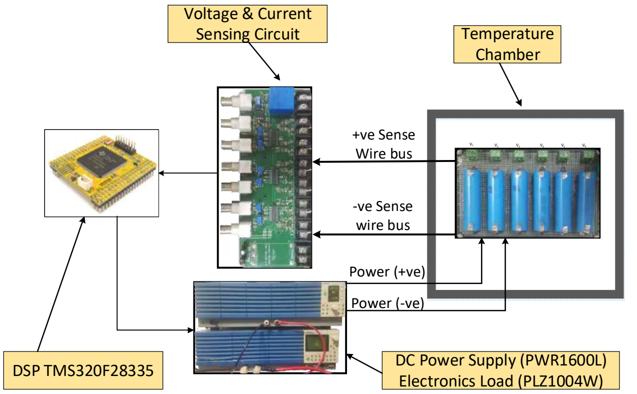


Fig. 8. Implementation of DNN in a DSP for validation with six battery cells.

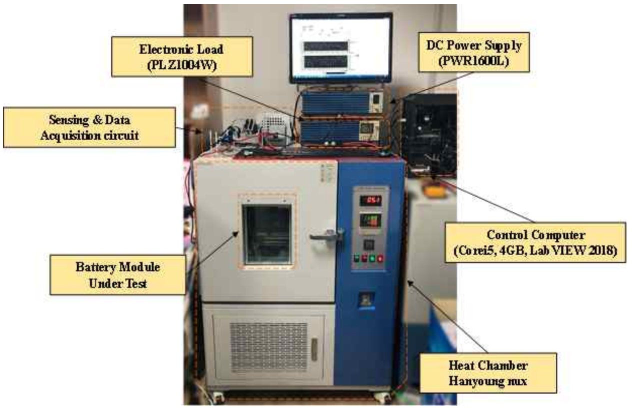


Fig. 9. Laboratory experimental setup for the validation.

In the first test, a UDDS profile shown in Fig 2 is applied to the six Lithium battery cells connected in series at 25°C. The DNN is allowed to train with cell 1 data and then tested to estimate the SOCs of the other cells. The results were compared with SOC values obtained with the AEKF. Fig. 10 shows the SOC estimation results of six cells by DNN at 25°C. Here, the UDDS cycle shown in Fig. 2 (a) is repeated until one of the battery voltage reaches the cut-off voltage (2.5V).

The MAEs of the SOC estimation of all cells are shown in Table V. It can be found from Table V that the DNN can predict SOCs of different cells with a max MAE less than 1.213%. Here, cell 2 shows the largest MAE while the other cells show almost similar MAEs.

TABLE V
MAE OF SOC ESTIMATION

Cell#	% Error (MAE)
Cell 2	1.213
Cell 3	0.564
Cell 4	0.591
Cell 5	0.588
Cell 6	0.580

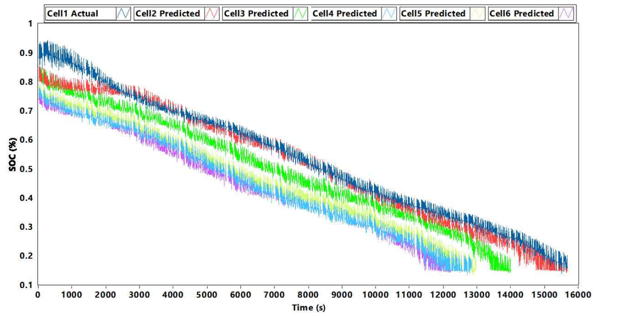


Fig. 10. SOC estimation results with six battery cells using UDDS DDC at 25°C.

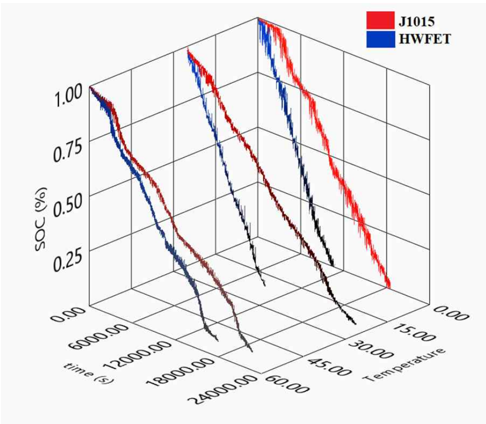


Fig. 11. SOC estimation results with HWFET and Japan 10-15 at 0°C, 25°C and 60°C.

In the second test, three different DDCs such as UDDS, HWFET and Japan 10-15 at different temperatures are applied to Lithium battery cells and the data is acquired and stored in a PC. In this test UDDS profile is used for learning and HWFET and Japan 10-15 are used to evaluate the performance of the DNN to estimate the SOC of the battery at different temperatures. The DDC profiles are repeated until one of the battery cells reaches cut-off voltage (2.5V). The UDDS profile shown in Fig. 2(a) is repeated eight times, HWFET profile shown in Fig. 2(b) is repeated nine times and Japan 10-15 profile shown in Fig. 2(c) is repeated eleven times. The SOC estimation results by DNN with HWFET and Japan 10-15 at 0°C, 25°C and 60°C are shown in Fig. 11.

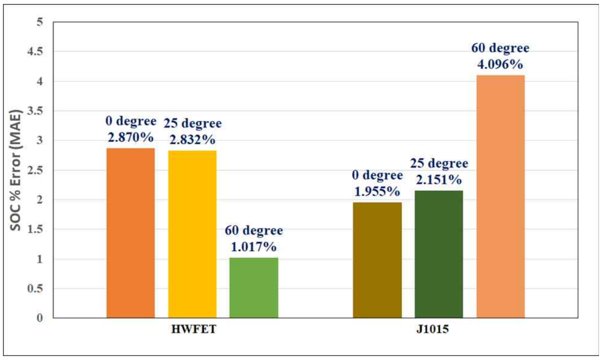


Fig. 12. SOC Estimation errors with HWFET and Japan 10-15 DDC at 0°C, 25°C and 60°C.

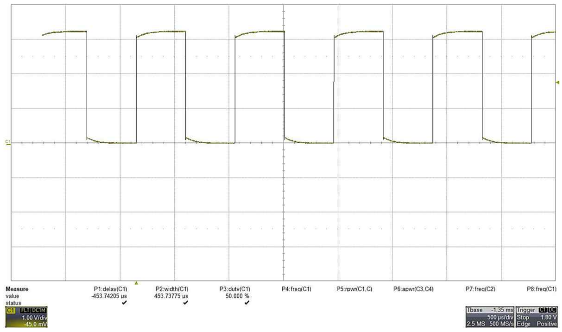


Fig. 13. The execution time of DNN in a DSP.

The MAEs of SOC estimation of HWFET and Japan 10-15 are shown in Fig. 12. In the case of HWFET, the MAE is 2.87% at 0°C, 2.832% at 25°C, 1.017% at 60°C, respectively. In the case of Japan 10-15 the MAE is 1.955% at 0°C, 2.151% at 25°C and 4.096% at 60°C, respectively.

In order to measure the execution time of the proposed algorithm, the time is measured by the oscilloscope. One of the digital output of the DSP is set to toggle at the beginning and end of the algorithm. As shown in Fig. 13 the total time taken by DNN to estimate SOC of a cell is 453μs. Typically, the SOC of a battery cell needs to be estimated every 1 second. Therefore, it is possible to estimate the SOCs of more than 2000 battery cells in a second if the proposed algorithm is employed.

5. Conclusion

In this paper, a novel DNN based the SOC estimation algorithm for the Lithium-ion battery has been proposed and its validity has been proved by the experiments. The SOC estimation of six battery cells has been successfully achieved with less than 1.213% error. The experimental results show that the trained

DNN with only one cell can be used to estimate the SOC of the same kind of battery cells with high accuracy. It can be found from many papers that, the typical value of error in SOC estimation by AEKF is around 3%. Therefore, the SOC estimation accuracy of the DNN would be better under the assumption that the provided data for training is almost close to the true value. As of now, the parameter deviations between batteries are assumed very small. However, parameter deviations between batteries may grow larger as the time goes by. In that case it is expected that the error in SOC estimation would become large. The trained DNN with the weights and biases extracted by the Python model has been successfully implemented in a DSP and the performance of it has also been verified. The proposed algorithm can be used for battery applications using many battery cells such as EVs and ESSs.

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.

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