CNN과 임피던스 스펙트럼을 이용한 배터리의 SOH 추정

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ABSTRACT

Battery capacity is the parameter that has a very close association with the SoH for a Li-ion battery. Due to the complex electrochemical mechanisms behind the degradation of battery life, the estimation of SoH encounters many difficulties. Till date, experiment-based methods, model-based methods and data driven models were developed to estimate the capacity using data from the charging curves. In case of EVs and HEVs, due to the unpredictable charge patterns of the user, we are always skeptical about the amount of charging data that will be available to predict the capacity at a given point of time. This paper presents a method to accurately estimate the capacity using impedance curves obtained from Electrochemical Impedance Spectroscopy (EIS) test and a Deep Convolutional Neural Network (DCNN). The results illustrate the accuracy and robustness of the proposed model.

1. INTRODUCTION

Li-ion batteries are being used in various applications, have become an integral part of our day to day activities. In recent times, Li-ion batteries are being extensively used in EV, HEV and ESS applications. Estimation of SoH is one of the key aspects to evaluate the present condition and remaining useful life of the battery. Till date, there is no standard definition or procedure to directly calculate the SoH of the battery. As battery capacity is very closely associated with SoH, many studies have proposed several methods to estimate the current maximum capacity of the battery and then calculate the SoH using the following equation.

\[
\text{SoH} (%) = \frac{\text{Present Maximum Capacity of the Cell}}{\text{Maximum Capacity of the New Cell}} \times 100
\]

Incremental Capacity Analysis Curves based on charging curves data at different charge currents, Depth of Discharge (DoD), temperatures were developed by Elie Riviere to be implemented in a standard BMS for EV application. Voltage and current data from the charging curves were used to develop the IC curves [1]. A method using Incremental Capacity Analysis curves along with Adaptive Neural Network (ANN) was proposed by Shuzhi Zhang. Five features (in the voltage range of 3.4V-3.6V) were extracted from each charge cycle out of which two features which have highest correlation with the capacity are identified using Pearson Correlation Analysis and given as input to the ANN model [2].

In both the above cases, the features from the input data that best relate to the capacity need to be identified and extracted manually and then used to predict the capacity. In [3] Sheng Shen developed the first Deep Convolutional Neural Network (DCNN) model to estimate the battery capacity using Constant Current (CC) charging data. Each CC charging curve was divided into 25 equal segments. The voltage, current and charge capacity for each segment were given as inputs to the DCNN model. Using DCNN relieves the burden of choosing the features manually that carry the most useful information to estimate the capacity. A method to estimate SoH using CNN along with transfer learning was proposed by Yang Li [4].

However, as all the above-mentioned data driven methods use charging data to predict the capacity, the predictions with partial charge curve data may not give accurate results if the partial data is too small. In practice, the user charge patterns are unknown for electric vehicle applications and hence the amount of charging data available for the model to make predictions each time is not fixed. In cases where the model does not have the necessary amount of data, the predictions may not be accurate. In order to overcome this limitation, this paper presents a deep learning model using CNN that can accurately predict the capacity of the battery with the impedance curves obtained from EIS test.

The rest of the paper is organised as follows: Section 2 gives an overview of the structure of DCNN and the architecture of the proposed model. Section 3 explains the procedure to extract the data from the experiment, building and training the model along with the training and testing results. Conclusion and information on future work prospects are mentioned in section 4.

2. OVER VIEW OF DCNN

Deep Convolutional Neural Network (DCNN) comes with an advantage of being able to extract important features from the data without any manual interaction. The other important feature of the DCNN is the parameter sharing. The same weights are used in multiple places thereby reducing the total number of parameters to be handled during the training.

DCNN consists of two kinds of layers: Convolution Layers (CL) and Fully Connected Layers (FCL). CL performs convolution operation over the entire input using the kernels (or filters) to extract important features. The two main important parameters corresponding to the CL are the number of kernels and the filter size. An example of basic convolution operation on the input using a filter is shown in Fig. 1. The number of features extracted from each CL is equal to the number of kernels used. In case of large sized data, the CL can be followed by a Pooling Layer (PL) which reduces the size of the data before sending it to the next CL. FCL function similar to a regular multilayer Artificial Neural Network (ANN). Only the features obtained from the last CL are given as input to the FCL thus reducing the total number of parameters to be trained.

Rectified Linear Units (ReLU) are used as an activation function after every convolution and fully connected layer (except for the output). The last layer of the fully connected layer is the output layer. The CL and FCL can be represented by the following equations (2) and (3) where ‘σ’ denote the activation function, ‘*’ represents the convolution operator, ‘x’ is the input and ‘b’ is the bias term.
Convolution Layer: \[ \sigma (W \ast x + b) \] (2)

Fully Connected Layer: \[ \sigma (W^T x + b) \] (3)

The architecture of the proposed DCNN model is shown in Fig. 2. The number of convolution layers, fully connected layers, and neurons in each fully connected layer purely depend on the complexity of the application and the relation between the input and output parameters. The model parameters used to build the model are detailed in Table I.

![Convolution operation example](image)

### TABLE I
**Details of DCNN Architecture used**

<table>
<thead>
<tr>
<th>Layer Type</th>
<th>Parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>Conv 2D-1</td>
<td>16 kernels, filter size 3 x 3</td>
</tr>
<tr>
<td>Conv 2D-2</td>
<td>32 kernels, filter size 3 x 3</td>
</tr>
<tr>
<td>Fully Connected-1</td>
<td>320 Neurons</td>
</tr>
<tr>
<td>Fully Connected-2</td>
<td>160 Neurons</td>
</tr>
<tr>
<td>Fully Connected-3</td>
<td>80 Neurons</td>
</tr>
<tr>
<td>Fully Connected-4</td>
<td>1 Neuron (output)</td>
</tr>
</tbody>
</table>

**3. PROPOSED MODEL**

#### 3.1 Data Extraction

The cell used for preparing training data is Samsung INR 18650-29E. Cell chemistry is NMC. In order to prepare the training data for the model, the cell was aged through charge/discharge cycles, and the AC impedance spectrum of every 5 cycles was measured through the EIS test, up to end of its life (75% of initial capacity). The details regarding the cell are shown in Table II.

![Details of the cell used for the experiment](image)

<table>
<thead>
<tr>
<th>Property</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Chemistry</td>
<td>Nickel Manganese Cobalt Oxide (NMC)</td>
</tr>
<tr>
<td>Size and shape</td>
<td>18650, cylindrical</td>
</tr>
<tr>
<td>Capacity. max</td>
<td>2,850mAh</td>
</tr>
<tr>
<td>Nominal Voltage</td>
<td>3.65V</td>
</tr>
</tbody>
</table>

Battery aging was maintained at 25 degrees Celsius using HYSCLAB's B.O.D Incubator. The battery charge/discharge test and EIS tests were done using WonATech's WEIS-500. The cell was fully charged and discharge every time. One full charge followed by one full discharge together is considered as one cycle. The EIS test was performed after every 5 cycles and the impedance spectrum was measured with a battery SOC of 100% by applying a perturbation of 60mV in a frequency range of 0.1 to 1 kHz.

The experiment for aging cylindrical battery was conducted up to 1035 cycles. After 1035 cycles, the capacity of the battery degraded to 75% and hence we considered it to be unfit for further use. The capacity was calculated by integrating the charging current for each cycle. The voltage, current used for charging and discharging are shown in Fig. 3. The capacity for each cycle and the AC impedance spectrum measured at 100% SOC for every 5 cycles through the EIS test are shown in Fig. 4 and Fig. 5, respectively.

#### 3.2 Model Training

The impedance curves data obtained after every 5 cycles has 41 data points and hence is made into a 3-dimensional array of size 41 x 2 x 1. The cell reached end of life at 1035 cycles. So, the total number of inputs to the model is 207 each of size 41 x 2 x 1. As we used 2D convolution layers, the input should be a 3D array. Out of the total data, 80% is used for training and 20% is used for validation. The data for training and validation were split randomly using the readily available function in TensorFlow library.

The set of unknown parameters are optimized by using the training data. Our model has been built with 2 convolution layers (2D) and 4 fully connected layers including the output layer. As mentioned earlier, the selection of model parameters purely depends on the application, amount of data available, and the relation between the input and output parameters. Also, there is no standard procedure that can be followed to choose the model parameters. How quickly one can arrive at the best possible combination completely depends on experience of the individual who is building the model.
of the corresponding CL. As we used 16 kernels in the 1st convolutional layer, the output is $41 \times 2 \times 16$ and as we used 32 kernels in the 2nd CL, the output of the 2nd convolution layer is $41 \times 2 \times 32$. In general, the parameter selection is done such that the number of kernels in the next layer is greater than that in the previous layers. The output of the 2nd convolution layer is flattened and converted into a 1D array to pass it as input to the fully connected layer. The fully connected layers function similar to the artificial neural network. Four fully connected layers are used with 320, 180, 160, and 1 neurons respectively. Each layer has ReLU function as activation function. The last layer is the output layer without any activation function. The optimizer used is Adam and the metrics used to evaluate the model performance are Mean Squared Error (MSE), Mean Absolute Error (MAE), RMS Error, Mean Absolute Percentage Error (MAPE).

3.3 Results
The model was trained with the 80% of the total data randomly selected by the algorithm of a built-in function and remaining 20% of the data was used for validation. As the optimizer used is Adam, the model learns and improves over every training epoch through backpropagation technique. The training of the model is continued by varying the model parameters until the validation loss (mean square error) falls into the desired limits. The training and validation loss (MSE) after completion of the training were found to be 0.54 and 0.61 respectively. The MAE and % MAE for validation were found to be 0.70 and 0.84, respectively. The plots of training and validation loss are shown in Fig. 6.

For testing the model performance on new data, EIS data of eight new cells were taken at same SoC and temperature. The plot of true values and predicted values are shown in Fig. 7 and the absolute error values for each sample is shown in Fig. 8. The maximum absolute error was found to be 0.8 which shows the accuracy of the model. The MAE and RMS error for the prediction data set was found to be 0.60 and 0.63, respectively.

4. CONCLUSION
In this paper, a novel method to accurately estimate the capacity of the cell by using EIS impedance curves and deep convolutional neural network (DCNN) is proposed. The performance of the model was evaluated using data from eight new cells and the results show that this method can be used to accurately estimate the capacity of the cell and hence its SoH value. The limitation of the current work is that the model can predict accurately only at a 100% SoC. The model can make predictions at other SoC levels also for which the same accuracy cannot be promised. Our future work is directed towards making the model to be more general so that it can predict SoH at any given SoC levels.

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References