CS230

Battery States Monitoring Using Deep learning and Ultrasonic sensors

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1 Introduction

Recent advancement in battery technology is bringing significant growth in the electrification of both ground and aerial vehicle platforms. However, battery storage in electric vehicles is an extremely complex system that has a very narrow operating range and may lead to premature unexpected failure [1-3]. In this regard, the role of the battery management system (BMS) is vital to 1) monitor the state of charge (SoC) and state of health (SoH), 2) protect individual battery cell, 3) safeguard the device's human operator and 4) prolong the life of batteries. However, state-of-the-art BMS technology relies only on the terminal voltage measurement to estimate both SoC and SoH, which alone is insufficient for accurately determining the two states. Moreover, the current BMS critically lacks a breakthrough technique for an independent direct and accurate probing of the physical properties of the batteries [4] for SoC and SoH determination. Recently, acousto-ultrasonic guided waves propagation characteristics have been demonstrated as a potentially strong, on-board alternative method to probe the mechanical behavior of lithium-ion batteries. Fig.1 shows the overview of using piezoelectric sensors, which could generate the ultrasonic guided waves, on real-time battery monitoring. But this method has yet to be tuned and integrated into the modular structure of BMS to function autonomously. Therefore, the main goal of this research is to develop a novel BMS framework where rich data available from ultrasonic guided wave sensors, data mining and deep learning will serve as powerful tools for modeling and predicting the battery condition under complexity and uncertainty. Here, the utilization of ultrasonic sensors and deep learning techniques will significantly improve the estimation of SoC and SoH in the BMS.

2 Related work

In battery monitoring domain, data-driven approaches, like machine learning, deep learning techniques are based on processing a great amount of multifaceted test data. These approaches have attracted increasing attention because of their flexibility and model-free characteristics compared with model-based techniques in this field. Some readily measurable data (e.g., terminal voltage, load current, historical state of charge (SoC), and operating temperature) or extracted characteristic features are the inputs for "black-box" models for batteries. For instance, such "black box" models have included artificial neural networks, relevance vector machines, and sparse Bayesian predictive modeling. You et al. [5] proposed a datadriven approach based on neural networks to trace SoH using dynamic condition data while leveraging their historical distributions. For degradation modeling, Zhou et al. [6] extracted mean voltage falloff of lithium-ion batteries, and a regression equation was established to estimate capacity. Hu et al. [7] used the sparse Bayesian predictive modeling methodology to capture the underlying correspondence between capacity loss and sample entropy of short voltage sequence.

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3 Dataset and Features

The sensor data are already collected and stored in mat format. Sensors data are collected at different state of charge of batteries and there are nine paths of sensor data at varying frequency. Figure 1 shows the example output of the data collected. The sampling frequency of the sensor is 48×10^{-6} Hz, with sampling points of 4000. At different states of the battery, the output signals of the sensors are different.Therefore, each samples have a dimension of 4000×9. And number of the samples are 1500. Fourier Transform is applied to these data and new data set of dimension of 4000×9 is generated.

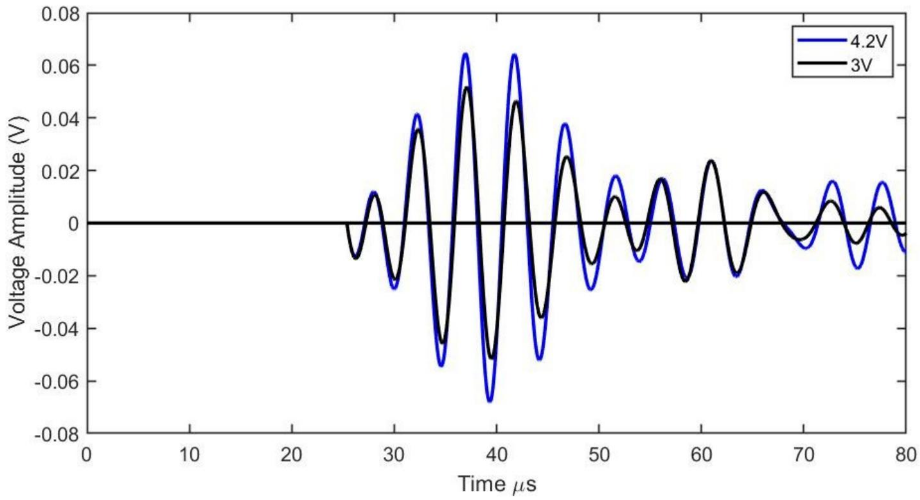

Figure 1: Example of output of sensors signals at different battery state of charge/voltages at 300kHz.

To reduce the computational effort, I down-sampled the output sensor signals into 400 sampling points and treat these data as the input of the network. So the input of the network is 400×9. For the output of the network, it's going to be the state of charge of the batteries. State of charge of batteries are defined as the ratio of available capacity and the maximum possible charge stored in a battery. For example, at fully charged voltage of lithium-ion battery is 4.2V which means the state of charge of battery is 1, while fully discharged voltage of lithium-ion battery is 3.0 V with state of charge of 0. So the range of the state of charge is from 0 to 1. After down-sampling the data, normalization was done on all data sets. Training and validation examples are divided by the ratio of 7 : 3.

4 Methods

4.1 Fully connected layer

In this case, the hidden layer we choose is fully connected layer with RELU activation layer. The loss function of fully connected layer is mea squared error (MES):

$$MSE = \frac{1}{N}\sum_{i=1}^{n}(y_{true} - y_{pred})^2$$

where N is the number of samples. y presents the variable being predicted, which is the state of charge in this case. $(y_{true} - y_{pred})^2$ is known as the squared error. The loss function in this case is simply taking the average over all squared errors. Therefore, the better predictions means lower loss. And I used mini-batch gradient descent to minimize the loss.

4.2 Convolutional Network

Convolutional Network is used in this application. There are two Layer of Convolution 2D layer followed by Batch normalization layer and Relu layer. In the end, one fully connected layer is added.

5 Experiments/Results/Discussion

Figure 2 shows the RMS after enough iteration at varying learning rate while keep the fully connected layer and other parameters fixed. The RMS is defined as

$$RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{n}(y_{true}(i) - y_{pred}(i))^2} \times \frac{100}{\sum_{i=1}^{n} y_{true}(i)}$$

As decreasing the learning rate, the RMS of the test sets are decreasing. Figure 3 shows the prediction and real values of test sets at learning rate equals to 0.01.The collected sensors data shows the nonlinear properties with respect to the state of charge of batteries. After applying the deep learning methods on the sensor data, the figure shows that deep learning methods successfully predict the state of charge. The RMS of using fully connected layer is 1.88%. And the RMS of using convolution neural network is around 3%. That may conclude that in this application and type of input data, it's not suitable to treat the input as "image" while using convolutional neural network. After wavelet transform or other signal processing, convolutional neural network may be useful in this application.

After applying the Fourier Transform, with the same settings as raw data. The RMS of Fourier Transform is 4.2%, while the raw data is 2.3%. This might cause by after applying the Fourier Transform, some important features in the time domain data is lost.

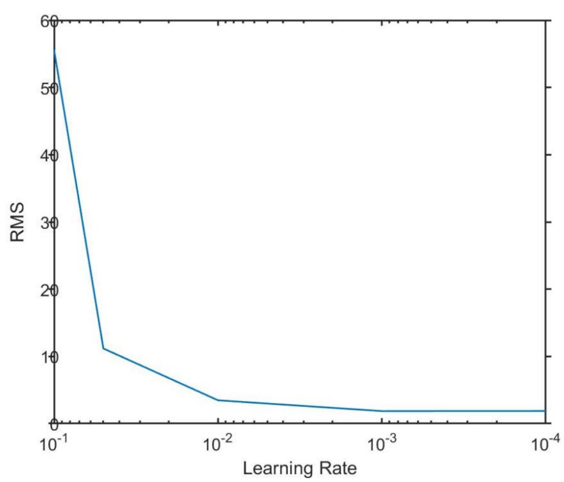

Figure 2: Prediction and Real Values of Test Sets

6 Future Work

In the project, raw data and Fourier transformed data are used as the inputs of the network. In the future, Wavelet Transform will the used to pre-process data. More data need to be collected to do the estimation of not only the battery states but also battery health.

References

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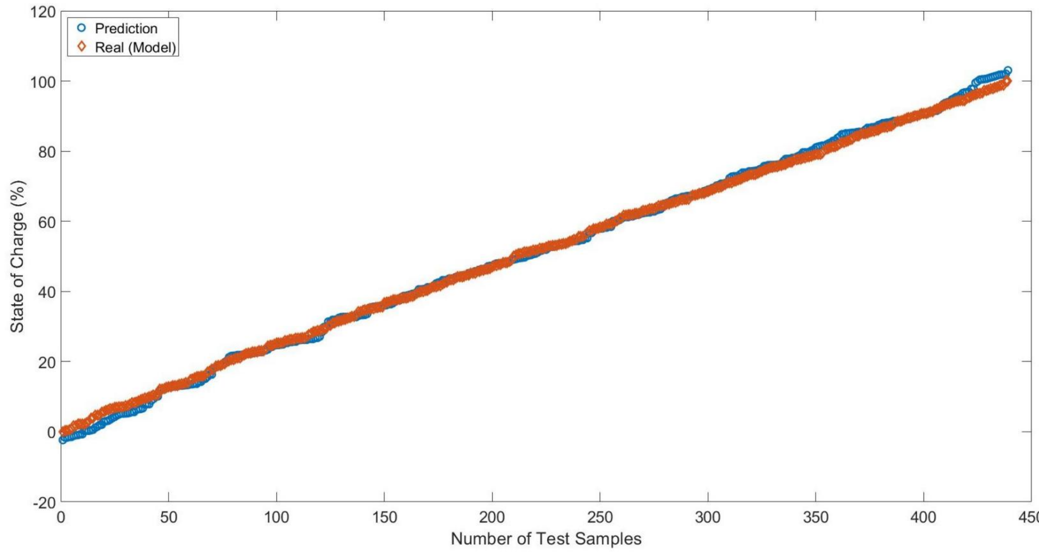

Figure 3: Prediction and Real Values of Test Sets

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