ONLINE CAPACITY ESTIMATION OF LITHIUM-ION USING DATA-DRIVEN METHODS

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Abstract

The recent years have seen increasing usage of lithium-ion (Li-ion) rechargeable batteries in varied applications including power backups/UPS, mobile devices. In a Lithium-ion batteries system, state-of-health (SOH) of individual batteries is one of the key signals to ensure safety and reliable operation. This thesis presents a deep learning method through a Convolutional Neural Network model, for cell-level SOH estimation based on the voltage, current and temperature of the battery cell. In experiments, we set up and recorded 2 batteries in 6 months. We also compare our proposed method with traditional machine learning methods including Particle Filter, K-Nearest-Neighbor and Relevance Vector Machine. The maximum estimation error in the proposed method between 5-6%. This indicates that the proposed method has high accuracy and robustness in the online estimation of Li-ion battery capacity.

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List of Acronyms

LIB Lithium-ion battery. 1–4, 21

PDE Partial differential equation. 4

RMSE Root mean square error. 14

SGD Stochastic gradient descent. 14, 15

SOC State of charge. iii, 6, 7, 17, 20, 29

SOH State of health. iii, 2–4, 6, 8, 18, 20, 21, 28–30

Chapter 1

Introduction

1.1 Motivations

Lithium-ion battery is a type of rechargeable battery commonly manufactured in the market. During the charging process, the positive ions (Li+) move from cathode to anode and vice versa in the discharging process (using time) to create the current. Lithium-ion battery is mostly used for mobile devices, especially lightweight wearables. However, it has sometimes been used for big moving objects such as cars, drones, unmanned aerial vehicles, etc.

During the recent two decades, the power systems using Lithium-ion battery have got high attention from the community and have been used in a lot of devices in the market [1]. Those outdoor moving objects, mobile devices, solar power devices are required to use Lithium-ion battery due to their features like lightweight, durability, high capacity, self discharge ability. Therefore, some additional features such as safety, durability without issues, number of working cycles, are highly demanding. Moreover, the requirement includes optimizing design to deliver a Lithium-ion battery with stable and durable working time. Recently, the main interests consist of overcharging, self-discharging, capacity

fading, impedance, shocks, aging [4].
Battery management system (figure 1.1) is sometime called a battery pack; helps to measure many crucial data from different Lithium-ion battery modules concurrently. Among those data, the and State of health are the most considerable. The reasons should be almost all the real time/ online applications have direct or indirect involvement to and State of health.Therefore, a real time system helps to monitor these data items will create meaningful support for battery risks and failure detection and prevention; increasing reliability greatly for the target system.

Figure 1.1: A battery management system. The top part is the system on a moving device. The bottom parts are the hardware devices inside it [1]

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Online state of health estimation is one of the most important module in battery management systems [5]. There are two features open used to evaluate state of health: cell capacity and resistance [6]. With good capacity estimation enables a battery replace right before the batteries reaches the end of its usefulness or lifespan and can no longer operate at anywhere close to the peak capacity. It is also important to monitor the current battery state of heath to enable failure prevention.

1.2 Problem Statement

The ultimate goal of being able to fully understand LIB system on the possibility to measure the SOH. The problem is that measurements of capacity, and thereby the SOH, are noisy and dependent on the measurement circumstances. It is therefore very difficult so see a general trend in the battery degradation, yet even more difficult to connect certain usage to accelerated aging. Instead, one would like an absolute SOH measurement. A measurement that does not depend on the outer circumstances. This leads to the problem statement of this thesis: **Could a data driven approach using Neural Networks constitute a feasible option for capacity based State-of-Health estimation in Lithium-ion battery and provide information about how usage age the battery?**

1.3 Literature review

State of health indicates the capacity of battery to store electric energy, and the percentage is generally used to indicate the health status of the battery. Here, SOH is defined as [7]

$$\mathrm{SOH} = \frac{\mathrm{Capacity}_{\mathrm{aged}}}{\mathrm{Capacity}_{\mathrm{rate}}} \times 100 \tag{1.1}$$

where $\mathrm{Capacity}_{\mathrm{aged}}$ represents the current capacity of the battery, and $\mathrm{Capacity}_{\mathrm{rate}}$ represents the rated capacity of the battery.Recent studies proposed many methods for online estimating the capacity of a Lithium-ion battery. These methods can be cluster to three groups:

1. Empirical model-based [8], [9].
2. Physical electrochemical models [10].
3. Data-driven models: kernel regression [11] and deep learning network [12]

In [8], Plett at el. used extended Kalman filtering for battery management systems of LiPB-based hybrid-electric-vehicle battery packs. The method is able to estimate , power fade, capacity fade and instantaneous available power, and is able to adapt to changing cell characteristics over time as the cells in the battery pack age. They build a mathematical model that quantities and battery state named sigma-point Kalman filter to capture prediction. Based on them, they estimated approximates the probability distribution capacity. The disadvantages of empirical methods are they are very depend on empirical method and they do not take in to account physical knowledge into models.
An other method to estimate is physical electrochemical models. In [10], Moura et al. developed an adaptive Partial differential equation observer for and State of health estimation. Their point of view is simultaneous state and parameter estimation design for a linear Partial differential equation with a nonlinear output mapping. They conjunction estimation algorithm with physical variables, voltage and current. In [13], Bartlett et al. presented an electrochemical model for a composite LiMn2O4-LiNi1/3Mn1/3Co1/3O2 (LMO-NMC) electrode battery that estimate the surface and bulk lithium battery and its' material in the composite electrode and the current split between each material. They extended Kalman filter, fixed interval Kalman smoother, and particle filter to compare the estimated capacities in time-series. This approach has difficult to accurately track physically meaning parameters based only on voltage and current measurements and with a low computational effort.
Other approaches is use data-driven build estimation Lithium-ion battery model.

Those approaches are state-of-the-art method because only dependent in data and do not need deep battery knowledge. With rise of the internet of things, sensing technology has collect a large amount of battery data. There are a lot of public battery data set: Oxford Battery Degradation dataset [14], NASA Ames Prognostics Data Repository [15], electrochemical performance of commercial 18650-format lithium-ion cells dataset [16]. In this approach, we use data to learn the relationship between cell characteristics and . Cell characteristics are current and voltage measurements. The approach also grouped into 2 subgroups [12]: kernel regression [11], [17] and deep learning [18], [19].

In kernel regression, an online estimation of lithium-ion battery capacity using sparse Bayesian learning were building. It used basic measurements (i.e., voltage and current) from the cell during charge then used Relevance Vector Machine [11] and regression machine learning [17] to employed a probabilistic kernel regression method to learn the complex dependency of the battery capacity on the characteristic features.

Deep learning network approaches build neural network to estimate from input features (voltage and current). In [18], You et al. build a neural network for online estimation battery of electric vehicle batteries, using current, voltage, and temperature with its historical distributions.

Traditional machine-learning techniques were limited in their ability to extract raw data to features. For decades, constructing a pattern-recognition or machine-learning system required careful engineering and considerable domain expertise to design a feature extractor that transformed the raw data into a suitable internal representation or feature vector from which the learning subsystem, often a classifier, could detect or classify patterns in the input[20]. The success of kernel regression machine learning algorithms generally depends on data representation, and we hypothesize that this is because different representations can entangle and hide more or less the different explanatory factors of variation behind the data. Although specific domain knowledge can be used to help design representations, learning with generic priors can also be used, and the quest for AI is motivating the design of more powerful representation-learning algorithms implementing such priors[21]. But it is not easy to find features that have useful information for the estimation .

To solved those issues, this thesis presents a time-series neural network model based on large volumes of charge data for achieving state-of-the-art accuracy in online estimation of Li-ion battery capacity. The advantages of the proposed method and detail architecture are present in chapter 2.

1.4 Battery States

1.4.1 State of health

With increasing using time or storage time, the maximum capacity and power of the cells will slowly decrease to the point at which the low capacity or power is not acceptable anymore. The SOH of the battery cell reaches 0%. A cell operating within specifications will, however, not undergo sudden death, but gradually experience performance degradation. This degradation does not only occur due to continuous use of the battery cell, but also during storage of the battery. The performance degradation during cycling occurs, however, much faster than storage under the same conditions.

1.4.2 State of charge

The state of charge is an indication of the amount of energy left in the battery cell as a percentage of the current capacity. The higher the SOC, the more energy is stored in the cell. This will mean the battery cell is more reactive, which will accelerate degradation of the cell.

At a high SOC the anode will be highly energized. Due to the high energy content in the cell the selfdischarge will also be higher. The effects of high SOC mentioned above are more profound during storage for a long time, but with cycling the influence of high SOC vary a lot. The amount of time spend at a certain SOC is very short, as the SOC quickly varies. The influence of high SOC can be limited if the cells are cycled at a low SOC. This is under the assumption that the cell will operate within the specified voltage range given by the manufacturer. In case of overcharge or over-discharge, which will be described respectively, other degradation mechanisms will be introduced and shorten the cell life.

1.5 Overview of the Thesis

In chapter 2, we present our time-series deep learning method and architecture of model to estimate of batteries. Chapter 3 introduces the implementation of deep learning model to verify the effectiveness of our method. In chapter 4 we explain the implementation result and some future of work are present in last chapter.

Chapter 2

The Proposed Method: Framework for State of health estimation

This chapter describes the proposed method for online estimating SOH. In section 2.1 we show traditional machine learning approach use to estimate SOH. Then, the methodology adopted in this thesis includes several steps such as pre-process data, validation for proposed data driven models to select best hyper-parameter values for the models and selection of best data driven model based on test results. Subsection 2.2 show the deep learning model used to train the model. In subsection 2.3 describes detail of data in online estimate SOH.

2.1 Traditional approaches for estimate SOH

2.1.1 Relevance Vector Machine (RVM)

We consider functions of a type corresponding to those implemented by another sparse linearly-parameterised model, the support vector machine (SVM). Given vectors input data $\{x_n\}_{n=1}^{N}$ and adjustable parameters (or 'weights') $\mathbf{w}$. The SVM makes predictions based on the function [22]:

$$y(\mathbf{x}; \mathbf{w}) = \sum_{i=1}^{N} w_i K(\mathbf{x}, \mathbf{x}_i) + w_0$$

where $K(\mathbf{x}, \mathbf{x}_i)$ is a kernel function. The relevance vector machine (RVM) is a Bayesian treatment of SVM [11] with probabilistic measurement. RVM learns the estimation relationship between the related features (such as charge voltage, charge current, resistance, temperature, ..) and the battery health status (SOC, SOH,). To implement this approach, the five characteristic data (in [11]) indicating most important features of input are extracted. The data is then put into the model to approximate a Gaussian distribution function. Later on, the probability distribution or probability density function (PDF) of output is generated.

2.1.2 Particle Filter (PF)

Particle Filter [23] is used very early for real time prediction of battery and other LIBs powermetry data. The framework of Particle Filter in these studies are similar. First, they generate randomly a number of particles. The weights are updated based on its closure to actual data in the early steps. After some iterations, particles with low probability from the actual measured data will be eliminated and the remaining particles will continuously be developed. Eventually, the output of PF model are weighted particles as well as mean and covariance. Particle Filter is powerful in non-linear and non-Gaussian relationship interpolation. However, the method to resample particles weights needs subjective approach may lead to wrongly eliminate feature data and therefore limit its output accuracy.

2.1.3 k-Nearest-Neighbor (kNN)

kNN is a simple, intuitive and efficient way to estimate the value of an unknown function in a given point using its values in other (training) points [24]. Let $S = x_1, ..., x_m$ be a set of training points. The kNN estimator is defined as the mean function value of the nearest neighbors

$$\hat{f}(x) = \frac{1}{k} \sum_{x' \in N(x)} f(x') \tag{2.1}$$

where $N(x) \subset S$ is the set of k nearest points to x in S and k is a parameter. A softer version takes a weighted average, where the weight of each neighbor is proportional to its proximity, such as:

$$\hat{f}(x) = \frac{1}{k} \sum_{x' \in N(x)} f(x') e^{-d(x,x')/\beta} \tag{2.2}$$

where d is the defined distance appropriately, Z is a normalization factor and β is a parameter. kNN has been applied in powermetry problems and with limited performance because of its lazy learning approach.

2.2 Proposed methodology of Deep neural networks

The neural network is one of algorithms for recognizing patterns and has been used in many problems [25]. In this section, we will discuss and show some terminologies about neural networks used in this thesis briefly .

Neural networks are weighted graphs. They have layers in orders. The neural networks have a input layer, hidden layer(s) and output layer, sequentially. Layers are a group of nodes. Nodes belonging to one layer are connected to the nodes in the following and/or the previous layers. These connections are weighted edges, and they are referred to as weights [2].

Given an input, neural network nodes have outputs, which are real numbers. The output of a node is calculated by applying a function (ψ) to the outputs of the nodes belonging to previous layers. Preceding that, the output of the input layer ($o^{(0)}$) is equal to the input (see Eq. 2.3). By calculating the layer outputs consecutively we calculate the output of the output layer. This process is called inference [26]. The output of node i in layer k determine by:

$$o^{(k)} = \begin{cases} \psi_k(o^{(k-1)}), \text{ if } k \geq 1, \\ x_n, \; k = 0 \end{cases} \tag{2.3}$$

Where

$o^{(k)}$: the output vector representing the outputs of node in $l^{(k)}$

ψ_k: : function to determine o^{ψ_k} given $o^{\psi_{k-1}}$

x_n: nth input data

2.2.1 Fully Connected Layers

For two following continuously layers to be fully connected, all nodes in the previous layer must be connected to all nodes in the following layer.

Let assume two continuously layers, $l_{(k-1)}$ and $l_{(k)}$ with number of nodes is $m_{(k-1)}$ and $m_{(k)}$ respectively. For these layers to be fully connected, the matrix connecting them would be $w^{(k)} \in \mathbb{R}^{m^{(k-1)} \times m^{(k)}}$ (figure 2.1). The output of a fully connected

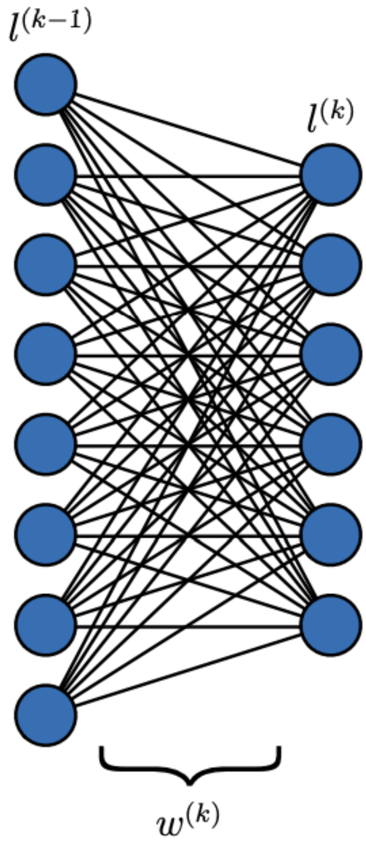

Figure 2.1: Fully connected between layer $l_{(k-1)}$ and $l_{(k)}$ with weight matrix $w_{(k)}$ [2]

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layer, $o^{(k)}$ would be calculated as Eq. 2.4 with $b^{(k)} \in \mathbb{R}^{m^{(k)}}$ is a bias term in the system.

$$o^{(k)} = (o^{(k-1)})^T \times w^{(k)} + b^{(k)} \tag{2.4}$$

2.2.2 Activation functions

To achieve non-linearity, we apply activation functions to ψ. There are many activation functions *tanh* or *sigmoid* but most commoly activation function is

ReLU [27]. ReLU of x is defined in Eq. 2.5

$$\mathrm{ReLU}(x) = \begin{cases} x, \text{ if } k \geq 0 \\ 0, \text{ otherwise} \end{cases} \tag{2.5}$$

In [28] shows that ReLU leads to sparsity. Given input, only a subset of node are non-zero. The ReLu allows a better folow of gradients and easier to computed compared to hyperbolic or exponential alternatives.

We define the fully connected $\psi^{(\mathrm{FC})}$ with activation function (σ) as Eq. 2.6

$$\psi^{(FC)}_{(k)}(o^{(k)}) = \sigma((o^{(k)})^T w^{(k)} + b^{(k)}) \tag{2.6}$$

$\psi^{(FC)}$ is one of the most basic blocks of neural networks. With different blocks configuration, we have different neutral network. The output of each layers are calculated as Eq. 2.7

$$O = \psi_{(k)}(o^{(k-1)}) | k \in [1, ..., L] \tag{2.7}$$

2.2.3 Loss functions

To represent the quality of an neural network, we are going to use a loss (or cost) function. There are two properties of loss function. First, loss is usually great than or equal zero, never negative. Second, with two neural network, which one has smaller loss is better than other. The evaluation matrix in the thesis include the root mean square error (RMSE), maximum error (ME), maximum relative error (MRE) and average error (AE) .

2.2.3.1 Root mean square

A commonly loss function is root mean square error (RMSE). Give an prediction $\hat{y}_n \in \mathbb{R}^n$ and actual output $y_n \in R^n$, RMSE can be as Eq. 2.8

$$\mathcal{L} = \text{RMSE}(\hat{y}, y) = \sqrt{\frac{\sum_{n=1}^{N}(\hat{y}_i - y_i)^2}{N}} \tag{2.8}$$

2.2.3.2 Maximum Error (ME)

Maximum error is the maximum difference between the point estimates and the actual parameters. The Eq.2.9 shows detail of how to calculate ME.

$$\mathcal{L} = \text{ME}(\hat{y}, y) = \max\{|\hat{y}_i - y_i|\}_{i=1}^{N} \tag{2.9}$$

2.2.3.3 Maximum relative error (MRE)

Maximum Relative Error is defined by:

$$\mathcal{L} = \text{MRE}(\hat{y}, y) = \max\{\frac{|\hat{y}_i - y_i|}{y_i}\}_{i=1}^{N} \tag{2.10}$$

2.2.3.4 Average Error (AE)

Average Error is defined by:

$$\mathcal{L} = \text{AE}(\hat{y}, y) = \frac{\sum_{i=1}^{N}|\hat{y}_i - y_i|}{N} \tag{2.11}$$

2.2.4 Optimize loss

To provide better estimation, we will try to optimize the neural network parameters. One common way to optimize these parameters is to use stochastic gradient descent (SGD). SGD is an iterative learning method that starts with some random parameters [29]. Given θ to be a parameter that we want to optimize. The learning rule assigning the new value of θ for a simple example would be:

$$\theta := \theta - \eta \Delta_\theta \mathcal{L}(f(x), y) \tag{2.12}$$

Where η is learning rate and $\Delta_\theta \mathcal{L}(f(x), y)$ is the partial derivative of the loss in terms of the given parameter θ and := is the assignment operator. One iteration is completed when we update every parameter for given train data. By performing many iterations, SGD aims to find a global minimum for the loss function, given data and initial parameters.

2.2.5 Convolutional Layer

The convolution operations always involves the full depth at each spatial location (see Figure 2.2). The spatial extension of the outputs therefore corresponds to the number of input positions at which a filter is applied. Each convolution layer applies not only a single filter but multiple filters whose two dimensional outputs are stacked resulting in one output channel per applied filter.
The hyper parameters of a convolution layer are the number of filters K, kernel size F, stride S and patches P. The stride describes how far the kernel is moved after each application. The number of positions for filter applications depends on stride and kernel size. Often the positions defined by stride and kernel size do not fit the input shape perfectly and adding zeros around the borders (padding with zeros) can help to cover the border of the input with filter positions. Restricting the output to positions for which the filter is entirely inside the input dimension and discarding possible border elements is often referred to as valid padding [3].
Let assume a 3 dimensional layer output $o^{(k-1)} \in \mathbb{R}^{\mathcal{H}_{k-1} \times \mathcal{W}_{k-1} \times m^{(k-1)}}$ where $\mathcal{H}_{k-1}$, $\mathcal{W}_{k-1}$ and $m^{(k-1)}$ respectively height, width dimension and number of node in

layer $(k-1)$. We will refer to the totality of these nodes repeated in width and height dimensions as feature. The convolutinal creates a sliding window of size $K \times K \times m^{(k-1)}$ goes through height and width. The contents of this sliding window are patches $(p^{(k-1)}_{(I,J} \in R^{K \times K \times m^{(k-1)}})$ where $0 < I \leq \mathcal{H}_k$ and $0 < J \leq \mathcal{W}_k$. We create $o^{(k-1)}_{(I,J)} \in R^{(1 \times m^{(k)})}$ by multiply $w^{(k)} \in R^{K \times K \times m^{(k-1)}}$ with $p^{(k-1)}_{(I,J)}$.

We define a convolutional layers:

$$\psi_k^{Conv} : \mathbb{R}^{\mathcal{H}_{k-1} \times \mathcal{W}_{k-1} \times m^{(k-1)}} \mapsto \mathbb{R}^{\mathcal{H}_k \times \mathcal{W}_k \times m^{(k)}}$$

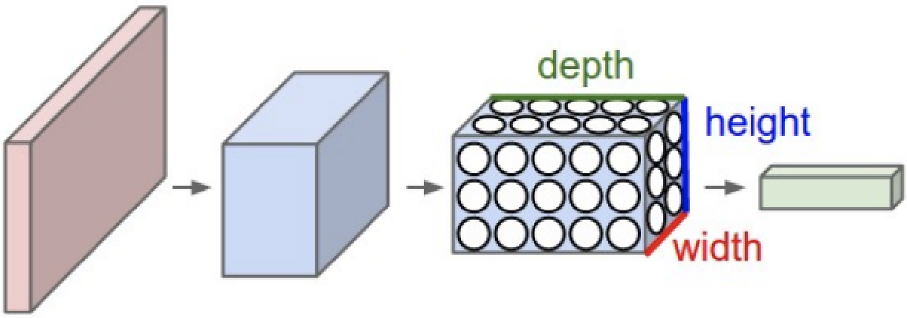


Figure 2.2: A 2D-Convolutional Neural Network processes three dimensional volumes of decreasing spatial extend [3]

2.2.6 Pooling

Pooling layers reduce dimensional of the data with no trainable parameters. Pooling windows similar to the filters of convolution layers are translated across the input. The output of pooling layers are aggregation of input values covered by the pooling window. Pooling methods work with patches P and strides S like convolutional layer.

2.3 Data structure

While batteries have many aspects to affect to aging, including SOC, temperature and their chemical ingredient. It is impossible take into account all factors reflect to estimation model but we argue use subset of those factors to build a framework that handles them effect. In this thesis, we address three features (voltage, current, and temperature) from battery sensors:

$$\mathbf{X} = \begin{pmatrix} I_1 & V_1 & T_1 \\ I_2 & V_2 & T_2 \\ \vdots & \vdots & \vdots \\ I_m & V_m & T_m \end{pmatrix}$$

Where I_t, V_t, T_t are current, voltage, and temperature respectively, at time t and m is number of of discretize parts in charge cycle. In this thesis, the $X \in \mathbb{R}^{m\times 3}$ joint distribution jointly represents data at time t as a data point.

For each data point, there is a corresponding discharge capacity output y, which is a scalar number and calculated using the coulomb counting method, integrating the discharge current over time for the entire discharge cycle [12]. The model try to find a non-linear function map from $\mathbb{R}^{m\times 3}$ to $\mathbb{R}^1$

Chapter 3

Implementation

Summary

The efficiency of the proposed deep learning method was verified based on experimental data from cycling test (i.e., repeated full charge/discharge cycles) on Li-ion prismatic cells. This section 3.1 introduces the battery data acquisition process. Then in section 3.2 we discuss about how cleaning data, transformation data to format we can feed to neural network. Finally, in section 3.3 we show the implementation of training, validation, and test for neural network in this experimental verification.

3.1 Battery data acquisition process

Before get battery data set as experimental data, we preprocess data by cleaning data, remove outlier points. Eventually, we obtain a sets of battery data with degradation characteristics per cycle as shown in Table. 3.1. Table 3.2 summarizes the procedure for SOH test. Each battery working voltage is set from 2.7V to 4.2V. The cycle test is performed by the battery testing system with the

Table 3.1: The detailed information of lithium-ion battery.

Parameters	**Value**
Chemical component	$Li(NiCoMn)O_2$
Capacity	3000 mAh
Nominal voltage	3.7V
Working voltage	2.7 - 4.2
Discharge current at 1C	3A
Working temperature	$0 - 55°C$

Table 3.2: State of health test procedures of lithium-ion battery

Step	**Battery operation**	**Control value**	**Extra Control Value**
1	Charging	Constant Current: 1.3A Constant Voltage: 4.2V	Voltage Limit = 4.2V Charging Current 0.05A
2	Rest	Time: 30 min	
3	Discharging	Constant Current: -1.3 A	Discharging Voltage $\leq$ 2.75 V
4	Rest	Time: 30 min	

charging and discharging rate at 0.5 C. Each cycle consists of four steps: charging, rest, discharging and rest. Rest step is performed to reduce the error caused by operating conditions. Battery charging is performed at constant current of 1.3 A until battery voltage reaches a limit of 4.2V and then at constant voltage of 4.2 V until current drops to 0.05A followed by a rest period of 30 minutes. Further, batteries are discharged at a constant current of -1.3 A until the discharging voltage reaches 2.75 V followed by a rest step of 30 minutes. Additionally, the experimental ambient temperature is set at $25°C$.

The variation in battery discharge capacity over charging cycles for 2 experimental batteries is depicted in Fig. 3.1 which is calculated by integrating discharge current over the discharge cycle duration. It can be observed from Fig. 3.1 that each battery exhibited a less homogeneous capacity fade behavior compared with the cycle index. Our goals was to investigate whether neural net-

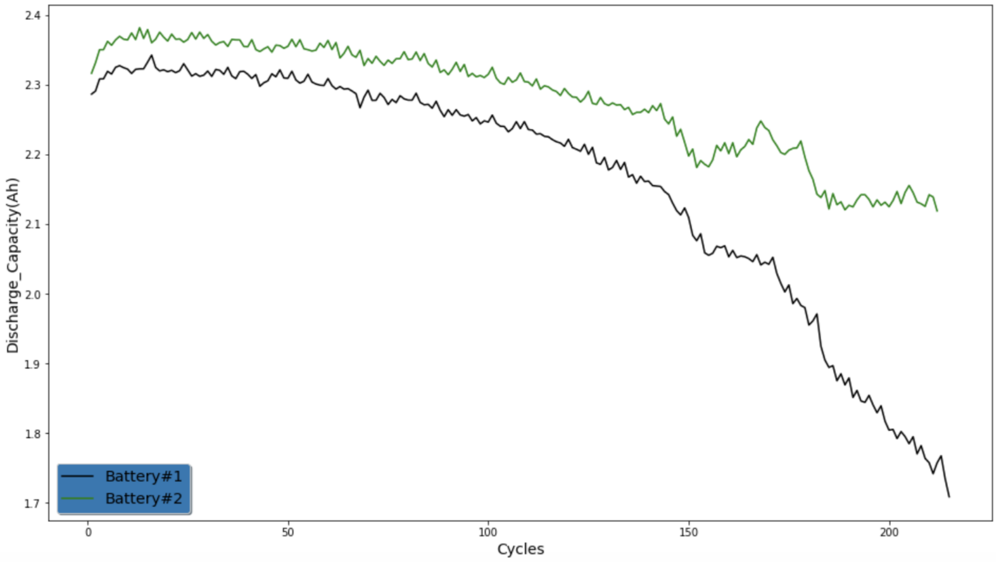


Figure 3.1: Discharge capacity curve vs. number of charging-discharging cycles for Li-ion battery.

work model could capture capacity estimates for the battery cycled with various cycling protocols and profiles. For safe and reliable use of battery, a threshold level for battery capacity can be used to determine SOC of the battery. Usually, a threshold level is prescribed as 70-80 percentage (depending upon the battery operation) of rated battery capacity. Fig. 3.2 show the setup of our testing system. Fig. 3.2a is the outlook of the experimental hardware with measurement tools and battery packs and Fig. 3.2b is the schematic diagram. The input of Test Channels provide different conditions for our experiment while the Monitoring Console shows log-data of the changing or discharging processes. Arbin stores the measurement information in its local storage and can be extracted later on. SOH of a battery are determined by monitoring the battery capacity at releasable ($C_{releasable}$) and at maximum chargeable (C_{max}) with respect to rated battery ca-

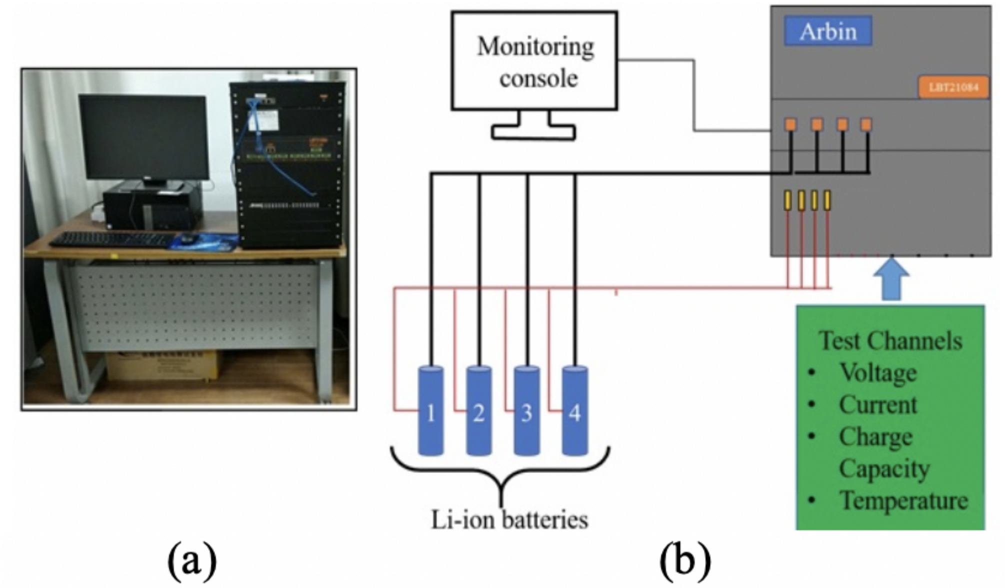


Figure 3.2: The battery testing setup: (a) experimental setup and (b) schematic diagram

pacity (C_{rated}) as defined in formula:

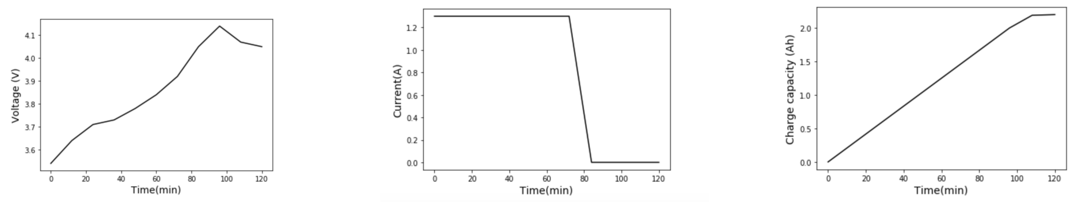
$$SOH = \frac{C_{max}}{C_{rated}} \times 100$$

3.2 Data preprocessing

Our input data is the collection of LIB battery from 14th Sep, 2018 to 16th Jan 2019. The data consisted of 2,777,529 data points for both 2 batteries. Data collected over 125 cycles for each battery. The head and tail of first cycle of battery #1 are display in Fig.3.3. From each cycle index, we calculated SOH = $\frac{\text{maximum discharge capacity in step 3 (discharging)}}{\text{battery capacity rate} = 3000 \text{ mAh}}$. As we discuss in 2.3, for each partial charge cycle we choice $m = 25$ for each of distribution of voltage, current and charge capacity. To better showing the inputs, the voltage, current and charge capacity distribution are show in Fig. 3.4. Each those distribution are discretized

	Date_Time	Test_Time(s)	Step_Index	Cycle_Index	Voltage(V)	Current(A)	Charge_Capacity(Ah)	Discharge_Capacity(Ah)
0	2018-09-14 16:39:49.863	60.010500	1	1	3.530674	1.299788	0.021548	1.761754e-09
1	2018-09-14 16:40:49.864	120.011800	1	1	3.558775	1.299831	0.043207	1.761754e-09
2	2018-09-14 16:41:49.853	180.000900	1	1	3.570162	1.299841	0.064868	1.761754e-09
3	2018-09-14 16:42:49.861	240.008900	1	1	3.576921	1.299820	0.086534	1.761754e-09
4	2018-09-14 16:43:49.860	300.007800	1	1	3.583076	1.299814	0.108199	1.761754e-09
...	...	...	...	...	...	...	...	...
234	2018-09-14 20:33:09.818	14059.965792	3	1	3.058974	-1.299524	2.216611	2.209313e+00
235	2018-09-14 20:34:09.820	14119.967692	3	1	2.996843	-1.299570	2.216611	2.230957e+00
236	2018-09-14 20:35:09.817	14179.964792	3	1	2.920110	-1.299566	2.216611	2.252634e+00
237	2018-09-14 20:36:09.816	14239.963192	3	1	2.821015	-1.299526	2.216611	2.274287e+00
238	2018-09-14 20:36:42.607	14272.754892	3	1	2.749995	-1.299587	2.216611	2.286119e+00

Figure 3.3: Sample data for battery #1



(a) Voltage (b) Current (c) Charge capacity

Figure 3.4: Typical charging cycle temporal distributions of battery

into $m = 25$ segments then fatten them as a vector in $\mathbb{R}^{75}$.

3.3 Implementation detail

The objective of the model is to lower the expected generalization error given by Eq.2.8. To achieve this objective, we will use the dataset as training and evaluation. By implementing the data-driven methods (kNN, RVM, Particle Filter) and a deep neural network model, we will come to a comparison which will be described in the Chapter 4. In the following section, we describe how the above methods work on our data.

3.3.1 k-NN

The data at each point is estimated by a set of N nearest neighbors; N is used as a hyperparameter. The k-NN algorithm uses the similarity concept to approximate the values of a new data points. In our application, a new prediction value is assigned a value based on how closely it resembles the points in the training set. We approximate N points closest to the predicting value and archive the average output from them. In validation and comparison, the errors are calculated by the difference from the prediction and the actual value.

3.3.2 RVM

In every charging cycle, we extract some values that we best describe one charge cycle. Particularly from the provided dataset, five inputs points are initial voltage, constant current charge capacity, constant voltage charge capacity, maximum charge voltage, last charge current, and last discharge capacity.
By using the above five features, the RVM is trained through all cycles collected. Obviously, important features of the battery cell reflects to prediction of appropriate features as output. Therefore, the CNN data that will be used to compare with that of RVM will be trained on the full dataset but predict on limited output values.

3.3.3 Particle Filter

Particle Filter (PF) is used to predict the capacity of every point during the cycles, similarly to the later neural network approach. We create a list of P (P is a parameter) particles, predicting and updating the weights based on the distance to actual point. Resample is used to remove the lowest probable particles. In prediction for a new point battery status, output of PF (mean and covariance together with the particles of the previous point) provide the estimation. And the errors to the actual data in validation are used to compare with other methods.

3.3.4 Neural network

The neural network model was trained with 100 epochs and a minibatch of 128 examples. An initial learning rate η in Eq.2.12 was set to 0.01 for all convolutional and fully-connected layers and this rate dropped by a factor of 5 for every 7 epochs. Summary of the model configuration are display in Table 3.3. A portion of 80% of our dataset is used for training and the remaining 20% is used for validation. In the next chapter, we will describe our experimental statistics data in details.

Table 3.3: Summary of the configuration of the Neural network model.

Layer	**Kernel size**	**Number of kernels**
Input	25 x 3 x 1	-
Conv. 1	1 x 2 x 1	16
Max pooling	3 x 1 x 1	-
Conv. 2	3 x 1 x 1	32
Conv. 3	1 x 2 x 1	40
Conv. 4	1 x 2 x 1	40
Conv. 5	1 x 2 x 1	40
FC. 1	40 x 1	-
FC. 2	40 x 1	-
FC. 3	1 x 1	-

Chapter 4

Experiments result and Comparison

Summary

This chapter details all the results of my thesis, it also contains a full discussion, interpretation and evaluation of the results.

4.1 SOH estimation results

The SOH estimation results in the whole life cycle for battery #1 and #2 are shown in Fig 4.1 and Fig 4.2. To further evaluate the efficiency of the proposed method, k-NN, Particle filter, RVM and Neural network algorithms are compared in the experiments. Table 4.1 and 4.2 show the quantitative the performance comparison results.

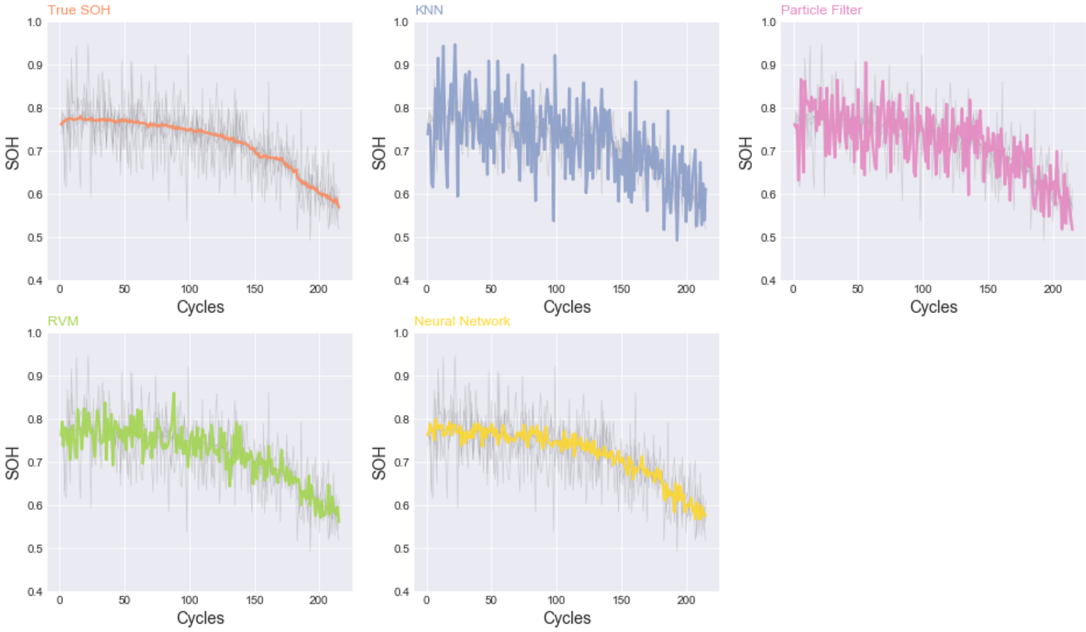


Figure 4.1: SOH estimation with basic algorithms and neural networks for battery #1

Table 4.1: Caparison of capacity prediction loss functions for battery # 1

Cost function	KNN	Particle filter	RVM	Neural network
RMSE	0.072	0.053	0.029	0.013
ME	0.209	0.137	0.106	0.034
MRE	0.280	0.179	0.140	0.053
AE	0.00130	0.00083	0.00065	0.00025

Table 4.2: Caparison of capacity prediction loss functions for battery # 2

Cost function	KNN	Particle filter	RVM	Neural network
RMSE	0.088	0.054	0.019	0.018
ME	0.248	0.157	0.059	0.050
MRE	0.315	0.198	0.076	0.064
AE	0.00149	0.00094	0.00036	0.00030

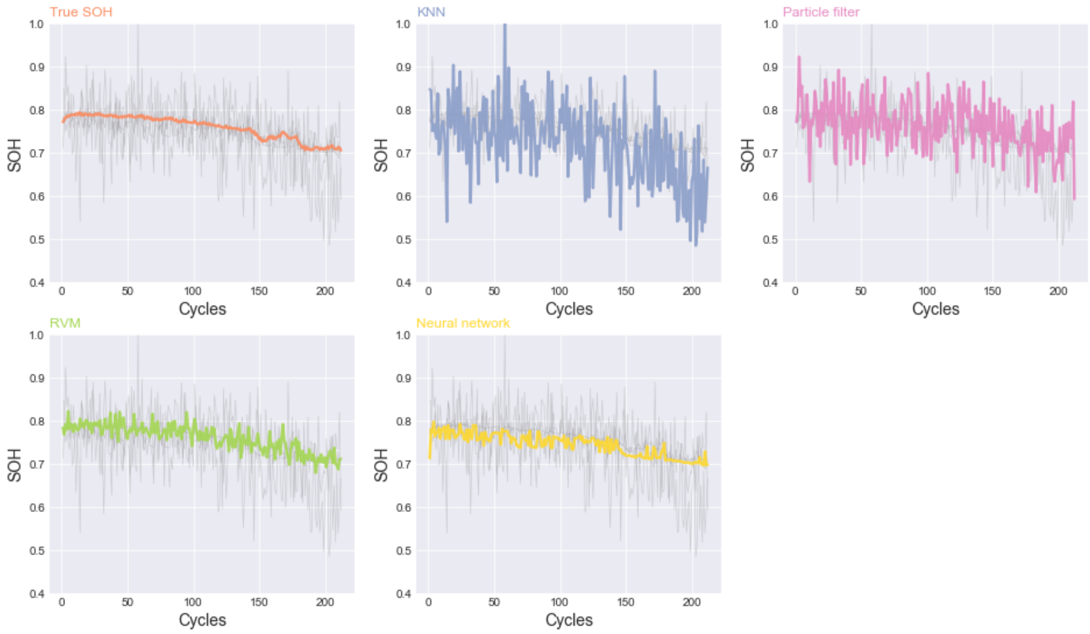


Figure 4.2: SOH estimation with basic algorithms and neural networks for battery #2

4.2 Experimental Discussion

From Tables 4.1 and 4.2, it can be obtained that neural network methods have good performance in battery SOH estimation, and the maximum relative error of SOH estimation is from 5-6%. This show that the method is suitable for non-linear system such as lithium-ion battery. Moreover, the proposed method has good adaptability on different types of lithium-ion batteries, which shows that the method has good robustness.

Chapter 5

Conclusions

Summary

This Chapter provides a summary of the work carried out in this thesis, discussing the role of each chapter in achieving the main objective of the thesis and the contributions made to the body of knowledge as a whole. An overall conclusion is then drawn and the scope for the future work which expand on this thesis is also set out.

5.1 Summary

The main objective of this thesis was to develop and optimise an online monitoring system for lithium-ion batteries which could adapt to changes imposed by varying operating conditions.

Various methods have been proposed from chemical, physical, statistical, and empirical approaches. Most of the existing models express SOH number of cycle life as the primary parameter. However, the cycle life is hard to trace because a battery in operation rarely undergoes a full charge/discharge process. This thesis developed suitable parameters and a new model for online SOH estimation. Thorough exploration of the test data revealed that a new variable, the unit time voltage, current and tempature in charge process, is appropriate for SOH modeling. The newly derived the SOH equation is linear, but has a modification factor as a function of the SOC. The proposed SOH models showed excellent accuracy when used to estimate the same batch of test battery data set. The robustness of the model was checked as well, and the results indicated that using any one of the same batch of batteries for the model construction yielded similar accuracy for all four cells.

As set out in Chapter 1, the motivation for the work carried out in this thesis is to increase the future uptake of lithium-ion battery energy storage devices in safety-critical applications. The battery management system and its estimation algorithms is identified as one the main areas of research for improving the future adoption of these delicate energy storage devices in a wider range of power applications. Hence, this thesis puts its focus on developing a novel model, whereby optimising the embedded BMS algorithms, not only the safety aspect of the battery. To complete a coherent piece of research, the state-of-the-art of battery energy storage systems, including a comparative study of different battery chemistries and the employed BMS structures, as presented in literature, is reviewed in Chapter 1. Empirical model-based then physical electrochemical models and data-driven method are provided. Battery status such as state-of-charge, state-of-health is undertaken. Various related methods are discussed.

In the Chapter 2, deep neural network are proposed, first the setup and procedures for experimental control and verification of the proposed battery estimation techniques in this thesis is explained. Next, at chapter 3, battery information use in experiment are showed and we also discuss about data acquisition process and data pre-processing technical. The detail implementation are also show in 3. In 4, evaluation methods are discuss and compare with others model.

5.2 Conclusions

This thesis aimed to develop an estimation model to increase estimate SOH for safety-critical applications. And also to make lithium-ion batteries a safer and more appealing choice for a wider range of battery-powered applications. Collectively, the proposed method in this thesis will allow for a better utilisation of lithium-ion batteries by continuously monitoring their SOHs, without the need for laborious and time-consuming characterisation tests which are non-ideal in a practical sense.

5.3 Future work

Conclusive section has been show the work in the thesis and benefits offered over the state of the art, there are areas which this thesis can expand on. In future work, the proposed method can be extended by take into account an online method which updates the parameters of physics-based equations affecting actual degradation in real-time practical operation.

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