# Cycle Life Prediction of Lithium-Ion Batteries Using Deep Learning

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Abstract: To improve the accuracy of lithium-ion battery life prediction, we decided to train multiple LSTMs separately, as each battery may have its own unique characteristics. When verifying the results, we found similarities between the verification and training batteries and used LSTMs to predict the verification battery, but we show that the results were not successful.

## 1 INTRODUCTION

I am surrounded by a plethora of portable electronic devices, including smartphones, all of which rely on lithium-ion batteries (abbreviated as LIBs). It has been a quarter of a century since LIBs were first commercialized. In particular, LIBs have become a ubiquitous electronic component in our daily lives, especially in mobile devices, owing to their high energy and power density, long lifespan, cost-effectiveness, and reliable safety when compared to other commercially available batteries. However, accidents involving LIBs continue to occur, and their incidence has been on the rise in recent years.To ensure the reliable and safe usage of LIBs in electric vehicles and other devices equipped with these batteries, it is crucial to monitor various parameters, including voltage, temperature, state of charge (SOC), state of health (SOH), remaining capacity, and cycle life. While some of these parameters, such as voltage and temperature, can be directly measured using sensors, others like SOC and SOH need to be estimated using algorithms based on measurement characteristics. Predicting cycle life is essential, but traditional prediction methods are highly complex, relying on physics-based modeling techniques and having to account for a wide range of operating conditions and significant device variability, even among batteries from the same manufacturer.In recent years, there has been a growing focus on machine learning-based methods to empirically learn and predict battery behavior. Accurate early prediction of battery cycle life not only enables rapid validation of new manufacturing processes but also allows end-users to identify performance degradation and replace failing batteries with ample time to spare. (Schmush, 2018).

## 2 RELATED RESEARCH

LIB life prediction methods include, in addition to simple empirical methods, physical models in which a person hypothesizes degradation phenomena and numerically solves electrochemical reaction equations, etc., and more recently, data-driven models that use machine learning to predict life based on charge-discharge cycle data. In particular, the data-driven method I am focusing on here has been evaluated for its ability to estimate LIB capacity, remaining service life, and cycle life. This method is based on limited test data, either empirical or mechanical, and does not consider modes of degradation. In Severson's study, the battery Severson's study used information from the first 100 cycles, when the battery is barely degraded, to predict the cycle life of the LIB, They achieved a very low testing error of 9.1%. This study is a promising data-driven approach for predicting the behavior of complex nonlinear systems. This study shows the promising power of data-driven methods for predicting the behavior of complex nonlinear systems.The goal of my research is to use data-driven deep learning to produce more accurate predictions than his. (Severson, 2019)

## 3 PRINCIPLE

The discharge characteristic data of the LIB is time series data. Therefore, LSTM, which is specialized for learning time-series data, is adopted in this study. Therefore, LSTM, which specializes in learning time-series data, was used in this study. Long Short-Term Memory (LSTM) is a specialized recur-



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rent neural network (RNN) architecture designed for handling sequential data. Unlike traditional RNNs, which struggle with maintaining long-term dependencies, LSTMs are adept at capturing and utilizing information over extended sequences.LSTMs achieve this by introducing memory cells and gating mechanisms. The memory cell can store information over time, while the gates control the flow of data into and out of the cell. The forget gate decides what to retain or forget from the previous cell state, the input gate manages new information input, and the output gate controls the information passed as output. LSTMs have become a crucial tool for tasks requiring the modeling of complex dependencies in sequential data.The model proposed in this study is a ”dedicated LSTM. The model proposed in this study is a ”dedicated LSTM, In order to compare the performance of the two models, I will explain the two models, ”conventional LSTM” and ”dedicated LSTM. The following is a comparison of the performance of the two models, ”conventional LSTM” and ”dedicated LSTM.

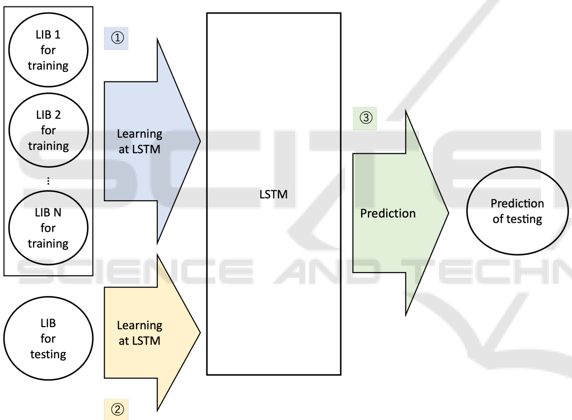



Figure 1: Conventional LSTM.

In figure1, N training batteries and 1 validation battery are used. That is, the LIB has N training batteries and 1 validation battery, each containing 5 variables. Step (1) uses N data to train one LSTM with data from the first to the Mth cycle of the LIB; the form of the data to be trained into the LSTM is N × M × 5. In step (2), the data from the first cycle to the Mth cycle of the test LIB is input to the learned LSTM. The form of the data here is 1 x M x 5. In step (3), the predicted values of the five features are output for the M+1st cycle. Incidentally, when predicting the life span, the number of cycles when the predicted value of the discharge capacity falls below a value of 0.88 is used as the life span.

Figure2 above shows the verification of data for testing using a dedicated LSTM. First, dedicated LSTM means that each battery is considered to be

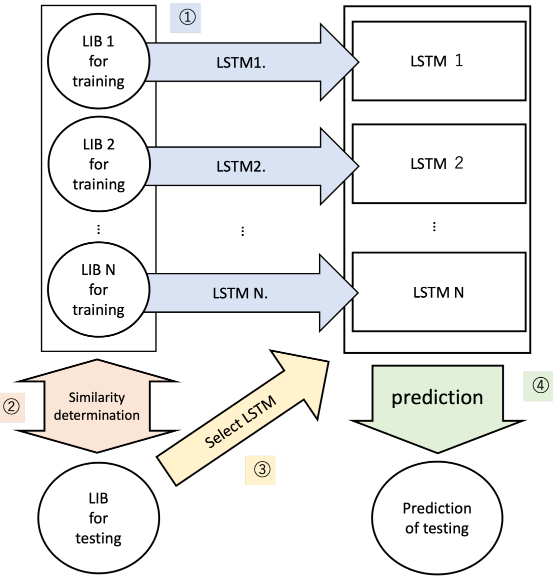



Figure 2: Dedicated LSTM.

different and predicted by its own LSTM after gurupturing from the initial cycle. In (1), N LSTMs are prepared for N training LIBs, and each battery is trained; in (2), the similarity between the training LIBs and the test LIBs is determined; and in (3), the similarity between the training LIBs and the test LIBs is determined. The difference between the discharge capacities of the 100th and 10th cycles of the test LIB is judged to be closer to the difference between the discharge capacities of the training LIB. In (3), cycle data is input to the LSTM that has learned the training LIB, which is similar to the test LIB in (2). In (4), the five predicted values for the M+1th cycle are output in the same way as in the conventional method.

## 4 DATA CONTENTS

This data set was used in the ”Data-driven prediction of battery cycle life before capacity degradation”. The data set consists of 124 commercial lithium-ion batteries that have been cycled 150 to 2300 times using 72 fast charge conditions for a total data set of approximately 96,700 cycles. Table 2 shows the 15 variables of the data set.

Manufactured by the A123 system (APR18650M1A), these lithium phosphate lithium ion (LFP)/graphite cells are circulating in a horizontal cylindrical fixture on a 48-channel Alvin LBT potentiometer in a forced convection temperature chamber set at 30 °C. Table 3.2 presents the battery specifications. The goal of this work is to optimize the rapid charging of lithium-ion batteries. Therefore,

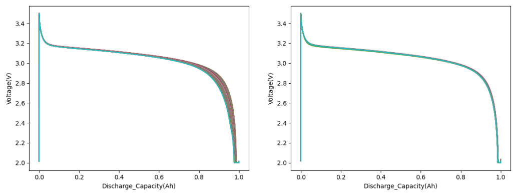
Table 1: Data set variables.

| | |
|---|---|
| Data Point | Test Time |
| Date Time | Step Time |
| Step Index | Cycle Index |
| Current | Voltage |
| Charge Capacity | Charge Energy |
| Discharge Capacity | Discharge Energy |
| dV/dt | Temperature |
| fff Internal Resistance | |

all cells in the dataset of are charged with a one-step or two-step fast charging policy. The format of this policy is ”C1(Q1)-C2”, where C1 and C2 are the first and second constant current steps, respectively, and Q1 is the state of charge (SOC, %) at which the current switches; the second current step ends at 80% SOC and the cells are then charged at 1C CC-CV. The upper and lower cutoff potentials are 3.6 V and 2.0 V, respectively. These cutoff potentials are fixed for all current steps, including fast charging. After some cycling, cells may hit the upper cutoff potentials during fast charging, leading to significant constant voltage charging. All cells are discharged at 4C. The data set is divided into three ”batches”, each representing approximately 48 cells. Each batch is defined by the ”batch date,” or the date the test was initiated. Each batch has some irregularities, as detailed on the individual batch pages. Temperature measurements are taken by attaching a T-type thermocouple to the exposed cell can with thermal epoxy (OMEGATHERM201) and Kapton tape after a small piece of plastic insulation has been removed. It should be noted that temperature measurements are not completely reliable. Thermal contact between the thermocouple and the cell can vary widely, and the thermocouple may lose contact during cycling. Internal resistance measurements were obtained during charging at 80% SOC by an average of 10 pulses of ± 3.6C with pulse widths of 30 ms (2017-05-12 and 2017-06-30) or 33 ms (2018-04-12). Table 3.3 presents the cycle life statistics.

## 5 DATA PREPROCESSING

First, standardization was performed to keep the values within a certain range. Next, the data was analyzed to improve the prediction accuracy. I examined the relationship between the cycle life and four variables: discharge capacity, discharge energy, charge capacity, and charge energy. The correlation coefficient for all four variables was approximately 0.6, which is not a very high correlation coefficient, but I considered that it would improve the accuracy of cycle life prediction, so I used these as characteristic quantities.



(a) short life span (b) log life span

Figure 3: Short and long life difference by discharge curve.

The figure3 shows the discharge curves for the short-life and long-life, both of which graph the change in discharge capacity and voltage after 100 charge/discharge cycles. Comparing the voltages near the discharge capacity of 0.8 in this figure, it can be seen that the short-life LIBs have progressively lower voltages. The correlation coefficient between the voltage dispersion by the discharge curve and the cycle life of the LIB is 0.8. Since a high correlation coefficient was obtained, this relationship is one of the characteristic quantities.

$$\Delta Q = variance(Q_0 - Q_i)(i = 1,2,3\cdots 100) \quad (1)$$

The equation(1) generates time series data for 100 cycles based on 0 cycles, where the voltage difference due to the discharge curve is distributed. (Pengcheng Xu, 2022)

## 6 EXPERIMENT

Before training, data is generated for each time step using 10 data to train LSTM on the feature-extracted data to predict the next value. The data generated for each time step was used to train the system.

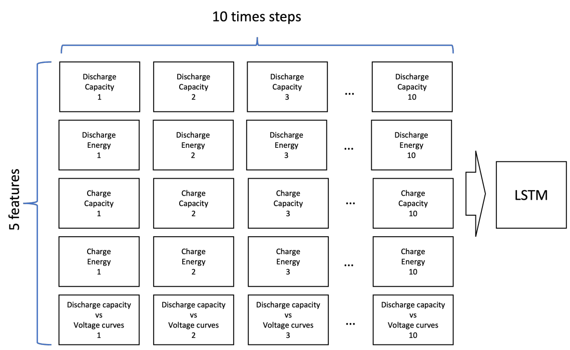



Figure 4: Time step.

The figure4 illustrates the time steps.This experimental evaluation will be conducted using RSME and MPE. In addition, the verification of training data for

”conventional LSTM” is omitted because ”dedicated LSTM” is difficult to verify for training data, and the main focus is on ”dedicated LSTM.

Table 2: Inspection result.

| convention | | dedicated | |
|---|---|---|---|
| RSME | 0.145 | RSME | 0.440 |
| MPE | 0.110 | MPE | 0.470 |

The results show that ”conventional LSTM” is more accurate than ”dedicated LSTM. The results show that the prediction accuracy of ”conventional LSTM” is higher than that of ”dedicated LSTM”. Possible causes One possible reason is that similarity judgment by ”Dedicated LSTM” may not be so effective with the discharge volume. The reason may be that the similarity judgment by ”Dedicated LSTM” is not so effective for the discharge volume. In feature extraction, a high correlation coefficient between cycle life and If the dispersion of the discharge curve with a high correlation coefficient with the cycle life is used for feature extraction, it may be possible to obtain more accurate results. It is thought that more accurate results could have been obtained if the variance of the discharge curve with a high correlation coefficient with the cycle life was used for feature extraction. In addition, instead of using 100 initial cycles, it may be better to use 100 initial cycles. It is also necessary to verify the results using 500 initial cycles instead of 100 initial cycles. It may also have been necessary to verify the results using an initial cycle of 500 instead of the initial cycle of 100. The results of this study were more accurate than those obtained by using the dispersion of discharge curves with a high correlation coefficient.

# 7 FUTURE DEVELOPMENT

As mentioned in the discussion, as a future development, I will examine the initial cycle as 500 as the initial cycle. I am also considering other uses for ”dedicated LSTMs. One is to use the data from the test LIBs in the study LIBs instead of using a single LSTM for similarity determination. One is to use all the LSTMs learned in the training LIB instead of using a single LSTM to determine similarity of the data in the test LIB. One is to use all LSTMs learned in the training LIB and average them as predictions, instead of using a single LSTM for similarity determination of the data in the test LIB. The other is to look at the predicted value as averaged over all the LSTMs studied in the training LIB. The other is to use the averaged cycle change (change in 6th-order features) predicted by all models to obtain the cycle life. The other is to calculate the cycle life by averaging the cycle changes (changes in 6D features) predicted by all the models.

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