Nanyang Research Programme

EEE12 Data-Driven Method for Li-Ion Battery Health Monitoring

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***Abstract* - Li-Ion batteries are increasing in usage due to the aim of sustainable development and other benefits it provides as compared to other batteries. Predicting the state-of-health (SOH) of Li-Ion Batteries has also grown in importance, and the method of data-driven model online SOH prediction is an efficient way of completing the task necessary. The prediction can be based on health indicator (HI) or machine learning (ML). ML-based predictions are a more effective method in this situation due to the complexities in the usage of HI. The framework of our proposed strategy involves preprocessing relevant data which only uses the battery's charge as a predictor and building a model using extracted data from previous charging and discharging curves of Li-Ion batteries to build a model that makes predictions of real-time data. We proposed a simple and effective ML framework with long short-term memory (LSTM) and Gated Recurrent Unit (GRU) model for this situation to predict SOH, avoiding the problems of high complexity, low interpretability, and high training costs. Predictions made using GRU have shown to be of high accuracy with an average root mean squared error (RMSE) of 0.724%. Furthermore, the GRU model takes significantly less time to train and evaluate.**

Keywords: Machine Learning, State of Health, Lithium-Ion Batteries, LSTM, GRU

1. INTRODUCTION

In line with its push towards sustainability and the lowering of carbon emissions outlined in the Singapore Green Plan 2030, Singapore has launched concerted efforts to transition its vehicle population to cleaner energy, in particular, electric vehicles (EVs) [1]. Worldwide, nearly 10% of global car sales were electric in 2021 [2]. The biggest concern about the promotion of EVs is the Li-Ion battery, which provides a higher charge density over conventional acid lead batteries. Furthermore, they are more resilient to constant charging and discharging, decreasing the degradation of the battery over multiple use cycles. A battery is recommended to be replaced when its state of health (SOH) degrades to its end-of-life (EOL) capacity threshold since the usable capacity is expected to decrease at a more rapid rate after exceeding EOL [3]. SOH prediction also extends the battery lifespan by adopting an ageing-level-based charging strategy to vary the charge current according to a cell's health status [4]. Thus, it is crucial to be able to predict the SOH of Li-Ion batteries for battery energy management and maintenance.

There are mainly two methods to evaluate the SOH of batteries. The first method is to estimate SOH by extracting health indicators (HI) from the equivalent circuit or electrochemical models. Liu et al. comprehensively reviewed indirect HIs based on offline measurements and direct HIs based on online measurements [5]. [6] proposed a framework to extract and optimise the HI of the batteries to model the degradation and the remaining useful time (RUL). The second method is to apply machine learning (ML) to predict battery SOH without knowing the exact battery model. Measurement data can be extracted from the offline datasets to train the ML model, such as Neural Networks [7] [8], Support Vector Machine [9], regression analysis [10] [11], reinforcement learning [12], and Extreme Learning Machine [13], which is then applied in the online prediction. Liu et al. proposed a data-driven online SOH estimation method using a novel energy-based HI from the discharge process [14]. Shen et al. proposed a theoretical framework for fast and accurate SOH prediction by quantitatively characterising the interactions among battery attributes and their aggregated impacts [15].

However, for SOH estimation methods based on HI extraction, accurate approximation of the SOH degradation process is difficult due to the complexity of the battery system and the uncertainty of working conditions in real life. Extreme Learning Machine (ELM) was one of the methods proposed in prediction of a battery's SOH [14], in which the proposed parameters of the machine learning algorithm would take into account the output voltage and the current, while other trained models assume the current was identical to that in the training dataset. However, ELM contains a large number of hidden neurons and is estimated from the training data, possibly leading to overtraining [16]. On the other hand, ML-based prediction methods address the drawbacks of model-based methods since they are modeless and data-driven. While some ML-based methods have achieved high accuracy and efficiency, the models are generally hard to train due to the complexity of their frameworks and model parameters which can hardly be interpreted from battery electrochemistry and are expensive for embedded devices with limited storage space and computational power.

Therefore, this project aims to propose a simple and efficient ML-based method for the SOH prediction of Li-Ion batteries. This project will propose a method based on popular ML models including long short-term memory (LSTM) and gated recurrent unit (GRU) to train the offline datasets and apply the method to the online prediction of SOH of batteries. Our focus will be on the ML architecture and algorithm of the SOH prediction framework. Our framework will be data-driven so that it will not be affected by the battery system working conditions, and also be accurate and efficient in SOH prediction.

The code we used to train and evaluate our models is available at *http://github.com/sileneer/NRP_2022_EEE12.*

2. OBJECTIVES

Our project aims to propose a data-driven method using ML, comparing the models of LSTM and GRU to predict the SOH of the battery cell using the data collected during charging. The proposed method can achieve both high efficiency and accuracy when evaluated using mean average error (MAE) and root-mean-square error (RMSE). Among the two models, GRU performs more accurately given the small size of the training dataset and can be trained more efficiently due to its less complex architecture.

3. METHODOLOGY

I. PROPOSED FRAMEWORK FOR SOH PREDICTION

In this section, we introduce a data-driven framework to predict the SOH of batteries. Based on the ML model, the framework consists of offline training and online prediction.

The offline training stage involves extracting SOH features from the datasets and normalising the data before inputting them into our machine learning model to train, which uses both LSTM or GRU. The benefit of this method compared to other proposed models of prediction of the battery's SOH, this takes a step back and simplifies the problem, reducing the challenge faced due to the interactions between each variable affecting the final result [15].

The online prediction stage uses data extracted from the charging curve of an existing Li-Ion Battery in real time and passes it through the model trained with the data previously gathered.

By applying the model trained with previously collected, offline data, we are able to train the model beforehand and apply it to data we collect in real time. This has the advantage over online training as the model trained can be applied to any new data readily, while incremental online training would be slower as new data is being fed into the ML model.

For real time data, we would use the MPG-200 battery cycler to collect data while charging the battery inside a thermal chamber to ensure consistent surrounding temperature. The aim of this setup is to keep as many variables constant as possible to ensure that the only variability from data collected would be due to the repetitive charging and discharging of the batteries. The charge output of the battery would then be collected together with the cycle number as a 'time' variable. This would be put through the model that have undergone offline training, allowing it to generate an output which would be the predicted capacity of the battery in that cycle.

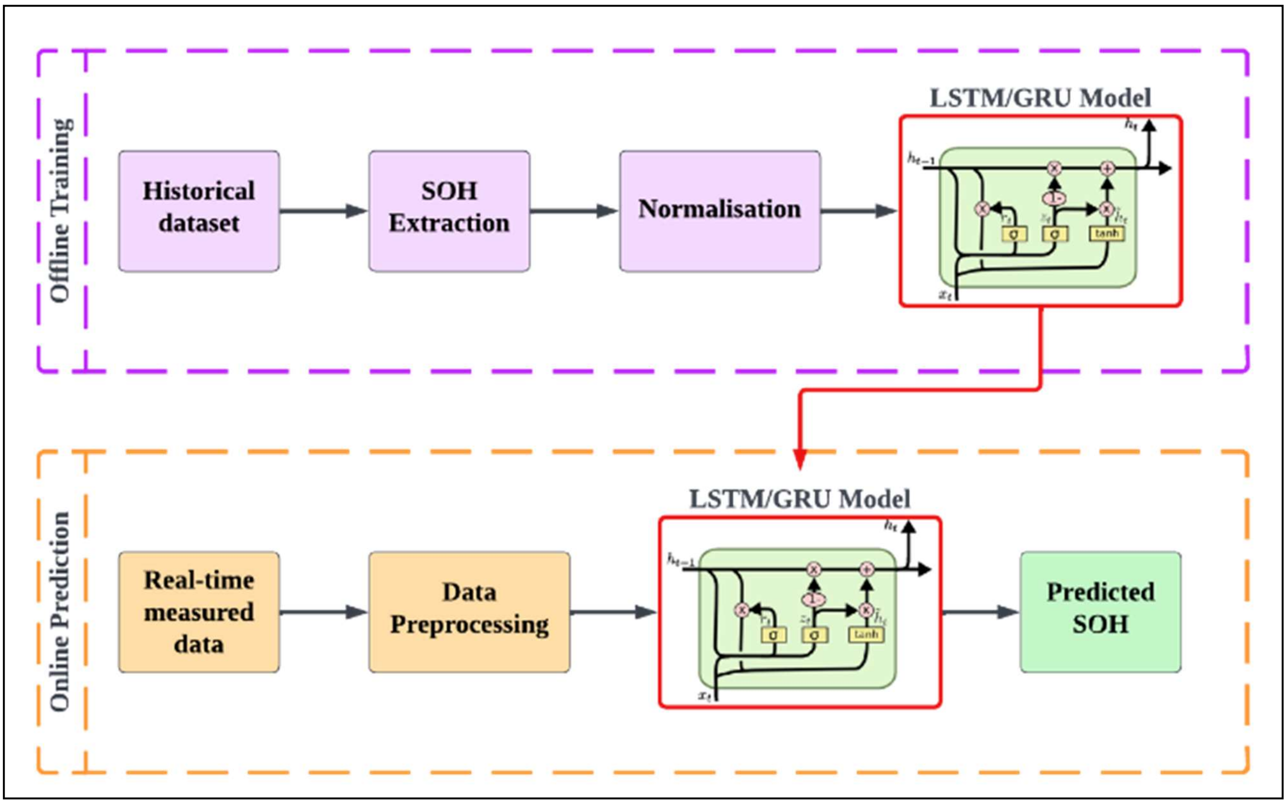

Figure 1. Proposed framework for SOH prediction

II. DATA PREPROCESSING

1) SOH EXTRACTION

An Open Database "Oxford Battery Degradation Dataset 1" is used for offline training [17]. It contains measurements of battery ageing data from 8 small lithium-ion pouch cells. The cells were all tested in a thermal chamber at 40℃. The cells were exposed to a constant-current-constant-voltage charging profile, followed by a drive cycle discharging profile that was obtained from the urban Artemis profile. Characterisation measurements were taken every 100 cycles. In our experiment, Cell 1-4 will be used as the offline training, while Cell 5-8 will be used to evaluate the accuracy respectively.

Table 1. File structure of "Oxford Battery Degradation Dataset 1"

Layer	Data
Layer 1	Cells (1-8)
Layer 2	Cycle number of characterisation cycles
Layer 3	1-C charge (C1ch), 1-C discharge (C1dc), pseudo-OCV charge (OCVch), pseudo-OCV discharge (OCVdc)
Layer 4	time (t), voltage (v), charge (q), temperature (T)

As the data for each cycle are collected chronologically, time series analysis can be implemented, in which the SOH is the output. Some cycle data are missing from the dataset during the data collection. Thus, the time interpolation technique is applied to estimate the missing values by focusing more on nearby points than far away points.

SOH is defined as the ratio of the current usable capacity of a battery compared to its nominal capacity:

$$SOH = \frac{C_{current}}{C_{nominal}} \times 100\% \qquad (1)$$

where $C_{current}$ is the maximum usable capacity of an aged battery at present and $C_{nominal}$ is the nominal capacity of a battery [5] [15]. In this dataset, the SOH data during the charge process 1-C charge (C1ch) is used for the training. Charge (q) represents the current usable capacity, and the maximum value is taken as $C_{current}$ for each cycle, while the nominal capacity for every cell in C1ch is $740mAh$. Therefore, SOH can be calculated by $\frac{q}{740}\%$ in each cycle.

2) NORMALISATION

To increase the efficiency and accuracy of the training, scaling is applied to all the SOH data. This is to ensure faster algorithm convergence when the input features are relatively smaller or closer to normal distribution. After comparing the different kinds of preprocessing methods, we settled on MinMaxScaler as it preserves the shape of the original distribution without changing the information embedded. The advantage this provides over other preprocessing features is that it preserves the scale of data in relation to one another as opposed to StandardScaler. The SOH data are then grouped into sequences as inputs to the model. The sequence length or look-back period is the number of SOH data points in history that the model will use to make the prediction.

In the dataset, there are missing cycles as mentioned in the documentation of the dataset. Therefore, we would have to fill in those missing data before we put the whole dataset into our ML model for training. To do this, interpolation of data is used, which uses the previous trends and values of data to fill in the missing data. This is done as it is faster to interpolate the data and use it for data input for the model than to have the model evaluate the predicted value of the missing data.

Last step to preprocessing the data is windowing. For the ML model to determine its accuracy, we need to compare predicted value from actual value in a repeated process called training. To do this, another step of preprocessing the data has to be done called windowing. Windowing allows the algorithm to break the data into blocks of sizes determined by the user. In this case, it uses 10 of the previous data to predict subsequent data points.

III. LSTM and GRU Model

The time series analysis is based on ML algorithms. A common ML model used is Recurrent Neural Network (RNN). The information that it learns from the past step can persist to the present task, allowing each pattern to be dependent on previous ones. In our time series analysis on SOH, we need the SOH information from past cycles to predict the SOH at the current cycle. Hence, RNN is useful in our task. However, as the gap between information grows, RNN becomes unable to learn to connect the information. This means that the information from past cycles may lose when using RNN to predict the current SOH in time series. Therefore, in this project, two improved algorithms are used – LSTM and GRU models.

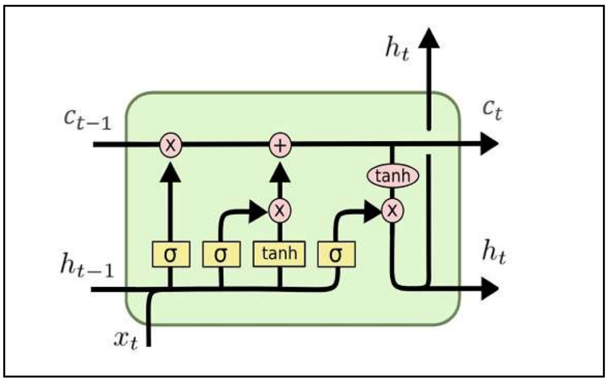

Figure 2. LSTM model architecture

Figure 2 [18] shows the LSTM framework. In each repeating module, unlike RNN with only one single neural network layer, there are four in the LSTM module, with three gates having the ability to optionally let information through. Thus, these gates can be trained to tell which information is relevant and consequently keep information from long ago. For a single LSTM module at cycle t, it will take the memory h_{t-1} and information C_{t-1} from the last cycle, and current input x_t as the input, and generate the memory at the current cycle h_t and carried information C_t as the output, using the formulae:

Forget gate: $$f_t = \sigma\left(W_f[h_{t-1}, x_t] + b_f\right) \quad (2)$$

Input gate: $$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i) \quad (3)$$

New information: $$\widetilde{C_t} = \tanh(W_C[h_{t-1}, x_t] + b_C) \quad (4)$$

$$C_t = f_t * C_{t-1} + i_t * \widetilde{C_t} \quad (5)$$

Output gate: $$o_t = \sigma(W_o[h_{t-1}, x_t] + b_o) \quad (6)$$

$$h_t = o_t * \tanh(C_t) \quad (7)$$

As an improved network from RNN, LSTM is also designed to handle sequential data, which makes it well-suited for our time cycle based prediction task. Its special architecture allows for improved gradient flow, which can make training faster and more stable. Additionally, LSTM can remember information from long periods of time, and is less sensitive to noise in input data, which makes them more robust to noisy or missing data.

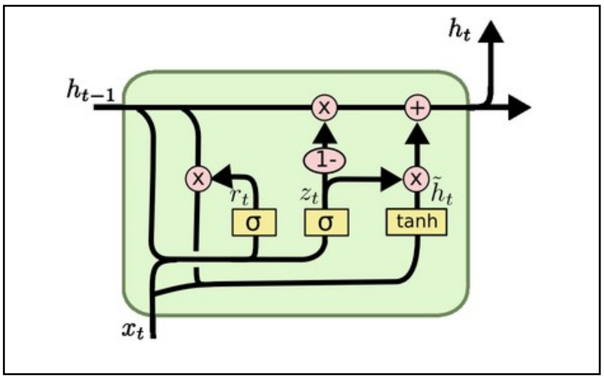

Figure 3. GRU model architecture

Figure 3 [19] shows the GRU framework. Similarly, it is an improved version of a standard recurrent neural network, with an update gate and reset gate, so that it can be trained to keep information from long ago, without washing it through time or removing information, which is irrelevant to the prediction, making it more effective. For a single GRU unit at cycle t, it will take the input from the memory at the last cycle h_{t-1} and current input x_t , and generate the memory at current cycle h_t as the output, using the formulae:

Update gate: $$z_t = \sigma\left(W^{(z)}x_t + U^{(z)}h_{t-1}\right) \tag{8}$$

Reset gate: $$r_t = \sigma\left(W^{(r)}x_t + U^{(r)}h_{t-1}\right) \tag{9}$$

Current memory content: $$h'_t = \tanh(Wx_t + r_t \odot Uh_{t-1}) \tag{10}$$

Output gate: $$h_t = z_t \odot h_{t-1} + (1 - z_t) \odot h'_t \tag{11}$$

LSTMs and GRUs are similar in terms of functionality, but the specific architecture and the way how they handle the information flow might differ. It is noteworthy that GRU has a simpler architecture than LSTMs, which makes them easier to train and understand. With fewer parameters than LSTMs, which can make training faster and require less computational resources. It is shown that shown that GRUs can achieve similar or better performance than LSTMs on certain tasks while being simpler and faster to train. Therefore, we expected that GRU can be trained faster and have better performance, which we will verify in the later sections.

IV. Evaluation

Comparing both ML model frameworks, it becomes clearer that LSTM would be more effective for larger datasets. While LSTM have an input gate for data from the previous gate, GRU does not have that function and evaluates each point on its own. In later parts of the paper, this is seen to be more accurate than LSTM due to the small dataset, but would not consider for more anomalous data in the set.

To evaluate the performance of each framework, mean average error (MAE) and root-mean-square error (RMSE) are used, given by:

$$MAE = \frac{\sum_{t=1}^{n}\left|\widehat{SOH_t} - SOH_t\right|}{n} \tag{12}$$

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n}\left(\widehat{SOH_t} - SOH_t\right)^2}{n}} \tag{13}$$

where t represents the cycle number, n represents the total number of cycles, SOH_t is the actual SOH value, and $\widehat{SOH_t}$ is the predicted SOH value from the time series.

Both two errors calculate the differences between the predicted SOH values and the actual SOH values. The two can be used as testing metrics to measure the accuracy of LSTM and GRU models.

4. EXPERIMENTAL RESULTS

I. EXPERIMENT ENVIRONMENT

To build the ML models, we use Pytorch 2.0.0, a Python package for deep learning. Among the total 8 cells in the dataset, Cell 1-4 is used for the training, from which 255 sets of data are extracted. The model will look back 10 data points. Thus, the input will be a 3D array with a shape $(255, 10, 1)$. Cell 5-8 is used for testing the performance of our model based on the value of MAE and RMSE. The models are set up and trained with the parameters:

Table 2. LSTM and GRU Model parameters used in training and evaluation

Number of layers	2
Hidden dimensions	256
Batch size	32
Drop probability	0.2
Epochs	100
Learning rate	0.001

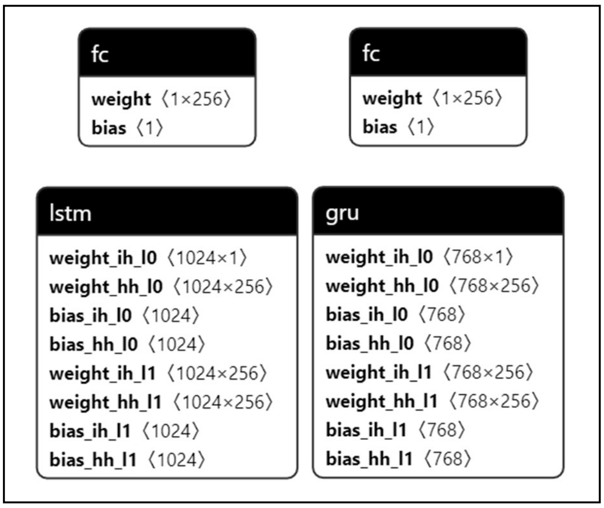

Figure 4. Visualisation of the trained LSTM and GRU model from Pytorch

Our model consists of three layers. Figure 4 visualises the LSTM or GRU layers and the FC layer after the model is trained in Pytorch. The input data with 1 dimension will first pass through two stacked GRU layers with 256 hidden dimensions, while 20% of the data will be dropped. Then the data will pass through a fully connected (FC) layer with 256 hidden features, outputting data with 1 feature. Finally, the data will pass through the Rectified Linear Unit (ReLU) activation function to introduce non-linearity into the model so that our model can learn a non-linear relationship between the inputs and outputs.

The model is trained and evaluated on Windows 11 Pro, with AMD R5-3500U CPU and 12GB RAM.

II. PREDICTION RESULTS

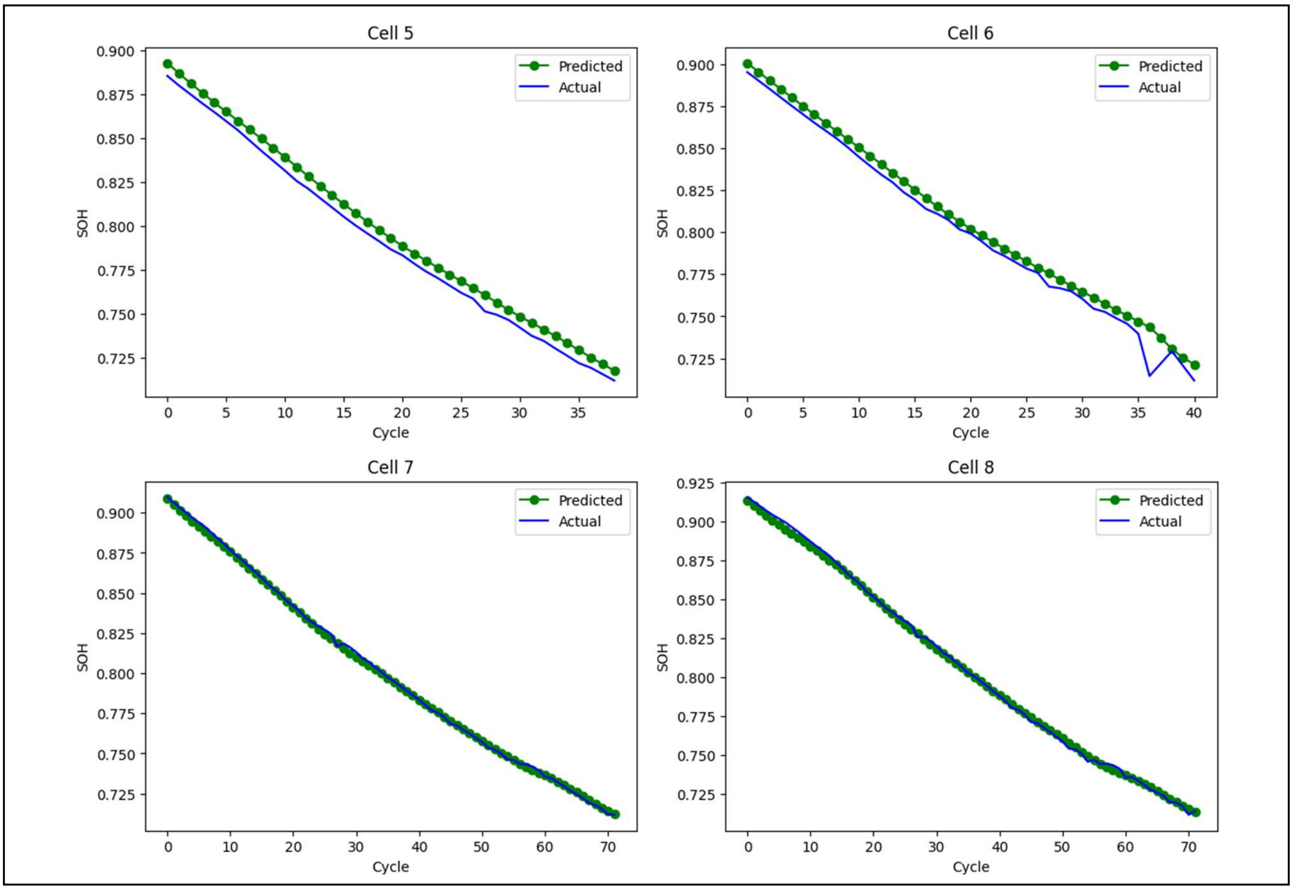

Figure 5. SOH Prediction results for Cell 5-8 from the LSTM model

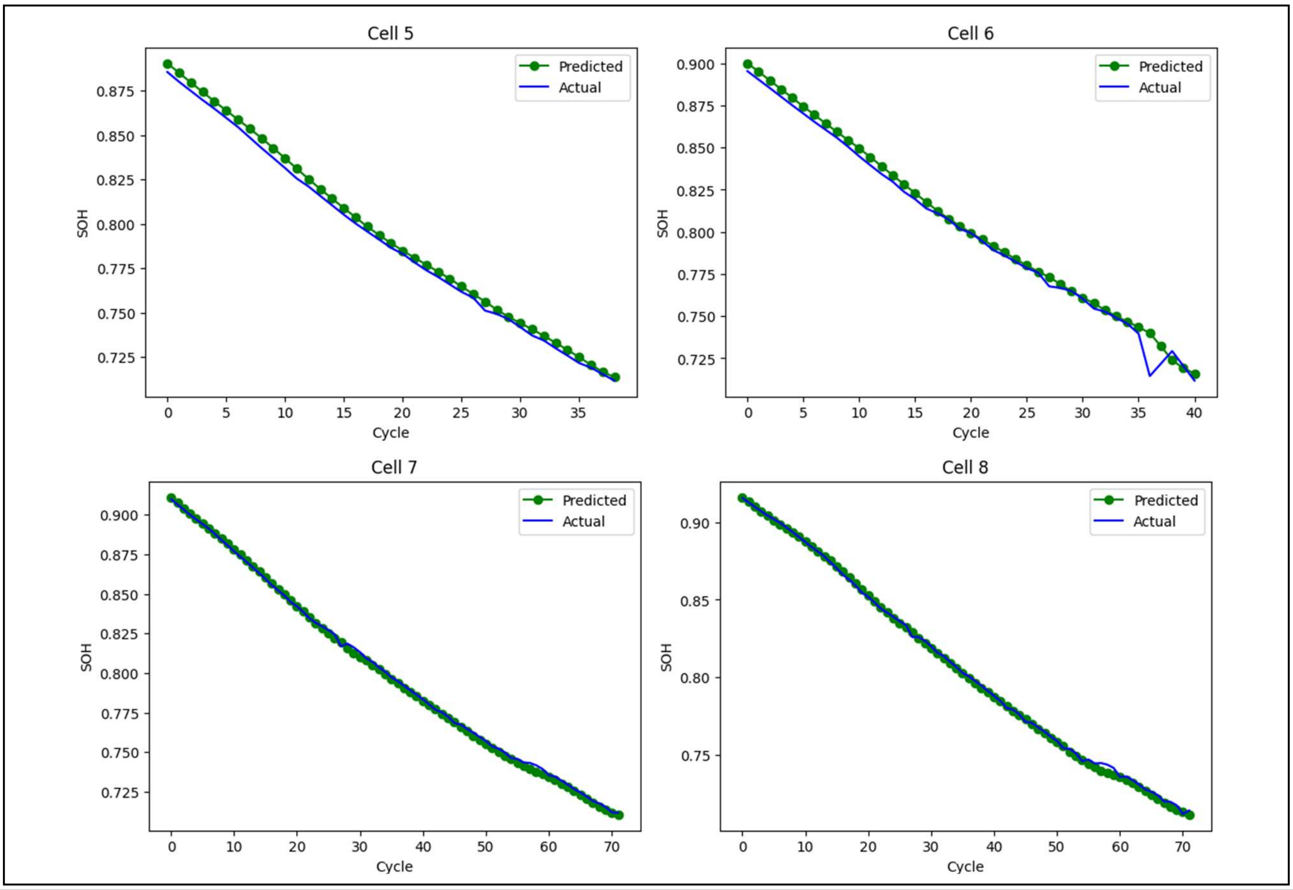

Figure 6. SOH Prediction results for Cell 5-8 from the GRU model

Table 3. Errors in MAE for SOH Prediction on Cell 5-8 (to 3s.f.)

Model	Cell 5	Cell 6	Cell 7	Cell 8	Average
LSTM	0.00661	0.00586	0.00118	0.00161	0.00382
GRU	0.00348	0.00366	0.00138	0.00127	0.00245

Table 4. Errors in RMSE (%) for SOH Prediction on Cell 5-8 (to 3s.f.)

Model	Cell 5	Cell 6	Cell 7	Cell 8	Average
LSTM	0.666	0.724	0.147	0.206	0.436
GRU	0.370	0.540	0.164	0.165	0.310

Table 5. Training time (s) on Cell 1-4 and evaluation time (s) on Cell 5-8 (to 3s.f.)

Model	Training Time	Evaluation Time				
	Total	Cell 5	Cell 6	Cell 7	Cell 8	Average
LSTM	160	0.0781	0.0469	0.156	0.109	0.0977
GRU	95.1	0.156	0.0938	0.0781	0.172	0.125

The above shows the SOH prediction results for Cell 5-8 based on the training from Cell 1-4. Figures 5 and 6 show that both GRU and LSTM models perform well as there is a clear correlation between the predicted SOH values and the actual values. However, comparing Table 3 and Table 4, clearly, MAE and RMSE from the GRU model are much smaller than those from the LSTM model except for Cell 7, indicating that GRU has a better performance in our task. This is because 255 sets of SOH data are used for training, which is relatively small compared to other ML tasks. Thus, the advantage of LSTM in using memory unit will vanish, and LSTM perform worse as it needs to learn a large range of parameters such as learning rates, and input and output biases.

As seen from Table 5, to train 100 epochs on the laptop, GRU takes much less time than LSTM. Although the evaluation time for GRU is slightly larger than that for LSTM, such a small difference during evaluation is less significant than that during training, and such a difference will become more significant as the size of the training dataset increases. As abovementioned, GRU has a less complex structure compared to LSTM, without having to use a memory unit. Therefore, they will perform more efficiently.

Within the limits of our experiment, both LSTM and GRU frameworks can be used to predict SOH based on the evaluation of the acceptably small value of MAE and RMSE. The data-driven method can then be applied to other battery cells with different working conditions. However, due to the size of our dataset, GRU performs better than LSTM as it has a lighter architecture. Nevertheless, we also expect that LSTM, when trained with more data, will give better results than GRU.

5. CONCLUSION AND FUTURE WORK

In conclusion, we proposed a simple and efficient data-driven method for the SOH prediction of Li-Ion batteries. Our proposed framework is simple as it uses common and efficient machine learning models including LSTM and GRU, and efficient as it takes significantly less time to train the model. Our framework is trained with offline datasets and applied to online prediction. Based on our evaluation of prediction results, we conclude that the GRU model is more accurate given the smaller size of the training dataset.

As our framework is data-driven, it can be applied to other battery cells after being trained. We have evaluated that our GRU model has achieved high accuracy with an average RMSE of 0.310%.

Given the limit of our experiment, in the future, we will train the model with more data and different models and parameters for a more accurate result. New prediction algorithms will be developed and integrated with the backpropagation of hyperparameters to model SOH degradation with better performance.

With future development of new technology for batteries, we could optimize these machine learning algorithms to work more efficiently, with a shorter evaluation time. However, GRU does not scale as well into larger datasets as LSTM does, therefore there would be a need for both of these models for smaller, repeated use of a single battery, which GRU would be more suitable, and mass productions of similar Li-Ion batteries, which LSTM could be used to predict the maintenance required for these batteries. There is much potential for these predictive algorithms for commercial use to ensure safety of consumers.

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