Li-Ion Batteries State-of-Charge Estimation Using Deep LSTM at Various Battery Specifications and Discharge Cycles

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ABSTRACT

Lithium-ion battery technologies play a key role in transforming the economy reducing its dependency on fossil fuels. Transportation, manufacturing, and services are being electrified. The European Commission predicts that in Europe everything that can be electrified will be electrified within a decade. The ability to accurate state of charge (SOC) estimation is crucial to ensure the safety of the operation of battery-powered electric devices and to guide users taking behaviors that can extend battery life and re-usability. In this paper, we investigate how machine learning models can predict the SOC of cylindrical Li-Ion batteries considering a variety of cells under different charge-discharge cycles.

CCS CONCEPTS

• **Computing methodologies** → **Neural networks**; **Supervised learning by regression**.

KEYWORDS

Lithium-ion battery, long short-term memory, recurrent neural network, state of charge estimation

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1 INTRODUCTION

The transition from fossil fuel to green energy is well known as the desired change in our society. To reduce the emission of Carbon dioxide (CO_2) from conventional transportation, the development of Electric Vehicles (EV) is growing quickly. Battery technology will be one of the most important key enablers for the green energy transition.

Lithium-ion batteries have been widely used in electric vehicles. It is projected that the global EV stock will expand to 140 million by 2030 [1]. Lithium-ion (Li-ion) battery is the most popular adopted power supply of EV due to its high energy density, long lifespan, lightweight, and low self-discharge rate [19]. Several factors could affect the performance and safety of Li-ion battery such as ambient temperature, **over-charge**, or **over-discharge** [20, 21]. A misuse of the battery can lead to a **shorter** battery life. To overcome these issues, Battery Management Systems (BMS) are applied to ensure the reliability and stability of the usage of Li-ion batteries.

One important parameter for the BMS battery health management is the battery State Of Charge (SOC) estimation which helps to prevent the battery from over-charge and over-discharge [10, 28]. SOC indicates the amount of available charge in the battery which can be represented by a value in percentage. This value is intended to remain between 0% and 100%, although it is possible to violate these limits in an over-discharge or over-charge situation [24]. The battery itself does not directly provide information on its SOC value. The measurement of SOC value is complex and error-prone due to the indirect estimation and the non-linear nature of electrochemical reactions in the battery. Relevant information such as the measured discharge current, voltage, and ambient temperature can be used to measure the SOC indirectly [5].

Incorrect measurement of SOC could lead to unstable EV performance and even shorten the battery life, therefore, reducing the environmental benefits of electrification. In general, the SOC estimation techniques studied in the literature can be divided into three categories: direct methods, model-based methods, and data-driven methods [25]. The direct methods look for the relationship between SOC and the physical battery characteristic parameters. The SOC value can be estimated according to the observed parameters[24],[25], [22]. The model-based SOC estimation methods mainly focus on modeling the chemical and electrical properties of the battery. Commonly, the model-based methods are used in collaboration with adaptive filters such as Kalman filter, H-infinity filter, and Particle filter, etc [25], [23]. Model-based methods require a comprehensive understanding of the electrochemical properties in the battery domain and cannot be used for SOC forecast[12][3].

This work proposes a data-driven approach for SOC estimation based on Deep Learning techniques. Deep learning, which can approximate non-linear functions, is a widely adopted data-driven method to tackle the battery SOC estimation problem [27]. Given a sufficient amount of training data and an appropriate configuration, the SOC value can be predicted accurately without the need for a sophisticated electrochemical model. Different types of neural networks (NNs) such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) have been studied in the literature to solve various problems of different nature [8, 14]. Among

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them, RNNs are designed to handle sequential data, and they have been well studied in the domain of speech recognition and natural language processing with successful outcomes [9, 30]. However, RNNs struggle to handle long-term dependencies as long time series could cause exploding/vanishing gradient during the training phase. To tackle this problem, Hochreiter and Schmidhuber [11] proposed the use of RNNs with Long Short-Term Memory (LSTM) cells which can correlate a long-range of precedent information.

In the literature, various applications of LSTM for SOC estimation have been proposed. Chemali, Kollmeyer, Preindl, Ahmed, and Emadi [4] showcased the ability of LSTM for SOC estimation. They used a dataset composed of discharge cycles obtained from a Li-ion battery cell with 2.9Ah nominal capacity [17] and collected through laboratory testing under different driving profiles. The proposed model was validated against various ambient temperatures with accurate estimation results achieved. Similarly, Yang, Song, Xu, and Tsui [29] proposed the use of a deep LSTM network with data collected from an experiment on a 1.1Ah nominal capacity battery cell. In [26], a neural network combining CNN and LSTM layers was proposed for battery SOC estimation. The research result has shown that the CNN part helps to extract the spatial features from the input data (voltage, current, and temperature) while the LSTM layers explore the correlation of current SOC and historical input data. Last but not least, the use of an LSTM encoder-decoder algorithm was proposed by Cui, Yong, Kim, Hong, and Joe [7] with accurate estimation result against both room temperature and various temperature conditions. The proposed model was trained and tested on 2.0Ah nominal capacity Li-ion battery cell data featuring various drive cycles.

Although the neural network data-driven approaches for SOC estimation are widely studied most of the literature mainly focuses on datasets containing only **one particular battery model** or setup. This study uses two different Li-ion cell datasets. The first one is original and it has been collected by the University of Bologna (UNIBO), namely the 'UNIBO Powertools Dataset'. The second one is public, the LG 18650HG2 Li-ion battery data [18]. The use of deep LSTM networks is proposed to perform SOC estimation. Due to the heterogeneity of the data collection process and the sampling rate of the two datasets, two deep LSTM models with different setups are employed in this research. The deep networks are tested on Li-ion battery cells with different nominal capacities, specifications, and brands; the discharge cycles are produced by both constant current discharge and several dynamic driving profiles (such as the Urban dynamometer driving schedule (UDDS) [2]).

The rest of this paper is organized as follows. The employed battery datasets are introduced in section 2. Then, section 3 explains the proposed deep LSTM models. In section 4, the results of the experiments are presented. Finally, section 5 concludes this paper.

2 LI-ION BATTERY DATASETS

In this paper, two Li-ion battery datasets – one original and one public – with different features are used. The UNIBO Powertools Dataset is presented here for the first time, and it is available here[1]. Only the discharge cycles are used in the experiments. The two datasets are briefly introduced in the following sections.

[1]https://doi.org/10.17632/n6xg5fzsbv.1

Table 1: UNIBO Powertools Dataset summary

Test type	Nominal capacity	Cell amount
Standard	4.0Ah	2
	3.0Ah	4
	2.85Ah	4
	2.0Ah	6
High current	3.0Ah	3
	2.85Ah	2
Preconditioned	3.0Ah	5

2.1 UNIBO Powertools Dataset

The UNIBO Powertools Dataset has been collected in a laboratory test by an Italian Equipment producer. The cycling experiments are designed to analyze different cells intended for use in various cleaning equipment such as vacuum and automated floor cleaners. The vast dataset is composed of 27 batteries, and it is summarized in Table 1. The main features of the dataset are: (1) the use of batteries from different manufacturers, (2) cells with several nominal capacities, (3) cycling is performed until the cell's *end of life* and thus data regarding the cell at different life stages are produced, which is useful to assess **how SOC is affected by the cell's age** and State of Health (SOH) as well as to validate the capability of the proposed model on estimating SOC under different health status. Three types of tests have been conducted. (I) The **standard test**, where the battery was discharged at 5A current in main cycles. (II), the **high current test**, where the battery was discharged at 8A current in main cycles. (III), the **preconditioned test**, where the battery cells are stored at 45°C environment for 90 days before conducting the test.

During discharge, the sampling period is 10 seconds. The experiments were conducted using the following procedure:

(1) Charge cycle: Constant Current-Constant Voltage (CC-CV) at 1.8A and 4.2V (100mA cut-off)
(2) Discharge cycle: Constant Current until cut-off voltage (2.5V)
(3) Repeat steps 1 and 2 (main cycle) 100 times
(4) Capacity measurement: charge CC-CV 1A 4.2V (100mA cut-off) and discharge CC 0.1A 2.5V
(5) Repeat the above steps until the end of life of the battery cell

2.2 LG 18650HG2 Li-ion Battery Data

The public LG 18650HG2 Li-ion Battery Dataset, published by Kollmeyer, Vidal, Naguib, and Skells [18], was obtained from Mendeley data. In the dataset, a series of tests were performed under six different temperatures. The battery was charged at 1C rate to 4.2V with 50mA cut off before each discharge test. The values measured in the discharge cycles are captured at 0.1 seconds sampling period. Different drive cycles such as UDDS, LA92, and US06, as well as mixes of them, are applied in the discharge tests. In this paper, the discharge cycles with temperature of 0°C, 10°C and 25°C were used for training and testing the proposed model.

3 METHODOLOGY

In this section, the basic theories of RNN and LSTM are introduced and the two proposed deep LSTM models are briefly introduced. Then, the normalization method used to scale the input data is reviewed. Lastly, the model's configuration is discussed.

3.1 Recurrent Neural Networks Primer

Recurrent neural networks are a class of neural networks that allows the information to persist over time. Different from the feed-forward neural networks that are acyclic directed graphs, RNNs have connections within layers forming cyclic directed graphs. This empowers neural networks to have a state, and thus memory. The information from the previous state is utilized as input along with the current time step. It is useful for sequential data prediction as relationships between current and past information are considered. An example of the architecture of an RNN for SOC estimation unfolded in time, is depicted in Fig. 1. The input vector at the time step t contains battery parameters such as voltage, current, and temperature, and it is denoted as $Input_t$. h_t represents the hidden state at time step t, while the output SOC value at time step t is denoted as SOC_t. Fig. 1 demonstrates a common approach for time-series called many-to-many, where multiple input steps are fed to the network with one prediction made at each step. Whereas, there are other approaches such as the many-to-one and one-to-many, where in the first case multiple time-steps are fed with one output produced, and in the second case one input is used to produce multiple time-steps. As the two battery datasets have very different sampling frequencies, we used the many-to-many approach for the first model (low-frequency sampling) while in the second one (high-frequency sampling) we used the many-to-one approach.

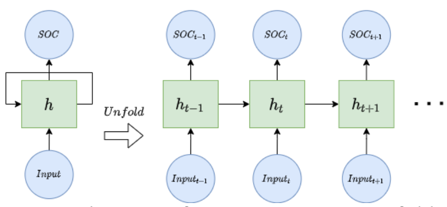


Figure 1: RNN architecture for SOC estimation unfolded in time

3.2 Long Short-Term Memory Primer

The long short-term memory is a type of RNN which is widely used to learn long-term dependencies without experiencing the exploding and vanishing gradient problems. The forward pass of an LSTM cell can be defined by the following steps. In the equations, f_t, i_t, o_t are the forget-gate, input-gate, output-gate; c_t and h_t are the cell state and hidden state at time step t respectively; σ is the sigmoid function; $\odot$ is the Hadamard product; W denotes the weight matrix; x_t is the input vector at time step t and b is the bias.

The first step in the LSTM cell is to determine what information will be forgotten from the cell state c_{t-1}. The forget-gate uses a sigmoid function, in which outputs are always between 0 and 1. The result represents therefore how much should be forgotten, with 0 and 1 representing respectively discarding everything or keeping everything from the previous cell's state. As shown in the equations, the decisions of gates are based on the current input and hidden state as well as on the network's weights and biases.

$$f_t = \sigma(W_x^f x_t + W_h^f h_{t-1} + b^f) \tag{1}$$

The second step determines whether the information will be stored in the cell state. There are two parts in the second step. Firstly, the input-gate with sigmoid output determines to what extent the value will be remembered. Secondly, the tanh layer generates the new value $\tilde{c}_t$ that is multiplied by the sigmoid output and then added to the cell state.

$$\begin{aligned} i_t &= \sigma(W_x^i x_t + W_h^i h_{t-1} + b^i) \\ \tilde{c}_t &= tanh(W_x^c x_t + W_h^c h_{t-1} + b^c) \end{aligned} \tag{2}$$

The cell state c_t is then update combining the previous cell state c_{t-1} with new value $\tilde{c}_t$ as mentioned above. The forget-gate f_t and input-gate i_t determine whether the values should be discarded or remembered.

$$c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}_t \tag{3}$$

In the last step, the output-gate with the sigmoid function decides which part of the cell state is propagated to the hidden state h_t. In the hidden state, the cell state c_t is passed via $tanh$ and multiplied by the output-gate to keep only the desired output.

$$\begin{aligned} o_t &= \sigma(W_x^o x_t + W_h^o h_{t-1} + b^o) \\ h_t &= o_t \odot tanh(c_t) \end{aligned} \tag{4}$$

3.3 Proposed LSTM Approach

There are two deep LSTM models proposed in this paper, one for each dataset, as they have very different cycle lengths. Scaled exponential linear units (SELU) [16] activation function is used in all the LSTM cells and hidden dense layers. In the output layer, the linear activation function is applied to produce the final SOC value.

The first model is used for the UNIBO dataset. It is a deep neural network with three LSTM layers followed by two dense layers to map the learned states to desired SOC output. The number of cells of each LSTM layer is 256, 256, and 128 respectively. Fig. 2 illustrates the architecture of the first proposed model. The first layer is the input layer with battery parameters including voltage V, current I, and temperature T at each step t. Since it is a deep LSTM network, each LSTM layer returns a sequence which means that each step is propagated to the next layer. Here, we adopted the many-to-many approach, the SOC value is therefore estimated at every step. The input time series fed to the deep LSTM network is defined as $[Input_{t0}, Input_{t1}, ...Input_{tn}]$, where n is the number of steps in the entire discharge cycle, and $Input = [V_t, I_t, T_t]$ represents voltage, current and temperature at each time step respectively. Although the entire discharge cycle is fed to the network, only the part that precedes the step under examination is available as input for SOC estimation, i.e., the hidden state from previous steps $t-1$ and the current input at step t are used to estimate the output at step t.

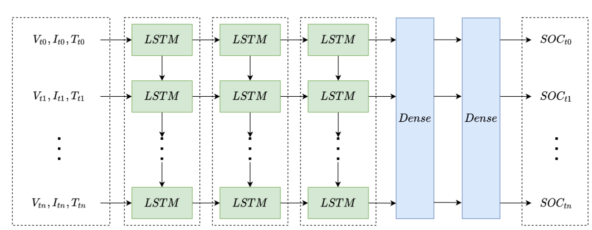


Figure 2: Architecture of the first model

The second model is used for the LG 18650HG2 Li-ion battery dataset. The model is composed of two LSTM layers followed by three dense layers. The number of cells of both LSTM layers is 256. Fig. 3 shows the architecture of the second proposed model. Since the second dataset contains more steps in one discharge cycle due to its higher sampling rate (0.1 seconds sampling time), the many-to-one approach is more appropriate. In this case, for each n step as input, one output is returned. In the implementation, we used 300, 500, and 700 as the number of steps. For example, given input steps $[Input_{t0}, Input_{t1}, ...Input_{t500}]$, the model should estimate the SOC value at step 500.

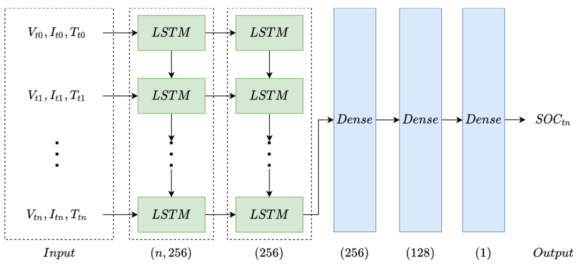


Figure 3: Architecture of the second model

3.4 Data Normalization

Since the input features have different ranges, such as the temperature has much higher values than voltage and current, the trained model could give more importance to this feature over the others due to its larger value. To avoid this problem, the minimum-maximum normalization method is used to scale all input features into the same common scale.

3.5 Model Training

The proposed models are implemented by using the Keras library [6]. The Adam algorithm [15] is chosen as the optimizer to update the network weights and biases with the learning rate configured as 0.00001. All proposed models are trained for 1000 epochs, but the training process would stop earlier if there is no further improvement of validation loss within 50 epochs. The Huber loss [13] is used as the loss function. Its peculiarity is that it can be quadratic or linear depending on the error value.

4 RESULTS AND DISCUSSION

The proposed deep LSTM models are trained and tested using the two aforementioned datasets. The model performance against each dataset is discussed in this section. The source code of the model implementation and results are available here[2].

Root Mean Square Error (RMSE) and Mean absolute error (MAE) are used to evaluate the proposed models. The Mean Square Error (MSE) is the sum of squared distances between the target and predicted variables divided by the number of samples. The RMSE is the square root of the MSE which scales the output value to the same scale as MAE. It is more sensitive to outliers as it penalizes the model by squaring the error. The MAE on the other hand is more robust to outliers as the error is not squared. MAE is an L1 loss

[2]https://github.com/KeiLongW/battery-state-estimation

Table 2: UNIBO dataset tests performance

Test type	Nominal capacity	MAE	RMSE
Standard	4.0Ah	2.68%	3.42%
	3.0Ah	0.52%	0.73%
	2.85Ah	0.31%	0.39%
	2.0Ah	0.59%	0.80%
High current	3.0Ah	0.46%	0.61%
	2.85Ah	2.13%	3.24%
Preconditioned	3.0Ah	0.47%	0.66%

function that calculates the sum of the absolute difference between the target and predicted variables. The MAE is more suitable for problems where the training data present outliers.

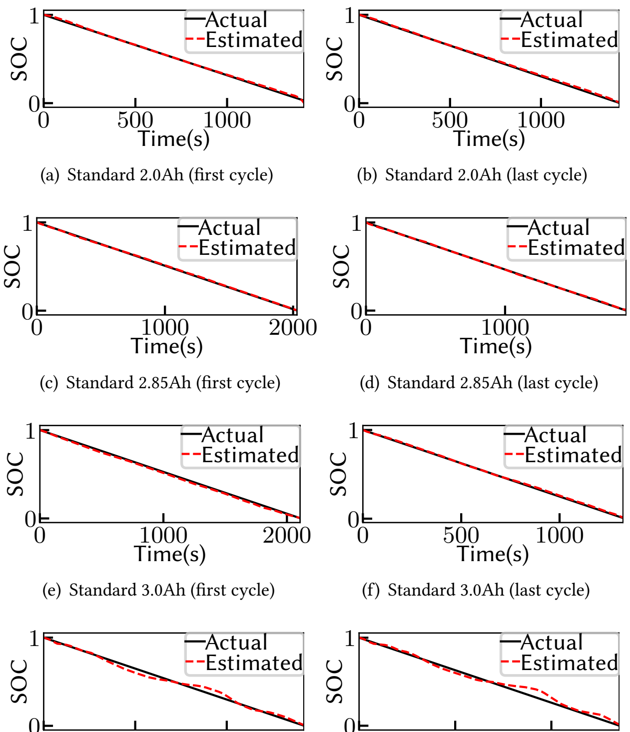
4.1 UNIBO Powertools Dataset

In the UNIBO dataset tests, the performance of the proposed model is evaluated over constant current discharge. The proposed model for this dataset was trained with a total of 7738 discharging cycles as the training set. One cell for each group of test types (standard, high current, pre-conditioned) and nominal capacity was extracted as testing data for evaluation purposes. The testing data is isolated from training data so that it is unseen during the training process. The overall MAE and RMSE on all testing data are 0.69% and 1.34% respectively.

To further investigate the performance of the proposed model, Table 2 shows the performance of each test type. The evaluation of standard test type with 4.0Ah nominal capacity and high current test type with 2.85Ah nominal capacity has the worst performance. This is expected as the dataset contains only two cell tests of the kind, resulting in one cell used for training and one for testing. Whereas, in the other test types with sufficient data the model can achieve accurate results with RMSE lower than 1%.

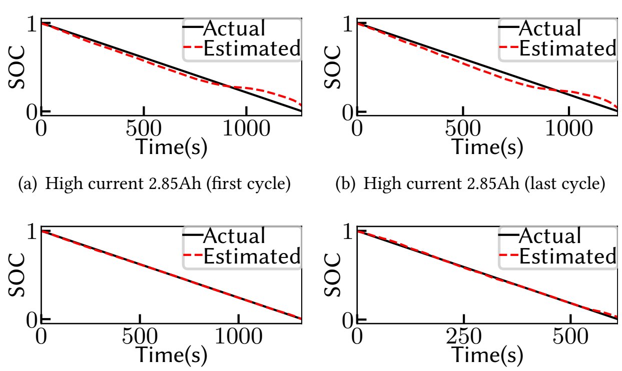
The examples of SOC estimation results of the proposed model on the standard, high current, and preconditioned test types are shown in Fig. 4, Fig. 5, and Fig. 6 respectively. The first and the last discharge cycles within the entire test of each battery cell are presented to demonstrate the SOC estimation performance under different health statuses. All results show the discharge process of SOC being discharged from 100% to 0%. The x-axis represents the discharge steps over the whole discharging cycle and the y-axis represents the SOC value at each step. The black line is the actual observed SOC value during the discharge process and the red dashed line is the SOC value estimated by the proposed model.

The model estimates the SOC of the 3.0Ah nominal capacity cells correctly and without large fluctuation in each of the three test types. Furthermore, the estimations of standard test types with 2.0Ah and 2.85Ah nominal capacity are accurate too. SOC in both the first and last cycle are estimated accurately which suggests that the proposed model is capable to estimate SOC under different battery health statuses. In addition, good performance is achieved from the preconditioned test type which demonstrates that the storage temperature before testing does not affect the battery discharging behavior significantly in terms of SOC estimation. On the other hand, there are some errors during the ending steps of standard 4.0Ah nominal capacity and high current 2.85Ah nominal capacity battery cell cycles. It is acceptable as there is only one training example of that kind of setup.



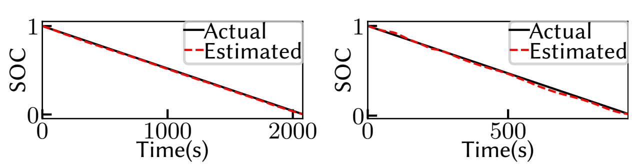
(a) Standard 2.0Ah (first cycle)
(b) Standard 2.0Ah (last cycle)
(c) Standard 2.85Ah (first cycle)
(d) Standard 2.85Ah (last cycle)
(e) Standard 3.0Ah (first cycle)
(f) Standard 3.0Ah (last cycle)
(g) Standard 4.0Ah (first cycle)
(h) Standard 4.0Ah (last cycle)

Figure 4: UNIBO dataset SOC estimation results (standard)



(a) High current 2.85Ah (first cycle)
(b) High current 2.85Ah (last cycle)
(c) High current 3.0Ah (first cycle)
(d) High current 3.0Ah (last cycle)

Figure 5: UNIBO dataset SOC estimation results (high current)



(a) Preconditioned 3.0Ah (first cycle)
(b) Preconditioned 3.0Ah (last cycle)

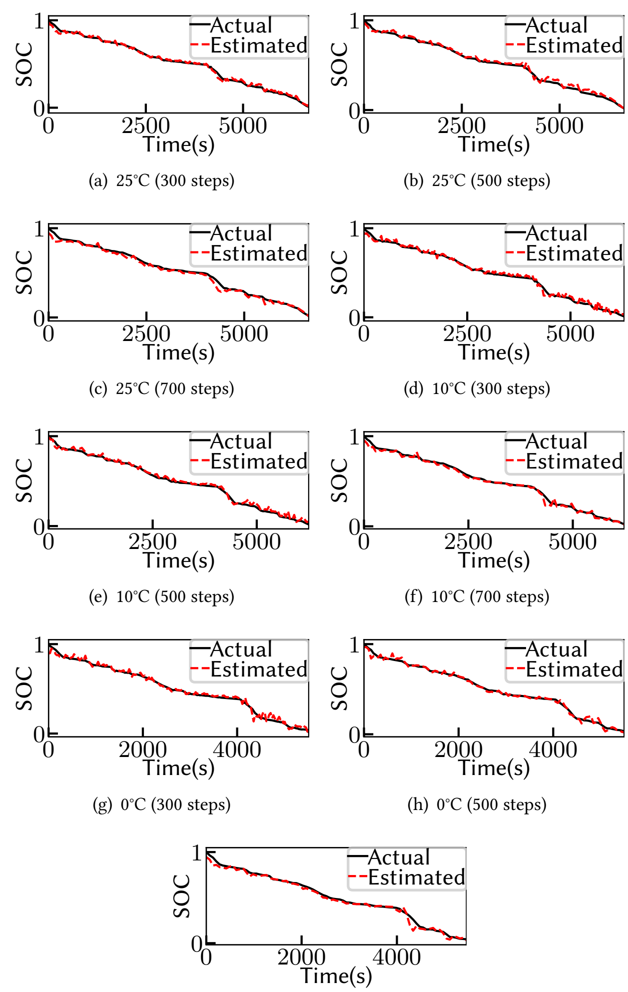
Figure 6: UNIBO dataset SOC estimation results (preconditioned)

Table 3: LG 18650HG2 data tests performance

Temp. (°C)	300 Steps		500 Steps		700 Steps	
	MAE	RMSE	MAE	RMSE	MAE	RMSE
0	1.69%	2.27%	**1.47%**	**2.23%**	1.65%	2.60%
10	1.61%	2.12%	**1.57%**	**2.12%**	2.22%	2.89%
25	**1.17%**	**1.57%**	1.59%	2.02%	1.92%	2.64%

4.2 LG 18650HG2 Li-ion Battery Data

In the LG 18650HG2 Li-ion battery dataset, the performance of the proposed model under dynamic discharge current is evaluated. Six mixed driving cycles for each of three different temperatures 0°C, 10°C, and 25°C were used as training set. We have also tested three different time series lengths, with a number of steps of 300, 500, and 700, which are approximately equal to 30 seconds, 50 seconds, and 70 seconds depth in time respectively. The test set was composed of a UDDS, an LA92, and a US06 driving cycle plus one mixed driving cycle for each of the three different temperatures available in the dataset.



(a) 25°C (300 steps)
(b) 25°C (500 steps)
(c) 25°C (700 steps)
(d) 10°C (300 steps)
(e) 10°C (500 steps)
(f) 10°C (700 steps)
(g) 0°C (300 steps)
(h) 0°C (500 steps)
(i) 0°C (700 steps)

Figure 7: LG 18650HG data SOC estimation results (mixed cycles)

The MAE and RMSE achieved by the 300 steps model are 1.47% and 1.99%. The 500 steps one reached an MAE and RMSE of 1.54% and 2.12%. The 700 steps model achieved 1.94% MAE and 2.72% RMSE. All the aforementioned results were tested with testing data under all temperatures. The model performance under each temperature with different input lengths is listed in Table 3. Among all the configurations, the best performance is achieved from testing data under 25°C temperature with 300 steps in input, which demonstrates that the battery operates most stably under room temperature. The model is able to learn the battery behavior under room temperature through the provided driving cycles without the need for a long history. While, under 10°C and 0°C temperatures, better performance is gained from the 500 input model. This indicates that increasing input steps could help to improve the estimation result under temperatures that are lower than room temperature. However, the worst results are from the 700 input steps which suggest that the increment of input steps must be selected carefully for the many-to-one approach as an inappropriate increment of input steps could result in performance degradation. The SOC estimation results on the mixed driving cycles under 0°C, 10°C and 25°C temperatures are displayed in Fig. 7. The estimation results under the three temperatures are competitive and without significant errors. Still, errors can be seen from the ending steps in mixed cycles under 0°C temperature due to their more dynamic discharge pattern.

5 FINAL REMARKS

In this paper, a deep LSTM NN is proposed to estimate SOC over two different Li-ion battery datasets. Discharge cycles with both constant and dynamic current under various ambient temperatures are used to train and test the proposed models. The evaluation results show that the proposed models can learn the battery dynamic behavior during discharge. Battery SOC can be estimated accurately by using the measured voltage, current, and temperature values, with 1.34% and 1.99% RMSE in constant current and dynamic current discharge cycle respectively. We have also shown how the proposed estimation is robust w.r.t. different State of Health statuses. The SOH is another important parameter for battery management. As future work, we suggest using deep LSTM networks for SOH estimation as we believe it can be effective as well.

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