

Deep Learning Based SoH Estimation of Lithium-ion Batteries

György Károlyi

Department of Electrical Engineering and Information Systems
University of Pannonia, Veszprém, Hungary
e-mail: karolyi.gyorgy@virt.uni-pannon.hu

Attila Göllei, Attila Magyar*

Department of Electrical Engineering and Information Systems
University of Pannonia, Veszprém, Hungary
e-mail: {gollei.attila; magyar.attila}@virt.uni-pannon.hu

ABSTRACT

An artificial intelligence-based approach of estimating remaining useful life for Li-ion batteries has been used in this work, where two different recursive neural networks were set up, trained and investigated for two different scenarios.

The investigated battery type is the widely used 18650 battery class. The training and prediction of both networks are performed on a publicly available high-quality dataset that serves as a base for several related research works. The batteries are charged/discharged until they reach their end of life by means of capacity degradation. The charge and discharge were performed under different charging current/load profiles.

Out of the available data-driven methods, LSTM (long-short term memory) and GRU (Gated Recurrent Unit) neural networks are the most promising candidate since they are capable of the handling of long-term processes, such as battery aging.

The two networks are parameterized, trained and tested for two different scenarios.

KEYWORDS

energy storage, Li-ion battery, remaining useful life, recursive neural network, prediction

INTRODUCTION

Battery aging is associated with how long it has been used since the production. The aging is originated from two different types of usage: storage and dynamic usage. Calendar aging describes the aging process caused by the storage of the battery. Lithium ion batteries irreversibly lose their capacity over time because of the electrochemical reactions on the electrodes. Capacity fading and the increasing internal resistance are the most conspicuous signs of battery aging [1] [2]. The degradation of the battery caused by the charging and discharging is known as cycle aging. The cycle aging is related to the utilization of the battery. The utilization mode depends on the different application areas which have different charging/discharging profiles.

There are several factors which affects the battery aging. The most important ones are the depth of discharge, current rate, charging/discharging voltage, resting time between cycles and temperature [3] [4]. These properties all contribute to the aging of the battery. They are usually examined in pairs when someone wants to develop a cycle life model.

* Corresponding author

Though the change of capacity and internal resistance are the two main symptoms of the battery aging, some papers concentrate only on the capacity fading when developing cycle life models. For example in [5] a capacity model is created which can be used to estimate the cycle life of the battery, or in [6] a capacity degradation model of lithium ion batteries was developed to predict remaining useful life. The battery capacity was estimated by nonlinear least-squares regression.

In [7] the aging of the battery is analysed under different conditions. During the experiments the dependence of the internal resistance and the capacity on the cycle number is examined. The capacity fading and the internal resistance are not independent of each other. In [8] the correlation between these two quantities was analysed during calendar and cycle life. For a more thorough literature review, see [9].

The aim of the present work is to develop an artificial intelligence-based method for the Remaining useful life estimation of Li-ion batteries. The structure of the paper is as follows. The necessary tools and information need for the understanding of the rest of the paper is summarized in Basic notions. Afterwards, the applied methodology is presented in detail. The list of abbreviations used in the paper is given in 3. Table.

BASIC NOTIONS

The most important notions used in the paper are introduced in this section.

Lithium-ion batteries

Lithium-ion batteries are used around the world and though over the last few years they have had some competitor, such as sodium and magnesium, the Li-ion batteries continue to be indispensable due to their high density and capacity. The main problem is that this metal lithium has major availability and concentration problems in the planet. Almost 85% of its reserves are in what is known as the Lithium Triangle, a geographical area in South of America found on the borders of Argentina, Bolivia and Chile. In addition, it seems that demand will rocket over the next few decades because of the implementation of electric vehicles. Each car contains about more than 7,000 cell phone batteries, so reusing their different components has become an issue of utmost importance.

18650 lithium-ion batteries are charged up to 4.2V and down to between 2V and 3V depending on the cell's specification for cut-off voltage. Exceeded this limitation batteries can damage and become unusable, can be dumped. That's why to be sure, never discharge lower than 3.0V unless you know your cell's specification. Discharging occurs anytime you use the battery for power. The electricity is drawn from your device, and the battery discharges current. It is important to use battery testing equipment to discharge a battery as well. To charge an 18650, should be used a special charger for lithium-ion cells.

Cycle life is determined by the difference in capacity of your cell taken from its first-use rating to its present rating. For example, if your cell started at 3000mAh, but now only has 2700mAh. 2700 mAh is 90% of the original capacity.

When this percentage reaches 80%, we say the cycle lifetime of the battery has ended. Despite this we may use for a few thousand more cycles out this battery.

Most modern 18650 batteries have a typical cycle life of 300 - 500 (charge, discharge cycles). When we use them in high-amp or high-drain situations, this can decrease substantially to 200 cycles. If you go over the maximum discharge current limit (in A) you can decrease the cycle

life all the way down to 50 cycles. In optimal conditions, your cells may achieve more than 500 cycles.

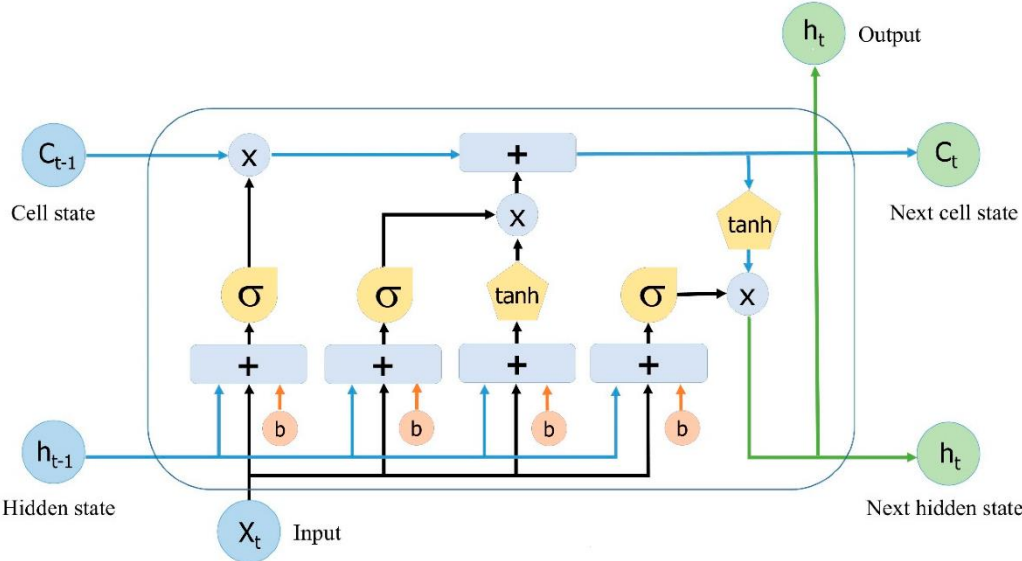
The main advantage of Li-ion batteries that they are not sensitive to the charging-discharging procedure regarding to the cut off the process. Especially the Ni-Cd and Ni-Mh batteries can be damaged or its capacitance hard decreases when this process has been interrupted frequently.

Recurrent Neural Networks

Long Short Term Memory

LSTM is a special kind of recurrent neural networks (RNN). The simple RNN suffers from a problem that is called short-term memory. It means, if a sequence is too long it is quite difficult carrying information from earlier cycles. During back-propagation, the RNN shows another problem called vanishing gradient, which means, the gradient decreases as it back propagates through the learning phase. If the mentioned gradient value gets exceedingly small, the actual layer stops learning.

LSTM RNN was created to solve short-term memory problem; its network architecture can be observed in the 1. Figure. The differences between the LSTM RNN and the simple RNN are the operations inside the LSTM cells. Typical LSTM network is comprised of memory blocks also known as cells. It has internal mechanisms called gates that are able to regulate the information flow.



1. Figure Network architecture of the LSTM RNN [10]

The cell state transfers the useful and relevant information through the sequence chain, as it acts like the memory of the network. During the operation the cell state and the hidden state are being transferred to the next cell. The main chain of data flow is the cell state [10]. As the cell state goes to the next step of the sequence, information is deleted or added via gates. Gates are independent neural networks and are able to learn what information is necessary to store or forget during the training [11]. These gates contain a sigmoid activation function that show return value in range 0 to 1.

The first step in constructing the network is to identify what information is not required. A sigmoid layer called forget gate is responsible for that. It takes the current input x_t , and the hidden layer at the previous moment h_{t-1} . For each state value of the internal state, forget gate returns a number between 0 and 1. 0 represents discarding the value, 1 represents keeping the state value.

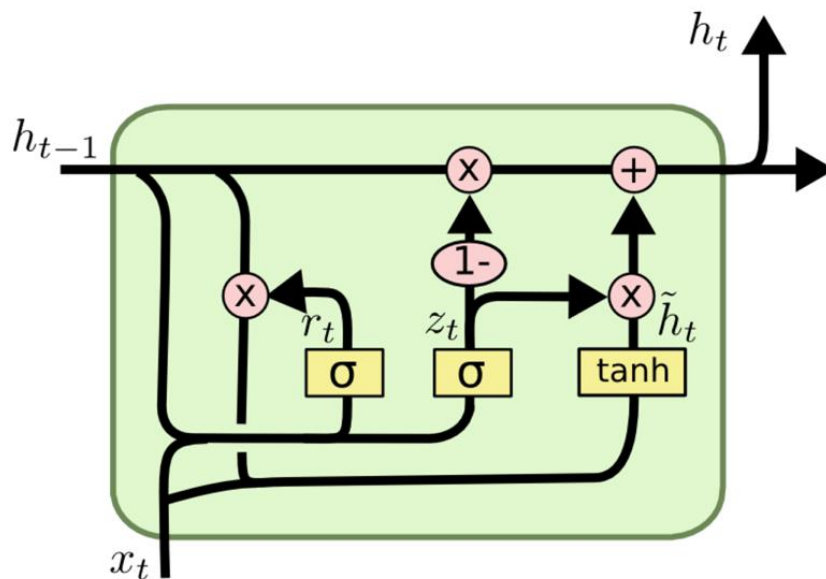
Input gate performs the next step that is choosing what new information is essential to store. The input gate consists of two part. A sigmoid, and a tanh layer. The previous hidden state and the current input are passed to the sigmoid function, that transforms them to be between 0 and 1, indicating the importance of the new information. The tanh function also gets the current state and the previous hidden state to help regulate the network. Finally, the sigmoid decides what information is important to keep from the output of tanh [11].

Now the LSTM have enough information to update the cell state. The cell state from $t-1$ moment gets multiplied by the output of the forget gate. Some value of the cell state can be removed. Then the output of the input gate does a pointwise addition and so updates the cell state. Now the LSTM has a new, updated cell state.

The last gate is the output gate. Its role is to determine the hidden state. Output gate has a sigmoid, and a tanh function similarly to the input gate. The previous hidden state and current input are passed to the sigmoid layer, and the new cell state to the tanh layer. Lastly, the outputs of the two activation functions are multiplied shaping the information of the new hidden state.

Gated Recurrent Unit

Gated Recurrent Unit (GRU) shares a several common attribute with the previously introduced Long Short-Term Memory. GRU is a newer generation of the recurrent neural networks. The main difference compared to the LSTM is GRU uses the hidden state for transferring the information through the sequence. It means, the hidden state stores all the required data to pass.



2. Figure Architecture of the GRU RNN [11]

Another important difference is the Gate Recurrent Unit network has less, only two gates. The update gate is something like the forget and the input gate of the LSTM model. It is responsible deciding which information is important to keep for further training: what information to throw away and what new information to add [11]. The second one is the so-called reset gate. Its task to determine how much of the past information to forget. The mechanism of the GRU has fewer tensor operation, thus it can be faster to train comparing to the LSTM.

METHODOLOGY

Measurement

The measurement data is originated from the freely available NASA dataset [10] where a set of four Li-ion batteries were run through three different operational profiles (charge, discharge and impedance) at room temperature. Charging was carried out in a constant current (CC) mode at 1.5A until the battery voltage reached 4.2V and then continued in a constant voltage (CV) mode until the charge current dropped to 20mA. Discharge was carried out at a constant current (CC) level of 2A until the battery voltage fell to 2.7V, 2.5V, 2.2V and 2.5V for batteries 5 6 7 and 18 respectively. Impedance measurement was carried out through an electrochemical impedance spectroscopy (EIS) frequency sweep from 0.1Hz to 5kHz. Repeated charge and discharge cycles result in accelerated aging of the batteries while impedance measurements provide insight into the internal battery parameters that change as aging progresses. The experiments were stopped when the batteries reached end-of-life (EOL) criteria, which was a 30 % fade in rated capacity (from 2Ahr to 1.4Ahr). This dataset can be used for the prediction of both remaining charge (for a given discharge cycle) and remaining useful life (RUL).

Data pre-processing

The measured data for several kind of Lithium-ion batteries are publicly available. They are stored in an array of structures in different MATLAB databases that are containing charge, discharge and impedance operations. In the aspect of this writing the most important data is the capacity which is stored in the discharge fields. Reaching the mention data set a MATLAB script was implemented to select the essential data to create a training set for teaching the neural network, then split them in to training and test sets. The training set is the 66,7 % of the whole sequence.

The training set needs further modification for the better learning rate. The sequence of the capacity values should be separated into input and output values. The so called look back means the neural network looks at the previous n values to predict the next one in the time series. If the look back is set to 3, the program uses the first three elements of any subset of the whole training set to predict the fourth one.

RNN setup and training

Various optimizer methods were tried for training the neural networks. For this data sequence the RMSprop showed the most acceptable solution. To measure the deviation Root Mean Square Error (RMSE) was calculated.

For accurate comparison both RNN had the same structure. It means they were examined in numerous variations and the two constructions shared the same parameters in each case. The neural networks had one LSTM or GRU layer, with the different number of neurons.

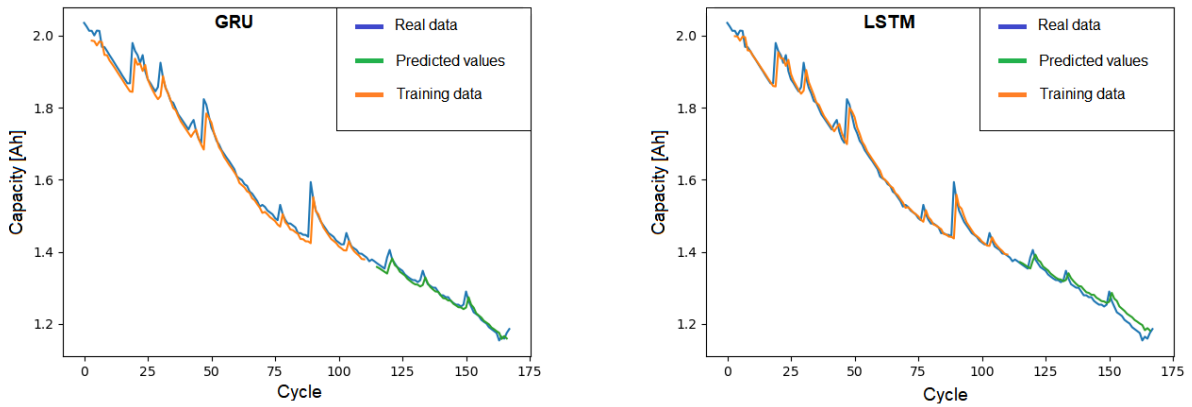
Two experiments have been performed with both LSTM and GRU networks in order to see the differences in the performance of the two different RNNs. One with a relatively low number of epochs and another with a higher number of epochs. 1. Table summarizes the experiment setup for the two different case.

1. Table Network parameters of the experimental comparison

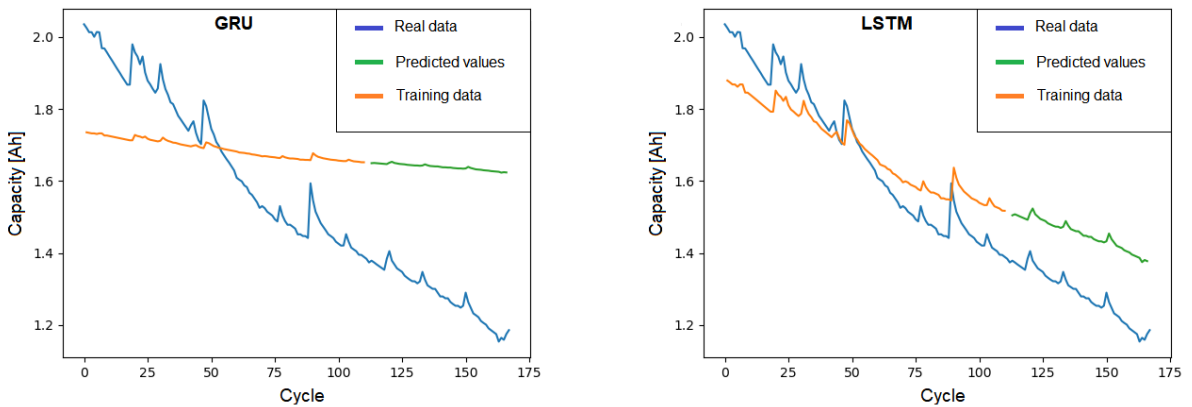
	Experiment 1	Experiment 2
epoch	500	10
number of neurons	10	3
look back	3	1
optimizer	RMSprop	adam

DISCUSSION OF THE RESULTS

The introduced tests would like to point on the advantages of both recurrent neural networks. As it can be seen on the pictures, the GRU can reach better accuracy but it needs more epoch to learn. Using higher number of neurons in the hidden layer can increase its efficiency as well. GRU networks requires more time to learn. The comparison of the two RNN based prediction for Experiment 1 (i.e. using higher number of epochs) is presented in 3. Figure.



3. Figure Comparison of LSTM and GRU based prediction in higher number of epochs (Experiment 1)



4. Figure Comparison of LSTM and GRU based prediction in lower number of epochs (Experiment 2)

2. Table Numerical comparison of the results for the two experiments by means of RMSE

	Experiment 1		Experiment 2	
	Train Score	Test Score	Train Score	Test Score
LSTM	0.03	0.02	0.09	0.17
GRU	0.03	0.01	0.17	0.36

LSTM is able to learn faster than the GRU. It is distinct in Experiment 2 (4. Figure) LSTM provides better results during the training, and in the test section. The Root mean square error of the LSTM are significantly less than that of GRU.

CONCLUSION

A data-driven approach of estimating remaining useful life for Li-ion batteries has been used in this work, where two different RNN solutions, LSTM and GRU were set up, trained and investigated for two different scenarios. The training and prediction of both networks are performed on a publicly available dataset that serves as a base for several related research works. The results clearly show that although LSTM learns faster, in case of a slower process (e.g. like battery charge-discharge) where a higher epoch number is acceptable, GRU outperforms LSTM in the prediction phase. In other words, it can be used as a basis of a reliable data-driven RUL predictor in any battery management system (BMS).

Further research directions include the inclusion of battery temperature measurements in the method. The cause is twofold. On one hand, battery temperature has a high influence on the aging process, i.e. knowing the actual (and historical) thermal circumstances makes it possible to perform a more precise prediction. On the other hand, all BMS includes an online temperature monitoring so it is expectable to have such onboard measurement data in a real-life situation in an electric vehicle.

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of Sciences. Attila Magyar was supported by the ÚNKP-19-4 new national excellence program of the Ministry for Innovation and Technology.

NOMENCLATURE

3. Table: List of abbreviations used in the paper

Abbreviation	Meaning
RUL	Remaining Useful Life
RNN	Recursive Neural Network
LSTM	Long-Short Term Memory
GRU	Gated Recursive Unit
BMS	Battery Management System

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