A deep long-short-term-memory neural network for lithium-ion battery prognostics

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Abstract

With the increasing challenges in energy storage, the importance of lithium-ion batteries reliability cannot be understated. The prediction of the battery exact time of failure can provide a cost-efficient maintenance plan. In this paper, we propose a novel data-driven approach based on deep long-short-term-memory neural networks LSTM for battery's remaining useful life (RUL) estimation. The suggested method uses the past battery capacity, the time to discharge and the operating temperature to directly predict the RUL. To validate the proposed model, we conduct experiments using the NASA lithium-ion battery dataset. The results show that our method produces exceptional performances for RUL prediction under different loading and operating conditions.

Keywords
Prognostics; Deep learning; Long-short-term-memory network; lithium-ion battery.

1. Introduction

Lithium-ion batteries are a core component in electric cars, unmanned aerial vehicles, power tools and personal devices (Walker, Rayman, and White 2015). Their increasingly widespread use is credited to their high energy density, their long cycle life, the absence of the memory effect, along with their lighter weight compared to other rechargeable batteries (Lu et al. 2013).
Recent studies suggest that lithium-ion batteries are prone to different failure modes from shelf discharge and thermal runaway to power and capacity fade (Arachchige, Perinpanayagam, and Jaras 2017). These issues are attributed to high operational temperature during usage or storage, overcharging, over-discharging, or an increasing number of charges/discharge cycles. Moreover, battery failure could lead to loss of operations, reduced performances, and even disasters (Widodo et al. 2011) (D. Zhou et al. 2017). Consequently, the reliability, availability, and safety of lithium-ion battery is of prominent importance.
A current approach to cope with the mentioned challenges is battery's prognostics and health management (PHM). Recent works intend to monitor the battery degradation process, assess its condition and predict the remaining useful life (RUL).This prediction can lead to an optimal mission or replacement interval planning.
There are mainly two approaches for lithium-ion battery PHM: physics of failure models and data-driven models. Complete knowledge of the non-linear dynamic electrochemical process governing the degradation is necessary for the physics of failure approach. This process is intractable, and the model parameters estimation may need complicated experiments and costly devices which reduce the use in practice (Liu et al. 2017).
On the other hand, by using run-to-failure sensors information combined with the corresponding operational and environmental conditions, artificial intelligence and statistical methods can capture the inherent relationship and trends between sensors values and the degradation state. This simplicity combined with the rising availability of sensors data sparked recent interests from the research community for data-driven lithium-ion batteries RUL estimation:(Wu, Fu, and Guan 2016) reviewed the data-driven approaches for vehicle lithium-ion batteries prognostics up until 2016,these works use methods ranging from relevance vector machine (RVM)(J. Zhou et al. 2013) ,and support vector regression (SVR)(Wang et al. 2014), to artificial neural networks(ANN)(Dong et al. 2012). Later works propose a gray model GM (1,1) (D. Zhou et al. 2017), a multi-kernel support vector machine (SVM) (Gao and Huang 2017), and a long-short-term-memory neural network (LSTM)(Zhang et al. 2017).

Nevertheless, there are several issues in most of these studies: first, the reliance on the construction of a health indicator (HI) can induce another source of generalisation error. Then, the forecasting of HI until its reach a failure threshold using one step or multi-step prediction can induce compounding errors. Finally, there's a lack of works that generalise the problem to different environmental and operational conditions.
Since 2012, deep learning models achieved significant breakthroughs in machine vision, voice recognition and games (LeCun, Bengio, and Hinton 2015). These achievements are attributed to the ability of deep neural networks to automatically learn proper representation directly from the raw data by stacking neural network layers.
As part of a generic prognostic framework (Hinchi and Tkiouat 2018), we propose a deep neural network model based on deep long-short-term-memory neural network (LSTM). The model uses the battery capacity, the discharge time and the operating temperature until the prediction time, and combined it with the prediction time and the condition for failure to automatically predict the remaining useful life RUL.
The rest of this paper is organised as follows: the deep neural network architecture is presented in details in section2. In section 3 we present the experimental validation. Then, conclusions are drawn in section 4.

2. The methodology

We define $rul_{t_i}^{(b)}$ the remaining useful life of the battery (b) at prediction time t_i, as the time until the battery's capacity had reduced to a predefined threshold $fin\text{-}cap^{(b)}$ .In this work, we model the function f that estimates the RUL of a battery given the past capacity series $cap_{t_{1:i}}^{(b)}$, the past discharge time series $discT_{t_{1:i}}^{(b)}$, the past operational temperature series $Temp_{t_{1:i}}^{(b)}$, the prediction time t_i and the threshold $fin\text{-}cap^{(b)}$:

$$\dot{rul}_{t_i}^{(b)} = f\left(cap_{t_{1:i}}^{(b)}, discT_{t_{1:i}}^{(b)}, Temp_{t_{1:i}}^{(b)}, t_i, fin\text{-}cap^{(b)}\right)$$

We model the function f using a deep neural network. By stacking an LSTM layer and several dense layers, the model can predict the RUL directly from the sensors and operational data. The following subsections describe the architecture and the overall training process.

2.1 The model architecture

Figure 1 shows the detailed architecture of our model.

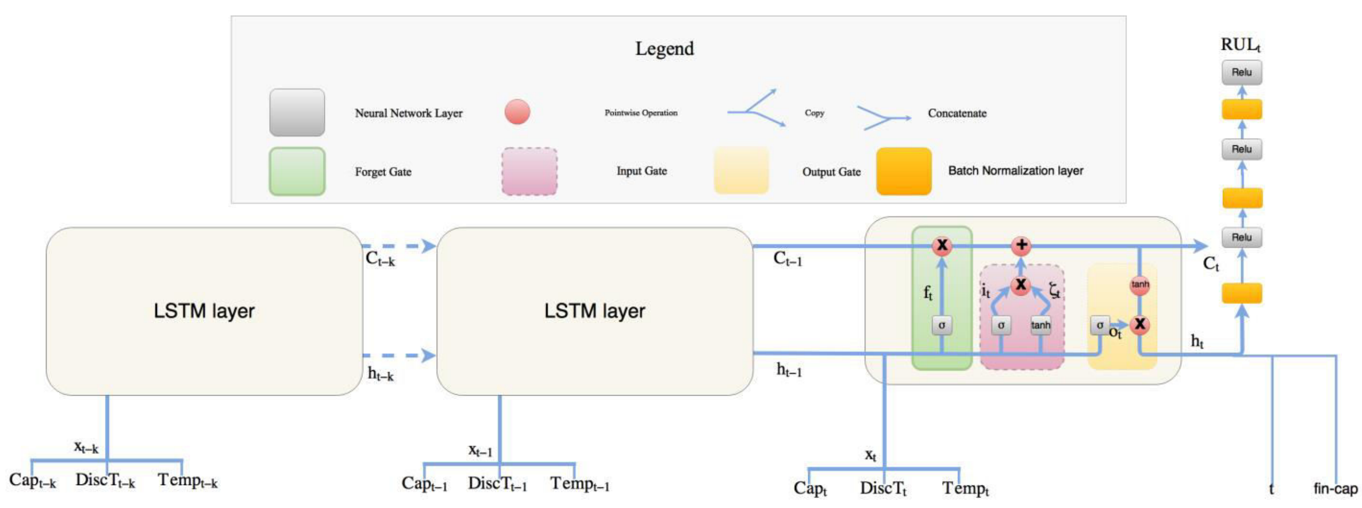

Figure 1. The architecture of the deep neural network

We take the combined capacity, discharge time and temperature vector sequence as an input layer; then the temporal degradation is represented by an LSTM layer.
Recurrent neural networks (RNNs) are a class of neural networks designed to model sequential and time series data. They are based on a recurrent connection where the hidden state at time t h_t is a function of the hidden state at time t-1 h_{t-1} and the input data at time t x_t :

$$h_t = \sigma\left(W\left[h_{t-1}, x_t\right] + b\right)$$

In practice, this simple form of RNN is rarely used as it displays an inability to learn long-term dependency.
The LSTM layer proposed by (Hochreiter and Schmidhuber 1997) solves this problem by offering a more complex internal state representation. The LSTM layer adds a cell state C_t to presents its long-term memory in addition to the hidden state h_t. The computation is then distributed into several gates executed sequentially: first, the forget gate determines the pieces of the long-term memory to continue remembering and the pieces to ignore using the new input:

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

Next, the input gate determines the information that should be extracted from the input:

$$\xi_t = \mathrm{Tanh}\left(W_\xi\left[h_{t-1}, x_t\right] + b_\xi\right)$$

$$i_t = \sigma\left(W_i\left[h_{t-1}, x_t\right] + b_i\right)$$

Finally the output gate update the cell state and the hidden state using the past and present information:

$$C_t = f_t C_{t-1} + i_t \xi_t$$

$$o_t = \sigma\left(W_o\left[h_{t-1}, x_t\right] + b_o\right)$$

$$h_t = o_t.\mathrm{Tanh}\left(C_t\right)$$

Where $(b_f, b_\xi, b_i, b_o, W_f, W_\xi, W_i, W_o)$ are the bias and the weight matrices, and σ is the sigmoid function.
Then, we concatenate the output of the hidden state with the prediction time and the threshold capacity. The next step is to stack the final three dense neural network layer and the corresponding batch normalisation (BN) layers (Ioffe and Szegedy 2015).The BN layer controls the input distribution across layers, consequently speeding up the training. Each dense layer is preceded by a BN layer and use a Relu(x) =max (0, x) activation function. For simplicity, we keep the same number of neurons across the hidden state of the LSTM layer, as well as the first and the second dense layer. The final layer is a neuron that predicts the RUL of the battery.

2.2 The training process

To train the model, we use the mean arctangent absolute percentage error (MAAPE) loss sfunction (Kim and Kim 2016). This function holds several advantages over the mean absolute percentage error (MAPE) function in measuring forecast accuracy; MAAPE is scale-independent, it does not produce infinite values near zero, and its range of values is limited which make the neural network training easier.

$$L = \frac{1}{N}\sum_{i=1}^{N} Arc\tan(\left|\frac{RUL_i - \hat{R}UL_i}{RUL_i}\right|)$$

We train the model to minimise the specified loss function using the backpropagation through time (BPTT) algorithm to compute the gradients of each mini-batch. Each mini-batch sample an input vector from every battery used in the training of our model. This training scheme avoids the bias inducted by batteries with a long lifetime. We use the Adadelta algorithm for optimisation (Zeiler 2012).

3. Experimental validation

We evaluate the proposed deep neural network using the battery dataset from NASA Prognostics Center of Excellence (PCoE) (Saha and Goebel 2007). In this dataset, The lithium-ion rechargeable batteries were run in batches of 4 through successive cycles of charge, discharge, and impedance at temperatures ranging from 4°C to 44°C. Charging was conducted in a constant current of 1.5A until the battery voltage reached 4.2V and then maintained in a constant voltage until the charge current dropped to 20mA.The discharge was carried at different current profiles until the battery reaches the end voltage.The experiments were terminated when the cells reached the threshold capacity.Table 1 shows the various experimental conditions of the different batteries. In the cases where the threshold capacity was not set, we took the last measured capacity as the threshold capacity.

Table 1. List of batteries and the corresponding loading and operational conditions.

Battery Identifier	**Discharge current(A)**	**End voltage (V)**	**Threshold capacity(Ahr)**	**Operating temperature (°C)**
Battery #5 Battery #6 Battery #7	2A 2A 2A	2.7V 2.5V 2.2V	1.4Ahr 1.4Ahr 1.4Ahr	24°C 24°C 24°C
Battery #25 Battery #26 Battery #27 Battery #28	A 0.05Hz square wave loading profile of 4A amplitude and 50% duty cycle	2.0V 2.2V 2.5V 2.7V		24°C 24°C 24°C 24°C
Battery #29 Battery #30 Battery #31 Battery #32	4A 4A 4A 4A	2.0V 2.2V 2.5V 2.7V		43°C 43°C 43°C 43°C
Battery #33 Battery #34 Battery #36	4A 4A 2A	2.0V 2.2V 2.7V	1.6Ahr 1.6Ahr 1.6Ahr	24°C 24°C 24°C
Battery #38 Battery #39 Battery #40	1A 2A 4A	2.2V 2.5V 2.7V	1.6Ahr 1.6Ahr 1.6Ahr	24°C and 44°C 24°C and 44°C 24°C and 44°C
Battery #42 Battery #43 Battery #44	Multiple fixed load current levels (4A and 1A)	2.2V 2.5V 2.7V	1.4Ahr 1.4Ahr 1.4Ahr	4°C 4°C 4°C
Battery #45 Battery #46 Battery #47 Battery #48	1A 1A 1A 1A	2V 2.2V 2.5V 2.7V	1.4Ahr 1.4Ahr 1.4Ahr 1.4Ahr	4°C 4°C 4°C 4°C
Battery #49 Battery #50 Battery #51 Battery #52	2A 2A 2A 2A	2V 2.2V 2.5V 2.7V	1.4Ahr 1.4Ahr 1.4Ahr 1.4Ahr	4°C 4°C 4°C 4°C
Battery #54 Battery #55 Battery #56	2A 2A 2A	2.2V 2.5V 2.7V	1.4Ahr 1.4Ahr 1.4Ahr	4°C 4°C 4°C

To benchmark our method, we use the same experimental framework employed by (Mosallam, Medjaher, and Zerhouni 2016) (i.e., the same dataset partition scheme, the same cost metric). The batteries are divided into a training and a testing set as shown in table 2.

Table 2.The training and testing dataset

Training dataset	Testing dataset
Battery #5	Battery #6
Battery #7	Battery #28
Battery #25	Battery #30
Battery #26	Battery #34
Battery #27	Battery #39
Battery #29	Battery #43
Battery #31	Battery #47
Battery #32	Battery #52
Battery #33	Battery #55
Battery #36	
Battery #38	
Battery #40	
Battery #42	
Battery #44	
Battery #45	
Battery #46	
Battery #48	
Battery #49	
Battery #50	
Battery #51	
Battery #54	
Battery #56	

The chosen metric is the mean absolute percentage error MAPE:

$$MAPE = \frac{1}{\mathrm{N}}\sum_{\mathrm{i}=1}^{\mathrm{N}}\left|\frac{\mathrm{RUL_i} - \hat{\mathrm{R}}\mathrm{UL_i}}{\mathrm{RUL_i}}\right|$$

The overall cost is the average MAPE:

$$MAPE_f = \frac{1}{\mathrm{N}}\sum_{\mathrm{i}=1}^{\mathrm{N}} MAPE_i$$

The model is implemented using the Keras library (Chollet 2017).The training and RUL prediction are run on an Ubuntu Linux machine with a Nvidia GTX 1070 GPU.
We set the parameters of the Adadelta optimiser to their default values. We train the model for 20000 epochs. The number of neuron in the output of the LSTM layer and the two dense layers is 18.
Table 3 presents the prediction results of the testing set. The prediction performance on all the tested batteries is satisfactory $(\min(\mathrm{MAPE}) < 5)$. Moreover, Figure 2 displays a plot of the predicted and real RUL for all cycles of the battery with the worst prediction performance (i.e., Battery #34). We can observe that the prediction is correct when the battery is close to its end of life.

Table 3.The batteries MAPE

Testing battery	MAPE
Battery #6	2.03
Battery #28	0.0
Battery #30	0.065
Battery #34	2.68
Battery #39	0.437

Battery #43	0.698
Battery #47	0.413
Battery #52	0.0
Battery #55	0.796

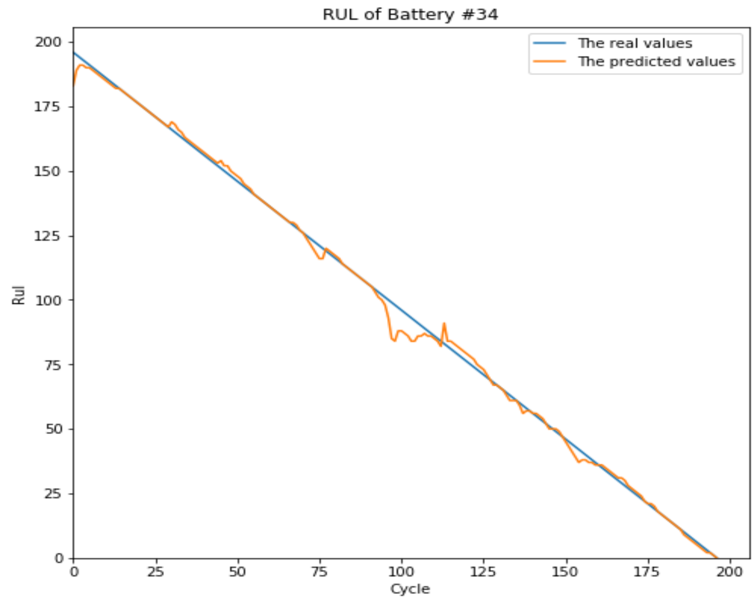

Figure 2. The Predicted RUL of Battery #34

Table 4 aggregates the results into the overall cost and compares it with the work of (Mosallam, Medjaher, and Zerhouni 2016). The significant discrepancy demonstrates the superiority of our approach.

Table 4.The model performance

$MAPE_f$ of our method	$MAPE_f$ of (Mosallam, Medjaher, and Zerhouni 2016)
0.7922%	26.3089%

3. Conclusion

In this work, we introduce an original deep neural network for lithium-ion battery prognostics based on LSTM layers. The proposed architecture demonstrates a clear performance advantage compared to the benchmark. Furthermore, the end-to-end nature eases the modelling process as no expert knowledge is involved.
However, in online applications, the capacity is difficult to measure.Moreover, in risk-sensitive applications uncertainty estimation is essential. Future works must extract features from the discharge voltage and the current directly without using the capacity and must provide calibrated uncertainty estimations.

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