Lithium-ion Battery Remaining Useful Life Prediction with Long Short-term Memory Recurrent Neural Network

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ABSTRACT

Lithium-ion batteries play critical roles in many electronic devices. It is necessary to develop a reliable and accurate remaining useful life (RUL) prediction approach to provide timely maintenance or replacement of battery systems. A novel RUL prediction approach based on Long Short-term Memory (LSTM) Recurrent Neural Network (RNN) is proposed in this paper. LSTM is able to capture long-term dependencies and model sequential data among the capacity degradation of lithium-ion batteries. The advantages of our proposed method include: 1) obtaining high prediction accuracy without accurate physics-based model or expertise and 2) decreasing the cumulation errors by multi-step ahead prediction each time, while traditional RUL method predicts one-step ahead once and then uses the current estimated value to predict next one, which causes cumulation errors increased. The Center for Advanced Life Cycle Engineering (CALCE) battery datasets are used to demonstrate the effectiveness of the proposed method. The results show that, compared with echo state networks (ESN), the proposed method has higher accuracy, more stable and reliable performance for lithium-ion batteries RUL prediction.

1. INTRODUCTION

Lithium-ion batteries have many advantages, such as high-energy density, long cycle life, high output voltage and low self-discharge rate. Lithium-ion batteries have been widely used in electric vehicles, consumer electronics, aviation, and aerospace technologies. As a result, battery degradation, prognostics and remaining useful life (RUL) estimation, have attracted much attention of researchers in the fields of energy, reliability engineering, and aerospace engineering (Liu, D., Xie, W., Liao, H., & Peng, Y., 2015).

The prediction approaches for lithium-ion battery RUL can be classified into two typical categories: model-based and data-driven (Liu et al., 2015). Model-based approaches can well reflect the physical and electrochemical properties of batteries, but they are difficult to obtain. Data-driven approaches have become a popular method for its flexibility and easy operation. There are many data-driven methods to model lithium-ion battery degradation and to predict the RUL of lithium-ion batteries like artificial neural networks (ANNs) (Yang, W. A., Xiao, M., Zhou, W., Guo, Y., & Liao, W., 2016), relevance vector machine (RVM) (Li, H., Pan, D., & Chen, C. P., 2014), particle filter (PF) (Miao Q., Xie L., Cui H., Liang, W. & Pecht M., 2013), or some hybrid prognostic approaches (Hu, C., Youn, B. D., Wang, P., & Yoon, J. T., 2012; Dong H., Jin X., Lou Y. & Wang C., 2014).

Existing prognostics methods have already made great achievements in lithium-ion battery RUL prediction. However, due to the diversity and complexity of lithium-ion batteries, existing methods show some limitations: (1) most methods rely heavily on accurate physics-based model; (2) the prediction performance should be further improved; (3) some methods like ANNs do not consider the sequential nature behind data, i.e., do not consider the order of the data.

The long short-term memory (LSTM) Recurrent Neural Network (RNN), which is a deep learning neural network, is able to remember information for long periods of time. Yuan, M., Wu, Y., and Lin, L. (2016) proposed an accurate fault location and RUL estimation method based on LSTM RNN model for aero engine. Zhao, R., Yan, R., Wang, J., and Mao, K. (2017) presented LSTM RNN to predict the actual tool wear, experiment results showed that the standard LSTM outperformed several state-of-the-art baseline methods like Linear Regression (LR), Support Vector Regression (SVR), Multi-layer neural network (MLP), and basic RNN. The capacity degradation data, which can cover thousands of charge/discharge cycles and represent the degradation evolution of batteries, can be regarded as long-term time series data. In this paper, LSTM RNN is firstly used to learn the long-term dependency of the degradation data of capacities and trained from several batteries data by cross-validation, and then the trained LSTM RNN is used to predict the RUL of lithium-ion batteries with its ability of accessing the previous context of each specific time step.

The rest of this paper is organized as follows: Section 2 briefly introduces related works of RNN and LSTM-RNN. Section 3 describes the LSTM-RNN-based RUL prediction method. In Section 4, CALCE battery datasets are used to demonstrate the effectiveness of the proposed method. Conclusions are drawn in Section 5.

2. RELATED WORKS

2.1. Recurrent Neural Networks

Recurrent Neural Networks (RNNs) were proposed for sequence data (Graves, A., Mohamed, A. R., & Hinton, G., 2013). RNNs build connections between units from a directed cycle. The basic RNNs diagram is showed in Figure 1.

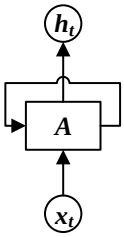

Figure 1. The basic RNNs diagram.

In Figure 1, A is a chunk of neural network, inputs x_t and outputs a value h_t. A loop allows information to be passed from one step of the network to the next.

RNN is able to map target vectors from the entire history of previous inputs, while the basic neural network can only map from input data to target vectors. However, the vanishing gradient problem hinders the performance of RNN (Zhao, et al., 2017). Therefore, LSTMs were presented to prevent the vanishing gradient problem.

2.2. Long Short-Term Memory Networks

Long Short-Term Memory networks – usually just called "LSTMs" – are a kind of special RNN, capable of learning long-term dependencies. They were introduced by Hochreiter & Schmidhuber (1997), and were refined and popularized by many people in following work (Nair et al., 2010). They work tremendously well on a large variety of problems, and are now widely used.

The key to LSTMs is the cell state. The cell state is kind of like a conveyor belt. It runs straight down the entire chain, with only some minor linear interactions. It's very easy for information to flow along it and remain unchanged.

The LSTM is able to remove or add information to the cell state by structures called gates. Gates are a way to optionally let information through. They are composed out of a sigmoid neural net layer and a pointwise multiplication operation. A LSTM has three of these gates (forget gate, input gate, output gate), to protect and control the cell state. The LSTM diagram is shown in Figure 2.

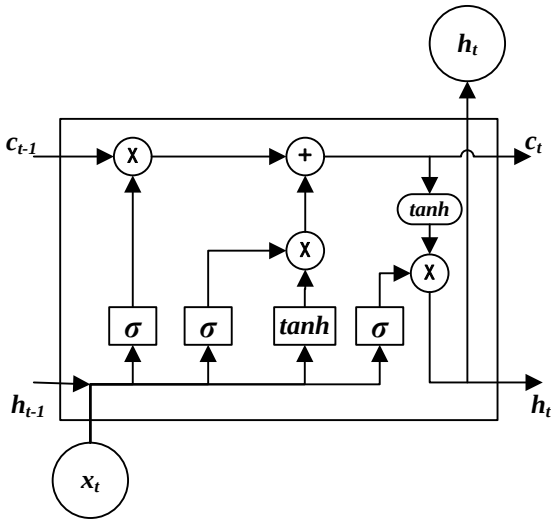

Figure 2. The diagram of LSTM.

Here, c_t is the cell state of time t, c_{t-1} is the cell state of time $t-1$, σ is the gate. Forget gates were introduced in LSTMs to avoid the long-term dependency problem. These adopted forget gates are able to control the utilization of information in the cell states. Considering that LSTMs are able to capture long-range dependencies and nonlinear dynamics in time series data, LSTMs have been successfully applied in various applications, including speech recognition (Graves, et al., 2013), natural language processing (Wang, S., & Jiang, J., 2015), and image captioning (You, Q., Jin, H., Wang, Z., Fang, C., & Luo, J., 2016) etc.

3. LSTM BASED RUL PREDICTION METHOD FOR LITHIUM-ION BATTERIES

It is essential to propose a robust prognostic solution that accurately predicts the RUL using data features extracted from battery degradation signals. For building such a RUL prediction framework, this paper proposes (i) a LSTM model constructing method which is trained by several batteries degradation data, and (ii) k-fold cross validation (CV) to evaluate the error metric associated with a candidate LSTM model. This section is organized as follows. Section 3.1 describes the overall procedure of the proposed approach. Section 3.2 presents the LSTM model for the RUL prediction. Section 3.3 describes the background of the k-fold CV and how it can be applied for estimating the accuracy of a LSTM model.

3.1. Overall procedure

The overall procedure of the proposed approach is composed of the offline process and online process. In the offline process, the offline training/testing process with the three-fold CV is employed to get the best model. The online prediction process conducts the RUL predictions using the best model obtained from the offline process. The prediction diagram is showed in Figure 3.

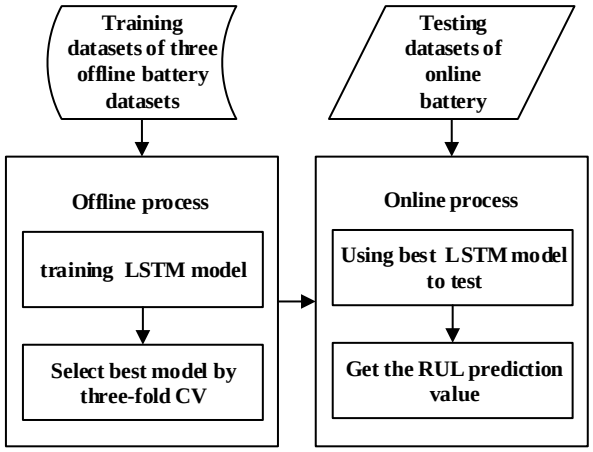

Figure 3. The lithium-ion battery RUL prediction diagram using LSTM.

The detailed procedures of the proposed prognostics approach are as follows:

STEP 1: Obtain the lithium-ion battery capacity degradation dataset regarding with charge/discharge cycle from 3 offline battery units, which are used as training datasets, and normalize the datasets to [0, 1].

STEP 2: Perform the offline training and testing processes with the three-fold CV with the training datasets.

STEP 3: Get the best model from the offline datasets.

STEP 4: Acquire testing datasets from online system.

STEP 5: Predict the online RULs of lithium-ion battery using the best model obtained from the offline training process.

3.2. LSTM model Construction

The core idea behind LSTMs lies in that at each time step, a few gates are used to control the passing of information along the sequences that can capture long-range dependencies more accurately. In LSTM, at each time step *t*, hidden state $h^{(t)}$ is updated by current data at the same time step $x^{(t)}$, the hidden state at the previous time step $h^{(t-1)}$, the input gate $i^{(t)}$ and input node $g^{(t)}$, the forget gate $f^{(t)}$, the output gate $o^{(t)}$ and a memory cell $c^{(t)}$. The following updating equations are given as follows:

$$\begin{aligned} f^{(t)} &= \sigma\left(W^{fX}x^{(t)} + W^{fh}h^{(t-1)} + b_f\right) \\ i^{(t)} &= \sigma\left(W^{iX}x^{(t)} + W^{ih}h^{(t-1)} + b_i\right) \\ g^{(t)} &= \tanh\left(W^{gX}x^{(t)} + W^{gh}h^{(t-1)} + b_g\right) \\ c^{(t)} &= g^{(t)} * i^{(t)} + c^{(t-1)} * f^{(t)} \\ o^{(t)} &= \sigma\left(W^{oX}x^{(t)} + W^{oh}h^{(t-1)} + b_o\right) \\ h^{(t)} &= \tanh\left(c^{(t)}\right) * o^{(t)} \end{aligned} \quad (1)$$

where *W* and *b* represent the layer weights and biases, respectively. σ is the sigmoid activation function.

Dropout was introduced during model training (Hinton et al., 2012). Via dropout, parts of the hidden outputs are randomly masked so that these neurons will not influence the forward propagation during training procedures. When it comes to testing phases, the dropout will be turned off, and the outputs of all hidden neurons will have effects on model testing. In our models, we adopt one dropout layer between LSTM models and the first fully-connected layer, and another dropout layer between the first fully-connected layer and the second fully-connected layer. Their masking probabilities are both set to 1.

Firstly, the LSTM is constructed to process the sequential data in time order. The output at the terminal time step is used to predict the output by a linear regression layer, as shown in the following equation.

$$\overline{pred} = relu\left(dropout\left(\left(W^{out}h^{(t)} + b_{out}\right),1\right)\right) \quad (2)$$

where W^{out} and b_{out} are the weights and biases of the output. In our tasks, the output is the battery capacity. For model training, the predicted battery capacity value is compared with the true battery capacity value y to obtain the Mean Squared Error (*MSE*) as model loss.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \overline{pred_i})^2 \quad (3)$$

where n is the training sample size.

3.3. Three-fold cross validation

The Three-fold cross validation is used in the offline process to evaluate the accuracy of a given model. We choose three offline batteries datasets (or folds) Y_1, Y_2 and Y_3 for training and validating different models. Among the three datasets, one is selected as the test set and the other two datasets are used as training sets, for example, if Y_1 and Y_2 are used as training datasets, so Y_3 will be testing datasets. The CV process is performed three times, with each of the three datasets used exactly once as the test set. Thus, the best model can be obtained by comparing the *MSE* on three test sets.

4. EXPERIMENTS AND RESULTS

4.1. Datasets Description

The lithium-ion battery experiment datasets are derived from Center for Advanced Life Cycle Engineering (CALCE) in University of Maryland (He W., Williard N., Osterman M., & Pecht M., 2011). In this experiment, the lithium-ion batteries were tested to discover battery capacity degradation. The test was implemented on the Arbin BT2000 battery testing system under the room temperature. The experiment datasets with 1.1 Ah rated capacity are used in this paper. Figure 4 shows the capacity degradation curves of #35, #36, #37 and #38 lithium-ion batteries.

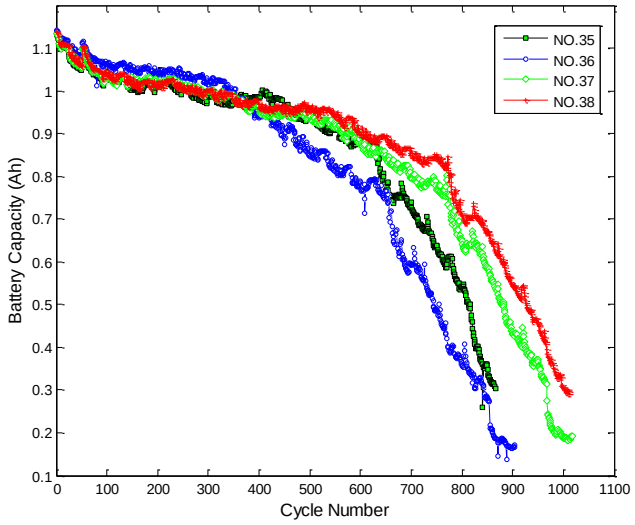

Figure 4. The capacity degradation curves of #35, #36, #37 and #38 batteries.

In this paper, the capacity is selected as the health indicator of lithium-ion batteries, and we set the same value of end of life (EOL) as literature (Liu et al., 2015), 501th cycle of #37 battery EOL, 522th cycle of #36 battery EOL and 482th cycle of #35 battery EOL.

4.2. Evaluation criterion

RUL predicted errors is used to measure the performance of the proposed method.

RUL_{error}: RUL predicted errors

$$RUL_{error} = \left| RUL_{pred} - RUL_{true} \right| \tag{4}$$

Where, RUL_{pred} is the predicted RUL value using the prediction method. In order to get the RUL_{pred}, we need to get EOP (End of Point) and SP (Starting Point of prediction), the EOP is the intersection point of two lines (one is the failure threshold line, and the other is our predicted curve), then RUL_{pred} = EOP-SP. RUL_{true} is the actual RUL value.

4.3. Experiment results

Table 1 shows the parameters of LSTM model used in this paper. Note that these parameters are selected based on trial-and-error.

Table 1. The parameters used in experiments.

Algorithm	Parameters	Value
LSTM	Input size	50
	Time steps	50
	Cell size	10
	Output size	50
	Learning rate	0.001

By setting the unit number of input layer for LSTM to 50, it means each sample consists of $\{x_i, x_{i+1}, \cdots, x_{i+49}\}$ as the inputs and $\{\bar{x}_{i+50}, \bar{x}_{i+51}, \cdots, \bar{x}_{i+99}\}$ as the output, where x_i is the actual battery capacity value of i th cycle. Taking #38 battery as an example, there are 900 charge/discharge cycles totally. If the SP is set to 700, the prediction process is described as follows:

$$\begin{cases} \{x_{651}, x_{652}, \cdots, x_{699}, x_{700}\} \rightarrow \{\bar{x}_{701}, \bar{x}_{702}, \cdots, \bar{x}_{749}, \bar{x}_{750}\} \\ \{\bar{x}_{701}, \bar{x}_{702}, \cdots, \bar{x}_{749}, \bar{x}_{750}\} \rightarrow \{\bar{x}_{751}, \bar{x}_{752}, \cdots, \bar{x}_{799}, \bar{x}_{800}\} \\ \{\bar{x}_{751}, \bar{x}_{752}, \cdots, \bar{x}_{799}, \bar{x}_{800}\} \rightarrow \{\bar{x}_{801}, \bar{x}_{802}, \cdots, \bar{x}_{849}, \bar{x}_{850}\} \\ \{\bar{x}_{801}, \bar{x}_{802}, \cdots, \bar{x}_{849}, \bar{x}_{850}\} \rightarrow \{\bar{x}_{851}, \bar{x}_{852}, \cdots, \bar{x}_{899}, \bar{x}_{900}\} \end{cases} \tag{5}$$

At SP 700, if the EOP is between the 701 and 750, then the RUL prediction result can be got by compute the intersection point of two lines (one is the failure threshold, and another is our prediction curve). On the other hand, if the EOP is not in the range of (701, …, 750), we need to conduct the next prediction cycle, and in the next prediction cycle, we use the predicted data ($\bar{x}_{701}, \bar{x}_{702}, \cdots, \bar{x}_{749}, \bar{x}_{750}$) to predict the capacity values between 751th cycle and 800th cycle, and so on, finally we can get the final RUL prediction result.

In this experiment, in order to compare the experiments results with existing works (Liu et al., 2015), we use the same parameters, i.e., the Starting Points of prediction for #37 are set to 301 and 401, the Starting Points of prediction for #36 are set to 322 and 422, the Starting Points of prediction for #35 are set to 282 and 382, respectively. The End of Life (EOL) of three batteries is 501 cycles (#37), 522 cycles (#36) and 482 cycles (#35), respectively. Figures 5-10 show the predicted curves using the proposed method. Inspection of these six figures indicates that the predicted curves of the proposed method are very close to the real degradation curves. The results show that the proposed method has stable performance on the RUL prediction of Lithium-ion batteries.

It is worth noting that, compared with the RUL estimation methods before, our proposed method can both predict single-step and multi-step, in this experiment, our method can once predict 50-step ahead. So, we can see from the figures that the predicted curves are not far away from the actual curves when the time steps increased. In other words, the cumulated errors are very small for the proposed method. On the contrary, most of the existing RUL estimation methods predict one-step ahead, and the predicted value is used to replace the actual value to predict the next step, which results in big cumulated errors.

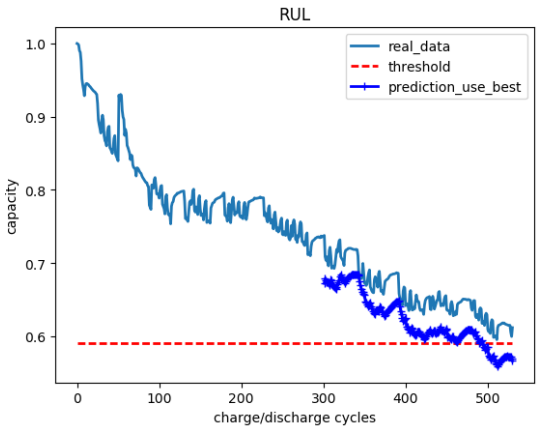

Figure 5. The predicted results by LSTM on #37 battery at starting point of 301.

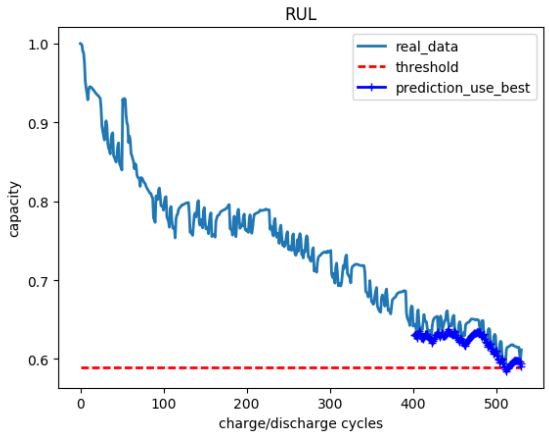

Figure 6. The predicted results by LSTM on #37 battery at starting point of 401.

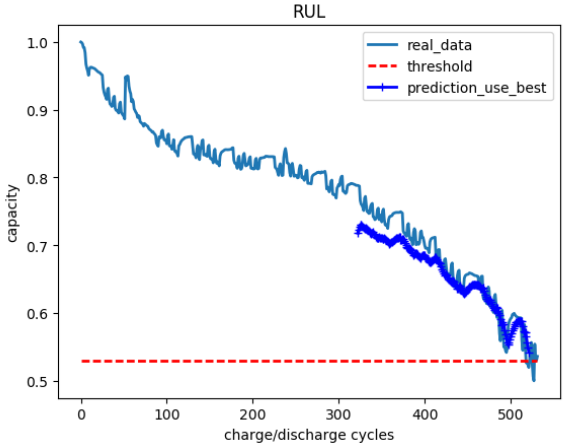

Figure 7. The predicted results by LSTM on #36 battery at starting point of 322.

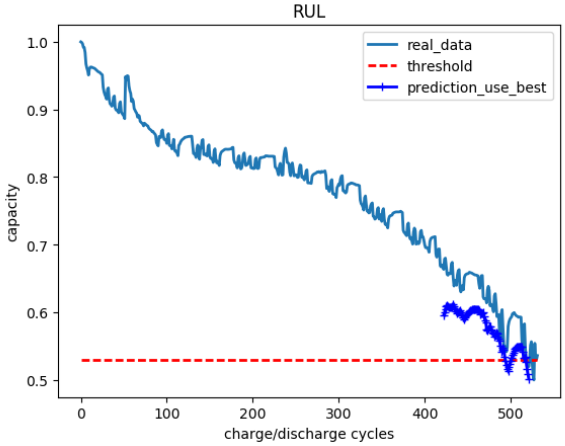

Figure 8. The predicted results by LSTM on #36 battery at starting point of 422.

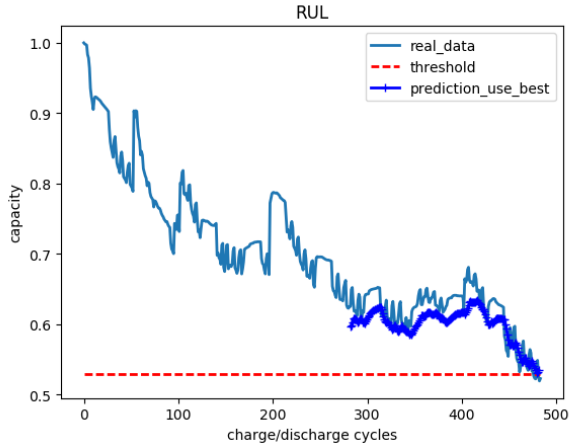

Figure 9. The predicted results by LSTM on #35 battery at starting point of 282.

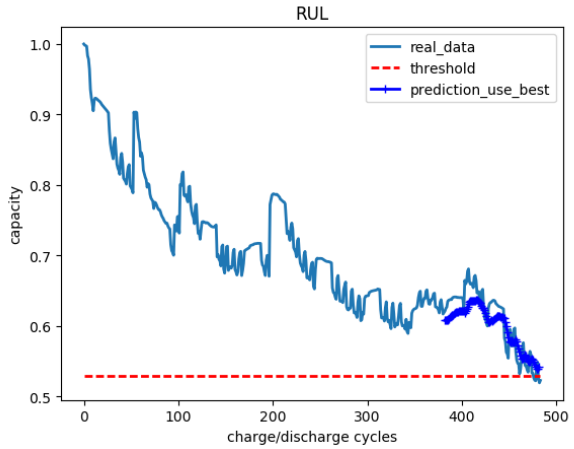

Figure 10. The predicted results by LSTM on #35 battery at starting point of 382.

Table 2. Lithium-ion battery RUL estimation results of two algorithms.

SP	RUL_{actual}	RUL_{pred} *(LSTM)*	RUL_{error} *(LSTM)*	RUL_{error} *(ESN)*
#37@301	200	192	8	19
#37@401	100	96	4	22
#36@322	200	199	1	13
#36@422	100	79	21	13
#35@282	200	197	3	55
#35@382	100	98	2	25

Table 2 summarizes and compares the proposed method with ensemble ESN (Liu et al., 2015) in terms of RUL prediction errors, which is shown with RUL_{error}. The smaller the RUL_{error} value is, the higher the RUL prediction accuracy. It is clear that the proposed method achieved the higher RUL prediction accuracy on all of lithium-ion batteries except the #36 battery at SP 422. The reason of the exception is discussed as follows. This issue can be explained by the degradation curve of #36 battery in figure 8. From figure 8 we can see that there are three intersection points, ie three EOPs. Obviously the third EOP is much closer to the real EOL, but we should choose the first EOP to obtain RUL prediction result according to the application situation. The cause of this problem is due to the fluctuating of #36 battery degradation curve. There is a steep increase on the degradation curve near the point of 500th cycle, before that the LSTM model does not have the similar memory until the new sample data come. In summary, our proposed LSTM model has the ability of remembering long short-term information of degradation tendency of lithium-ion battery, and can predict multi-step ahead with high accuracy, has more stable and reliable prediction performance.

5. CONCLUSION

This paper proposes a LSTM-based RUL prediction method for lithium-ion battery, which is a data-driven battery RUL predictor. The design and implementation of the proposed method are discussed in detail. Experiments on CALCE lithium-ion battery datasets are presented to demonstrate the effectiveness of the proposed method. The results show that the proposed method has higher prediction accuracy, more stable and reliable prognostic performance than ESN. Our future work will focus on the improvement of training speed and the uncertainty expression of predicted results.

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