Long Short-Term Memory Approach to Estimate Battery Remaining Useful Life Using Partial Data

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ABSTRACT Due to the increasing demand of electrical vehicles (EVs), prognostics of the battery state is of paramount importance. The nonlinearity of the signal (e.g. voltage) results in the complexity of analyzing the degradation of the battery. Aging characteristics extracted from the voltage, current, and temperature when the battery is fully charged/discharged were commonly used by previous researchers to determine the battery state. The drawbacks of the previous prediction algorithms are insufficient or irrelevant features to explicitly model the battery aging and the use of fully charged/discharged datasets, which might result in poor prediction accuracy. Therefore, this study proposes a feature selection technique to adequately select optimum statistical feature subset and the use of partial charge/discharge data to determine the battery remaining useful life (RUL) using Recurrent Neural Network – Long Short-Term Memory (RNN-LSTM). The proposed approach demonstrated exceptional RUL prediction results, with the root mean square error (RMSE) of 0.00286 and mean average error (MAE) of 0.00222 using partial discharge data. The proposed method shows prediction improvement in comparison with the use of full data and state-of-the-art outcomes from previous studies of the same open data from the National Aeronautics and Space Administration (NASA) prognostic battery data sets.

INDEX TERMS Recurrent neural network, long short-term memory, remaining useful life, battery management systems, feature selection.

I. INTRODUCTION

Considering the high threat of increasing global warming due to unprecedented environmental pollution caused by the use of fossil fuels, the need to use clean energy has gained great attention. Electric vehicles (EVs) have emerged as the uttermost environmentally friendly solution to tackle problems caused by fossil fuels. This resulted in steep demand for EVs, and there were over 7.2 million EVs deployed around the world by the end of 2019. The sales of electric cars topped 2.1 million globally and accounted for 2.6% of global car sales in 2019 indicating a continuous and rapid shift toward EVs popularity and use [1].

The lithium-ion (Li-ion) battery is widely used in electric vehicles because of its exceptional high cell voltage, high energy density, electromotive force, high output voltage, long lifetime, high charging efficiency, low self-discharge, low voltage drop, easy maintenance, and recycle [2]–[4]. These advantages have contributed to wider applications of lithium-ion batteries in more areas such as vehicles, household equipment, communications, aerospace, and other fields [5]. Even though there are noticeable advantages, aging is the most drawback of most lithium-ion batteries. After repeated cycling, the Li-ion cells are degraded and this affects the cell energy storage and output power capability [6]. The performance reduction of the battery in terms of cycle life can be greatly accelerated by overcharging, deep discharging, or operating the lithium-ion battery at elevated temperatures [7]. The capacity gradually deteriorates whether the battery is in use or not, eventually leading to failure. In the case of self-driving EVs, the capacity loss induces an autonomy reduction [8]. Thus, accurate estimation of the battery...
capacity degradation is essential to avoid safety risks and provide reliable information that helps in prior maintenance planning and timely replacement of the battery.

Management of the battery life is of key importance in achieving highly efficient EVs. The remaining useful life (RUL) is a key parameter for scheduling repairs, evaluating the battery state, increasing the safety, and reducing accidents by providing an alarm before faults reach critical levels [9], [10]. The RUL is the useful life left at a particular time of operation or available service time left before the capacity reaches an unacceptable level [10]. The battery RUL is measured by the remaining number of charge and discharge cycles for the given battery. Currently, the model-based and data-driven methods are two techniques that are mostly used to predict the lithium-ion battery RUL. Model-based prognostics require a deep understanding of the composition of the model, in which mathematical expressions are used to describe the complex electrochemical process [11]. Goud et al. [7] developed a mathematical model to estimate the RUL of single cell Li-ion battery by considering the DC resistance during usage. However, the method can only be applied at the determined operating temperature with predetermined constants K1 and K2 (capacity loss when the battery is charged and discharged at different temperature conditions) and the RUL accuracy greatly decreases with the increase of the predicted cycles. Zhang et al. [12] used the F-distribution particle filter and kernel smoothing algorithm to predict the RUL. Their results indicated improved applicability and robustness by dynamically adjusting the particle weight in the prediction stage, thus realizing the battery RUL prediction. Even so, there is no evidence to suggest that the model can be applied to various working conditions such as high temperatures. The RUL prediction approach for lithium-ion batteries using Kalman filter and an improved particle filter (combining Kalman filter and particle swarm optimization) was conducted by Mo et al. [13]. The method not only improves the precision over standard particle filter but also overcomes the particle degradation due to particle resampling. Even though the results indicate better accuracy compared to particle filter (PF), the addition of the particle swarm optimization algorithm to solve the problem of particle degeneracy due to the resampling method further increases the complexity of the mathematical model. Other model-based methods were carried out such as Wiener Processes, sliding-window grey model, etc. [14]–[16].

Despite some success of model-based methods, in practice, it is difficult to have a precise and well-established model that would allow tuning and updating the parameters during the prediction phase with different operational conditions [17], and there are not well-established failure physical models [3]. Considering the above-mentioned drawbacks of model-based approaches to predict the RUL, data-driven methods have proven to be more efficient because there is no need for mathematical modeling to compute the battery degradation. Besides, the development of battery-related technology has increased, and more data on the energy storage devices have been produced. This facilitated the implementation of a data-based approach to estimate the RUL using accumulated historical data. The data-driven approaches can achieve simple noncomplex prediction of lithium-ion battery aging characteristics with acceptable accuracy. Li et al. [18] used a grey support vector machine (GSVM) to predict the RUL of the Li-ion battery and obtained 3.18% mean square error. Xu et al. [14] introduced a novel data-driven approach for lithium-ion battery RUL using an improved exponential model particle filter. The results showed that the capacity fade can be well captured.

Amongst the many data-driven methods to analyze the RUL, recurrent neural network (RNN) using long short-term memory (LSTM) cells emerged more powerful due to the ability to avoid the vanishing problem in gradient descent by learning long-term dependency (remember information for long periods) of capacity degradation tendencies for different conditions. The LSTM approach was utilized by Choi et al. [20] using a multi-channel charging profiles approach to estimate the remaining capacity. The prediction performance indicated a better prediction accuracy of the LSTM model compared to the feedforward neural network (FNN) and convolutional neural network (CNN). Zhang et al. [21] proposed LSTM to synthesize a data-driven RUL applying the Monte Carlo (MC) simulation to generate RUL prediction uncertainties. The required training data was 20-50% less using LSTM compared to particle filter (PF), and the performance results indicated that the LSTM generally predicts more accurate and precise than the support vector machine (SVM) and simple recurrent neural networks (SimRNNs). Park et al. [3] compared LSTM method with basic RNN, gated recurrent unit (GRU) and simple recurrent unit (SRU) using multi-channel charging profiles, and the mean absolute percentage error (MAPE) of the LSTM was better than basic RNN, GRU, and SRU by 32-52%.

This study adopted the LSTM method due to its superiority in predicting the RUL because it presents better performance compared to other models. However, effective feature extraction from the raw signals is crucial in estimating the RUL of the battery. The drawbacks of the previous LSTM algorithms are insufficient or irrelevant features to explicitly model the battery aging. In this study, a forward selection-long short-term memory (FS-LSTM) technique was developed to adequately select an optimum feature subset by disregarding irrelevant features for faster computation and better prediction. In addition, the effective data range from the charging/discharging signals was studied. The results show that predictions of the RUL perform much better with the partial data. The remaining sections are structured as follows: Section II briefly describes the LSTM architecture and RUL computation. In section III, data preprocessing is considered whereby the lithium-ion battery experiments are explained and the statistical methods used to extract the relevant features are given. The proposed FS-LSTM algorithm and partial charging/discharging data selection are introduced in section
IV. Section V presents the results and discussion. Finally, the conclusions are given in section VI.

II. ESTIMATION OF BATTERY REMAINING USEFUL LIFE

A. LONG SHORT-TERM MEMORY

The LSTM introduced by Hochreiter and Schmidhuber [22] in 1997 is a unique type of RNNs. The traditional RNN takes one or more inputs and produces one or more output vectors. The basic RNN is not capable of learning long term dependencies and mostly results in the vanishing gradient problem. The LSTM, however, was introduced to solve this problem with the ability to map the input to the output vector while remembering the information for a long duration of time. The LSTM uses memory cells as compared to hidden nodes in ordinary RNN. The cell state \( c_t \) is the basis of the LSTM method.

Figure 1 shows the basic architecture of the LSTM. The charging/discharging datasets of the battery are regarded as long-term time-series data; thus, the LSTM can learn the long-term dependency of the degradation data of the capacities and predict the lithium-ion battery’s RUL [23]. The LSTM consists of three special gates, namely the forget \( f_t \), input \( i_t \), and output \( o_t \) gates. These carefully regulated structures (gates) can optionally decide what information should pass through [21]. The current input \( x_t \) and output from the previously hidden layers \( h_{t-1} \) at each step are used to compute the output with the respective weights (i.e. forget gate weight \( w_f \), input gate weight \( w_i \), input node weight \( w_c \), and output gate weight \( w_o \)), biases, the state activation functions \( \text{tanh} \), and gate activation functions \( \sigma \).

The forget gate controls the internal recurrent. It determines the information from the previous output \( c_{t-1} \) that will be discarded, updated, and stored. The forget gate is computed as:

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

The input gate determines the information passed to the cell state. It contains the sigmoid activation function \( \sigma \) that regulate the information to be updated and a hyperbolic activation function \( \text{tanh} \) that generates a new vector \( \tilde{c}_t \) that is added to the cell state. The input gate is calculated as:

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

\[
\tilde{c}_t = \text{tanh} \left( w_c [h_{t-1}, x_t] + b_c \right)
\]

The new cell state value \( c_t \) is obtained by multiplying the previous output \( c_{t-1} \) with the output of equation (1) and combining with the product of (2) and (3) as:

\[
c_t = i_t \times \tilde{c}_t + f_t \times c_{t-1}
\]

The output gate uses the sigmoid activation function and determines the output information. The output gate is calculated as:

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

The hidden state \( h_t \) can finally be computed by passing the cell state \( c_t \) through the activation function, \( \text{tanh} \), and multiplying with the output of the output gate [21]:

\[
h_t = o_t \times \text{tanh} (c_t)
\]

B. ESTIMATION OF REMAINING USEFUL LIFE

The remaining useful life of a battery is described as the actual remaining cycles before the given specific end of life, which is usually defined by the critical degraded capacity. Assuming that \( \alpha \) is the current number of charge/discharge cycles, and \( \beta \) is the number of cycles estimated at the end-of-life (EOL). By predicting the EOL cycles, we can get the battery RUL as follows [24]:

\[
RUL = \beta - \alpha
\]

The RUL is closely related to battery capacity and internal resistance. The complex aging mechanisms and the high cost of measuring the internal parameters of the battery make the use of internal resistance difficult in practical engineering [24]. However, the data-driven models have been developed using those accessible signals. Therefore, in this study, the relationship between capacity and the operating conditions such as terminal voltage, current, and temperature is employed to estimate the RUL. The RUL error is calculated as the difference between the actual and predicted remaining cycles:

\[
RUL_{\text{error}} = RUL_{\text{predicted}} - RUL_{\text{actual}}
\]

The capacity was calculated by integrating the current over time:

\[
C_{Ah} = \int_{t_0}^{t_1} I(t) dt
\]

where \( t_0 \) is the start of charge/discharge of each cycle, \( t_1 \) is the end of charge/discharge, and \( I(t) \) is the corresponding current.
TABLE 1. Specifications of the battery datasets.

| Battery type | Maximum charging voltage (V) | End of discharge (V) | Battery number | No. of cycles |
|--------------|-----------------------------|----------------------|----------------|--------------|
| Li-ion       | 4.2V                        | 2.5V                 | B0006          | 168          |
|              |                             | 2.2V                 | B0007          | 168          |
|              |                             | 2.5V                 | B0018          | 132          |

III. DATA PREPROCESSING

To achieve a better estimation of battery RUL, the inputs of the model were extracted from the battery charge/discharge data. Two steps of LSTM model training were conducted. In the first step, the raw data was preprocessed into different features. Different combinations of the features were tested as the inputs, and the performance was compared to find out the best combination of the inputs. In the second step, only part of the data within specified ranges were utilized in the model training. The results show that the utilization of partial data performs better than the use of the full data.

A. DATA

The lithium-ion battery datasets were obtained from NASA Prognostic Center of Excellence [25]. A constant current and constant voltage principles were used to charge and discharge the batteries. Charging was carried out at 1.5 A until the maximum voltage of 4.2V, then constant voltage was controlled until charging current drop to 20mA. Discharging was carried out at 2 A until the cut of voltage for the specified batteries as listed in Table 1. The capacity of 1.4 Ah was considered as the end of life (EOL), which is 30% decrease of the initial rated capacity of 2Ah. The battery signals of terminal voltage, output current, time, and temperature were retrieved from battery No. 5, 6, 7, and 18.

Figure 2 shows the experimental discharge voltage, current, and temperature signals of battery No. 5. The current goes to negative because it flows out of the battery at the initial discharge. The battery voltage and temperature significantly changed with time during the discharging process. The voltage decreases, while the temperature increased due to several sources, such as electronic circuit elements located around the battery conducting heat into the cells, waste heat including protection, and gas gauge circuits inside the battery itself. Thus, the signal dynamics can be utilized to characterize distinctive features and estimate the remaining useful life.

B. FEATURE EXTRACTION

Feature extraction can be described as the reduction process whereby meaningful attributes are extracted from the raw signals to reduce the dimensionality without compromising the properties of the input data patterns. In this study, statistical methods were used to extract the relevant features. The capacity degradation is affected by many factors such as loading, temperature, humidity, cyclic life, depth of discharge, recharge rate, etc. It is practically difficult to consider all these factors. Therefore, the voltage, current, and temperature signals were considered in this study. A total of 18 features were extracted from the data. These features include energy signal, mean, power signal, standard deviation, skewness, and kurtosis of the signals in each cycle. The statistical features are computed as shown in equation (10)-(15).
The energy signal ($e_j$) is calculated by taking the integral of the magnitude square of the input signals ($x_i$) from the initial charging/discharging time ($t_0$) to the end of charge/discharge ($t_1$) in each cycle:

$$e_j = \int_{t_0}^{t_1} |x_i|^2 \, dt$$

(10)

where $j$ represents the voltage, $V$, current, $C$, or temperature, $T$.

The power signal ($p_j$) is the natural logarithm of the average energy over time, which is calculated as:

$$p_j = \ln \left( \frac{1}{T} \int_{t_0}^{t_1} |x_i|^2 \, dt \right)$$

(11)

The mean of the signals represented by $m_j$ is the average of the signals in each cycle.

$$m_j = \frac{1}{n} \sum_{i=0}^{n} x_i$$

(12)

To compute the standard deviation, the sum of the square of the deviation between $x_i$ and $m_j$ is taken before computing the average. The square root is used to compensate for the initial squaring:

$$d_j = \sqrt{\frac{1}{n} \sum_{i=0}^{n} (x_i - m_j)^2}$$

(13)

The skewness and kurtosis features are calculated similarly to standard deviation, but the cubic and quadruple of the differences between $x_i$ and $m_j$ are taken before the average and divided by their respective standard deviation power:

$$s_j = \sqrt[3]{\frac{1}{n} \sum_{i=0}^{n} (x_i - m_j)^3}$$

(14)

$$k_j = \sqrt[4]{\frac{1}{n} \sum_{i=0}^{n} (x_i - m_j)^4}$$

(15)

The features were in different units and scales. Therefore, the signals were transposed to the data range between 0 and 1. The input/target data was normalized prior to training and testing processes. This is crucial to obtain good results by reducing the complexity of the data structure. However, the model performance was carried out using the denormalized predicted capacity output of the test cycles and the measured experimental capacity. The normalization was conducted on each battery dataset.

$$\bar{x}_i = \frac{f_i - \min f_i}{\max f_i - \min f_i}$$

(16)

where $f_i$ is the input feature and $\bar{x}_i$ represents the normalized input feature.

The estimation of RUL has mostly been conducted using charge/discharge signals considering battery datasets containing full charge/discharge data. However, the use of charge or discharge data in a full cycle includes insignificant charge/discharge signals considering battery datasets containing full charge/discharge data. To select partial data, this study considered the voltage range as the benchmark for the extraction of partial datasets. Thus, the voltage range of $v_{n,1}$ to $v_{n,2}$ was selected, where $v_{n,1}$ represents the upper limit of the selected voltage, and $v_{n,2}$ is the low limit. Different partial data such as current, time, and temperature were selected in correspondence to the voltage range. Figure 2 shows the selected partial discharge data (3.8 – 3.0 V) for cycles 1, 84, and 168.
that the current and temperature samples are selected in the same given period based on the defined voltage range. This allows the extraction of features from all the cycles based on the same standard and provides the battery degradation phenomena without compromising the total number of cycles of the original data.

In this study, the capacity was used as the RUL indicator. The flowchart of the proposed method to predict the RUL of the lithium-ion battery is represented in Fig. 4. In summary, features were extracted from voltage, current, and temperature signals. Capacity was used as the target class and data was normalized before training and testing. The input features were selected using the forward selection method. The selected global best feature subset $f_s$ was used as the input of the LSTM model to predict the RUL.

V. RESULTS AND DISCUSSION

In this study, the LSTM architecture was carried out using the LSTM Toolbox in Matlab 2019a. The layer specifications for training the model includes the input size corresponding to the number of the features and 50 hidden layers with a fully connected layer. Adam optimizer with 0.001 learning rate, 500 epochs, and a batch size of 50 was used.

Root mean square error (RMSE) and mean absolute error (MAE) were used to evaluate the performance of the trained model considering the difference between the actual and de-normalized predicted capacity after each discharge cycle in the whole battery life.

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (|x_a - x_p|)^2}$$

$$MAE = \frac{1}{n} \sum_{i=1}^{n} |x_a - x_p|$$

where $x_p$ and $x_a$ are the predicted and actual capacities, respectively.

A. PERFORMANCE OF FS-LSTM METHOD

In the first step, the full charge and discharge data in each cycle were calculated into the features as the inputs of the LSTM model. Feature selection is essential because the RUL prediction depends on the accuracy of the training model. The extracted 18 features were used as the input data to train the model. The performance of different feature subsets was evaluated based on the forward feature selection method presented in section IV. Battery No. 5 dataset was used to test the trained model and perform feature selection. The other three battery datasets (No. 6, 7, and 18) were used for model training.

Tables 2 and 3 indicate the 10 best performance feature subsets based on the results of MAE using charge and discharge dataset, respectively. The results clearly show the importance of feature selection to yield a minimum error. When insufficient or irrelevant features are selected, the model performs poorly. It is indicated that the use of many features does not necessarily guarantee better performance. The model can perform better using only 3 or 4 features than the inputs with all the features. Therefore, the input data size can be significantly reduced, while the accuracy is increased by using the developed feature selection method.

Table 2. Top 10 testing performance of the feature subsets using charge dataset of battery No. 5.

| RANK | FEATURE | RMSE | MAE  |
|------|---------|------|------|
| 1    | $e_c p_{v} m_{v} s_{v} d_{c}$ | 0.01498 | 0.01166 |
| 2    | $e_c p_{v} m_{c}$ | 0.01638 | 0.01229 |
| 3    | $e_c p_{v} m_{v} s_{v}$ | 0.01632 | 0.01267 |
| 4    | $e_c p_{v} m_{v} s_{c}$ | 0.01632 | 0.01270 |
| 5    | $e_c p_{v} m_{v} s_{c}$ | 0.01671 | 0.01230 |
| 6    | $e_c p_{v} m_{v} s_{v} d_{c}$ | 0.01592 | 0.01278 |
| 7    | $e_c p_{v} m_{v} s_{v} d_{c}$ | 0.00137 | 0.01289 |
| 8    | $e_c p_{v} m_{v} s_{v} d_{c}$ | 0.01654 | 0.01302 |
| 9    | $e_c p_{v} m_{v} s_{v} d_{c}$ | 0.01717 | 0.01311 |
| 10   | $e_c p_{v} m_{v} s_{v}$ | 0.01735 | 0.01313 |
|      | all     | 0.03549 | 0.03026 |

Table 3. Top 10 testing performance of the feature subsets using discharge dataset of battery No. 5.

| RANK | FEATURE | RMSE | MAE  |
|------|---------|------|------|
| 1    | $e_c p_{v} m_{d} s_{v} d_{c}$ | 0.00286 | 0.00222 |
| 2    | $e_c p_{v} m_{v} s_{c}$ | 0.00287 | 0.00224 |
| 3    | $e_c p_{v} m_{v}$ | 0.00313 | 0.00245 |
| 4    | $e_c p_{v} m_{v}$ | 0.00325 | 0.00246 |
| 5    | $e_c p_{v} m_{c}$ | 0.00332 | 0.00253 |
| 6    | $e_c p_{v} m_{c}$ | 0.00344 | 0.00275 |
| 7    | $e_c p_{v} m_{c}$ | 0.00358 | 0.00287 |
| 8    | $e_c p_{v} m_{v}$ | 0.00358 | 0.00290 |
| 9    | $e_c p_{v} m_{v}$ | 0.00372 | 0.00301 |
| 10   | $e_c p_{v} m_{v}$ | 0.00386 | 0.00308 |
|      | all     | 0.01195 | 0.01123 |
Figure 5 presents the results and an estimation of the battery capacity using charge and discharge data with the proposed feature selection algorithm. The results of the feature selection algorithm using discharge data perform much better than the charge data for all the batteries.

**B. REMAINING USEFUL LIFE PREDICTION USING PARTIAL DATA**

In the second step, the RNN-LSTM was used with partial charge/discharge data as the input and the measured capacity as the target to predict the RUL of the battery. The partial data was chosen considering the voltage range as the benchmark. The current and temperature was selected in correspondence to the voltage range as described in section III. The full charge and discharge data specifications were described in Table 1 for all the selected batteries. The RMSE and MAE were used to evaluate the performance considering the measured experimental capacity and predicted battery capacity values. The best performance of partial voltage ranges is listed in Tables 4 and 5. The partial range selection...
is carried out using battery No. 5 with 50 cycles as the training datasets, and the remaining cycles were used to test the model.

The initial parameters were learning rate of 0.0001, 500 epochs, and a batch size of 10 using Adam optimizer. The results indicate that the best range of 3.6-4.2V and 4.0-3.1V greatly improve the performance of the FS-LSTM model compared to full charge and discharge data respectively. The RMSE of 0.13054 and MAE of 0.11911 were obtained using partial charge data, and RMSE of 0.06448 and MAE of 0.06125 were achieved using partial discharge data. The utilization of partial data performs much better than the full data as presented in Tables 4 and 5. However, the range of 3.6-4.2V does not represent all the cycles because in some cycles the initial charging starts at 3.8V. Therefore, the partial charge range of 3.8-4.1V was selected to perform the RUL. The study of the partial data range indicates that the use of the full data does not guarantee a better prediction accuracy. Improved performance by using partial data can be attributed to the minimum disturbance in the selected signal range as there are high fluctuations during the initial charging and discharging phases in the experiments.
FIGURE 6. RUL prediction using full and partial charge/discharge data of (a) battery No. 5, (b) battery No. 6, (c) battery No. 7, and (d) battery No. 18.
TABLE 5. Performance of partial discharge data with different voltage ranges.

| Battery | RANGE | RMSE  | MAE  |
|---------|-------|-------|------|
| No. 5   | 4.2 - 2.7 | 0.09531 | 0.08817 |
|         | 4.0 - 3.1  | 0.06448 | 0.06125 |
|         | 4.1 - 2.7  | 0.06468 | 0.06141 |
|         | 4.1 - 3.0  | 0.06652 | 0.06311 |
|         | 4.0 - 3.1  | 0.06801 | 0.06410 |
|         | 3.6 - 3.2  | 0.07039 | 0.06747 |
|         | 4.1 - 2.8  | 0.07201 | 0.06814 |
|         | 4.0 - 3.3  | 0.07312 | 0.06865 |
|         | 3.6 - 3.3  | 0.07349 | 0.06893 |
|         | 4.0 - 3.0  | 0.07444 | 0.06981 |
|         | 4.0 - 2.9  | 0.07471 | 0.07007 |

Figure 6 illustrates the RUL performance using partial charge (3.8-4.1V), partial discharge (4.0-3.1V), and full charge/discharge data for battery No. 5, 6, 7, and 18. The training cycles of 40, 60, and 80 were utilized to evaluate the RUL for all the batteries. The capacity of 1.4 Ah was considered as the end of life (EOL), i.e. 30% decrease of the initial rated capacity of 2Ah. The results of the RMSE and MAE are listed in Tables 6 and 7 for charge and discharge data. When 40 cycles were used to train the model, it can be observed that the proposed model using partial data outperforms the use of full charge data. When 60 cycles were used to train the model, a similar trend of the error is observed with partial data outperforming full discharge data for battery No. 5, 6, and 7. The RUL prediction for battery No. 18 presents an increase in the error when partial charge data were used compared to the use of full charge data. However, when the training data were increased to 80 cycles, better RUL prediction was achieved. Both the proposed partial charge/discharge and full charge/discharge data presented excellent prediction accuracy as shown in Tables 6 and 7. Table 8 indicates the RUL error for battery 5, 6, and 18 using 60 and 80 cycles as the prediction starting point. The partial data has an excellent RUL prediction error, however, full charge data performed better on battery No. 18 in comparison with partial data. Fig. 6 shows the predicted results for all the selected batteries. Thus, the RUL prediction using partial data performs better or equal to the prediction using full discharge data, although the results converge with more cycles. In addition to better accuracy, the use of partial data can be of great significance in reducing the input size when a large amount of data is used for model training. Hence, the shorter training time and better performance of the model are expected.

To validate the performance of the selected partial range for both charge and discharge data, the results were compared to the results presented by Park et al. [3]. Table 9 and Fig. 7 shows the results of the proposed FS-LSTM using partial charge and discharge data and MC-LSTM. Both the partial charge and discharge results of the FS-LSTM outperform MC-LSTM for battery No.5, 7, and 18. However, the MC-LSTM has better accuracy for battery No. 6.

The shortcoming of the proposed partial range is that the selected range of 3.8-4.1V and 4.0-3.1V for charge and discharge data might not necessarily represent the best partial data range for battery No. 6, 7, and 18. This is observed with the results of battery No. 18, where the full charge and discharge data performs better than the partial data. The best partial charge/discharge ranges that represent each battery can be further investigated using the proposed algorithm, and a universal range for all the batteries would be selected to train the model. Thus, selecting the best range for all the batteries will provide a global partial charge/discharge range that can be generally applied to predict the RUL of all battery datasets with improved accuracy. The study of charge data also shows better performance than the state-of-the-art results [20], although it is not as good as the discharge data. Nevertheless, using charge data may be more practical because the battery is usually discharged non-continuous.
FIGURE 7. RUL prediction comparison of the proposed FS-LSTM with MC-LSTM [3].

| Start Point | Battery No. | Full Charge | Partial Charge | Full Discharge | Partial Discharge |
|-------------|-------------|-------------|----------------|---------------|------------------|
|             |             | $RUL_{act}$ | $RUL_{pred}$  | $RUL_{error}$ | $RUL_{act}$  | $RUL_{pred}$  | $RUL_{error}$ | $RUL_{act}$  | $RUL_{pred}$  | $RUL_{error}$ |
| 5           | 64          | -           | -              | 86            | +22             | 81            | +17            | 77            | +13            |
| 60          | 6           | 48          | 50             | +2            | 46              | -2            | 53             | +5            | 47              | +1              |
| 18          | 36          | 39          | +3             | 21            | -15             | 40            | +4             | 43            | +7              |
| 5           | 44          | 48          | +4             | 44            | 0               | 47            | +3             | 46            | +2              |
| 80          | 6           | 28          | 25             | -3            | 26              | -2            | 29             | +1            | 28              | 0               |
| 18          | 12          | 16          | +4             | 16            | +4              | 15            | +3              |

TABLE 9. Comparison of the proposed FS-LSTM and MC-LSTM models.

| Method            | Battery No.5 | Battery No.6 | Battery No.7 | Battery No.18 |
|-------------------|--------------|--------------|--------------|---------------|
|                   | RMSE         | MAE          | RMSE         | MAE           | RMSE         | MAE          | RMSE         | MAE           |
| FS-LSTM (charge)  | 0.0111       | 0.0073       | 0.0443       | 0.0328        | 0.0066       | 0.0045       | 0.0104       | 0.0084        |
| FS-LSTM (discharge)| 0.0091       | 0.0079       | 0.0197       | 0.0138        | 0.00401      | 0.0033       | 0.0057       | 0.0046        |
| MC-LSTM (Park 2020 [3]) | 0.0168 | 0.0146 | 0.0152 | 0.0103 | 0.0085 | 0.0068 | 0.0388 | 0.0261 |
Since this study is limited to open access NASA data, more experiments have to be conducted to ascertain the validity of the developed feature selection algorithm and RUL prediction approach using partial charge/discharge data. Also, extensive analysis of the training time difference between the full and partial charge/discharge data can be studied to investigate the tradeoff between computation time and accuracy.

VI. CONCLUSION

A forward feature selection algorithm was developed in this study to select the best feature subset for better prediction accuracy of the remaining useful life of lithium-ion battery using the RNN-LSTM model. The algorithm effectively selects a significant feature subset which results in high accuracy of RUL prediction using charge/discharge data. In addition, the use of partial charge/discharge datasets to predict the battery RUL performs equal or better than the full data. To further ascertain the superiority of the model, better capacity prediction accuracy was achieved compared to the state-of-the-art results. The results in this study indicate that the feature selection method and the use of partial data can reduce the number of inputs and the amount of data to be processed, while the prediction accuracy is increased. Although the performance of the charge data is not as good as that of the discharge data, it may be more applicable in practical usage. This study is limited to the open access battery charge/discharge data. The robust feature selection and partial data range could be decided with more relevant data.

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