Predicting the Remaining Life of Lithium-ion Batteries Using a CNN-LSTM Model

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***Abstract*—Accurate predicting the remaining useful life of lithium-ion batteries is essential for the market of Electrical Vehicles (EVs) and the battery industry. However, diverse ageing processes, substantial battery variability, and dynamic operating circumstances are identified as main challenges for predicting the remaining useful life (RUL) of lithium-ion batteries (LIBs). This study proposes a machine learning solution for estimating the RUL of LIBs by using a Convolutional neural network (CNN) model with an extra Long Short-term memory (LSTM) layer. The developed CNN-LSTM model is trained by a dataset containing data extracted from 124 commercial lithium-ion batteries cycled under fast-charging conditions. In this study, we use only 100 cycles to predict the remaining cycles. The developed model achieved a competitive loss value of 0.0206 and the mean absolute error value was 0.1099 for the current cycle of the battery and 0.0741 for the remaining ones.**

Keywords—convolution neural network, Lithium-ion battery, remaining useful life, long short-term memory, electrical vehicle

I. Introduction

The global market for electric vehicles (EVs) would have a total revenue of 802.81 billion dollars in 2027, demonstrating a rising demand for battery production, management, storage, and recycling [1]. LIBs are the primary energy source for EV manufacturers and suppliers because of their high efficiency and low cost [2], which presents an excellent opportunity for the development of LIBs. At the same time, evaluating the health condition of LIBs is significantly important in complying with the safety-critical and energy-efficient criteria. In order to evaluate the health status of LIBs, various indicatorshave been used such as state of charge (SOC) [3], state of health (SOH) [4], [5], and remaining useful life (RUL). RUL will be used to demonstrate the performance of LIB. However, the traditional RUL prediction methods (Support Vector Machine [6], Gaussian process regression [7]) are time-consuming and economically expensive.

Therefore, a quick and accurate prediction method is needed to estimate the RUL using the early-stage test cycle data. For example, if the RUL of a LIB with 1500 life cycles could be estimated using the first 200 cycles, the remaining 1300 cycles could be averted; thus, it could save 86% of time and cost. In this study, a convolutional neural network (CNN) combined with a long short term memory (LSTM) approach has been used based on the parameters operated by feature selection from a public experimental dataset [8] containing 124 fast-charge commercial LIBs under 30°C. The dataset is detailed in Section III. In summary, the main contribution of this study is developing a robust CNN-LSTM model for predicting the RUL. The model was developed with detailed features (linearly interpolated temperature (Tdlin), linearly interpolated discharge capacity (Qdlin)) and scalar features (Internal Resistance (IR), Quantity of discharge (QD) and Discharge Time (T)). The developed CNN-LSTM model is compared with a CNN model and the results are reported in Section IV.

The remaining of this paper is as follow; in the next section the similar studies are investigated, the developed method is explained in Section III followed by the results in Section IV, and finally this study is concluded in Section V.

II. Literature Review

Statistical and machine learning techniques have emerged into the frontier research because of the advanced computing power enhanced by the graphics-processing unit. For instance, a support vector machine (SVM) is commonly used in linear and non-linear systems because of its capability to map the input parameters to a higher level feature space through the kernel. Klass et al. has proposed SVM based on the state-of-health estimation method that extracts the parameters like current, voltage and temperatures. Patil et al. [9] combined the classification model providing gross estimation and SVM regression model to predict the RUL of batteries, when the battery is closed to the end of life, with features extracted from voltage and temperature profiles. This model achieved an RMSE of 0.357.

Artificial neural networks is another approach for predicting the state of health (SoH) of LIBs. Rastegarpanah et al. developed a neural network model to predict the SoH for high power lithium-ion batteries based on the preditors, parameters extracted from the impedance data of 13 Nissan Leaf 2011 battery modules. This model predicted the state of health with a root mean square error of (1.729 ± 0.147), which is a competitive result compared to other NN models [10].

CNN is a network model that Lecun et al. proposed in 1998 [11]. CNN is a type of neural feed-forward network that has been commonly used in applications like image processing and natural language processing. It has been used to predict time-series effectively. CNN substantially minimises the local perceptually and weight sharing, therefore boosting the model-learning performance. Yang proposed a

This research was conducted as part of the project called "Reuse and Recycling of Lithium-Ion Batteries" (RELIB). This work was supported by the Faraday Institution [grant number FIRG005].

2022 8th International Conference on Mechatronics and Robotics Engineering (ICMRE) | 978-1-6654-8377-3/22/$31.00 ©2022 IEEE | DOI: 10.1109/ICMRE54455.2022.9734081

hybrid CNN method, made of a 3D CNN, to combine the voltage, current and temperature curves (V/I/T), and a 2D CNN to find the hidden features behind them. As a result, 1.1% test error for early prediction of battery life and 3.6% for RUL was observed [12]. Even though the CNN method could achieve a good performance regarding the multi-dimension features, it has no capability in handling the features that contain time-series related information.

The recurrent neural network (RNN) is commonly adapted to train a model for a time-series dataset. Liu et al. demonstrated that an adaptive recurrent neural network (ARNN) produces better learning results than classical machine learning algorithms, such as relevance vector machine and particle filter [13]. However, the traditional RNN could not work with long time dependencies that were commonly existed among the parameters for the early-cycle dataset. Long short-term memory (LSTM), a special type of RNN, was introduced to solve these problems. It was developed by Schmidhuber et al. in 1997 [14]. It was created to address the long-standing problems of gradient expansion and gradient disappearance in RNN. It has been frequently utilised in applications like speech recognition, emotional analysis, and text analysis since it has its memory and can do pretty accurate forecasts, which could also be applied to battery assessment. LSTM is an appropriate method for predicting the RUL as it has capability to handle the features with time-series. LSTM memory cell includes three main cores: the forgotten gate, the input gate and the output gate. Mamo et al. developed an LSTM model with using an attention mechanism to predict the charging status of two LIBs, and the results suggested reasonable predictive root mean square errors of 0.9593, 0.8714, and 0.9216 at three different temperatures [15]. In order to improve the accuracy and performance of the RUL, Long et al. proposed an auto-LSTM model that tunes the hyperparameters into a feature selection [16]. The method has been tested on both NASA and CALCE datasets [17] showing a good result for promoting random search and tree Pazen estimator on most cases for predicting the state of health of LIBs [16]. Uncertainty quantification is another core research field for predicting the RUL. Liu et al. developed an LSTM model to estimate the remaining Gaussian process regression for learning the correction from time-series data [18]. With respect to the advantages of machine learning methods in predicting the RUL of LIBs, a CNN model with an extra LSTM layer for early prediction of the cycle life of LIBs and their RUL using early cycle data is proposed in this study.

III. Materials and Methods

A. Data Library

This study has used the data extracted from 124 commercial LIBs, which has cycled to failure under fast-charging conditions. Each cell has a capacity of 1.1 Amp hours and a voltageof 3.3V. Each battery (cell) has three types of data: (i) the descriptive data which includes charging policy, cycle life; (ii) the summary data that shows the information based on the cycle level; including cycle number, discharge capacity, charge capacity, internal resistance, maximum temperature, average temperature, minimum temperature and charge time; (iii) the cycle data consisted of important information such as time, charge capacity, current, voltage, temperature, discharge capacity and linearly interpolated discharge capacity (Qdlin) and linearly interpolated temperature (Tdlin).

B. Feature Selection

Quantity of discharge (QD) and discharge time are main parameters in predicting the RUL and evaluating the performance of LIBs. In this study, we investigate the influence of these parameters individually and interaction of them on RUL. IR is a standard indicator for predicting the RUL of LIBs becauseof its effect on the polarization of positive and negative electrodes which could lead to battery degradation [19]. The cycle increment is linearly proportional with IR (Fig. 1.a). Also, as shown in Fig. 1.b the profile of charge and discharge of a battery cell had the same trend. Linear interpolation is a proper method to apply to discrete datasets. Wu et al. has proven that it is practical to use linear interpolation to reduce the training samples [20]. As shown in Fig. 2.a, for the same cycle period of the same battery, the Qdlin is smoother than the quantity of charge (Qc). Under the same circumstance, Tdlin is also a better indicator than using the temperature itself because it has less noise which will improve the accuracy for model prediction. As shown in Fig. 2.b, the minimum and maximum temperatures are 29.85° and 34.30° for T, and 29.84° and 34.16° for Tdlin; that shows the minimum and maximum values for T and Tdlin are approximately the same (Fig. 2).

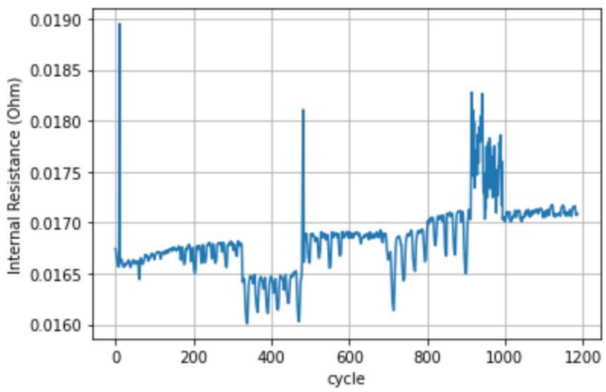
C. Input Dataset Collection

In this study, five necessary parameters (IR, QD, Qdlin, Tdlin and Discharge Time) have been used to train the machine learning models. The input dataset should contain these five feature parameters and additional information from the battery cells such as current battery cycle of the cell and the remaining cycles which have been used for training, predicting and testing. After creating the input data pipe, now each data unit contains the feature parameters and cycle information.

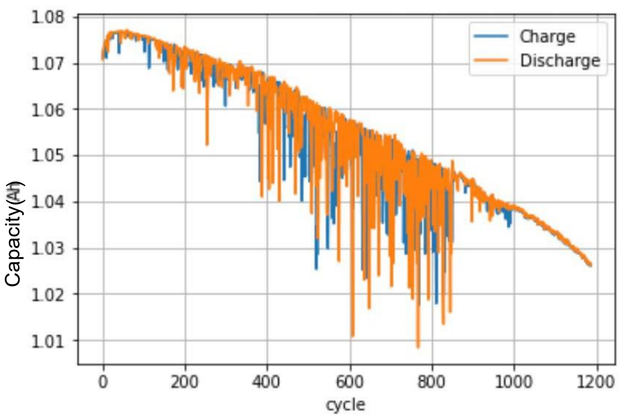
D. Convolutional Neural Network Model

This CNN model used Qdlin and Tdlin as detailed features and IR, QD and discharge time as scalar features. Prior to generating the CNN model, some other parameters were calculated and defined such as number of filters, window size, strides, learning rate, steps, kernel size of 2D and 1D, dense layer number units etc.

The model takes two detail features input layers with a window size of 100; after concatenating the detail features, a 100×32 2D conventional layer is performed with 32 filters. Then, a 2×1 max-pooling is operated, followed by a 2D conventional layer with 64 filters. At the same time, the scalar features have been concatenated and adapted 1D conventional layer with 32 filters, followed by another 1D conventional layer with 64 filters. Then, a 1D max-pooling is added. All detailed (Qdlin and Tdline) and scalar features are followed by flattening layers, preceding with dropout layers. These two different features are concatenated together, and the above procedure was repeated. The detailed structure of the developed CNN model is depicted in Fig. 3.

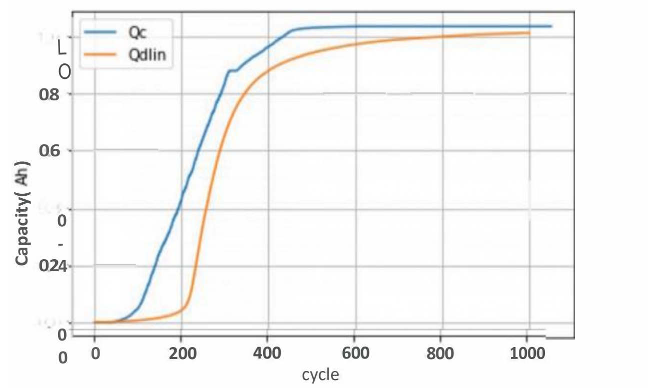


(a) Internal Resistance

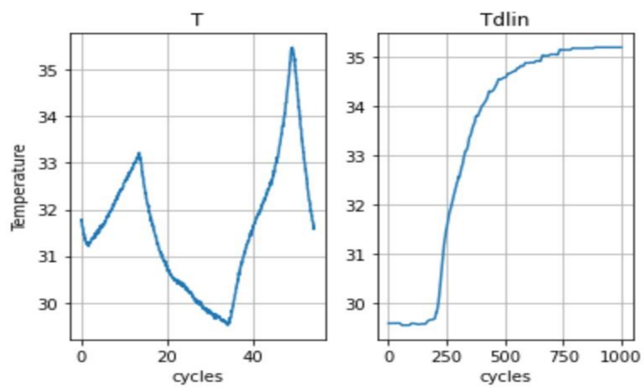


(b) Quantity of Charge vs Qdlin

Fig. 1. Feature Selection for IR and Quantity of Charge



(a) Quantity of Charge vs Qdlin



(b) Discharge Time-T(°C) vs linearly interpolated temperature-Tdlin(° C)

Fig. 2. Linearly interpolated Qdlin and Tdlin vs their original parameters

The neural network model was trained in Python using TensorFlow 2 machine learning library [21] with a learning rate of 0.001, 0.3 for drop out rate (preventing over-fitting for the small dataset) and rectified linear activation function for dense and output layers.

E. CNN-LSTM Model

The CNN model can handle the selected features (Qdlin, Tdlin, IR, QC and Discharge time in this study); however, it has no capability to expand based on the hidden time features inside Qdlin and Tdlin, while LSTM has this advantage to cope with these features. Therefore, the traditional CNN model (as explained in section III.D) has no capability to predict the RUL of LIBs effectively. Therefore, in this study a CNN-LSTM model is proposed to predict the URL of LIBs.

The developed CNN-LSTM model uses the same detailed features (Qdlin and Tdlin), used in the CNN model, as significant input and the scalar features (IR, QC and Discharge Time) with an input layer consisting of window size of 100. Incomparison with the 2D conventional layer in the CNN model,this CNN-LSTM adopts a time distributed 1D conventional layer with 32 filters. Time distributed layer is functional, working with time-series data, which allows a single layer to apply to each input and then let the LSTM layer to helpand to manage the time data. Then, a time distributed max- pooling layer is operated to reduce the output size. Another 1D time-distributed conventional layer containing 64 filters repeats the above process, followed by a flattening and a drop out layer. More importantly, the scalar features have concatenated with the Qdlin and Tdline. After processing the CNN part,an LSTM layer with 128 units and the hyperbolic tangent activation function (tanh) were applied to the concatenated one. A dense output layer was obtained working with an LSTM dropout and the hidden dense layer consisting of 32 units. The structure of the developed CNN-LSTM model is depicted in Fig. 4. The neural network model was trained in Python using TensorFlow 2 machine learning library [21] with a learning rate of 0.001 for CNN layer, 0.3 for LSTM dropout rate (which prevents from over-fitting of a small dataset) and rectified linear activation function for the dense and output layers.

IV. Results and Discussion

In order to evaluate the performance of the developed CNN-LSTM model, the results are compared with those of obtained from the CNN model. The data pipeline has been divided into two parts: train dataset and validation dataset. Train datasetfits both the CNN model and the CNN-LSTM model, and the validation dataset evaluates the models. Typically, mean absolute error (MAE) measures the errors (e) between paired observations under the same condition and it is formulated in (1). For the CNN-LSTM model, 1,008,386 variables have been trained, and the result after five epochs is shown in Table I. The MAE has been applied to both current (MAE CURRENT) and remaining cycles (MAE REMAINING).

$$MAE = \frac{1}{n}\sum_{t=1}^{n}|e_t| \tag{1}$$

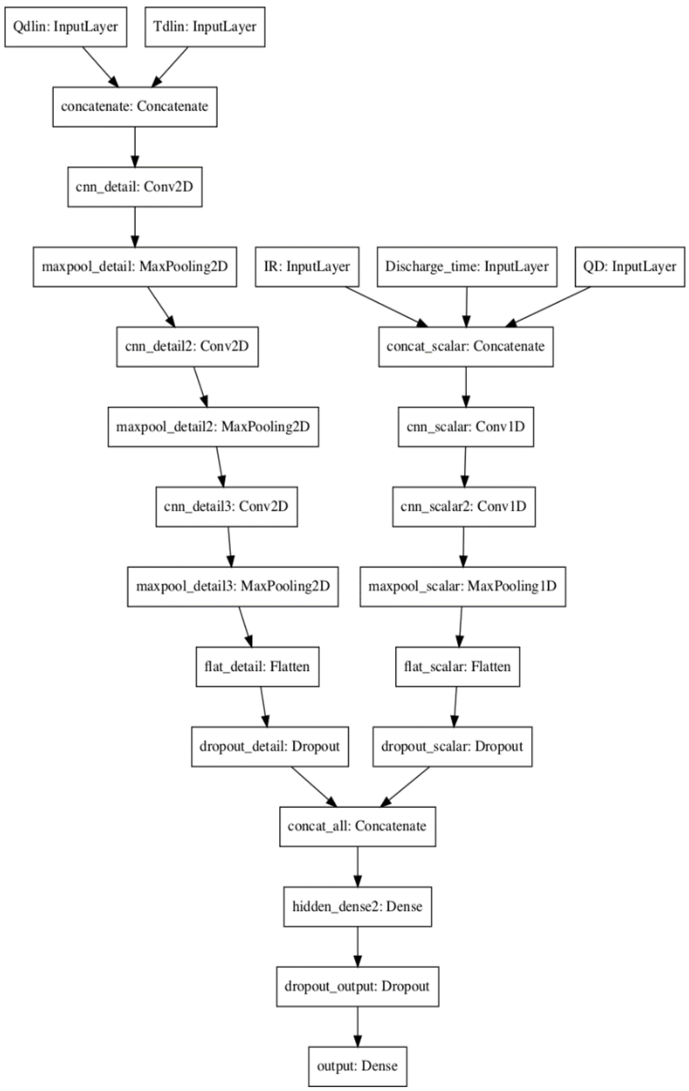


Fig. 3. Full-structure interpretation of the CNN model: 2D Convolution layer handles Qdlin and Tdlin, 1D Convolution layer handles IR, QD and Discharge Time.

TABLE I: MAE RESULTS FOR CNN-LSTM

Epoch	Loss Value	MAE CURRENT	MAE REMAINING
1	0.0347	0.1308	0.1190
2	0.0215	0.1147	0.0824
3	0.0209	0.1140	0.0775
4	0.0185	0.1107	0.0716
5	0.0194	0.1099	0.0741

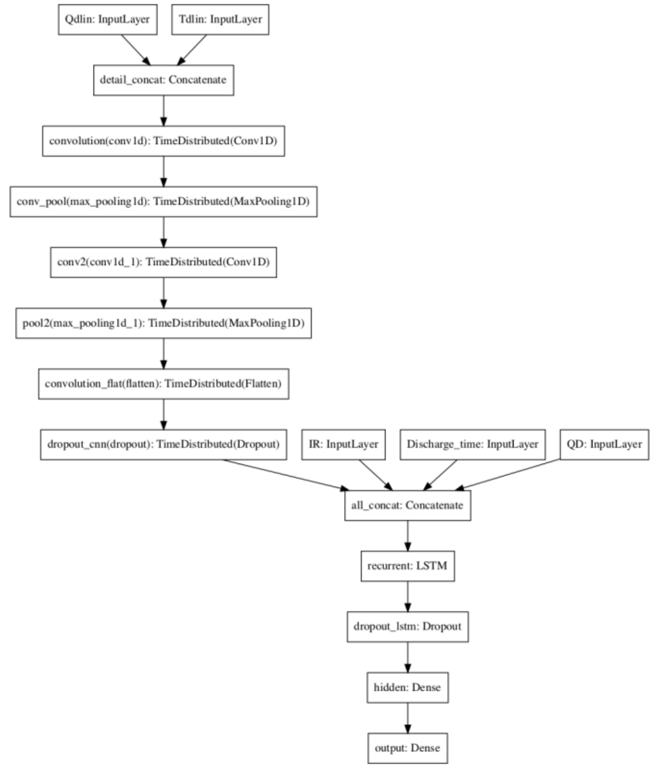


Fig. 4. Full-structure interpretation of the CNN-LSTM model: The Convolution layer handled Qdlin and Tdlin and concate- nated with IR, discharge time and QD followed by LSTM.

For training the CNN model 1,411,458 variables have been used and the result after five epochs is shown in Table II.

Another important measurement matrix for predicting the RUL is the mean absolute percentage error (MAPE), which calculates the accuracy of the prediction in percentage. MAPE is calculated by (2):

TABLE II: MAE RESULTS FOR CNN

Epoch	Loss Value	MAE CURRENT	MAE REMAINING
1	0.0357	0.1368	0.1307
2	0.0336	0.1299	0.1215
3	0.0312	0.1329	0.1119
4	0.0283	0.1272	0.1028
5	0.0267	0.1247	0.1026

$$MAPE = \frac{100\%}{n}\sum_{t=1}^{n}\left|\frac{e_t}{y_t}\right| \tag{2}$$

Where n represents the number of fitted points, e represents the difference between the actual value and the predicted value,and y demonstrates the actual value.

For the CNN-LSTM model and the CNN model, 1,008,386 variables and 1,411,458 variables have been trained respectively, and the results after five epochs are depicted in Table III and Table IV.

TABLE III: MAPE RESULTS FOR CNN-LSTM

Epoch	Loss Value	MAPE CURRENT	MAPE REMAINING
1	0.0299	12.3921	10.5403
2	0.0197	11.1105	7.4877
3	0.0216	11.6464	8.2188
4	0.0202	11.2576	7.5537
5	0.0186	10.9457	6.9226

As shown in Table III, the difference between current cycles and remaining ones is high compared with other epochs, and this is caused by the employed LSTM layer which has agreat capability for handling the time-series data. However, as shown in Table I and Table II, the MAE difference for the current cycles of the CNN model and the CNN-LSTM model is small (0.01 in average) which indicates the efficacy of the CNN-LSTM. Since the scalar features were not completely added into the CNN model, the feature itself may contain hidden information which could be used to increase the performance of MAE.

TABLE IV: MAPE RESULTS FOR CNN

Epoch	Loss Value	MAPE CURRENT	MAPE REMAINING
1	0.0364	13.7522	12.9190
2	0.0274	12.4028	10.1061
3	0.0280	12.6283	9.9091
4	0.0258	12.1370	9.3340
5	0.0256	12.5660	8.9049

In summary, the results suggested that the developed CNN-LSTM model outperformed the CNN model. The minimum MAE value for the current cycle of the CNN-LSTM model was 0.1099 (Table I), while its counterpart in the CNN model was 0.1247 (Table II). In addition, the MAPE results confirmedthe better performance of the CNN-LSTM model, by lowest MAPE value of 10.9457 for the current cycle (Table III), than the CNN model with a minimum MAPE value of 12.1370 (Table IV). It is clear that with the increased number of epochs, the performance is enhanced due to the effectiveness of themodel.

V. CONCLUSION

This paper proposes a conventional neural network with a long short-term memory layer for predicting the RUL of LIBs. An extra LSTM layer increases the accuracy of the prediction model, and this is validated by comparing results of the developed CNN-LSTM model with those of obtained from the CNN model, using the same detailed features (Qdlin,Tdlin) and the scalar features (IR, QC, and discharge time). The dataset was made of data extracted from 124 LIBs. The results (MAE and MAPE) suggested that the CNN-LSTM model outperformed the CNN model in predicting the RUL. At the same time, the MAE and MAPE results are highly competitive compared with other prediction methods; mainly because of effectiveness specification of the CNN model in handling the features, and advantage of LSTM in handlingthe time-series data. In future, Deep learning model will be developed for predicting the RUL and the results will be compared with those of obtained from the CNN-LSTM model.

CONFLICT OF INTEREST

The authors declare that they have no conflict of interest.

DATA AVAILABILITY

The datasets generated for this study can be found in the Figshare repository with DOI 10.6084/m9.figshare.16772548.

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