Lithium Battery Life Prediction Based on Edge Computing and Deep Learning

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Abstract. Lithium batteries have become the main power source for many electronic devices, and its accurate life expectancy is of great significance to ensure the reliability of electronic devices. Due to the limited computing power of the terminal, the real-time performance of cloud data transmission is not strong. In order to prevent the sudden failure of lithium batteries, this paper proposes a lithium battery life prediction based on edge computing and deep learning. By using the temporal pattern of the original data and the pre-relevance of cross-data, terminal voltage, current and battery temperature, etc., the prediction model is established to predict the life of lithium batteries faster and more accurately. It has better real-time performance and more accurate prediction ability for online and rapid prediction of lithium battery life.

Keywords: Lithium battery · Edge computing · Deep learning · Life prediction

1 Introduction

In recent years, high-energy-density lithium-ion battery is playing an increasingly important role in electric vehicles, energy storage systems, and information technology systems. The environmental energy collection and doubling of the demand for electric vehicles make lithium-ion battery market more prosper [1]. However, the instability of lithium-ion batteries is widely considered to be a significant obstacle [2]. For example, energy storage systems are often connected to the energy grid for forming GWh level energy storage, but there is without preventive protection. In such a system, an unexpected lithium-ion battery failure may ignite the entire ESS, which will lead to a catastrophic explosion.

In order to ensure reliable prediction of the operation and protection of lithium-ion batteries, the prediction of remaining useful life (RUL) of lithium-ion batteries are proposed in recent years. The studies are mainly divided into two types. The one is based on the physical model, which mainly predicts RUL from the perspective of the physical characteristics of the battery. And it is based on physical models of several degradation mechanisms: Loss of Lithium Inventory (LLI), Loss of Active Material (LAM), and increase in internal resistance [3]. As in reference [4], the Solid Electrolyte Interface

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(SEI) physical model was used to estimate Lithium Inventory and internal resistance. The they applied structural cracking and chemical degradation model to evaluate Loss of Active Material. These mechanisms and chemical models have successfully in predictions, but their results are sensitive to the operating conditions of the battery. The other is an emerging research field of data-driven RUL prediction. It applied statistical analysis and machine learning with a large amount of data. Instead of a complex physical model, they try to find a prediction between the electric measurements of the battery charge and discharge cycle and RUL [5]. And these require a large amount of data to make predictions of chemical unknowns and no-operation conditions. The most common is the combination of exponential empirical model and advanced filtering methods, such as particle filtering or Kalman filtering. Other work uses machine learning methods to predict capacity degradation, such as Box-Cox transform [6], Relevance Vector Machines (RVM) [7], Gaussian Process Regression (GPR) [8].

Recently, many studies have used deep learning algorithm to make better predictions. These works applied Recurrent Neural Network (RNN) [9] or improved Long Short Term Memory (LSTM) [10] to make prediction of time sequential capacity degradation. In order to overcome the problems of over fitting, the reference [11] combined RNN and CNN in a hybrid model. However, from the abstract mode of charge-discharge cycles to a single discharge capacity value, it can make a rough degradation with capacity degradation curve c. It is known that the difference in discharge capacity of lithium-ion battery in the initial state can be ignored, so the technology based on degradation curve requires more than 25% of target battery charge-discharge data to make accurate prediction.

Reference [12] uses ground penetrating radar (GPR) to predict remaining useful life from artificially defined features. The breakthrough study shows that when the evolution of discharge voltage curve is in a cycling, the elastic network can predict RUL using only data of the first 100 cycles (about 12.5% of the entire life cycle). It is also a research direction to predict RUL by extracting the fluctuation of voltage, temperature and current, with Support Vector Regression (SVR). It builds deep neural net-works to make predictions by more complex timing related features during charge and discharge.

In order to predict the RUL more effective, we need to solve two following problems.

(1) The complexity and high coupling nonlinearity of degradation mode in lithium-ion batteries. Due to this complex situation, the degradation of lithium-ion batteries will not be directly reflected in the capacity attenuation. The performance degradation of lithium-ion battery is reflected in its working mode. The complexity of operation mode makes it difficult for human to analyze them in a suitable rule-based algorithm.
(2) The rapid RUL prediction. That is, in manufacturing and operation, only a small number of data cycles of the target can be used for RUL prediction before new possible prediction protection methods. Without such predictive protection, battery manufacturers needed to minimize the risk of sudden battery death and ensure the safety of new batteries by numbers of charge-discharge cycles. The rapid prediction of RUL can reliably detect abnormal units in a short time, thus greatly reduce the production costs. The method can also rapid diagnose the lithium-ion battery and minimize the probability of accidental failure in advance.

However, the amount of data in deep learning is large. Due to the limited data transmission in network, there are large number of lithium battery RUL data collected from the mobile terminal need to be processed and analyzed by centralized cloud computing structure with heavy data transmission. Edge computing distributes the computing tasks from the centralized data center to the edge unit which is closed to the Internet of things devices. It can greatly reduce the data transmitted through preprocessing procedures. Edge computing has better performance when the input data is more than intermediate. It is feasible for deep learning to divert learning layers at the edge and the centralized cloud server can receive the simplified intermediate data.

Privacy protection of intermediate data transmission is another advantage of deep learning in edge computing [13]. The source data always has different semantics from intermediate data produced by deep learning. For example, features of source info are very difficult to understand in the convolutional neural network (CNN) [14].

Therefore, we applied deep learning on edge computing environment for improving learning performance and reduce network traffic in this paper. We establish a elastic deep learning models. We proposed an edge computing and deep learning framework to predict the RUL of lithium-ion batteries with terminal voltage, current and battery temperature directly from the time series of battery operation to solve the unbalanced cost of intermediate data processing and preprocessing overhead of prediction. This paper attempts to extract all aspects of features like feature-based RUL prediction, but these features are automatically extracted through the deep learning model in the framework of this paper. we automatically extracted as much as possible features for feature-based RUL prediction through the deep learning model and adopt deep learning model with edge computing to increase the real-time prediction. The features for RUL prediction extracted by the end-to-end deep learning model have a good performance.

2 The RUL Prediction Model of Lithium-ion Battery

2.1 The Overall Architecture of the Model

In this paper, we applied edge computing and Deep Learning on RUL prediction problem of lithium-ion batteries. Edge computing is the computing way that computing task is transferred to closest node rather than centralized cloud servers. There are two major improvements in edge computing. First, edge nodes can preprocess lots of nearby data before transmitting to the central cloud. Second, edge nodes can optimize cloud resources with computing power.

Deep learning model training needs to collect a wide number of training data. However, it is still possible to make arbitrary decisions that may lead to serious failures in industrial applications. Moreover, the deep learning model is large, and the training model in the mobile terminal will occupy a lot of device resources, which will have varying degrees of impact on the normal use of the device by users. It is very important to propose the method for rapid prediction of lithium-ion batteries.

In this paper, we use time series data of terminal voltage, current and battery temperature in the battery management system to train neural network for directly predicting RUL of the target lithium-ion battery. We train the deep neural networks to analyze the original data and automatically capture the complex association and features in voltage, current and temperature, rather than artificially abstracting features. It makes RUL prediction faster and more accurate. Figure 1 illustrates the overall prediction framework.

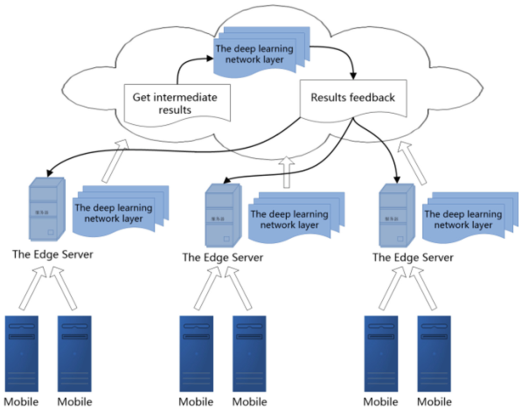

Fig. 1. The overall framework

The size of the intermediate data generated by the upper layer is usually less than by the lower layer in the process of deep learning. It can reduce more network traffic by deploying more layers on edge servers. However, compared with cloud servers, the server capacity of edge server is limited. And an edge server is impossible to handle infinite tasks. Each layer of deep learning network would impose additional computational overhead on the server. We deploy part of the deep learning network to edge servers.

The collected data will be sent toto the first layer of the edge servers. The edge server loads intermediate data processed by the lower layer and then transmits the result to the cloud server as the input data for the upper layer. We first deploy in the gateway, process the intermediate data and then send it to the cloud for final prediction and evaluation. The deep learning network model is shown in Fig. 2.

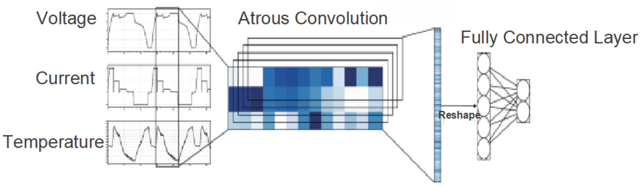

Fig. 2. The network model

2.2 Data Preprocessing

In this paper, we make a comprehensive analysis of lithium-ion battery from the perspective of temperature, current and voltage, and considers the problem from the overall perspective, but there are different dimensions and orders of magnitude between different characteristic parameters. Therefore, data preprocessing is necessary before training. And synthesize the different index information of the battery life so as to facilitate the overall evaluation.

We use the Z-Sore for standardization, which is known as standard deviation standardization and it gives the mean and standard deviation of the data for data standardization. We uniformly calculate the Z-score values of voltage, current and temperature to ensure the comparability between the data. The processed data conforms to the standard normal distribution, that is, the mean value is 0 and the standard deviation is 1. The transformation function is as follows:

$$x* = (x - \mu)/\sigma \tag{1}$$

x represents the real value of the detected data, μ is the mean value of all sample data and σ representsthe standard deviation of all samples. Through the above formula, we can convert different data to the same magnitude and realize standardization.

2.3 The Neural Network Architecture for RUL Prediction Based on Edge Computing

Liu et al. [15] first introducing deep learning into edge computing environment. They adopt the service infrastructure based on edge computing and propose a food recognition application based on deep learning. As shown in their work, edge computing can improve the performance of deep learning task by reducing response time and resource consumption. In this paper, we use mobile phones as the edge nodes. Since we focus on the battery life, we deploy edge servers on gateways that are capable to execute deep learning algorithms.

The capacity of lithium-ion batteries decreases as it is used. Unfortunately, the degradation curves of the same type of lithium-ion battery may also differ from each other because of deviations in the manufacturing process and operating conditions. It makes the prediction of RUL particularly difficult. Generally, the lithium-ion batteries are considered to have reached their end when they degrade to 80% of their initial capacity. The RUL of lithium-ion battery can be defined as follows:

$$RUL = C_{EOL} - C_M \tag{2}$$

The C_{EOL} represents the service life, and C_M represents the number of cycles used at the end of the measurement.

In this paper, we use convolutional neural network to predict the RUL of battery. In order to analyze the aging of lithium-ion battery in cycle using, this paper takes the data of more than one charge and discharge cycle as the input. The fully charge and discharge of a battery may take hundreds of seconds or more. There are many variants of RNN and Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) are most popular. These architectures provide the most advanced performance for various of sequential tasks which are applied in language modeling, sentiment analysis and speech recognition. However, it is limited for them to capture long-term relationships. And it is difficult for them to achieve good results with limited edge computing capabilities.

On the other hand, the atrous convolution has been proved to be able to capture the long-term relationship in time series data. An amplified CNN can generate natural human voices at the original audio level, which requires understanding thousands of steps in time series data. The atrous convolution is applied to the input signals with a certain gap in kernel level.

Figure 3 shows that we design an atrous convolution to get the long-term relationship in the input data. The receptive field of atrous convolution grows exponentially with the number of layers, compared with traditional CNN which grows linearly. As can be seen from Fig. 2, the exponentially growing size provides a broad acceptance domain for CNNs. In this paper, we meticulously optimize the kernel and dilation size to build a neural network that is most suitable for RUL tasks.

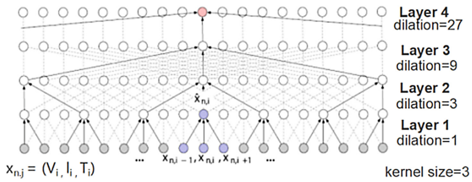

Fig. 3. The explanation of Dilation convolution operation.

The main component of our neural network architecture is atrous convolution. Temporal patterns of multivariable input sequences are used in the first five layers of atrous convolution. We doubled the expansion size of each layer to create receptive field for RUL prediction in this paper. The normalized convolution output generated by each layer will be loaded the next layer. Normalization makes the training process faster and more stable because of each layer of the neural network has the similar input domain. And we adopted Rectified linear unit (ReLU) as the activation function.

In this paper, we maintain the size of each output sequence generated by atrous convolution and meanwhile increase channel of temporal information. Then, we obtain the basic characteristics by compress the output data of the final atrous convolution layer with one-dimensional CNN. Finally, we use three layers of fully connected neural network to obtain the nonlinear mapping of extracted features for RUL prediction.

3 Experiments

3.1 Experimental Data

In this paper, we use the open lithium-ion battery dataset (available online) from reference [16] to evaluate our framework. The open dataset was generated by 124 commercial high-power units with a nominal capacity of 1.1AH and a nominal voltage of 3.3V. With the same discharge capacity, we use various battery cycle charging schemes to maintain the EOL in the controlled environment about 30 °C. Lithium-ion batteries use one of 72 different strategies with charging states ranging from 0% to 80%. The charging time of 0%~80% SOC is 9~13.3 min, and they collect temperature, voltage and current every second.

The edge computing framework proposed in this paper uses truth label of RUL and the continuous original charge-discharge data of voltage, current and temperature. In general, the larger the size and diversity of datasets, the better the performance and robustness of deep learning. Therefore, we expand the data with overlapping window slices. Firstly, we get obtain the lifetime time series data by connecting the continuous cycle data of a single battery to obtain the lifetime time series data of terminal voltage, current and battery temperature. Then, we split the lifetime data L into the window size which loaded by the neural network and S is sliding size. Finally, we marked each slice sample with the number of cycles remaining through its whole life. Because the model requires more than three cycles of sequence data to make better prediction, we set the parameters of L = 2500 and S = 500.

The dataset consists of three batches of battery measurement. Different batches of products use different cycle ranges. There is a problem of inductive bias that machine learning model will have large bias in prediction with different distribution of training data and test data. In this paper, we created a training dataset by extracting specific parts of batteries from batches to minimize the influence of induction bias. We use the same strategy to create validation datasets and test datasets, so that datasets can cover the whole cycle. About 70% of the data is used for the deep learning training and the remaining data is used as the verification dataset and test dataset.

3.2 Experimental Results and Conclusions

We evaluate the RUL prediction performance of various deep learning models and artificial feature-based baseline models. And the results are shown in this section. The deep learning model uses data of 2500 s corresponding to about 3 charge and discharge cycles as model input. The previous baseline model uses the data of 100 cycles as the input. In this paper, because of the superior performance in many time series tasks, we choose Multilayer Perceptron (MLP), CNN and CNN-LSTM as the control group of deep learning models. This paper designs the neural network structures and hyperparameters of choosed models, such as kernel size and channel size. And we fine-tune the hyperparameters based on experience from conventional rules in previous works.

The framework of this paper is designed to predict RUL, which does not consider the time point of the data received from the whole battery cycle. The Fig. 4 and Fig. 5 show the training loss and test error in different periods.

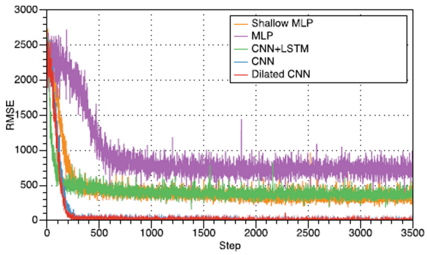

Fig. 4. The variation of training loss without considering position.

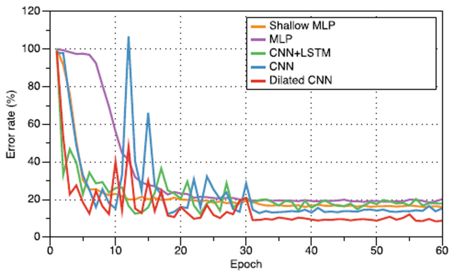

Fig. 5. The test error without considering position.

In this paper, we also evaluate the ability of the model to predict RUL at 2500 s of data at any location in a given life cycle and marked the setting as “Complete”. We set the shallow MLP model with the same number of parameters in CNN model and MLP models. However, our model architecture has lower error rates than both shallow MLP model and deep MLP model. They show better performance because CNN and LSTM are designed to be more suitable for time series prediction. Nevertheless, the dilated CNN still has the best performance in error rate. Figure 6 and Fig. 7 show the training error and test error of the "Complete" mode respectively.

In the “Complete” setting, the performance difference is more obvious. Due to the nonlinear and complex degradation behavior of lithium-ion battery, the RUL prediction algorithm using early data may be very different from that using later data. The neural network with the “complete” setting should be able to detect data location and predict the RUL related to the phase with different algorithms. Due to the difficulty of the “completely” setup, the shallow MLP and MLP models failed in solving the task. The model proposed in this paper is obviously superior to other algorithms and the error rate is about 10%.

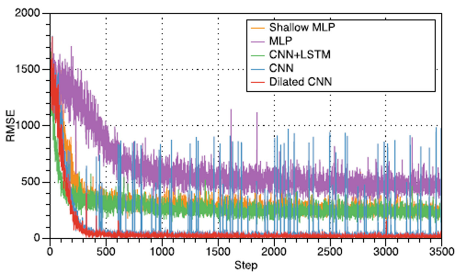

Fig. 6. The variation of training loss in “Complete” mode

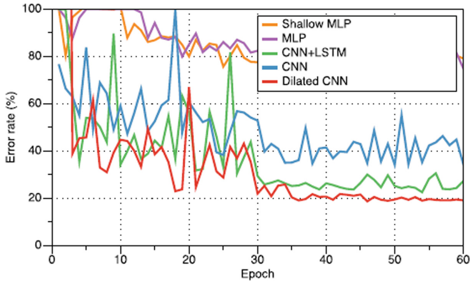

Fig. 7. The test error in "Complete" mode

4 Conclusion

In this paper, we applied deep learning with edge computing environment to optimize the network load and protect the privacy of users uploaded data. The edge computing reduces the network and computing load from IOT devices to cloud servers because edge nodes preprocess input data instead of sending the origin data.

We proposed a lithium battery prediction model based on deep learning with edge computing. The model solved the challenge of predicting the remaining battery life and reduced the detection time. The proposed framework significantly improves the prediction of remaining useful life by predicting the target battery with less than 4 data cycles, while the previous model requires 100 data cycles. Among various deep learning models, the dilated CNN error rate of the lithium battery life detection based on edge calculation and deep learning proposed in this paper is 10.6% lower than 14.6% of the previous models. This paper also introduced a deep learning training algorithm and metrics to quantify the uncertainty in neural network predictions which have prediction errors or new features found in the training dataset. Finally, we make a in-depth analysis with neural networks in this paper and reveals the possibility of analyzing lithium-ion battery data using deep learning methods of edge computing for battery related tasks.

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