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A Multitask Data-Driven Model for Battery Remaining Useful Life Prediction

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Abstract– **Lithium-ion batteries (LIBs) have recently been used widely in moving devices. Understand status of the batteries can help to predict the failure and improve the effectiveness of using them. There are some lithium-ion information that define the battery health over time. These are state-of-charge (SOC), state-of-health (SOH), and remaining-useful-life (RUL). Normally, a LIB is working under charging and discharging cycles continuously. In this paper, we will focus on the data dependency of different time-slots in a cycle and in a sequence of cycles to retrieve RUL. We leverage multi-channel inputs such as temperature, voltage, current and the nature of peaks cross the cycles to improve our prediction. Comparing to existing methods, the experiments show that we can improve from 0.040 to 0.033 (reduce 17.5%) in RMSE loss, which is significant.**

Keywords– **Lithium-ion battery, time-series, Conv2DLSTM, RUL.**

1 Introduction

Lithium-Ion Battery (LIB) is a type of rechargeable battery commonly manufactured in the market. Basically, there are two typical periods including charging and discharging. During the charging process, the positive ions (Li+) move from cathode to anode and vice versa in the discharging process to create the current. The looping process of charging and discharging usually follows a typical routines called CC-CV (constant current, then constant voltage). LIBs are mostly used for moving objects, especially in lightweight wearable devices [1]. However, in some cases, LIBs appear in big moving objects such as cars, drones, unmanned aerial vehicles, etc. The power system using LIBs gained much attention in industry with a giant number of LIBs-enabled devices [2]. Those outdoor moving objects, mobile devices, solar power devices... are required to use LIBs due to their features like lightweight, durability, high capacity, and self-discharge ability. Moreover, to maintain a good performance of LIBs in outdoor environments, some other features such as safety, durability, issue-free stability and, high quantity of working cycles,... are highly demanding [2]. Nowadays, thanks to the continuous development of battery technologies, people keep requiring on improvement of overcharging, self-discharging, capacity fading, impedance, shocks, and aging [3].

A battery full-charge capacity usually degrades over different cycles of using it. The degrading levels follow time-series trend and seasonality that are specific to LIBs nature. Internal information in a cycle of charging and discharging such as Voltage (V), Current (A), Temperature (°C), Charge Capacity (Ah), Discharge Capacity (Ah) or Resistance (Ω) should relate to the output capacity of a battery (SOH) by a combination of relationships. There are a major numbers of studies try to find this correlation and utilize it for later prediction. The regression outputs mainly are SOC, SOH as these are the key battery values.

Figure 1 shows the typical SOH degradation of the four batteries over different cycles. And Figure 2 describes the changes of Voltage, Current during charging and discharging process. Obviously, capacity data of LIBs are time-series over full cycles of charging and discharging. Moreover, the trend and seasonality of SOH, SOC are specific to LIBs dependencies. Therefore, recent studies try to extract the relationship from this time-series correlation for future regression. Base on the physical constrains, it is considered that battery health data SOC, SOH and RUL are obvious output because they are required to notify a warning message or alternate a working procedure of some battery-using devices. As the result, prediction on these output creates crucial impact to detect a relevant status or a problem, making sure the power system is working properly.

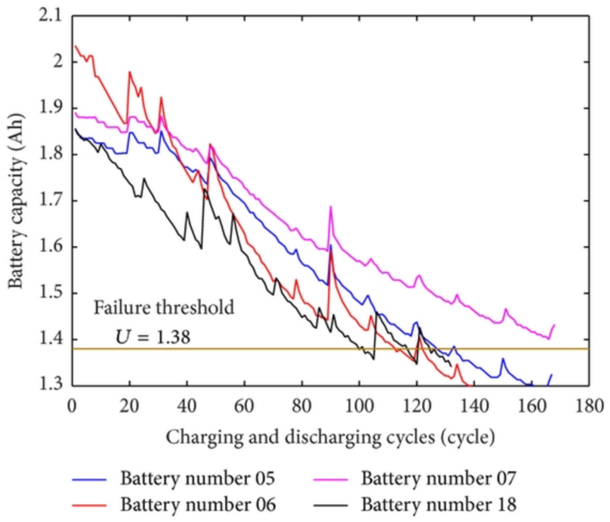

Figure 1. NASA normal battery usage dataset.

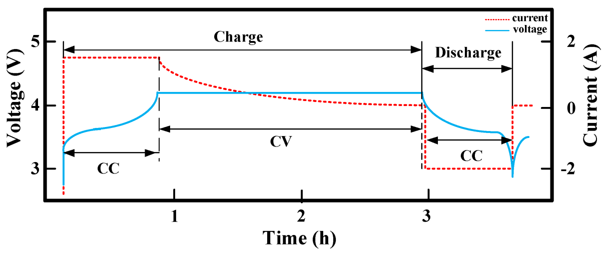

Figure 2. Charge and discharge process of Li-ion battery in one cycle [4].

Recently, according to the software analysis of Battery Management System (BMS) [2], there are two different approaches including traditional model-based methods (class-1) using the classical model and regression and AI-DL models (class-2) [5, 6]. In class-1, the equivalent circuit models were popular during the years 2000-2012, including some studies using finite elements of LIBs [6]. The methods used finite elements required deep domain knowledge (including physical, material, chemistry of the cells) to optimize the models. Therefore, these approaches need experience from LIBs hardware experts. Lately, people are focusing on the class-2, using AI-DL models to improve measurement and prediction of LIBs data, as well as to reduce the domain knowledge and maintain the high accuracy output. In this paper, we focus on methods of class-2 to predict SOH. The baseline is a state-of-the-art paper using an encode-decode multi-channel LSTM base [7], and we engage our improvement by analyzing data dependencies (data-driven) with some adaptation into the model structure. Moreover, observing that seasonality of SOH data plays an essential part in degradation, we engage peak data as another factors to go along with SOH output (multitask). The experiments shows that our analysis significantly improved the prediction output.

The structure of this paper is as follows: Section 2 describes existing feasible regression methods and the characteristics presented in the literature. Section 3 discusses our methods for online implementation and presents its pros and cons. The comparison of the legacy and our approach with quantitative data and accuracy is shown in Section 4 - Experimental Result. And finally, Section 5 concludes the paper.

2 Literature Review

2.1 LIBs Studies

It is noticeable that today technologies have deeply relied on battery development, especially for moving devices. Recently, since LIBs are highly dominated due to high power density, durability, and environmental friendliness [8], LIBs are advancing into the field of transportation, especially electric vehicles (EVs) [9]. The power supply systems are asked for range-per-charge and weight-ratio over the whole main moving machines. Therefore, to achieve the above energy density goals, many studies are developing high-capacity cathode and anode materials of LIBs [10, 11]. For LIBs materials, researches show that Ni-rich materials have been considered as powerful candidates by high capacity and anode with silicon-based or tin-based carbon composites will provide long-life capacity as well as cycling stability. However, the drawbacks of these materials include thermal stability reduction [12].

Beside capacity density, battery safeness is another crucial matter to be considered. Reports show a wide range of casualties due to malfunctional issues from EV portable batteries. Unsafe behavior of LIBs may be caused by internal exothermic. Basically, the exothermic reactions consist of: (1) excessive delithiation of cathodes cause irreversible structure change of cathodes, oxygen release and oxidization of organic solvents; (2) lithium dendrites formed on anodes react with electrolytes to generate a great sum of gas, heat and lithium dendrites, then penetrate the separator and result in an internal short circuit of batteries; (3) the melting of PE-based separators (when the temperature is greater than 130°C), also leads to internal short circuit; and (4) the electrolyte is easily decomposed at high temperature (>200°C) and high voltage (about 4.6 V) will also generate high warmth [9].

Recently, thanks to the development of electrochemical technologies, there are many studies that enhance the design novel, safety, and material of cathodes and anodes. In addition, stabler electrolytes and separators improve batteries with high energy density. In practical applications, LIBs are assembled into battery modules, and the safety awareness of the battery system is different from that of a standalone cell. Beside the safety, it is also crucial to improve real-time internal status monitoring capabilities to follow the state of charge (SOC), state of health (SOH), remaining-useful-life (RUL), electrolyte leakage, and dendrite growth of the cells to keep the quality of LIBs under better working conditions.

2.2 SOH Predictions

Predicting SOH is a challenge job due to trending and seasonality of battery full charge over different cycles.

Since the output data play crucial part in the working behaviours of the battery, there are a great deal of researches on this topic. Conventionally, some model-based methods go with hardware, measurement tools, online data collection, and the computation models are Kalman Filter (EKF), Taylor Series Sigma-Point Kalman Filter (SPKF), and Particle Filter [6] or Relevance Vector Machine (RVM) [13]. On the other hand, AI-DL methods such as Neural Network (NN), Convolution Neural Network (CNN), Relational Neural Network (RNN), or Long Short-Term Memory (LSTM) are proving their dramatic improvement recently. [7] provide a LSTM-based multi-channel method of encode-decode model to predict SOH over time-series representation, using NASA dataset [14] and Center for Advanced Life Cycle Engineering (CALCE) [15]. We will use [7] as the baseline for our experiment. Another study [16] approaches similarly by adding some features extraction inside a cycle to improve the output. However, the use of discharge cycle for SOH predict is an unfair approach for prediction once we are at the full internal information of discharging and accumulating for the predicting data.

Therefore, although there are many studies, the main concerns are the accuracy of measurement devices, and the cost to be spent in controlling different options. Another concerning topic would be how much LIB physical and chemical related information is required and how much noise-tolerance can the system handle based on big input data existing.

In this paper, we approach base on [7] using NASA dataset. Some of big-data sources are NASA [14], Oxford [18], Center for Advanced Life Cycle Engineering (CALCE) [15] or Sandia National Labs [19] and 124-cells of [20]. Since conventional model-based methods provide relevent results, yet require the full capability to analyze the dependency of the large volume of data, physical and chemical knowledge of LIBs. To avoid the dependency of battery domains expertise, we will mostly focus on AI-DL methods and the [7] is used as the baseline for our experiment. AI-DL is a classical topic in computer science. Previously, in the years 2010s, neural network and similar algorithms were not considered much due to high computation time and low performance. However, recently, there are a great deal of improvement in parallel processing on hardware and libraries, deep learning methods have been developed majorly and contribute to the significant wave over the last 10 years. Deep learning for time-series forecast, which battery RUL prediction is included, is a clear example of this deep-learning-is-everywhere era.

Recently, there are a number of studies described machine-learning based methods for battery health estimation using NASA [21] or CALCE [15] data-set. These studies archive rel event performance comparing with conventional approaches. A research [22] provided estimation on EV battery story with recurrent nonlinear auto-regressive with exogenous inputs (RNARX) algorithm and similar methods using some validation of hybrid pulse power characterization (HPPC) and claimed that they archive the smallest MAE (Mean Absolute Error) as well as RMSE (Root Mean Square Error) results. Lately, [23] provided prediction on SOC and SOH by data-driven machine learning. [7] is a state-of-the-art paper predict RUL using multi-channel input from different cycles. We will use the same data-set (NASA) and create an approach to change the input engagement of data-driven highlights, trying to outperform [7] in accuracy manner.

In the later sections, we will describe our approach then present the experimental results with some analysis on the different attempts.

3 The Proposed Method

3.1 Data Analysis

In order to have the same data approach, we also use 4 NASA battery sets (B0005, B0006, B0007 and B0018) similar to baseline [7]. The data will be used for training, validation and testing. We also have pre-processing steps such as min-max normalization, outliers removal. After that we respect the remaining noisy data and the pre-processed portions are used to feed into the models. The way we separate train/val/test is based on cross-validation recommended by [7]

Figure 3 shows the sharing of train, validation and test combinations that will be fed into our model. As mentioned earlier, the test portion is not overlapped to any part of training and validation separations. This help the comparison of the models to be fair and independent on training. The RMSE test loss is used for model fine-tuning.

3.2 Data Extraction

There are two approaches in our data extraction. Internal data of a cycle and global accumulation data are considered.

3.2.1 Internal Cycle Extraction: Base on [17], we extract those data points from which will best represent the changing trend of charging cycle. Figure 4 shows different points inside a cycle. It is obvious that the first part of the battery cycle is unstable in 30% timeline, and is suggested to be a Non-sampling interval. The middle part is observed to be not very much high-variant, so we will extract 3 points. The close-end of the cycle we archive data from 3 points. And finally, we extract another 4 condensed data points by end of the charging cycle. Totally we extract 11 points base on it's corresponding position at [35, 52, 70, 88, 90, 92, 94, 96, 98, 99, 100] of the whole rated 100 data points of charging step. At each point, 3 information (Current, Voltage, Temperature) are used.

The above internal channel-wise extraction create 3×11 matrix data for a cycle.

3.2.2 Global Cycle Extraction: Base on [24], we will accumulate global data. Initially, [24] suggested that we should find x_1, x_2, x_3, x_4, x_5. These 5 features represent crucial characteristics of the battery at the current CC-CV process.

- x_1: Initial charge voltage.

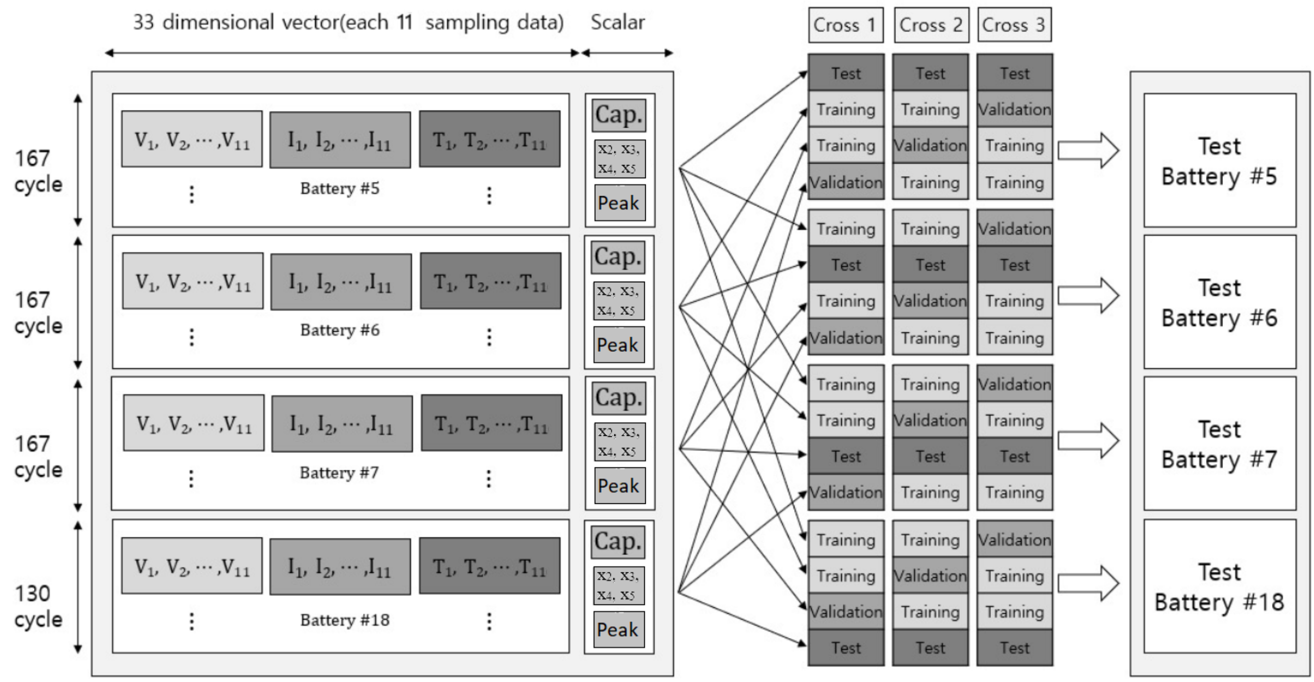

Figure 3. Cross validation and the method to separate train, val and test for the dataset [7].

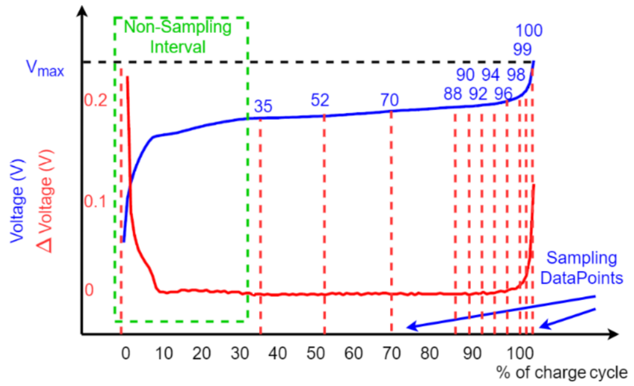

Figure 4. Multi-channel data extraction [17].

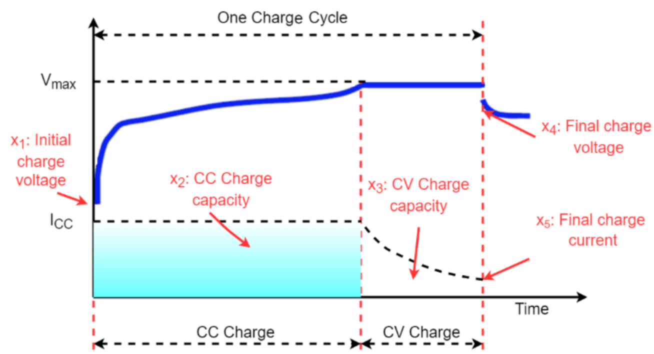

Figure 5. Five charge-related features in an illustrative charge cycle [24].

- x_2: CC charge capacity, calculated by accumulation the rectangle $I_{CC} \times t$, where I_{CC} is the constant current in the charge, and t the duration of CC period.
- x_3: CV charge capacity, accumulated by the integral of the area of decreasing current during CV period.
- x_4: Final charge voltage (Voltage measured at battery terminal).
- x_5: Final charge current (Current measured at battery terminal).

However, [17] explained that x_1 is archived in the non-sampling interval, which is not stable and should not be consider. As the result we only take x_2, x_3, x_4, x_5 into our consideration.

Figure 5 shows the global data that will be archived and accumulated. Moreover, other global inputs that will be taken into account are peak and SOH. To find peak, observing the nature of SOH seasonality, trending, and noise, we find that peaks maintain for around 5 cycles and the nature impact deeply into prediction accuracy. To decide a peak data point, we compare current value with mean value of previous $n = 5$ SOH, base on a rated threshold. The peak data is binary and lasts as long as the mention rule satisfies.

SOH global data is simply the regression SOH of current cycle.

From the above global data, we construct 6 inputs for a cycle. Therefore, to maintain the crucial extracted features, we concatenate channel-wise internal data with cycle-wise global portion. As the result we have the matrix of $(3 + 6) \times 11$ or 9×11 for each charging cycle.

Similar to baseline [7] we will use $n = 10$ look ahead cycles to predict SOH for $m = 2$ cycles. In loss comparison, we mainly use result of the current cycle $m = 1$ to analyse and fine-tune the models. Other results of the later cycle are almost unused.

3.3 Baseline Model

Figure 6 is the best baseline model. In this structure, they use a multi-channel extraction from $n = 10$ cycle.

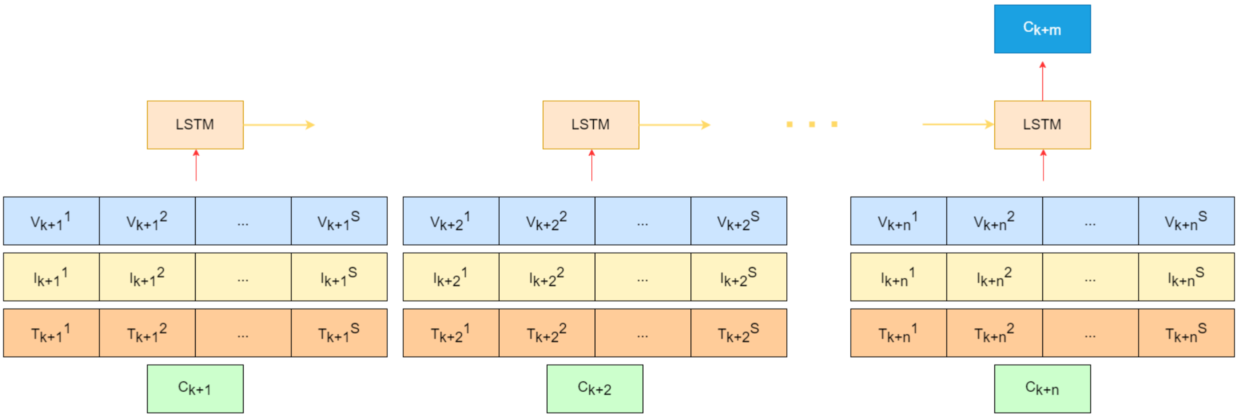

Figure 6. The many-to-many multi-channel baseline model [24].

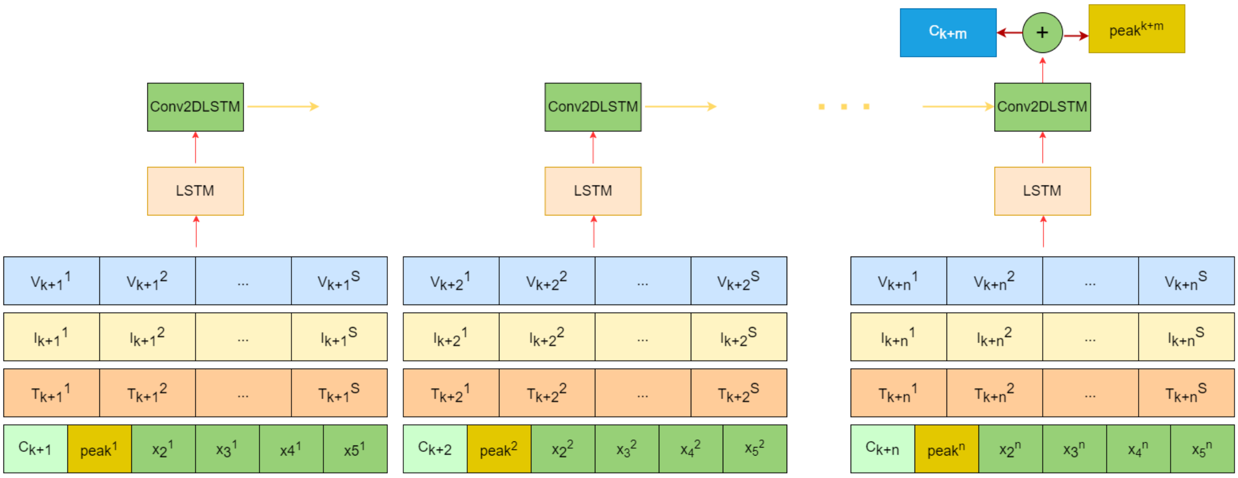

Figure 7. The proposed data-driven model.

In each cycle, they extract $S = 10$ data points. And at each data point within a cycle, the voltage V, the current I and the temperature T are archived. This encoding method provide feed data for LSTM decoder. Finally, the output is the SOH of their next $m = 2$ cycles.

3.4 The Proposed Model

Observing the nature of the battery data, we have introduced some changes in both encoder and decoder of the prediction. First, as mentioned, we archived global data of a cycle and concatenate them with channel-wise V, I, T. This improvement is introduced at the input layer. Second, there is an order of 11 data points extracted in a cycle, and there is another order of $n = 10$ input cycles which are engaged. Therefore, it is a sequence-in-sequence (seq-in-seq) constraint in the data. As the result, we introduce a Conv2DLSTM at the encode layer to preserve the data spatial dependency [25]. Finally, at the output layer, we introduce peak as another portion of output. The peak data is expected to create more engagement to loss functions so that the output model can represent better with the seasonality of battery data.

Figure 7 shows the structure of the proposed model. Compare to the baseline multi-channel Figure 6, we add a Conv2DLSTM layer after the normal LSTM on the encoder. This layer extracts constraint from the sequence of 11 channel-wise data points. After that, the features are engaged into another sequence of 10 channel-wise cycles (seq-in-seq). Moreover, the multi-task output let the model to be back propagated based on both C_{k+m} and $peak^{k+m}$ output. The portion-weight is a trainable parameter. As the result, by introducing the above improvement artifacts, the proposed model has been enabled with multi-channel, multivariate and multitask configuration. Therefore, we aim to create significant improvement in different experiments. The next session shows our result recorded.

4 Experimental Result

Firstly we re-implement the [7] using the same dataset [14]. We also reuse multi-channel approach and cross-validation methodology. Besides, after some basic data pre-processing, outliers removal and normalization, we do not remove remaining noisy portions to respect the variant nature of battery data. We have two models working based on this approach named E_1D_1 and E_2D_2 coincide with number of LSTM layer(s) they have in encoding and decoding layers. The E_1D_1 uses one LSTM in encoding and one LSTM in decoding approach while the E_2D_2 uses two LSTM layers in both

Table I
THE E_1D_1 MODEL STRUCTURE

Layer(type)	Output Shape	Number of Params
Input	10×36	-
LSTM 1	100	54800
Repeat vector	2×100	0
LSTM 2	2×100	80400
Time distributed	2×36	3636
Total params		138.836

Table II
THE E_2D_2 MODEL STRUCTURE

Layer(type)	Output Shape	Number of Params
Input	10×36	-
LSTM 1	10×50	17400
LSTM 2	50	20200
LSTM 3	2×50	20200
LSTM 4	2×50	20200
Time distributed	2×36	1836
Total params		79.836

Table III
THE PROPOSED MODEL SUMMARY

Layer(type)	Output Shape	Number of Params
Input	10×11×7	-
LSTM 1	50	-
LSTM 2	50	-
Conv2DLSTM	1×9×32	31616
Flatten and Dense	5762×2	11524
Total params		43,140

Table IV
THE LOSS SUMMARY

Methods	RMSE Loss
Multi-channel [7] with E_1D_1	0.045
Multi-channel [7] E_2D_2	0.040
Propose method - Multi-task - Without Conv2DLSTM	0.038
Propose method - Multi-task - Conv2DLSTM	**0.033**

encode and decode ends of the model. In the test, after some normal fine-tuning steps, we archive the RMSE loss of 0.045 and 0.040 for these two models. Tables I and II show the number of trainable hidden parameters work for the two models.

Next, we introduce some improvement in both multi-task and multitask with Conv2DLSTM. Since the E_2D_2 is potential, we base on it to enhance the model. As the result, we improve the performance and reduce the loss consistently to 0.038 and 0.033. The summary is listed in Table IV.

As expected, is is proved by experiments that our proposed method works consistently better by both improve multitask and Conv2DLSTM, base on the NASA dataset.

5 CONCLUSION

We propose a data-driven approach to introduce some improvement to a time-series LIB SOH prediction. Base on the nature distribution of data, we develop dat all input layer, the encode layer and the output multivariate layer of the prediction. Even we have not spend much time in fine-tuning, the proposed method can create significant improvement (17.5%), compare to the baseline.

The next steps from this research would be enhancing the input data with different sources of datasets (from NASA, CALCE and Oxford). After that, based on better input, we will continuously study the data dependency (data-driven) and introduce more model adjustment to improve the model performance.

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