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A Remaining Useful Life Prediction Method for Lithium-ion Battery Based on Temporal Transformer Network

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Abstract

The remaining useful life prediction is significant for Lithium-ion batteries to ensure safety and reliability. Due to the advantages of handling time sequence data, recurrent neural network based methods have achieved impressive performance on RUL prediction. However, most of these methods develop the RUL prediction model without considering the operating time of the battery, which is an important factor on capacity degradation. Therefore, this paper proposed a Temporal Transformer Network (TTN) for RUL of Lithium-ion batteries. The proposed method combines the self-attention mechanism of the Transformer Network with Denoising Autoencoder to implement the noise of raw data. More importantly, the proposed method designs a temporal encoding layer to introduce the operating time to the input of RUL prediction model. The performance of the proposed method is evaluated on two frequently used battery datasets. The proposed method achieves the best result compared with other frequently used RUL prediction methods.

Keywords: Remaining Useful Life Prediction; Transformer Network; Lithium-ion Battery

1. Introduction

Due to prominent characteristics such as high energy density and long life cycle, lithium-ion batteries (LIB) have been widely applied in various devices, including smartphones, laptops, electric vehicles, and energy storage systems [1]. To ensure the safety and reliability of battery, it is of great significance to monitor the lithium-ion battery by an effective battery management system (BMS) [2], whose most fundamental functions include accurate estimation for remaining useful life (RUL) [3] [4]. The RUL refers to the remaining time from the current moment to the time when the battery requires maintenance. An accurate RUL prediction for battery contributes to the predictive maintenance, which allows the optimal maintenance strategy to be taken with sufficient time, so as to save resources, reduce costs and ensure safety [5].

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Recently, more and more research efforts focus on the prediction of RUL for LIB [6] [7]. The RUL prediction methods for LIB can be categorized into two classes, i.e. model-based methods and data-driven methods [1] [8]. Model-based methods assess the degradation states of LIB by developing mathematical models. Saha et al. proposed a coupled numerical RUL prediction method for LIB of electric vehicles [9]. Yu et al. utilized a state-space model with a new battery health assessment criterion based on Bayesian-inference probabilistic to assess RUL [10]. He et al. utilized a double exponential model to estimate the degraded trajectory of the LIB capacity [11]. Su et al. proposed an improved method to integrate various LIB capacity models based on interaction multimodel particle filter [12]. However, it is difficult to establish mathematical models due to the complex internal electrochemical characteristics [13] [5].

Data-driven methods, which can refine models by fitting them to a large amount of data without establishing the complex chemical model, have become a hot research spot of battery RUL estimation in recent years. Patil et al. utilized support vector regression (SVR) by features extracted from voltage and temperature curves to predict RUL accurately [14]. Hu et al. proposed an model based on sparse Bayesian predictive modeling (SBPM) to estimate the RUL [15]. Liao et al. proposed an RUL prediction model based on enhanced restricted Boltzmann machine, which can extract more suitable features for RUL prediction [16]. Li et al. utilized the Support Vector Machine (SVM) with the variation characteristics of derivative among voltage and voltage during charging process to predict the RUL [17]. With the development of deep learning, deep learning methods have become popular in the field of time sequence prediction. Zhang et al. ultilized Recurrent Neural Network (RNN) to track the latent long-term dependencies during the degradation process of LIB capacity, which can improve the accuracy of prediction results [18]. Zraibi et al. combined Convolutional Neural Network (CNN), Long Short Term Memory (LSTM), and Deep Neural Networks (DNN) to develop an RUL prediction model for batteries [4]. The Transformer architecture [19] is a newly proposed sequence transduction model that deploys a self-attention mechanism to capture the long-term dependencies between elements in a sequence without considering their distance. The influence when the length of the sequence increases is smaller on Transformer Network than traditional methods such as RNN and Long Short Term Memory (LSTM) [20]. For data-driven method, one of the most common challenge is that the noise in the offline training data will influence the accuracy of RUL prediction [1] [7]. Besides, the time (calendar aging) and use (cycle aging) are the key factors of the battery performance degradation [21]. However, most of data-driven methods ignore the influence of operating time when developing RUL prediction model. Considering these problems, we propose an RUL prediction method based on Temporal Transformer Network (TTN). Denoising Autoencoder (DAE) is utilized to decrease the noise of the raw data and extracts embedded features. Besides, a temporal encoding layer is proposed to represent the operating time and further introduce to the input of TTN. The contribution of this paper can be summarized as follows.

- (1) Unlike most of RUL prediction methods, the proposed method proposes a temporal encoding layer to introduce the operating time to the input, which can improve the accuracy of RUL prediction.
- (2) The propsosed method design a unified architecture to combine DAE with Transformer network, which can achieve training the whole network simultaneously.

The rest of this paper is organized as follows. Section II introduces the related work. Section III illustrates the details of the proposed method. Section IV presents the experiment details and results. Section V concludes the paper and discusses some future work.

2. Related Work

Data-driven methods can develop models by capturing the relationships between the capacity degradation process and the monitoring parameters automatically. The monitoring data is a kind of time sequence data, time sequence analysis approaches are widely applied in LIB RUL prediction tasks. In this section, we briefly review recent deep learning based time sequence analysis methods for RUL prediction of batteries.

RNN and its variants always achieve good performance have been widely applied in RUL prediction tasks. Liu et al. proposed an adaptive recurrent neural network (ARNN) for RUL prediction which can improve accuracy by utilizing previous states based on adaptive feedbacks [22]. Song et al. proposed a new recurrent neural network (RNN) with Gated Recurrent Unit (GRU) for LIB RUL prediction [23]. The proposed method addresses the shortcomings of RNN when dealing with long-term relationships. Park et al. proposed an RUL prediction model based on LSTM which improves the performance by utilizing many-to-one structure [24]. To improve the prediction accuracy, CNN is combined with LSTM model to take advantage of its powerful feature extraction ability. Zhang et al. [25] and Zhang et al. [26] apply the hybrid algorithm LSTM-RNN for the LIB RUL prediction. Zraibi et al. proposed a hybrid model named CNN-LSTM-DNN for LIB RUL prediction [4]. The combination of CNN and LSTM can provide the spatial features and temporal features, so that DNN is able to improve the prediction accuracy with these features. Ren et al. proposed a new RUL prediction method for batteries based on an improved CNN with LSTM named Auto-CNN-LSTM [1]. An Autoencoder is used to reduce the dimension of raw data to improve the training efficiency. Considering the performance degradation of RNN-based models due to the long-term dependency, Transformer Network is also applied in RUL prediction of batteries. Chen et al. proposed an improved Transformer Network named DeTransformer for LIB RUL prediction [7].

Despite many research efforts have been focused on deep learning based methods, most of these methods do not take the operating time in consideration when develop model. The operating time is also a significant factor in the battery performance degradation. In this paper, we design a temporal encoding layer to introduce the operating time to the input, so as to improve the prediction accuracy.

3. Proposed Method

3.1. Problem Definition

Let $C = \{c_i\}_0^t$ denote the monitoring capacity. At a certain moment t, a subset of capacity are selected in sequence with a time window w ahead t, which can be represented as $C^t = \{c_{t-w+1}, \cdots, c_t\}$. A sequence $S^t = \{S_i^t\}_1^l$ is further generated from the subset C^t, where $S_i^t \in R^d$, d is the dimension of S_i^t, l is the length of the sequence. $S_i^t = \{c_{t-d-(l-i)s+1}, \cdots, c_{t-(l-i)s}\}$, where $s = (w-d)/(l-1)$. The sequence generation process is shown in Fig. 1. The proposed method can predict the capacity at time $t+1$ with the input of sequence S_i^t by Eq (1).

$$\hat{c}_{t+1} = f(S^t) \tag{1}$$

where $\hat{c}_{t+1}$ represents the capacity at time $t+1$. The predicted $\hat{c}_{t+1}$ will be integrated to the original monitoring data C, and a new sequence $\hat{S}^{t+1}$ can be generated. The future capacity can be predicted recursively by the above steps until exceeds to the threshold ρ. The RUL of the battery at time t can be defined as follows.

$$rul = \{rul | f(\hat{S}^{t+rul-1}) > \rho \,\&\, f(\hat{S}^{t+rul}) \leq \rho\} \tag{2}$$

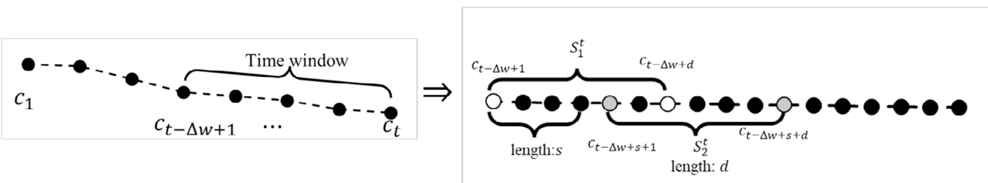


Fig. 1. Process of Sequence Generation

3.2. Temporal Transformer Network

The remaining useful life of the battery depends on the current state and the operating time of the battery. However, most existing methods develop RUL prediction model based on the monitoring states, but ignore the operating time. To solve this problem, we propose an RUL prediction method based on Temporal Transformer Network (TTN) to introduce the operating time as a feature to RUL prediction. The architecture of the TTN is shown in Fig. 2.

As discussed in Section 3.1, the input is a sequence of capacity with a time window w ahead t. In practice, the raw data usually contain noise due to the charge/discharge regeneration. Developing RUL model with raw data directly will influence the accuray of the model. Therefore, we utilize Denoising Autoencoder (DAE) to reduce the noise and extract low-dimensional feature from raw data. DAE is an unsupervised feature extraction method which can extract instrinsic features by minimizing the reconstruction error. Let $C^t = \{c_{t-w+1}, \cdots, c_t\}$ represent the input is a sequence of capacity. An encoder is used to map the input with additional added Gaussian noise to a low-dimensional hidden feature space. Subsequently, a decoder is used to reconstruct the input from the feature space. The process can be summarized as follows.

$$\begin{aligned} \widetilde{C}^t &= C^t + N(\mu, \sigma^2) \\ h^t &= \phi(W\widetilde{C}^t + b) \\ z^t &= \phi'(W'h^t + b') \end{aligned} \tag{3}$$

where W and W' are weights of the encoder and the decoder, respectively. Similarly, b and b' are biases. ϕ and ϕ' represent the acitivation function. N denote the Gaussian Noise. h^t is the hidden features, and z^t is the output of the decoder, which is the reconstruction of the input. The objective of DAE is minimizing the reconstruction error, which can be defined as follows.

$$\mathcal{L}_{DAE} = \frac{1}{n}\sum_{i=1}^{n}(\widetilde{C}^i - z^i)^2 \tag{4}$$

After extracting the hidden features, a sequence S^t of input to TTN is generated as described in Fig. 1, where $S^t \in R^{l\times d}$, l is the length of the sequence, d is the dimension of the sequence. The TTN consists of Positional Encoding (PE) layer, Temporal Encoding (TE) layer, Decoder layer and Linear layer. To make full use of the position information inside of the input sequence, relative position tokens are added to the input. The Positional Encoding can be defined as follows.

$$\begin{aligned} PE(i, 2k) &= \sin(i/10000^{2k/d_{h^t}}) \\ PE(i, 2k+1) &= \cos(i/10000^{2k/d_{h^t}}) \end{aligned} \tag{5}$$

where k denotes the position step, i is the relative position of the samples in the sequence, d_{h^t} represents the dimension of the h^t. Different from the original Transformer Network, we utilize a Temporal Encoding layer to introduce the temporal information to the input. The definition of TE is similar to PE, which is shown in Eq. (6).

$$\begin{aligned} TE(t, 2p) &= \sin(t/10000^{2p/d_{h^t}}) \\ TE(t, 2p+1) &= \cos(t/10000^{2p/d_{h^t}}) \end{aligned} \tag{6}$$

where p denotes the time step, t represents the monitoring time of the current sequence. The decoder layer is similar to the original Transformer Network, which is stacked by Multi-Head Attention (MHA) layer and Feed Forward (FF) layer. The MHA layer utilizes multiple heads numbered m to conduct self-attention in parallel. Self-attention involves query (Q), key (K) and value (V) vector. The Q, K and V can be calculated as follows.

$$Q = \hat{S}^t W_q^t, K = \hat{S}^t W_k^t, V = \hat{S}^t W_v^t, \hat{S}^t = S^t + PE + TE \tag{7}$$

where $W_q^t, W_k^t, W_v^t \in R^{d_{h^t} \times d}$, they are weight metrices respectively. Then, the Scaled Dot-Product Attention (SDA) can be given as follows.

$$SDA(Q, K, V) = softmax(\frac{Q \cdot K^T}{\sqrt{d_k}})V \tag{8}$$

where $d_k = d_{h^t}/m$. The m SDAs are concatenated together and multiplied by a weight matrix to generate the final attention of MHA. The process can be represented in Eq. (9).

$$\begin{aligned} MHA(Q, K, V) &= Concat(head_1, head_2, \cdots, head_m) \cdot W^O \\ head_j &= SDA(Q_j^t, K_j^t, V_j^t) \end{aligned} \tag{9}$$

After the MHA layer, the FF layer consists of a nonlinear operation and a linnear operation as follows.

$$FFN = ReLU(MHA \cdot W_1 + b_1)W_2 + b_2 \tag{10}$$

where W_1, W_2 are weights, and b_1, b_2 are biases respectively. The final prediction of the capacity $\hat{c}_{t+1}$ will be given by a full connection layer with the input of FFN. The loss function of TTN can be defined as follows.

$$\mathcal{L}_{TTN} = \frac{1}{n} \sum_{i=1}^{n-1} [\alpha(\widetilde{C}^i - z^i)^2 + (\hat{c}_{i+1} - c_{i+1})^2] \tag{11}$$

where α is the adjustment weight.

4. Experiment

To evaluate the performance of the proposed method, two frequently used battery datasets are utilized in this paper, which are NASA battery dataset and CALCE battery dataset.

4.1. Dataset Description

4.1.1. NASA Battery Dataset

The battery dataset provided by NASA Prognostics Center of Excellence Data Repository contains the monitoring data of batteries under three repearting different operations, i.e. charging, discharging and impedance at room temperature [27] [28]. In the experiment, we utilize #5, #6, #7 and #18 batteries for training and testing. The constant-current

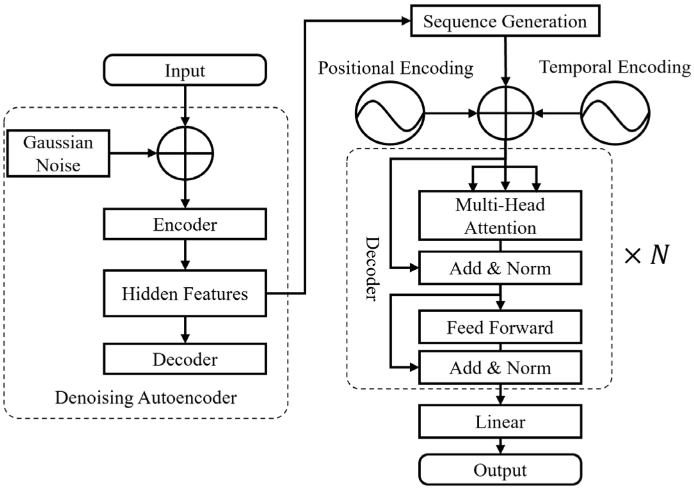


Fig. 2. The Architecture of Temporal Transformer Network

constant-voltage (CCCV) charging process is applied on the batteries. At first, the battery is charged with the constant current of 1.5A until the voltage reaches 4.2V remains constant. Then the charging process continues until the current drops to 20mA. The #5, #6, #7 and #18 batteries is discharged at constant current of 2A until the voltage drops to 2.7V, 2.5V, 2.2V and 2.5V, respectively.

4.1.2. CALCE Battery Dataset

The dataset is provided by the Center for Advanced Life Cycle Engineering (CALCE) at the University of Maryland, in which the most widely used battery dataset is CS2 [11] [29]. In CS2 dataset, we choose #35, #36, #37 and #38 batteries for training and testing, which can be represented as CS2_35, CS2_36, CS2_37 and CS2_38. The charging and discharging processes of batteries in CS2 are the same as NASA Dataset, except for the different values of current and voltage.

4.2. Baselines

To demonstrate the performance of the proposed method, the proposed method was compared with four baseline methods. Method 1 [22] is an LIB RUL prediction method based on adaptive recurrent neural network (ARNN) which can utilize previous states based on adaptive feedbacks to improve performance. Method 2 [25] utilizes the hybrid algorithm LSTM-RNN for RUL prediction of LIB. Method 3 [30] is a GRU-RNN based method for battery states estimation. Method 4 [31] utilizes dual-LSTM to achieve RUL prediction. Apart from these baselines, we also conducted the proposed method without the temporal encoding layer to validate the effectiveness of the TE layer.

4.3. Evaluation Metrics

In this paper, three commonly used evaluation metrics are utilized to assess the performance of RUL prediction, including relative error (RE), mean absolute error (MAE) and root mean square error (RMSE). They can be defined

Table 1. RUL Prediction Results of NASA Dataset and CALCE Dataset

Dataset	Metric	ARNN	LSTM-RNN	GRU-RNN	Dual-LSTM	**Ours without TE**	**Ours**
NASA Dataset	RE	0.2581	0.2648	0.3044	0.2557	0.2252	**0.0128**
	MAE	0.0749	0.0829	0.0806	0.0815	0.0713	**0.0550**
	RMSE	0.0848	0.0905	0.0921	0.0879	0.0802	**0.0740**
CALCE Dataset	RE	0.1614	0.0902	0.1319	0.0885	0.0764	**0.0445**
	MAE	0.0938	0.0582	0.0671	0.0636	0.0613	**0.0513**
	RMSE	0.1099	0.0736	0.0946	0.0874	**0.0705**	0.0713

as follows.

$$\begin{aligned} RE &= \frac{|RUL_{pred} - RUL_{true}|}{RUL_{true}} \\ MAE &= \frac{1}{n - t_{start}} \sum_{t=t_{start}+1}^{n} |c_t - \hat{c}_t| \\ RMSE &= \sqrt{\frac{1}{n - t_{start}} \sum_{t=t_{start}+1}^{n} (c_t - \hat{c}_t)^2} \end{aligned} \tag{12}$$

where t_{start} represents the starting time for RUL prediction. RUL_{pred} and RUL_{true} denote the predicted RUL and true RUL at time t_{start} respectively.

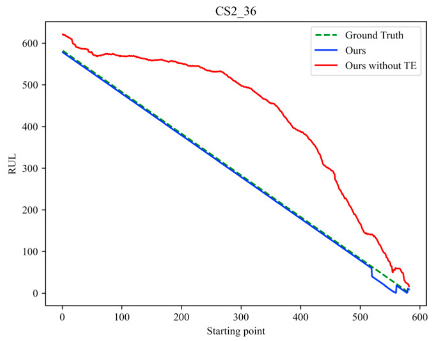
4.4. Result Discussion

In the experiments on two datasets, three of the batteries are selected for training and the remaining battery is used for testing. The average scores of three metrics on two datasets is shown in Table 1. The results show that the proposed method achieved the best performance compared with baseline methods. Especially for the RE score on NASA Dataset, the RE score of the proposed method is 20 times smaller than the baseline methods. Compared the results of the proposed method on two datasets, the results on NASA Dataset is better than CALCE Dataset. It is mainly because of the charge-discharge cycles of NASA Dataset is much less than CALCE Dataset, which means that the degradation process of batteries on NASA Dataset is much faster than CALCE Dataset. A relatively larger capacity degradation in each cycle will appear on batteris of NASA Dataset than CALCE Dataset, which makes it easier to be captured by the proposed method. Besides, the performance of our method without TE layer is also better than the baselines, which demonstrates the effetiveness of the Transformer architecture.

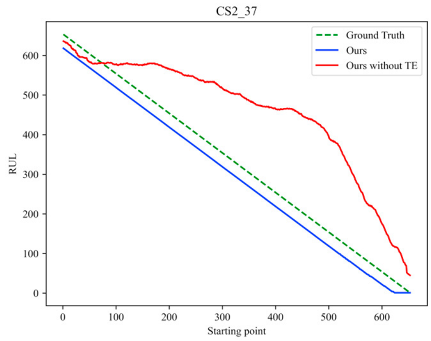
Compared the proposed method with TTN without TE layer, the scores of the proposed method are better than the TTN without TE layer, except for RMSE score on CALCE Dataset. To further evaluate the effectiveness of the TE layer, the RUL prediction results of CS2_36 and CS2_37 obtained by TTN and TTN without TE at different starting time are visualized in Fig. 3. From Fig. 3, the RUL prediction results of both methods are close to the true RUL at the begining and the end of the lifecycle. However, the results of the proposed method is much better than TTN without TE in the middle of degradation process. The results demonstrate the effectiveness of the TE layer.

5. Conclusion

In this paper, an RUL prediction method for Lithium-ion batteries based on Temporal Transformer Network is proposed. The proposed method combines the DAE and Transformer Network to decrease the noise of the raw data and extract features for RUL prediction. Besides, a temporal encoding layer is designed in the proposed method to introduce the operating time to the prediction of RUL. The proposed method is tested on NASA Dataset and CALCE



(a) Results of CS2_36



(b) Results of CS2_37

Fig. 3. RUL Prediction Results of CS2_36 and CS2_37 in CALCE Dataset

Dataset. The proposed method achieves the best result among the baseline methods. Besides, the comparative results of the proposed method with and without TE layer demonstrate the effetiveness of the TE layer.

However, the proposed method has some limitations. On one hand, the proposed method takes no consideration of the different working conditions between the training data and testing data. The working conditions including temperatures and currents will lead to a big difference of the degradation trends. On the other hand, the capacity of the battery is not always available in practice. Therefore, the future work can be extended in the following aspects. An RUL prediction method based on transfer learning will be further studied to predict RUL of batteries under different working conditions. Moreover, the proposed method will be further developed to extract a health index to describe the degradation states and conduct RUL prediction based on the health index.

References

[1] L. Ren, J. Dong, X. Wang, Z. Meng, L. Zhao, M. J. Deen, A data-driven auto-cnn-lstm prediction model for lithium-ion battery remaining useful life, IEEE Transactions on Industrial Informatics 17 (5) (2020) 3478–3487.

[2] P. Li, Z. Zhang, R. Grosu, Z. Deng, J. Hou, Y. Rong, R. Wu, An end-to-end neural network framework for state-of-health estimation and remaining useful life prediction of electric vehicle lithium batteries, Renewable and Sustainable Energy Reviews 156 (2022) 111843.

[3] X. Hu, L. Xu, X. Lin, M. Pecht, Battery lifetime prognostics, Joule 4 (2) (2020) 310–346.

[4] B. Zraibi, C. Okar, H. Chaoui, M. Mansouri, Remaining useful life assessment for lithium-ion batteries using cnn-lstm-dnn hybrid method, IEEE Transactions on Vehicular Technology 70 (5) (2021) 4252–4261.

[5] D. Zhou, Z. Li, J. Zhu, H. Zhang, L. Hou, State of health monitoring and remaining useful life prediction of lithium-ion batteries based on temporal convolutional network, IEEE Access 8 (2020) 53307–53320.

[6] M. Catelani, L. Ciani, R. Fantacci, G. Patrizi, B. Picano, Remaining useful life estimation for prognostics of lithium-ion batteries based on recurrent neural network, IEEE Transactions on Instrumentation and Measurement 70 (2021) 1–11.

[7] D. Chen, W. Hong, X. Zhou, Transformer network for remaining useful life prediction of lithium-ion batteries, IEEE Access 10 (2022) 19621–19628.

[8] Z. Tong, J. Miao, S. Tong, Y. Lu, Early prediction of remaining useful life for lithium-ion batteries based on a hybrid machine learning method, Journal of Cleaner Production 317 (2021) 128265.

[9] B. Saha, K. Goebel, S. Poll, J. Christophersen, Prognostics methods for battery health monitoring using a bayesian framework, IEEE Transactions on instrumentation and measurement 58 (2) (2008) 291–296.

[10] J. Yu, State-of-health monitoring and prediction of lithium-ion battery using probabilistic indication and state-space model, IEEE Transactions on Instrumentation and Measurement 64 (11) (2015) 2937–2949.

[11] W. He, N. Williard, M. Osterman, M. Pecht, Prognostics of lithium-ion batteries based on dempster–shafer theory and the bayesian monte carlo method, Journal of Power Sources 196 (23) (2011) 10314–10321.

[12] X. Su, S. Wang, M. Pecht, L. Zhao, Z. Ye, Interacting multiple model particle filter for prognostics of lithium-ion batteries, Microelectronics Reliability 70 (2017) 59–69.

[13] D. Liu, W. Xie, H. Liao, Y. Peng, An integrated probabilistic approach to lithium-ion battery remaining useful life estimation, IEEE Transactions on Instrumentation and Measurement 64 (3) (2014) 660–670.

[14] M. A. Patil, P. Tagade, K. S. Hariharan, S. M. Kolake, T. Song, T. Yeo, S. Doo, A novel multistage support vector machine based approach for li ion battery remaining useful life estimation, Applied energy 159 (2015) 285–297.

[15] X. Hu, J. Jiang, D. Cao, B. Egardt, Battery health prognosis for electric vehicles using sample entropy and sparse bayesian predictive modeling, IEEE Transactions on Industrial Electronics 63 (4) (2015) 2645–2656.

[16] L. Liao, W. Jin, R. Pavel, Enhanced restricted boltzmann machine with prognosability regularization for prognostics and health assessment, IEEE Transactions on Industrial Electronics 63 (11) (2016) 7076–7083.

[17] X. Li, X. Shu, J. Shen, R. Xiao, W. Yan, Z. Chen, An on-board remaining useful life estimation algorithm for lithium-ion batteries of electric vehicles, Energies 10 (5) (2017) 691.

[18] C. Zhang, P. Lim, A. K. Qin, K. C. Tan, Multiobjective deep belief networks ensemble for remaining useful life estimation in prognostics, IEEE transactions on neural networks and learning systems 28 (10) (2016) 2306–2318.

[19] A. Vaswani, N. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A. N. Gomez, Ł. Kaiser, I. Polosukhin, Attention is all you need, Advances in neural information processing systems 30 (2017).

[20] Z. Zhang, W. Song, Q. Li, Dual-aspect self-attention based on transformer for remaining useful life prediction, IEEE Transactions on Instrumentation and Measurement 71 (2022) 1–11.

[21] S. Wang, S. Jin, D. Deng, C. Fernandez, A critical review of online battery remaining useful lifetime prediction methods, Frontiers in Mechanical Engineering 7 (2021) 719718.

[22] J. Liu, A. Saxena, K. Goebel, B. Saha, W. Wang, An adaptive recurrent neural network for remaining useful life prediction of lithium-ion batteries, Tech. rep., National Aeronautics And Space Administration Moffett Field CA Ames Research ... (2010).

[23] Y. Song, L. Li, Y. Peng, D. Liu, Lithium-ion battery remaining useful life prediction based on gru-rnn, in: 2018 12th international conference on reliability, maintainability, and safety (icrms), IEEE, 2018, pp. 317–322.

[24] K. Park, Y. Choi, W. J. Choi, H.-Y. Ryu, H. Kim, Lstm-based battery remaining useful life prediction with multi-channel charging profiles, Ieee Access 8 (2020) 20786–20798.

[25] Y. Zhang, R. Xiong, H. He, M. G. Pecht, Long short-term memory recurrent neural network for remaining useful life prediction of lithium-ion batteries, IEEE Transactions on Vehicular Technology 67 (7) (2018) 5695–5705.

[26] Y. Zhang, R. Xiong, H. He, Z. Liu, A lstm-rnn method for the lithuim-ion battery remaining useful life prediction, in: 2017 Prognostics and System Health Management Conference (PHM-Harbin), IEEE, 2017, pp. 1–4.

[27] B. D. Set, Nasa ames prognostics data repository, NASA Ames Research Center: Moffett Field, CA, USA (2008).

[28] B. Saha, K. Goebel, Uncertainty management for diagnostics and prognostics of batteries using bayesian techniques, in: 2008 IEEE aerospace conference, IEEE, 2008, pp. 1–8.

[29] Y. Xing, E. W. Ma, K.-L. Tsui, M. Pecht, An ensemble model for predicting the remaining useful performance of lithium-ion batteries, Microelectronics Reliability 53 (6) (2013) 811–820.

[30] B. Xiao, Y. Liu, B. Xiao, Accurate state-of-charge estimation approach for lithium-ion batteries by gated recurrent unit with ensemble optimizer, Ieee Access 7 (2019) 54192–54202.

[31] Z. Shi, A. Chehade, A dual-lstm framework combining change point detection and remaining useful life prediction, Reliability Engineering & System Safety 205 (2021) 107257.