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TCRDN: Allied Temporal Convolution-Recurrent Diagnosis Network for the Thermal Health Management of Lithium-ion Energy System

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ABSTRACT

With the intensification of energy crisis and environmental crisis, countries have accelerated the development of new energy sources. Lithium-ion energy systems occupy an important position in the energy storage market because of their excellent performance, but temperature-related issues still hinder their further development. In order to solve this problem, researchers are committed to more accurate prediction of the temperature of lithium-ion energy system. Long and short-term memory network (LSTM) has always been considered to be able to process time series well. The emerging temporal convolution network (TCN), as a special convolutional network, has also been proven to be able to handle sequential tasks well. In this paper, a new allied temporal convolution-recurrent diagnosis network (TCRDN) is constructed by combining LSTM and TCN using an adaptive boosting algorithm. The proposed model is experimentally demonstrated to be able to predict the change of surface temperature of lithium-ion energy system more accurately.

Keywords: Lithium-ion energy system, Long and short-term memory network, temporal convolution network.

NONMENCLATURE

Abbreviations	
RNN	Recurrent Neural Network
LSTM	Long and Short-term Memory Network
TCN	Temporal Convolution Network
TCRDN	Temporal Convolution-Recurrent Diagnosis Network
MSE	Mean Square Error
Symbols	
T_s	The surface temperature of the battery (℃)
T_{amb}	The ambient temperature of the battery (℃)
Q	Heat generation rate (J/s)
SOC	State of charge (Ah)
e	Regression error rate
E	Maximum error
a	Number of samples
α'_{TCN}	The wight of TCN prediction
α'_{LSTM}	The wight of LSTM prediction

1. INTRODUCTION

The world is currently facing a common ecological crisis and energy crisis. The use of new energy is the key to solve these problems. The construction of clean transportation system with battery and motor instead of internal combustion engine is an effective way to solve greenhouse gas emissions [1]. Whether it is the use of clean energy or the popularity of electric vehicles, a safe and efficient energy storage system has played an important role.

Lithium-ion batteries are widely used in various energy storage systems due to their superior characteristics with the high energy density, negligible memory effect and low self-discharge rate [2]. However, temperature-related problems are still problems that need to be overcome for the popularization of lithium-ion batteries [3]. There are often news that high temperatures cause lithium-ion battery explosions. Therefore, in order to achieve the long life and safe operation of the battery, it is necessary to optimize the thermal health management of the lithium-ion energy system .

There are two main methods for predicting the temperature of lithium-ion energy system. one is the model-based method [4,5]. The key of model-based method is to establish an appropriate model and identify the model parameters accurately. However, these methods require complex work of model establishment and parameter identification. In order to overcome this problem, researchers have begun to adopt data-driven methods, among which deep learning methods have been widely used.

For dealing with time series problems, recurrent neural network (RNN) has been considered as a good method. [6] proposed a special RNN—— long and short-term memory network (LSTM), which has been widely used because of its excellent performance. Although convolutional neural network is usually used to deal with image problems, it can also be used to model and predict sequence problems after appropriate modification. [7] proposed a temporal convolution network (TCN), which has been proved to have better performance than RNN in many sequential tasks TCN has overcome some of the shortcomings of RNN, so it has begun to be used to deal with various sequence problems, and has preliminary applications in the state of charge and remaining useful life prediction of lithium-ion batteries [8].

The work of this paper is as follows. Because LSTM and TCN have their advantages, we use the adaptive boosting algorithm to combine the two networks to form an allied temporal convolution-recurrent diagnosis network (TCRDN). First, we established the LSTM model and the TCN model. Then the measurement signals for 20 seconds are input into two networks respectively to obtain the predicted value of the surface temperature of the lithium-ion battery in the next 60 seconds. Finally, we use the adaptive boosting algorithm to optimize the prediction results of the two networks to obtain more accurate predictions. There is noise in the real measurement signal, so the input fed to the network in the experiment contains noise to estimate the performance of the designed method under noise. The effectiveness of the TCRDN is proved by experiments.

2. METHODOLOGY

2.1 Long and Short-term Memory Network

Recurrent neural network (RNN) is a kind of network that can deal with time series. LSTM is a special recurrent neural network, which not only solves the problem of gradient explosion and disappearance during the back-propagation process of RNN, but also overcomes the long-term dependencies of RNN. The key to overcoming the long-term dependence of LSTM lies in the addition of cell state. The structure of a recurrent LSTM cell is shown in Fig. 1. Each LSTM cell is made of input, forget, and output gates. The calculation process is shown in (1) [9].

$$\begin{cases} f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \\ i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \\ \overline{C}_t = \tanh(W_c \cdot [h_{t-1}, x_t] + b_C) \\ C_t = f_t \cdot C_{t-1} + i_t \cdot \overline{C}_t \\ \tanh(x) = \dfrac{e^x - e^{-x}}{e^x + e^{-x}} \\ o_t = \sigma(W_o [h_{t-1}, x_t] + b_0) \\ h_t = o_t \cdot \tanh(C_t) \end{cases} \tag{1}$$

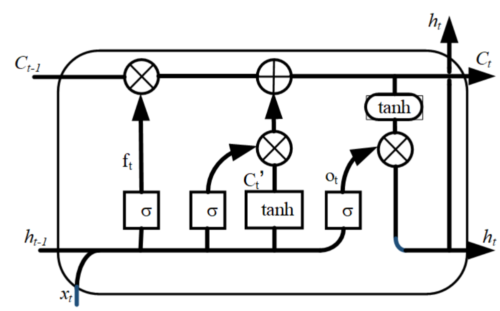

Fig. 1. Structure of Long Short-term Memory

2.2 Temporal Convolution Network

Temporal convolutional network (TCN) is a special convolutional network for processing sequential tasks with causal constraints. Based on 1D convolution, causal convolution and dilated convolution, it can process and predict different length sequences according to the causal relationship between the latter and the former. LSTM will forget the useless information, but TCN based on causal convolution will not miss the past information, nor will it reveal the future information [10].

2.2.1 Causal convolution

Causal convolution conforms to a strict time constraint. For the next layer, the value at moment t is obtained by convolving the values at moment t and earlier in the previous layer. The unidirectional structure of causal convolution avoids the leakage of future information. Also to ensure that the output sequence has the same length as the input sequence, zero padding is required. The causal convolution is ensured by performing zero padding only on the left side.

2.2.2 Dilated Convolution

We hope that the output of the network depends on the complete historical information, which requires that the receiving field of the network is larger than the length of the input sequence. In order to ensure enough receiving fields and reduce the amount of computation, the dilated convolution is proposed [11].

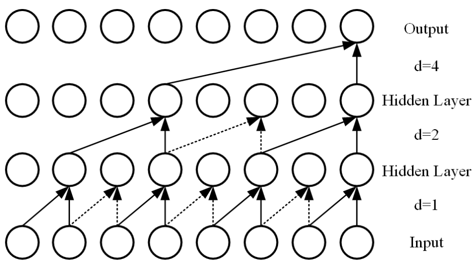

Fig. 2. Dilated Convolution with Kernel Size 2. *d* is the dilation factor.

As shown in Fig. 2, the size of convolution is expanded by adding “empty holes” in the convolution window, so as to expand the range of receiving field. There are more “empty holes” in the upper convolution window, so the convolution window is larger, which ensures that the value of the last element in the last layer depends on the complete historical information. The dilated convolution operation *F* on element s of the sequence is defined as:

$$F(s)=(x *_d f)(s)=\sum_{i=0}^{k-1} f(i)\cdot x_{s-d\cdot i} \tag{2}$$

where *x* is the input sequence, *f* is the mapping relation of the filter, *d* is the dilation factor, *k* is the filter size, and s – d·i accounts for the direction of the past.

2.2.3 Skip Connection and Residual Block

With the deepening of the network depth, there will be gradient dissipation and neural network degradation problems. The application of skip connection can improve the problem of gradient dissipation in the process of neural network backpropagation and neural network degradation [12]. Skip connection is a linear superposition of the input and the result of a nonlinear transformation of the input. Its expression is as follows:

$$O=F(x)+x \tag{3}$$

where *O* is the output, *x* is the input and *F(x)* is the result of the nonlinear transformation of input.

In TCN, the simple convolution layer is replaced by residual block. The composition of a residual block is shown in Fig. 3.

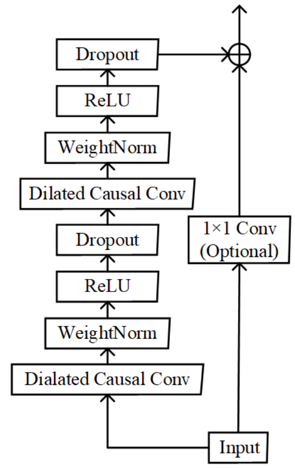

Fig. 3. Residual Block

2.3 *Adaptive Boosting*

Adaptive boosting (AdaBoost) is an iterative algorithm. The improved AdaBoost can be used to solve the regression problem and the weighted summation is adopted to combine the surface temperature predicted by the two models [13]. Then the data-model alliance module is established.

Firstly, the regression error rate is calculated by (4).

$$e=\frac{1}{a}\sum_{t=1}^{a}\frac{(\overline{T}_{s,t}-T_{s,t})}{E^2} \tag{4}$$

Here, $\overline{T}_{s,t}$ is the predicted surface temperature of the model at the time t. $T_{s,t}$ is the real surface temperature of the battery energy storage system at the time t. a is the number of samples needed for each update of weight. *E* is the maximum error in the training set.

$$E=\max\left|\overline{T}_{s,t}-T_{s,t}\right| \tag{5}$$

The weight is then calculated by

$$a=\ln(\frac{1-e}{e}) \tag{6}$$

Then the weights of the TCN prediction a_{TCN} and the LSTM network prediction a_{LSTM} are calculated through (4) and (6) respectively. Then, the weights of TCN prediction and LSTM prediction are modified by (7) and (8), so that the sum of the two weights is 1.

$$a_{TCN}^{'}=\frac{e^{a_{TCN}}}{e^{a_{LSTM}}+e^{a_{TCN}}} \tag{7}$$

$$a_{LSTM}^{'}=\frac{e^{a_{LSTM}}}{e^{a_{LSTM}}+e^{a_{TCN}}} \tag{8}$$

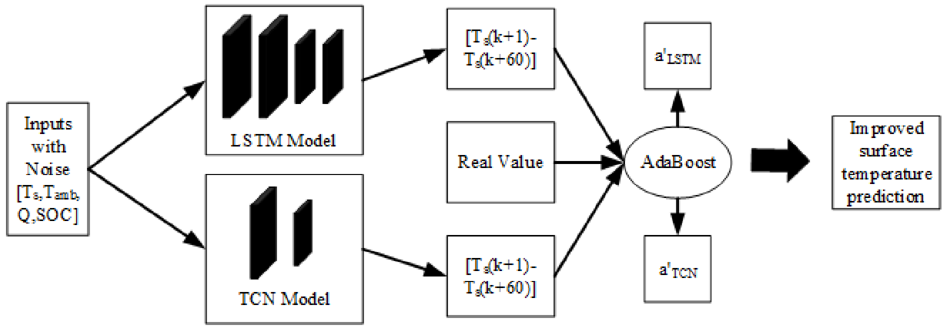

Fig. 4. The Process of Temporal Convolution-Recurrent Diagnosis Network.

Finally, the coupled surface temperature $\overline{T}s$ is predicted by

$$\overline{T}_s = a'_{TCN} \cdot \overline{T}_{s,TCN} + a'_{LSTM} \cdot \overline{T}_{s,LSTM} \tag{9}$$

Here, $\overline{T}_{s,TCN}$ and $\overline{T}_{s,LSTM}$ are the surface temperature predicted by the TCN and LSTM neural network respectively. This paper uses the data of ten sampling points to calculate the weight, that is, a = 10.

2.4 Allied Temporal Convolution-Recurrent Diagnosis Network

Firstly, we build the LSTM network and TCN network respectively. LSTM network consists of two LSTM layers and two dense layers. The first dense layer uses relu as the activation function to make the model nonlinear, and the second dense layer is used for regression. The TCN network consists of three residual blocks and a density layer for regression. In order to keep the number of training parameters of both networks approximate, reasonable network parameters were chosen for each of the two networks. The kernel size of TCN network is 3, the number of filters is 64, and the dilation factors are 1, 2 and 4, respectively. In the LSTM network, the first LSTM layer includes 64 neurons, the second LSTM layer includes 64 neurons, and the first dense layer includes 128 neurons.

Due to the inaccuracy of the measuring instrument and the error in the process of signal transmission, the inputs of the neural network are noisy measuring signals. Then, the continuous 20-second sequences of measurement signals with noise such as surface temperature, ambient temperature, heat generation rate and SOC are fed into the established TCN network and LSTM network, respectively. The output is the predicted value of the battery surface temperature for the next 60 seconds.

Finally, the AdaBoost algorithm and sliding window are applied to process the prediction values of TCN network and LSTM network to get better prediction values. The window length is 10 seconds. In each window, equations (4)-(8) are applied to update the weights a'_{TCN} and a'_{LSTM}. And then equation (9) is used to correct the predicted value of the surface temperature at the next time. The above process is repeated at each time to obtain the correction value of the surface temperature at the next sixty sampling times. The process of the TCRDN is shown in Fig. 4.

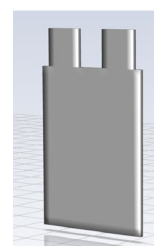

Fig. 5. Battery Model

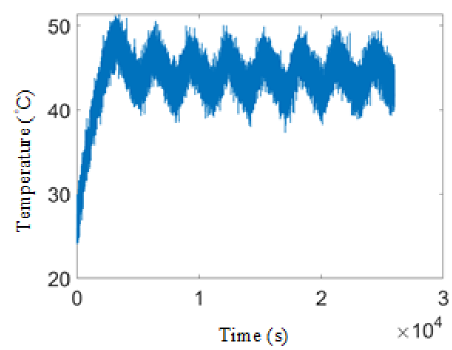

Fig. 6. Surface temperature after adding 1.3 times the noise.

3. EXPERIMENTS

We used the commercial software FLUENT to perform finite element simulation of a 10Ah prismatic LiFePO4-Graphite battery to obtain the battery data. First, a finite element model of the lithium-ion battery is established, as shown in Fig. 5 Then use the commercial software FLUENT to calculate and solve the lithium-ion battery terminal voltage, terminal current, SOC, internal resistance and temperature under certain working conditions. The result obtained by finite element simulation is shown in Fig. 7. And the measured data from the simulation were added with different sizes of

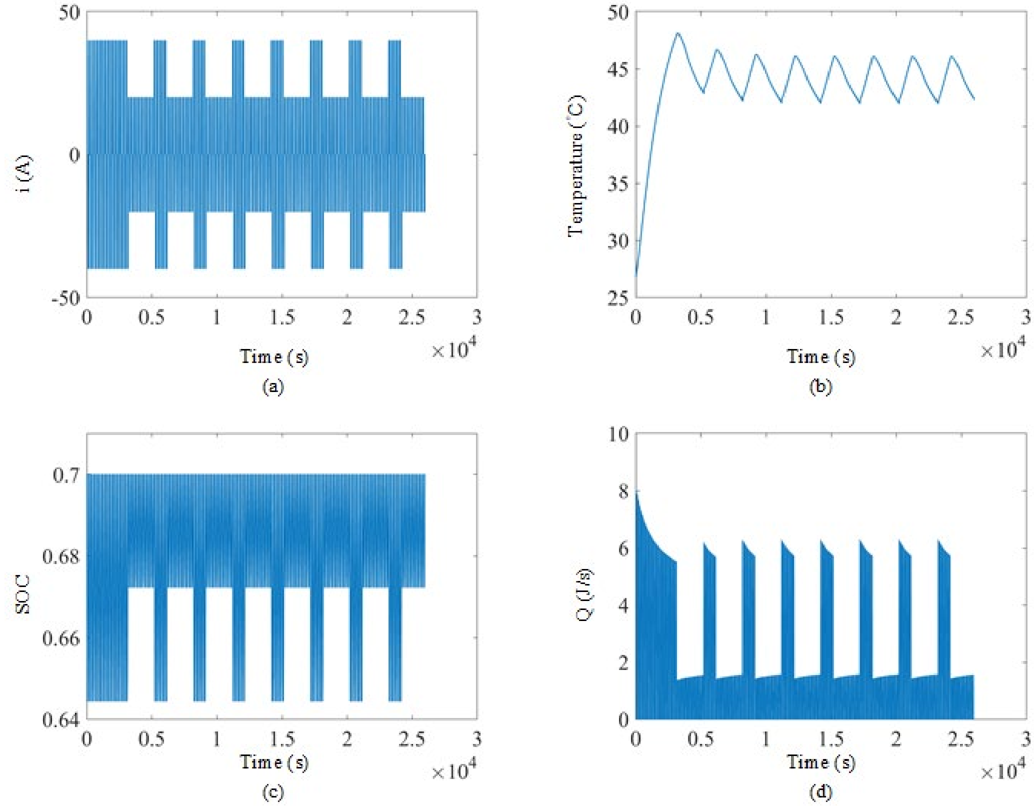

Fig. 7. Results of finite element simulation. (a) is the terminal current of the battery; (b) is the surface temperature of the battery; (c) is the state of charge; (d) is the heat generation rate of the battery

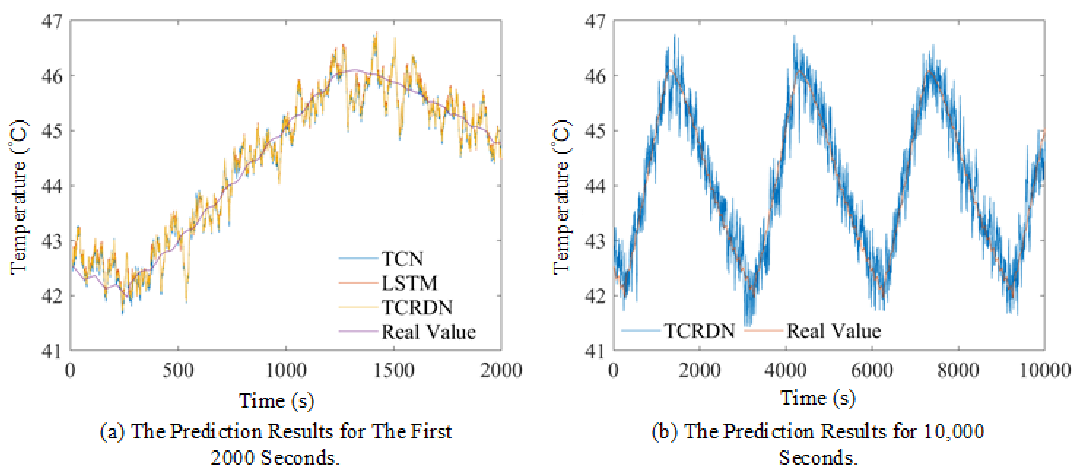

Fig. 8. The Comparison of Prediction Results of Surface Temperature by Different Methods. Here is a comparison of the three methods for predicting the surface temperature for the next 1 second. (a)intercepts the prediction results of three methods in the first 2000 seconds. (b) shows the complete prediction results of TCRDN alliance network on the entire test set.

noise to simulate the real input of the network. We use the randn function in MATLAB to generate noise. The randn function returns a random value obtained from the standard normal distribution, thereby generating Gaussian random noise. Fig. 6 shows the results of adding 1.3times the noise to the temperature obtained from our finite element simulation.

The trained LSTM model and TCN model are combined with AdaBoost algorithm to form the proposed TCRDN. In the case of 1.3 times noise, the comparison of surface temperature prediction results of TCRDN with simple LSTM model and TCN model is shown in Fig. 8. It can be seen from Fig. 8 that since the inputs of the three networks are noisy measurement signals, the output results of the three networks also fluctuate, but they can basically keep up with the real surface temperature variation of the Li-ion battery. Compared with the simple LSTM or TCN network, the TCRDN proposed in this paper can reduce the fluctuation peak and the estimation error.

We have done many experiments under the noise of different magnifications, and the mean square error (MSE) of the prediction results of the three networks on the surface temperature is summarized in Table 1. As can be seen from Table 1, from the perspective of MSE, under different magnification noises, the prediction error of the TCRDN is lower than that of the simple LSTM and TCN.

Table 1. The Mse of Predicted Surface Temperature

Magnification	1.3s	1.5s	1.8s	2.0s	3.0s
TCN Model	0.1174	0.1562	0.1690	0.2008	0.4366
LSTM Model	0.1202	0.1545	0.1650	0.2014	0.4304
TCRDN	0.1168	0.1540	0.1593	0.1953	0.4188

4. CONCLUSION

In this paper, we not only applied TCN, a special convolutional network for processing sequential tasks, to lithium-ion battery temperature prediction, but also combined LSTM and TCN to construct a new allied temporal convolution recurrent diagnosis network (TCRDN). The TCRDN can use the noisy measurement signals for 20 seconds to predict the change of the surface temperature of the lithium-ion energy system in the next 60 seconds. The experiments have proved that the network established in this paper can combine the advantages of LSTM and TCN, so as to more accurately predict the temperature changes of lithium-ion batteries. From the perspective of MSE, the TCRDN has a maximum reduction of 0.01 compared to the simple TCN network; the reduction can reach 0.02 compared to the simple LSTM network. More accurate prediction of the temperature of lithium-ion energy system will be conducive to more effective thermal health management. However, the current work still has some shortcomings. For example, each network needs to be trained separately, which takes a lot of time. In the future, we will replace each part with a complete network for unified training.

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REFERENCE

[1] Wada M. Research and development of electric vehicles for clean transportation. Journal of Environmental Sciences 2009;21:745–9.
[2] Hannan MA, Hoque MdM, Hussain A, Yusof Y, Ker PJ. State-of-the-Art and Energy Management System of Lithium-Ion Batteries in Electric Vehicle Applications: Issues and Recommendations. IEEE Access 2018;6:19362–78.
[3] Liu H, Wei Z, He W, Zhao J. Thermal issues about Li-ion batteries and recent progress in battery thermal management systems: A review. Energy Conversion and Management 2017;150:304–30.
[4] Murashko K, Pyrhonen J, Laurila L. Three-Dimensional Thermal Model of a Lithium Ion Battery for Hybrid Mobile Working Machines: Determination of the Model Parameters in a Pouch Cell. IEEE TRANSACTIONS ON ENERGY CONVERSION 2013;28:9.
[5] Pan Y, Hua Y, Zhou S, He R, Zhang Y, Yang S, et al. A computational multi-node electro-thermal model for large prismatic lithium-ion batteries. Journal of Power Sources 2020;459:228070.
[6] Hochreiter S, Schmidhuber J. Long short-term memory. Neural Comput 1997;9:1735–80.
[7] Bai S, Kolter JZ, Koltun V. An Empirical Evaluation of Generic Convolutional and Recurrent Networks for Sequence Modeling. ArXiv:180301271 [Cs] 2018.
[8] Liu Y, Li J, Zhang G, Hua B, Xiong N. State of Charge Estimation of Lithium-Ion Batteries Based on Temporal Convolutional Network and Transfer Learning. IEEE Access 2021;9:34177–87.
[9] Li W, Sengupta N, Dechent P, Howey D, Annaswamy A, Sauer DU. Online capacity estimation of lithium-ion batteries with deep long short-term memory networks. Journal of Power Sources 2021;482:228863.
[10] Liu C, Zhang L, Yao R, Wu C. Dual Attention-Based Temporal Convolutional Network for Fault Prognosis under Time-Varying Operating Conditions. IEEE Transactions on Instrumentation and Measurement 2021;70:1-10.
[11] Yu F, Koltun V. Multi-Scale Context Aggregation by Dilated Convolutions. ArXiv:151107122 [Cs] 2016.
[12] He K, Zhang X, Ren S, Sun J. Deep Residual Learning for Image Recognition. 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2016, p. 770–8.
[13] Li D, Zhang Z, Liu P, Wang Z, Zhang L. Battery Fault Diagnosis for Electric Vehicles Based on Voltage Abnormality by Combining the Long Short-Term Memory Neural Network and the Equivalent Circuit Model. IEEE Trans Power Electron 2021;36:1303–15.