SNNFT: Sequential Neural Network-Fuzzy Thermal Early Warning System for Lithium-ion Batteries

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Keywords

≪Battery≫, ≪Artificial intelligence ≫, ≪Deep Learning≫, ≪Optimization method≫, ≪Safety≫.

Abstract

Due to the promotion of electric vehicles and new energy sources, lithium-ion batteries have been widely used. However, temperature has a great influence on the performance and safety of lithium-ion batteries during operation. Therefore, it is very important to predict the temperature of lithium-ion batteries and implement thermal early warning. In order to solve this problem, this paper designed a Sequential neural network-fuzzy thermal early warning system (SNNFT). First, the SNNFT uses a denoising autoencoder to eliminate the noise in real-time measurement. Then it combines the long short-term memory network and the temporal convolutional network that can handle the time series problem well to realize the accurate prediction of the lithium-ion battery temperature. And the SNNFT applies interpretable adaptive network-based fuzzy inference system model to build thermal early warning system. Complete experiments are conducted to verify the reliability advantages.

Introduction

Lithium-ion batteries have been widely used as the important energy storage supplies. However, the status of the lithium-ion batteries need to be monitored during operation to ensure its safe operation. Temperature is critical to the safe use of lithium-ion batteries. High temperatures will accelerate the side reactions of lithium-ion batteries, so lithium-ion batteries cannot continue to operate at high temperatures. Therefore, it is very important to predict the temperature of the lithium-ion battery and make a correct thermal diagnosis, which can ensure that there is enough time to adjust the heat generation and heat dissipation of the lithium-ion battery to avoid battery damage.

Part of the thermal research is devoted to the development of a physical or chemical model that can accurately estimate the temperature changes of lithium-ion batteries [1, 2, 3]. However, model-based methods usually require complex parameter measurement experiments in advance to obtain some modeling parameters of lithium-ion batteries. As a black-box model, methods based on neural networks do not need to know any physical or chemical characteristics of lithium-ion batteries in advance, so they are gradually being applied in the temperature prediction of lithium-ion batteries [4, 5, 6]. The traditional artificial neural network method has been proved to be effective, but for the time series problem of temperature prediction, the long short-term memory network is currently applied more [7]. However, the applications of these models in temperature prediction are relatively basic and single. Different from the traditional single simple network model, this paper combines multiple advanced network models for processing time series.

In addition, adaptive network-based fuzzy inference system (ANFIS) is also a nonlinear system modeling tool that can reflect the complex relationship between input and output [8]. ANFIS can construct an input and output mapping in the form of fuzzy if-then rules [9]. Fuzzy inference system based on fuzzy if-then rules can simulate human knowledge and reasoning process, so it is more explanatory and reliable than neural networks. However, ANFIS has not been tested and applied in lithium-ion battery state estimation and thermal diagnosis. The application of ANFIS in the thermal diagnosis of lithium-ion batteries not only avoids the complexity of model establishment and the need for a large number of expert experience, but also is more interpretative and more acceptable than the neural network model.

This paper attempts to make some contributions and improvements to the current technology of temperature prediction and thermal diagnosis of lithium-ion batteries. The temperature prediction part and the thermal diagnosis part constitute the complete thermal early warning system established in this paper. The four main contributions are as follows:

1. Due to various reasons such as measurement errors and signal transmission errors in the measurement of lithium-ion battery status, noise often exists in the data obtained from real-time measurement. Therefore, an LSTM denoising autoencoder is designed to reduce the noise of the measured data.

2. A temporal convolution-recurrent network (TCRN) is then proposed to accurately predict the surface temperature changes of lithium-ion batteries. TCRN not only integrates long short-term memory network (LSTM) and temporal convolutional network (TCN) to combine the advantages of those two models, but also adds a third input to enhance important features. During the training process of TCRN, Bayesian optimization is applied to optimize and adjust the model parameters to improve its prediction ability.

3. An interpretable adaptive network-based fuzzy inference system model (ANFIS) is established to realize the thermal early warning of lithium-ion battery. ANFIS model based on fuzzy system and neural network has interpretable rules, which makes it more credible and easier to be used in engineering field. In the training process, unlike traditional ANFIS, this paper uses a swarm intelligence technology—particle swarm algorithm to optimize the premise parameters and consequence parameters of ANFIS, which further enhances the inference capability.

4. This paper combines TCN, LSTM, and ANFIS for the first time to form a complete sequential neural network-fuzzy thermal early warning system (SNNFT). SNNFT realizes multi-step ahead prediction of the surface temperature of lithium-ion batteries and conducts thermal diagnosis of lithium-ion batteries according to the prediction results to determine whether there is a danger of thermal instability.

Methods

Prediction of surface temperature of lithium-ion battery

Denoising autoencoder

Autoencoders (AE) usually consist of an encoder and a decoder. Firstly, the input vector is mapped into feature vector by weighting, which is represented as the process from input layer to hidden layer in neural network. This process is usually completed by the encoder. Then the decoder reconstructs the feature vector into the original input vector by reverse weighting, which is the process from the hidden layer to the output layer in the neural network [10]. Ideally, the input and output should be the same [11].

The denoising autoencoder (DAE) is based on the autoencoder. In the training process, add noise to the input vector, and then make the autoencoder learn to obtain the real input that has not been polluted by noise, that is, the DAE has the function of removing noise [12]. Its architecture is shown in Fig. 1. Encoders and decoders can usually be composed of convolutional networks, recurrent networks and other ways. Since the task here is to reduce the noise of the measurement data of lithium-ion batteries, the input is a sequence. Therefore, an LSTM DAE is constructed, which is implemented by the sequence data autoencoder of encoder-decoder LSTM architecture. Fig. 2 shows the LSTM DAE established by Keras in this paper.

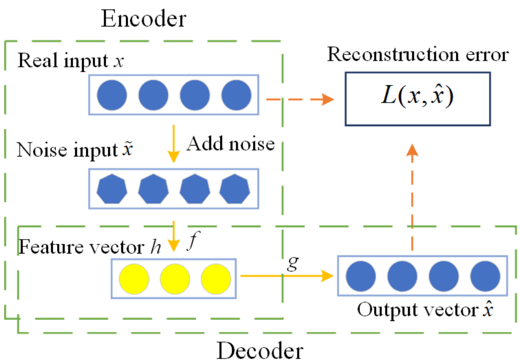

Fig. 1: The architecture of denoising autoencoder.

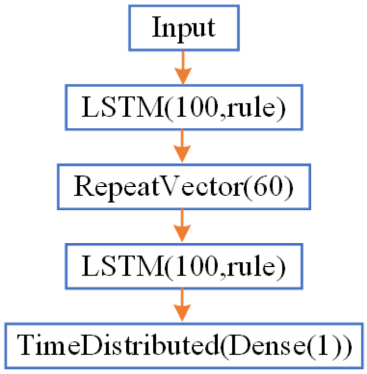

Fig. 2: LSTM denoising autoencoder.

Temporal convolution-recurrent network

Long short-term memory network (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 [13]. The key to overcoming the long-term dependence of LSTM lies in the addition of cell state. Each LSTM cell is made of input, forget, and output gates. The calculation process is shown in (1).

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

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. Causal convolution conforms to a strict time constraint. Dilated convolution is proposed to ensure enough receiving fields and reduce the amount of computation. In TCN, the simple convolution layer is replaced by a residual block. The composition of a residual block is shown in Fig.3 .

Based on the unique advantages of LSTM and TCN networks, the paper designed a temporal convolution-recurrent network (TCRN). TCRN is a network with three inputs and a single output and its stucture is shown in Fig. 4. Input 1 and input 2 are fed into LSTM and TCN respectively, and then connected to the fully connected layer to ensure that the output dimension is consistent with input 3. Then the three parts are connected in series through a concatenation layer, and the final output is obtained through the fully connected layer. Input 3 is added to enhance important features, thereby enhancing the predictive ability of the network.

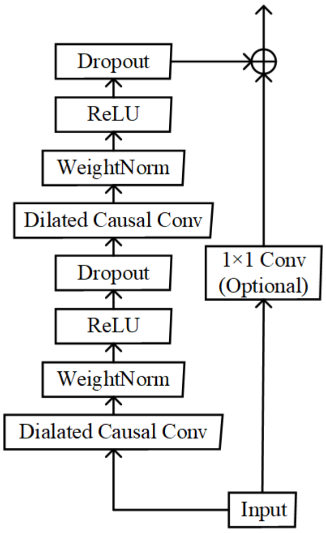

Fig. 3: Residual Block

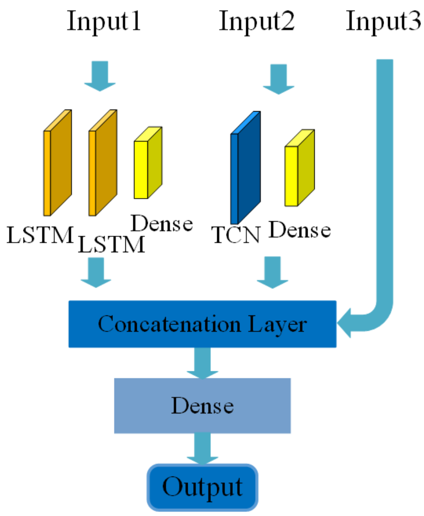

Fig. 4: Temporal convolution-recurrent network

The thermal early warning system of lithium-ion battery

Based on the adaptive network-based fuzzy inference system optimized by the particle swarm optimization algorithm, this paper designs a classifier to determine whether the surface temperature of lithium-ion batteries is out of bounds, and decides whether to issue an early warning signal.

Adaptive network-based fuzzy inference system

Adaptive network-based fuzzy inference system (ANFIS) integrates the fuzzy system and the artificial neural network to combine the advantages of the two methods [14]. Fuzzy system is a promotion of deterministic system. It captures the fuzzy characteristics of human brain thinking and imitates the way people make decisions on inaccurate and non-digital information [15]. Fuzzy system uses If-Then rules to realize the conversion from input to output, so as to deal with the difficult problem of fuzzy information processing. As a fuzzy inference system based on the Takagi-Sugeno model, ANFIS has rules as shown in 1 and 2 [16].

1. Rule1: if x is A_1 and y is B_1 then $z = p_1x + q_1y + r_1$;
2. Rule2: if x is A_2 and y is B_2 then $z = p_2x + q_2y + r_2$;

where x and y are two inputs, A and B are the linguistics labels and z is the output. Therefore, compared with artificial neural network, ANFIS is interpretable and more meaningful.

However, the traditional fuzzy inference system is generally formed based on expert experience, which lacks an effective learning mechanism. ANFIS realizes the three basic processes of fuzzy control through the method of neural network: fuzzification, fuzzy inference and defuzzification. Thus the process of establishing fuzzy inference system is simplified. It can automatically extract the dependent rules from the training data set. The structure of the first-order TSK-type ANFIS is shown in Fig. 5 [9]. Where the square nodes are the node with variable parameters and the circular nodes represent the node with immutable parameters.

The functions of each layer of ANFIS are shown in (2):

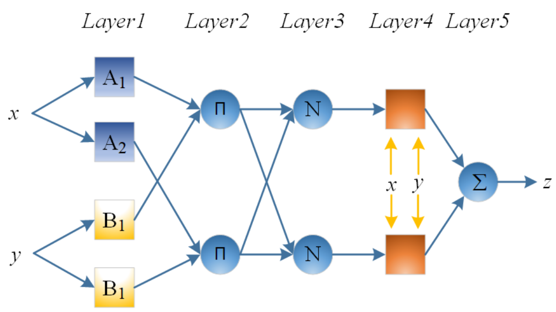

Fig. 5: The structure of the first-order TSK-type ANFIS.

$$\begin{cases} O_{1,ij} = \mu_j(x_i) = 1/(1+\left|(x_i - c_{ij})/a_{ij}\right|^{2b_{ij}}); \\ i = 1,2,\ldots,N; j = 1,2,\ldots,M \\ O_{2,r} = \prod_{i=1}^{N} \mu_j(x_i) = w_r; r = 1,2,\ldots,R \\ O_{3,r} = w_r/(\sum_{r=1}^{R} w_r) = \bar{w}_r \\ O_{4,r} = \bar{w}_r(\sum_{i=0}^{N} p_{ri}x_i), x_0 = 1 \\ O_5 = \sum_{r=1}^{R} O_{4,r} \end{cases} \tag{2}$$

where N is the number of input features, M is the number of membership functions corresponding to the ith input and R is the total number of rules.

Particle swarm optimization

There are two parts of the parameters in the ANFIS architecture that can be adjusted during the training process: the premise parameters (a_{ij}, b_{ij}, c_{ij}) in layer 1 and the consequence parameters (p_{ri}) in layer 4. The traditional ANFSI uses the least square method to update the consequence parameters in the forward propagation process, and then uses the gradient descent method to update the premise parameters in the backpropagation process. In the paper, the particle swarm algorithm (PSO) is used to adjust ANFIS parameters.

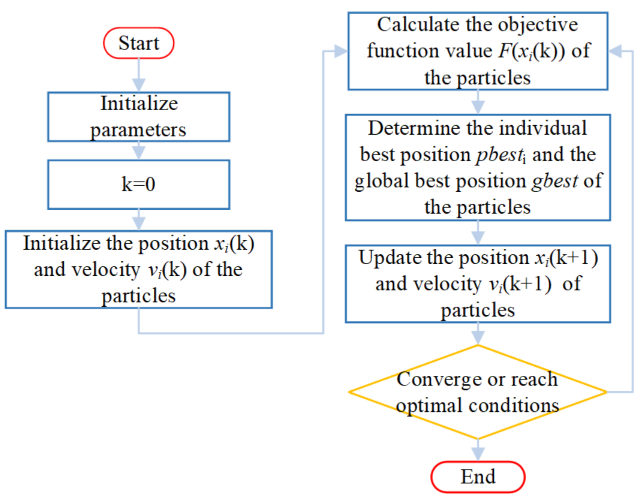

Fig. 6: The particle swarm optimization algorithm.

Originating from the study of the behavior of bird flocking, Eberhart and Kennedy proposed a new swarm intelligence technology—particle swarm optimization(PSO) [17]. As a population-based search method, PSO designed a massless particle to simulate birds in a flock of birds, in which each particle with the two attributes of speed and position is a candidate solution [18]. By simulating the cooperation and competition mode of individuals in the group, the particles of particle swarm will adjust their speed and position according to the current individual extreme value and the global extreme value shared by the whole particle swarm until they reach equilibrium or optimal state. The PSO algorithm is shown in Fig. 6. The update equations for the position and velocity of the particles are as follows:

$$\begin{aligned} v_i(k+1) = wv_i(k) + \rho_1(pbest_i - x_i(k)) + \\ \rho_2(gbest - x_i(k)) \end{aligned} \tag{3}$$

$$\begin{cases} \hat{v}_i(k+1) = \min(\max(v_{\min}, v_i(k+1)), v_{\max}), \\ \qquad LB \leq x_i(k) \leq UB \\ \hat{v}_i(k+1) = -r * \min(\max(v_{\min}, v_i(k+1)), v_{\max}), \\ \qquad x_i(k) \leq LB\text{or}UB \leq x_i(k) \end{cases} \tag{4}$$

$$x_i(k+1) = x_i(k) + \hat{v}_i(k+1) \tag{5}$$

where v_{max} and v_{min} are the maximum and minimum particle velocity. LB and UB are the lower and upper bounds of the particle position.

Sequential neural network-fuzzy thermal early warning system

This paper established a sequential neural network-fuzzy thermal early warning system (SNNFT), and its architecture is shown in Fig. **??**. First, the LSTM denoising autoencoder is used to reduce the noise of the lithium battery data measured in real-time. Then, the denoising data are used as the input of TCRN to predict the surface temperature of lithium battery in the next 4 seconds. Finally, the predicted surface temperature of 4 seconds is fed into the ANFIS-based classifier to determine whether a thermal early warning signal is required. In the training process, we use Bayesian optimization to optimize the training parameters of network and use PSO to adjust the premise and consequence parameters of the ANFIS model.

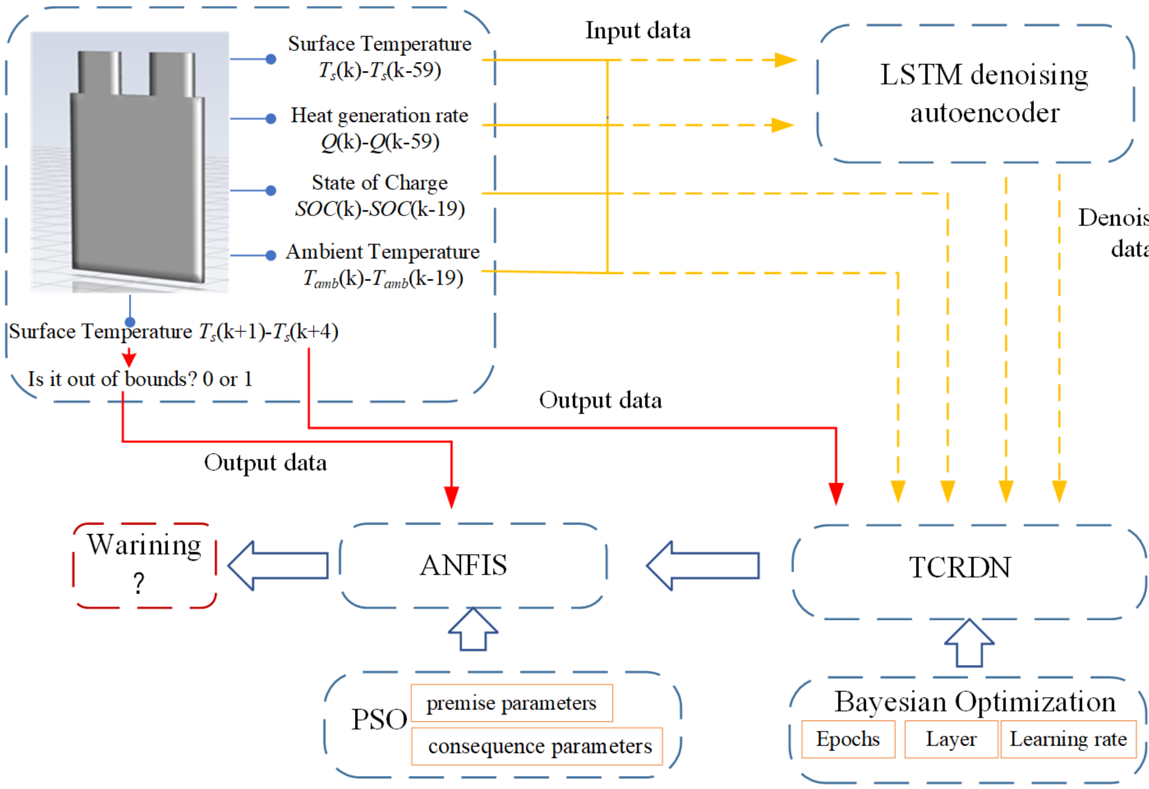

Fig. 7: Sequential neural network-fuzzy thermal early warning system.

Prediction results and discussion

Data preparation

We used the commercial software FLUENT to perform finite element simulation of a 10Ah pouch LiFePO4-Graphite battery to obtain the battery data. First, a finite element model of the lithium-ion battery is established, as shown in Fig. 4. The parameters of the battery are set as follows: Nominal Cell Capacity = 10Ah; Min Stop Voltage = 3V; Max Stop Voltage = 4.3V; Solution Method = MSMD; E-Chemistry Models = NTGK Empirical Model; Initial Soc = 0.7. The profile of the load current of the battery is shown in Fig.8(a), which is mainly for the thermal performance of the lithium-ion battery under high rate current, and the maximum load current can reach 4C. Because the SOC of the battery is usually cycled within a limited range of 20%-80% or 30%-70% which the SOC has little effect on the heat generation of the battery, this paper sets a cycle of SOC in a small range [19]. 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. 5. In order to simulate the noise signal under real conditions, this paper used the randn function to add 1.5 times Gaussian noise to the temperature and heat generation rate signals obtained by the finite element simulation. The randn function returns a random value obtained from the standard normal distribution, thereby generating Gaussian random noise.

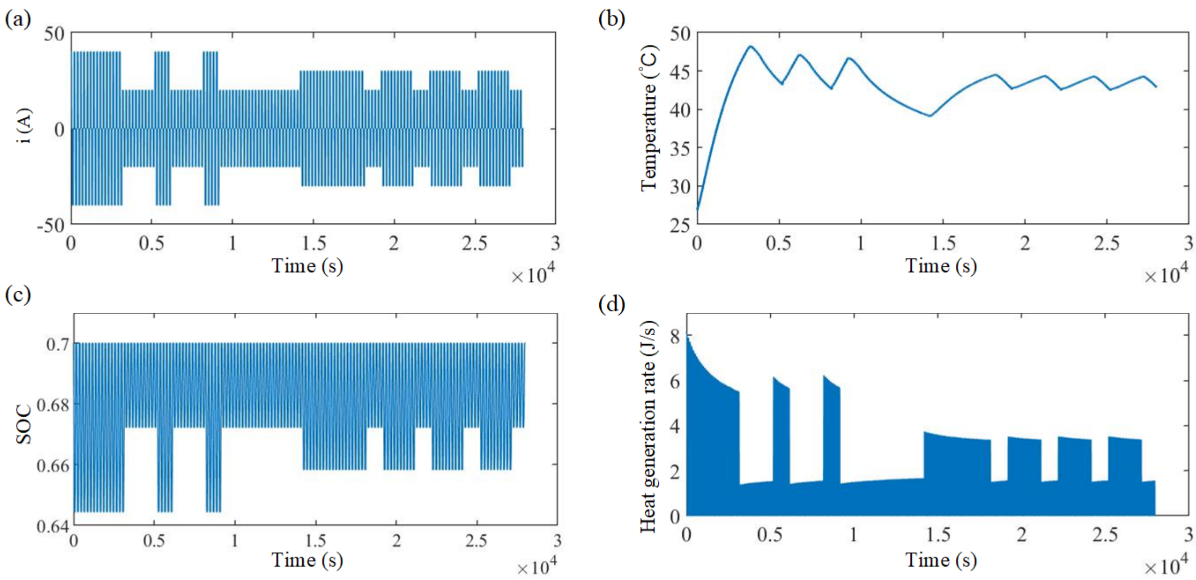

Fig. 8: Results of finite element simulation. (a) is the terminal current of the battery; (b) is the surface temperature of the battery; (c) is the state of charge; (d) is the heat generation rate of the battery.

Prediction results of surface temperature of lithium-ion battery

This paper obtains the measurement data of finite element simulation in real-time, and feeds the noise-added data into the LSTM denoising autoencoder through the sliding window method. The window length is 60 seconds. Take the first second test of each window as an example to show the noise reduction capability of the LSTM denoising autoencoder, as shown in Fig. 9.

It can be seen from Fig. 9 that the LSTM denoising autoencoder has a very good effect in reducing noise. After noise reduction, the data fluctuates less, the temperature change trend is clearer, and big error messages are removed.

The denoising data and measurement data are then fed into TCRN to predict the surface temperature for a period of time in the future. This paper used Keras to build the TCRN architecture. The input 1 and input 2 of TCRN are the surface temperature, heat generation rate, ambient temperature and SOC for 20 consecutive seconds. Because the surface temperature is a very important feature, the input 3 of

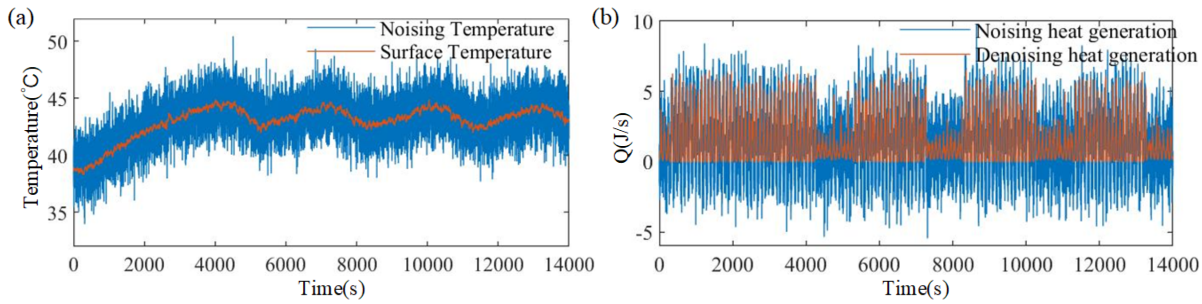

Fig. 9: The test results of LSTM denosing autoencoder. (a) surface temperature. (b) heat generation rate.

TCRN is the denoising measured value of the surface temperature for 60 seconds. In order to get a better prediction model, Bayesian optimization algorithm is used to optimize the layer, learning rate, epochs and other important parameters of the model during the training process. Set the prediction length to 4 seconds, Table 1 compares the mean square error of the prediction results when the input is noising data, the input is denoising data and Bayesian optimization is added.

Table I: The mse of prediction with the prediction length of 4s.

MSE	Noising Data	Denoising Data	Bayesian optimization
Train	0.0541	0.0305	0.0296
Test	0.0597	0.0475	0.0378

It can be seen from Table 1 that the prediction of TCRN that uses the denoising data as the input is more accurate. Under the same learning rate, the number of training epochs required with the noisy input is much more than the denoising input. This shows that the advantages of the denoising data obtained by the LSTM denoising autoencoder are more obvious, which can enhance the effect of prediction. On the other hand, Bayesian optimization is a very effective hyperparameter optimization method. Using Bayesian optimization to adjust hyperparameters not only saves a lot of manual tuning time, but also is more efficient and performs better than grid search and random search. After Bayesian optimization, a better TCRN model was obtained, which improved the accuracy of prediction.

Thermal diagnosis results of lithium-ion battery

Finally, the output of TCRN is fed into the classifier based on ANFIS to judge whether it is necessary to send an early warning signal, where 0 is not required and 1 is required. The ANFIS model established in this paper adopts the generalized bell membership function, and its equation is shown in (2). In the training process, PSO algorithm is used to adjust the premise membership function parameters and consequence parameters of ANFIS. When the prediction length is 4 seconds, the main PSO parameters used in ANFIS model training are as follows: the number of agents is 42; and the number of iterations is 250. The membership function finally obtained after PSO algorithm training is shown in Fig 10.

Each input corresponds to three generalized bell membership functions, and the linguistic labels are high, medium and low respectively. As the number of membership functions increases, the rules will increase exponentially. Therefore, when the prediction length is 5 seconds, in order to speed up the calculation time and save calculation resources, the membership function corresponding to each input is reset to 2.

In this paper, several experiments have been done under the scenarios of different prediction lengths, and compared with other advanced methods. The paper uses four indicators of accuracy, precision, recall and F1 score to evaluate these methods. The results are shown in Table 2. Where ANFIS-PSO: the method proposed in this paper; ANFIS: the traditional ANFIS method trained using least square method and gradient descent method; ANFIS-ANFIS: Train two traditional ANFIS models for 0 and 1 signals respectively, and finally perform MAX operation [20]; Skmoefs-ngsa3: Multi-Objective Evolutionary

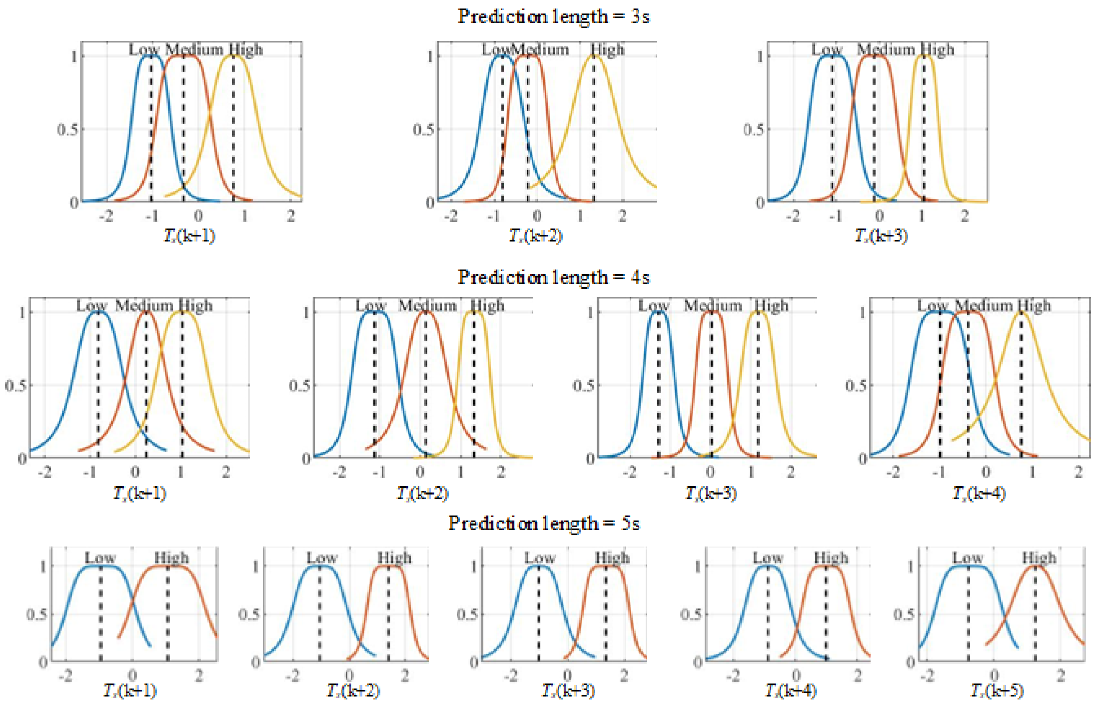

Fig. 10: The membership function.

Fuzzy Systems- Non-dominated Sorting Genetic Algorithm3 [21]; NN: neural network with 16 neurons in the hidden layer; MLP: Multilayer perceptron with three hidden layers and the number of neurons is 8, 16, 4, respectively. It can be seen from Table 2 that the ANFIS-PSO model established in this paper has achieved the highest prediction accuracy in scenarios with various prediction lengths. And when the prediction length is 4 seconds and 5 seconds, the ANFIS-PSO model outperformed other models in the four indicators of accuracy, precision, recall and F1 score. The ANFIS-PSO model maintains the performance not inferior to traditional neural network methods while possessing stronger interpretability.

Table II: Comparison of diagnosis ability of different methods

Prediction Length = 3s (Accuracy, precision, recall and F1 score)									
ANFIS-PSO	**0.8941**	0.9005	**0.8941**	0.8965	ANFIS	0.8799	0.8933	0.8799	0.8865
ANFIS-ANFIS	0.8905	0.8916	0.8905	0.8910	NN	0.8913	**0.9008**	0.8913	0.8944
Skmoefs-ngsa3	0.8950	0.9007	0.8950	**0.8971**	MLP	0.8919	0.9007	0.8919	0.8949
Prediction Length = 4s (Accuracy, precision, recall and F1 score)									
ANFIS-PSO	**0.8943**	**0.9007**	**0.8943**	**0.8966**	ANFIS	0.8658	0.8881	0.8658	0.8763
ANFIS-ANFIS	0.8773	0.8825	0.8773	0.8794	NN	0.8756	0.9912	0.8756	0.8819
Skmoefs-ngsa3	0.8824	0.8887	0.8824	0.8848	MLP	0.8763	0.8828	0.8763	0.8789
Prediction Length = 5s (Accuracy, precision, recall and F1 score)									
ANFIS-PSO	**0.8924**	**0.9005**	**0.8924**	**0.8952**	ANFIS	0.8641	0.8956	0.8641	0.8732
ANFIS-ANFIS	0.8687	0.8958	0.8687	0.8758	NN	0.8911	0.8994	0.8911	0.8940
Skmoefs-ngsa3	0.8878	0.8943	0.8878	0.8902	MLP	0.8904	0.8991	0.8904	0.8934

Conclusion

This paper established a sequential neural network-fuzzy thermal early warning system (SNNFT), which includes two parts: lithium-ion battery temperature prediction and thermal early warning. Firstly, aiming at the problem of noise in real-time measurement, an LSTM denoising autoencoder is applied. Then a temporal convolution-recurrent network (TCRN) integrating LSTM and TCN is designed to predict the surface temperature change of lithium-ion batteries in the future. The experiments show that when the input is denoising data, the MSE of the predicted result of the TCRN model after Bayesian optimization is reduced by 45%. Finally, the ANFIS model optimized by the particle swarm algorithm constitutes the thermal early warning part. By comparing the four indicators of accuracy, precision, recall and F1 score, it can be seen that the SNNFT established in the paper is notably the best compared to other methods.

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