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Comprehensive battery monitoring and warning system based on hierarchical temporal convolutional network (HTCN)

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ABSTRACT

Battery management system (BMS) is crucial to ensure the efficiency and safety of the Lithium-ion battery pack by monitoring the real-time voltage, current, and temperature. In particular, the monitoring and warning system of the BMS is especially vital and demanding. However, most researchers separate the battery states as individual tasks and discuss them respectively, while state of charge (SOC), state of health (SOH), and state of temperature (SOT) are coupled and should be estimated simultaneously in one model. To satisfy the demand for the online monitoring and warning system, this paper proposed an integrated estimation model based on temporal convolution network (TCN) and multi-task learning taking the mutuality of the SOC, SOH and SOT into consideration. Specifically, four assessing indexes were obtained by analyzing the relationship, tendency and characteristic of the temperature and capacity during the battery aging process. Then, a multi-timescale model was built combined with the conception of multi-task learning, namely the hierarchical temporal convolutional network (HTCN), and the temperature varying tendency is predicted along with the battery states as different output tasks. At last, the model was transferred to test datasets to validate the generality, accuracy and robustness. Results show that the mean average error (MAE) of the SOC, SOH and SOT estimation are 1.37%, 0.95% and 1.01%, respectively. This paper provided a novel, practical and reliable route for the comprehensive BMS construction.

Keywords: BMS, co-estimation, multi-time-scale model, multi-task learning

NONMENCLATURE

Abbreviations	
BMS	Battery management system
CC-CV	Constant current-constant voltage
DOD	Depth of discharge
SOC	State of charge
HTCN	Hierarchical temporal convolutional network
SOE	State of energy
SOH	State of health
SOT	State of temperature
SOP	State of power
MAE	Mean-average error
MSE	Mean-square error
RMSE	Root-mean-square error
R^2	R-squared

1.1 Battery state estimation

The Battery Management System (BMS) is an important link between power batteries and electric vehicles. It estimates the states of the entire battery pack by monitoring the status parameters of the battery cells, such as voltage, current, and temperature. The accurate state estimation makes corresponding control adjustments and strategy implementation for the power battery system, and realizes the charge and discharge management of individual cells to ensure the safe and stable operation of the electric vehicles.

Battery state estimation is an essential role of BMS, including State of Charge (SOC), State of Health (SOH) and State of Temperature (SOT), etc. It is intended for effective charging, thermal management and health monitoring prerequisites of the battery [1]. SOC and SOH cannot be measured by instruments directly and are

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usually estimated using model-based methods or data-driven methods. Model-based methods mainly use electrochemical models and equivalent circuit models to describe the internal structure and aging mechanism of batteries. However, high interpretability models require considerable parameters obtained by a series of complicated experiments. In addition, model-based methods are usually designed for specific batteries and are difficult to apply widely. Unlike the above way, the data-driven methods avoid modeling the complicated internal mechanism of lithium-ion batteries and instead use a large amount of data to establish a mapping function between input attributes and battery status. In addition to simplifying the modeling process, it also provides high accuracy and robustness. Therefore, it has become a research hotspot in the field of battery management systems.

Roman et al. [2] developed a machine learning-based method for predicting SOH and tested it on 179 battery cells to demonstrate the efficiency of machine learning for the task of estimating SOH. Cai et al. [3] and Lipu et al. [4] constructed SOH estimation algorithms from an optimization perspective. Li et al. [5] and Lin et al. [6] are committed to exploring input indicators that can be effective for SOH. In addition, most researchers study SOC as an independent task and optimize the estimation accuracy with the similar idea. Although these methods have achieved high prediction accuracy, they are difficult to apply in reality due to their large amount of calculation and redundant models. Therefore, Tian et al. [7] simultaneously estimated SOC and SOH in one model and achieved good accuracy. However, this method ignored that SOC and SOH are at different time scales, and it is challenging to obtain satisfactory results using input data of shorter time scales. Therefore, it is necessary to study unified deep-learning network structures under different time scales to estimate multiple battery states simultaneously.

1.2 Early battery thermal warning

Lithium-ion batteries have high energy density, and chemical reactions continue proceeding during the working process, so they are highly temperature sensitive, causing temperature to have an important impact on their safety and cycling life. Thermal runaway is one of the fatal safety accidents forms of battery failure, resulting from thermal abuse, electrical abuse, or mechanical abuse. For thermal abuse, heat accumulates inside the battery, further accelerating the reaction rate, causing a sharp rise in temperature, producing flammable gas and destroying the internal structure of the battery, eventually causing fire or explosion. If the battery constantly works in a high temperature or overcharged/discharged, it will accelerate the aging of the battery. At the same time, the internal resistance of the battery will increase, the service life will be shortened, and the probability of thermal runaway will increase. Therefore, it is very important to accurately predict the battery heat generation and temperature change trends, and timely mobilize the battery thermal management system based on the battery's thermal status information to dissipate heat efficiently and reasonably to prevent heat accumulation.

Many researchers have conducted relevant investigations on thermal early warning applying multiple methodologies. Li et al. [5] proposed a sequential-transformer thermal early warning system (STTEWS) for prismatic LiFePO4-Graphite battery composed by a new allied temporal convolution-recurrent diagnosis network (TCRDN) and a complete transformer thermal diagnosis network (TTDN), which managed to reach the thermal diagnosis accuracy of 95%. To predict the thermal runaway (TR) of the battery pack, Zhang et al. [8] established a data-driven fusion model named Multi-Mode and Multi-Task Thermal Propagation Forecasting Neural Network (MMTPFNN) applying the thermal image and the discrete operating data of 18650 cells. Besides, a temperature-based TR propagation grading warning strategy was proposed to improve the applicability of the model with the temperature threshold of 60 ℃. Overcharge tests on LiFeO4 batteries were conducted at various current rates (C-rates) and the indicators of voltage, gas, and temperature during overcharge were analyzed by Zhang et al. [9] to monitor, warn and mitigate the TR process, especially in Stage II (gas detected stage). Lyu et al. [10] discovered and validated the feature that when the cell started to be overcharged, the slope of the dynamic impedance in a specific frequency band would transfer from negative to positive, and the method based on this feature managed to warn 580 s before the fatal TR. Furthermore, they also developed an online device to conduct this warning method by measuring the dynamic impedance. To prevent the TR caused by overcharging, an indicator named virtual temperature was proposed by Jia et al. [11] based on Fiber Bragg Grating (FBG) sensor, which is a composite parameter influenced by both temperature and strain. Besides, a TR early warning method containing three stages was invented by integrating the changes of three evaluation indexes. Exploiting the influence of the temperature and deformation on Electrochemical Impedance Spectrum

(EIS), a two-stage early thermal warning model containing 3 indexes ranging in three frequency spectrums was generated by Dong et al. [12], while practical issues including measurement feasibility and flexibility were taken into consideration.

1.3 Research significance

Correct estimation of battery states is a prerequisite for effective battery service. However, current research usually treats different battery status estimation and thermal warning as independent tasks, ignoring the strong coupling and interaction between them. In addition, existing research rarely involves the prediction of temperature trends. The battery thermal management system can only receive implemented temperature information, and it takes time from starting heat dissipation to reaching the appropriate operating temperature, resulting in the thermal management system being unable to respond timely, making it less efficient, less effective, more energy consuming, and may even cause safety accidents such as thermal runaway.

To fix the aforementioned defects, this paper proposes a comprehensive monitoring and early warning system for battery states based on cross-time-scale convolution, which combines multi-time scale and multi-task learning methods to comprehensively estimate temperature trends and health states under a unified model to achieve more accurate and reliable battery monitoring and early warning system design. In addition, considering that indicators under different time spans will have a significant impact on the results, this design proposes four effective indicators based on the battery aging mechanism for multi-state prediction. On this basis, a software interface is designed according to the model structure, and the prediction process is transformed into a user-friendly operation interface to facilitate practical application.

2. METHODS

This paper aims to construct a reasonable method for comprehensive estimation of multiple battery states, including how to extract effective input indicators from voltage, current, and temperature, construct a model to predict the battery state at different time scales, and design a loss function to balance different prediction tasks. The schematic diagram is shown in Fig. 1.

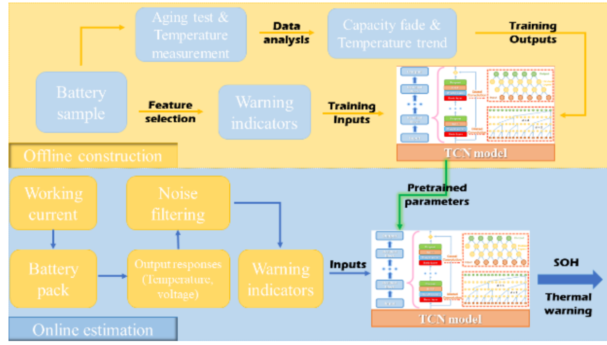


Fig. 1. Systematic diagram of the estimation model

2.1 feature selection

According to the parameters' varying trend during the aging process of lithium batteries and the coupling relationship among different parameters, this paper concludes the voltage, current, and temperature at different scales into four input indicators (I_1, I_2, I_3, and I_4) required in the early warning and health prediction process, as listed in Table 1.

Table 1. Comprehensive estimation index

Index	Expression	Description
I_1	R_0	Ohmic resistance
I_2	$\dfrac{\frac{dU}{dt} IR_0 \int (It)dt}{\Delta T}$	Temperature rising potential
I_3	$\dfrac{V_2 - V_1}{I\Delta t}$	Voltage change rate
I_4	$\dfrac{T_{V_2} - T_{V_1}}{I\Delta t}$	Temperature change rate

<u>2.1.1 Ohmic resistance</u>

Since the internal resistance of the battery will gradually increase with the working cycles, the ohmic internal resistance can reflect the health state of the battery, so it is selected as the health evaluation index I_1. As shown in Fig. 2, the voltage and discharge current at the discharging instant are used to obtain R_0 in a short time window:

$$R_0 = \frac{\Delta V_R}{I} \qquad (1.1)$$

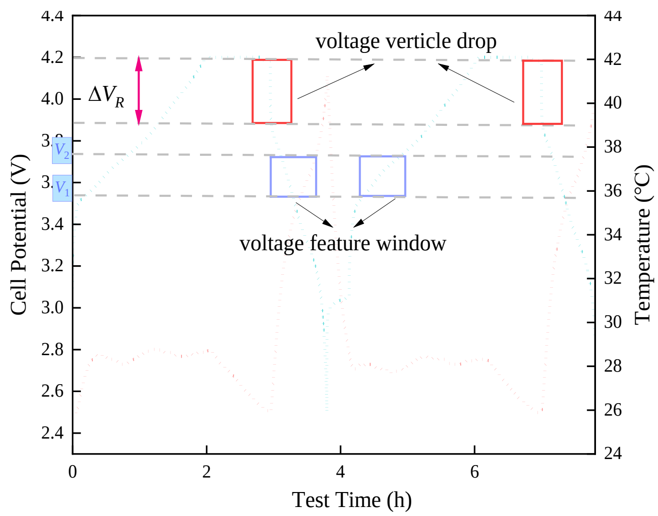


Fig. 2. Feature selection in CC-CV cycles

2.1.2 Temperature rise potential

Observing the voltage, temperature, and capacity change curves in the cycling process, it can be seen that the greater the voltage changing rate leading to the faster temperature rise, and the slope of the voltage curve is almost mirror symmetrical with the slope of the temperature curve. When the depth of discharge (DOD) gets larger, the battery haven been working for longer time, which means the more heat accumulation, resulting in the faster temperature rises. If the charge/discharge current is bigger, the internal chemical reaction of the battery will be more violent, inducing the more the heat generation. The ohmic internal resistance is part of the internal resistance, which indicating the aging degree of the battery, and also deciding the heat generation ability due to the Joule's law. The difference between the battery and the ambient temperature is related to the extent of heat natural convection. The battery tends to exchange more heat with coolant if this gap is larger, and the easier for temperature to drop. Based on the above analysis, the factors for battery temperature lifting are placed in the numerator, while the factors that leads the battery temperature dropping are listed as the denominator to obtain the temperature rise potential I_2.

$$I_2 = \frac{\Delta P_{heat} \times R_0 \times C_{capacity}}{P_{dissipate}} = \frac{\frac{dU}{dt} I R_0 \int (It)dt}{\Delta T} \tag{1.2}$$

2.1.3 Voltage change rate and temperature change rate

The voltage curve characteristics in the charging and discharging process are rich, so the more moderate voltage window V_1-V_2 (3.55-3.75 V) is selected as the observation interval of the characteristics, and the voltage change rate and temperature change rate in the voltage characteristic window under different health states are analyzed, which are listed as I_3 and I_4, respectively.

$$I_3 = \frac{V_2 - V_1}{I\Delta t} \tag{1.3}$$

$$I_4 = \frac{T_{V_2} - T_{V_1}}{I\Delta t} \tag{1.4}$$

2.2 Model construction

2.2.1 Temporal Convolutional Network

The aging process of lithium batteries is closely related to time, and most of the existing methods use Recurrent Neural Network (RNN) and Long-short Term Memory Network (LSTM) to learn the mapping function between input features and battery state. Unfortunately, when the input sequence is lengthy, RNN and LSTM suffer from catastrophic forgetting, which causes them to forget information from previous times while learning new ones. Therefore, it is difficult for the above models to learn the entire life decline process of the battery. The Temporal Convolutional Network (TCN) [13] can extract the features of sequences of different lengths under multilayer convolution by using dilated convolution to obtain larger receptive fields, and the residual module is used to effectively avoid gradient disappearance. However, due to the rapid change of microelectrochemical parameters, the state of batteries such as SOC/SOP/SOE usually changes in real-time, which causes the low-level timescale. Because of the physical structure and heat transfer characteristics of the battery, the macroscopic temperature distribution evolves at intermediate-level timescale. SOH with high-level timescale changes only slightly during a period of time, manifested by slow changes in parameters such as internal impedance/resistance and capacity [14]. In summary, the SOC, SOT, and SOH of lithium batteries vary at different time periods, and their feature length is different, making it challenging to predict them simultaneously. Therefore, we focus on establishing an effective mapping between the characteristics of different time levels and battery states.

2.2.2 Multi-task learning

Most studies design independent frameworks estimated SOC, SOT, and SOH, respectively. However, this mode cuts the coupling characteristics between multiple parameters in the battery working process, which no longer meets the current requirements for simultaneous prediction of multiple indicators. Multi-task learning can mine the potential common information in the training samples of related tasks, provide additional training information for each task, and finally learn in parallel for multiple tasks with shared expression characteristics, thereby improving the performance of each single task. BMS obtains voltage, current, and surface temperature through sensors, but how to construct a reasonable loss function to predict the different states of the battery through a unified input, balancing multiple tasks is another research emphasis of this work.

<u>2.2.3 Model structure of hierarchical temporal convolutional network (HTCN)</u>

We develop a hierarchical temporal convolutional network, as shown in Fig. 3, to simultaneously predict the battery's SOC, SOH, and SOT in a period online. This model can play the role of both thermal warning and health monitoring.

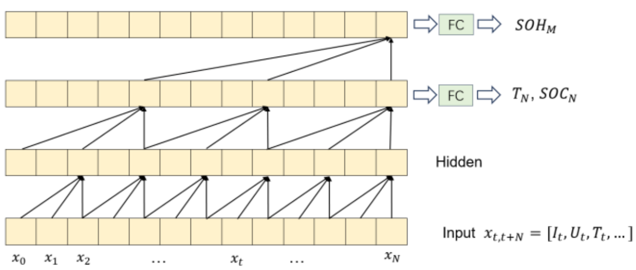


Fig. 3. Multi-time-scale estimation model

Specifically, we construct a multi-layer dilated convolution that can receive longer time-scale input data to capture long-term dependencies and reach higher accuracy. In order to simultaneously predict the battery states of different time levels, multi-level fully connected layers are built, which can predict both short-time SOC and long-time SOH. In addition, to realize thermal early warning, the temperature in the coming 3~5 minutes is predicted at intermediate-level timescale, namely the time left for the battery thermal management system to start cooling. The process can be expressed as:

$$[SOH, SOC, T] = f\left(x_{t,t+N}\right) \tag{1.5}$$

where *f(·)* represents our hierarchical temporal convolutional network, SOH is the battery health under the current number of cycles, SOC is the remaining battery capacity at *t* time, and *T* is expressed as the predicted temperature after a while. The workflow of the multi-time-scale and multi-task prediction structure is depicted as Fig. 4.

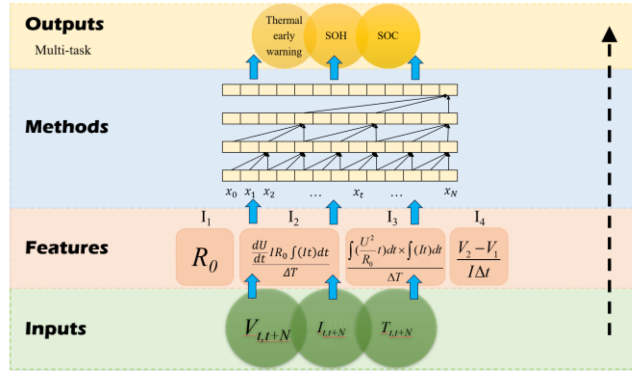


Fig. 4. Workflow of the HTCN estimation process

2.3 *Data processing*

This paper is carried out on the Oxford Battery Degradation Dataset 1, which contains measurements of battery aging data from 8 small lithium-ion pouch cells. The cells were all tested in a thermal chamber at 40 under a constant-current-constant-voltage charging profile, followed by a drive cycle discharging profile that was obtained from the urban Artemis profile. Measurements were taken every 100 cycles. Charging and discharging were carried out with 1C and the monitoring process continued to the final aged stage.

Given the battery charge and discharge data over a period of time, the voltage, current and temperature obtained by its sensor are recorded as $\{V\}_{t,t+N}$, $\{I\}_{t,t+N}$, $\{T\}_{t,t+N}$, and four index I_1 are calculated from its data, I_1, $\{I_2\}_{t,t+N}$, $\{I_3\}_{t,t+N}$, $\{I_4\}_{t,t+N}$, where I_1 is a scalar quantity, calculated after each charge and discharge. In the time dimension, the above indicators are connected with voltage, current, and temperature to form the input data over a period of time, where the input at time *t* is represented as $x_t = \{V_t, I_t, T_t, I_1, I_{2t}, I_{3t}, I_{4t}\}$, in order to eliminate the dimensional influence of the input data, reduce data noise and outliers, the input data is normalized. Secondly, a certain time window is used to divide the entire charge and discharge data for the model training.

3. RESULTS AND DISCUSSION

In our experiments, we refer to the work of [7] and use cell 1-6 in Oxford Battery Degradation Dataset 1 for training, while the rest cell 7-8 are arranged as test objects.

3.1 *Model performance*

The model performance can be closely related to window size in case of time-sequence estimation, when window size is set as 1024, the estimation performance indicators of MAE, RMSE and R^2 for the three battery states are tabulated as Table 2.

Table 2. Performance metrics for different tasks

Estimation tasks	MAE (%)	RMSE (%)	R^2
SOC	1.37	2.05	0.9838
SOH	0.95	1.23	0.9957
SOT	1.01	1.25	0.9587

3.2 Visual analytics

The estimation results of the three battery states are depicted along with the measured value in Fig. 5, which visualizes the model performance through the test cycles.

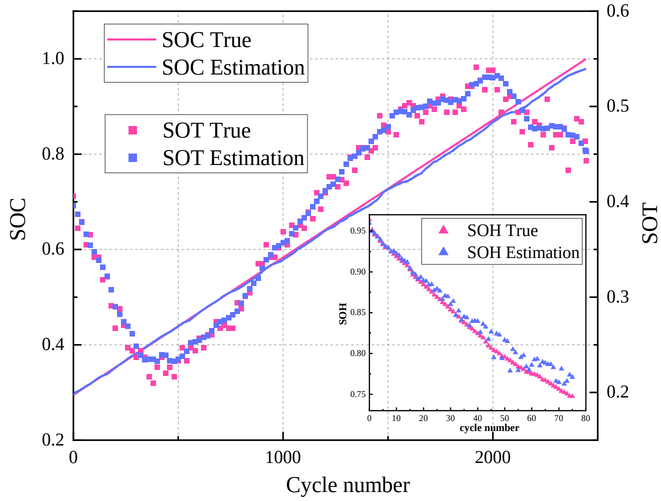
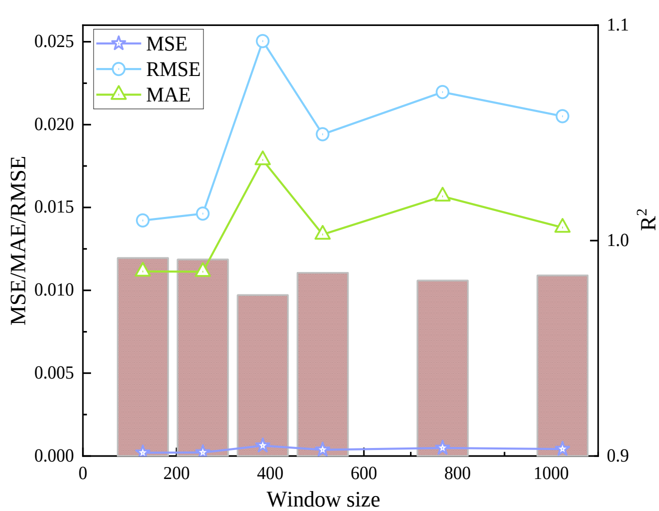


Fig. 5. Estimation results for three states

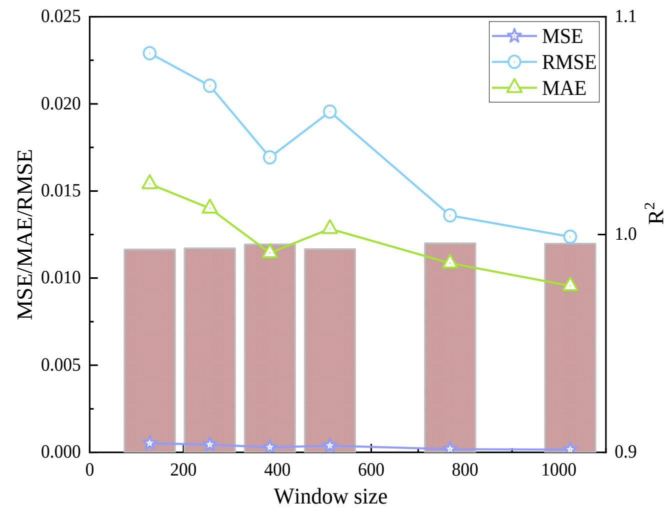
3.3 Effects of time window size

These three indicators are at different time levels, and it can be found that SOT is basically not affected by window size, as shown in Fig. 6 (a). SOC estimator performs slightly better at larger window as depicted in

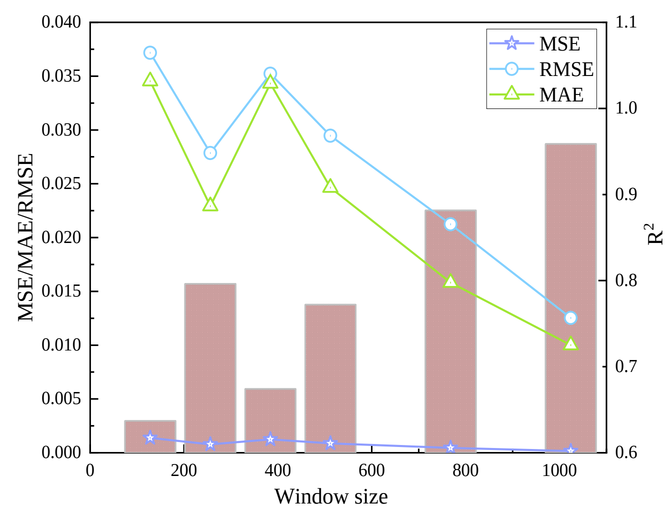


(a) SOT

Fig. 6 (b), while SOH prediction results rely heavily on the window size, and the longer window brings the better performance, as shown in Fig. 6 (c). It can also further validate that these three indicators are at different time levels.



(b) SOC



(c) SOH

Fig. 6. Effects of window size for different tasks of (a) SOT, (b) SOC and (c) SOH

3.4 Comparison with other ML models

To better validate the superiority of the proposed HTCN model, we compared three other commonly used machine learning networks which are also capable of this mission, which means predict the three states simultaneously. The comparison models are designed as follows:

CNN+MLP: we first use a single-layer CNN to reduce the feature dimension of the input to 1, then build 3 linear to predict SOT, SOC, and SOH, respectively.

LSTM and RNN: we use LSTM/RNN units with 128 neurons to capture information in the time dimension and use 3 linear layers with different weights to predict SOT, SOC and SOH, respectively.

The comparison was conducted under the same condition of time window size =1024, and the results are shown in Table 3. It can be found that other models cannot make predictions well at different level of time scales, and our model (HTCN) can achieve higher accuracy due to the near-pyramid structure.

Table 3. Comparison with other three ML models

Method	SOT			SOC			SOH		
	MAE (%)	RMSE (%)	R^2	MAE (%)	RMSE (%)	R^2	MAE (%)	RMSE (%)	R^2
CNN+MLP	1.25	1.59	0.9902	1.61	2.09	0.9809	3.85	5.47	0.3528
LSTM	1.24	1.59	**0.9902**	1.62	2.98	0.9754	4.45	6.31	0.1687
RNN	1.51	1.85	0.9868	2.25	2.91	0.9768	4.69	6.36	0.1240
Our (HTCN)	**1.01**	**1.25**	0.9587	**1.37**	**2.05**	**0.9838**	**0.95**	**1.23**	**0.9957**

4. CONCLUSIONS

1) A comprehensive monitoring and early warning system for battery health and thermal state is designed, which takes into account the coupling relationship and interaction between temperature characteristics and capacity attenuation during aging, and conducts online monitoring and early warning of health state and temperature rise trend at the same time to ensure the efficiency and safety of battery usage.

2) According to the parameter varying trend of the battery in the charge-discharge cycling test and the principle of battery construction, four indicators are proposed to evaluate the comprehensive state of the battery, which effectively quantifies the health stage and thermal safety degree of the battery in the whole life cycle.

3) Using the time series convolutional neural network combining the multi-task learning method to establish a comprehensive early warning model, the MAE in SOC, SOH, and temperature estimation are 1.37%, 0.95%, and 1.01%, respectively, which is also highly universal and can be generalized to a variety of application scenarios.

4) Compared with other similar traditional machine learning models, the HTCN model proposed in this paper performs best in the three estimation tasks of SOT, SOC and SOH, which shows the effectiveness and advancement of the design.

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DECLARATION OF INTEREST STATEMENT

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. All authors read and approved the final manuscript.

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