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TCN method development for SOC prediction of Li-ion batteries

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Abstract:
Lithium battery state-of-charge (SOC) estimation is a core function of battery management system, which directly affects the safety and range performance of electric vehicles. Aiming at the nonlinear modelling limitations of traditional methods under dynamic operating conditions and battery aging scenarios, temporal convolutional networks (TCNs) have become a research hotspot in the field of SOC estimation. This paper reviews the recent progress of TCN methods: through the introduction of attention mechanism, migration learning and hybrid architecture, it effectively solves the challenges of data missing sensitivity and poor cross-cell generalisation; combined with genetic algorithm, grey wolf optimisation and other strategies, it further optimises the network structure and hyperparameters.

Keywords: component, lithium battery, state of charge estimation, temporal convolutional network, attention mechanism, transfer learning, battery management system, optimization algorithm

1. Introduction

SOC (State of Charge) is the core technical indicator of new energy vehicles, which directly determines vehicle performance, safety and user experience. As the "eyes" of the battery management system, SOC dynamically optimizes the charging and discharging strategies through real-time monitoring of the remaining battery charge, avoiding the damage to the battery life caused by overcharging or over-discharging, and at the same time accurately predicting the remaining range in combination with the temperature, driving conditions, and other data, so as to alleviate the mileage anxiety of the users.

Researchers and scholars at home and abroad have conducted a lot of research on battery SOC estimation methods, and the main methods are classified into ampere-time integration method, open-circuit voltage method, Kalman filtering method, neural network method, etc. Different estimation methods have different principles, which lead to a large gap between the process and the result accuracy. The neural network method predicts SOC based on machine learning, which can deal with nonlinear relationships and complex situations, and has significant effect on the estimation of battery SOC which is unpredictable, and the combination of it with deep learning can have strong adaptability and learning ability, which is suitable for all kinds of batteries, and has been favoured by domestic and foreign researchers and scholars.

The commonly used deep learning methods for SOC estimation are Recurrent Neural Network (RNN) and

Convolutional Neural Network (CNN). Long Short Term Memory Network (LSTM), Gated Recurrent Unit (GRU) are introduced to improve RNN. Time Convolutional Network (TCN) is introduced to improve CNN.LSTM solves the nonlinear problems of dynamic working conditions and battery aging that are difficult to be dealt with by traditional methods, and inputs the time series data such as voltage, current, and temperature when estimating the SOC, but the many parameters lead to long time-consuming training and difficulty in embedded deployment; GRU simplifies the structure of LSTM and reduces the cost of computation, with fewer parameters, quicker training, significantly fewer parameters, and Better real-time; CNN and RNN combine to extract uncertain features of multi-sensor data; TCN solves the problem of gradient vanishing of traditional RNN and becomes a new choice to deal with long sequences, improves the efficiency of parallel computation, is suitable for embedded deployment, and effectively copes with the problem of long-period effects such as battery aging, and combines with other optimisation algorithms to enable parameter tuning.

Chung et al. proposed a deep learning model based on LSTM-RNN for lithium-ion battery state-of-charge estimation, which achieves high-precision SOC prediction under dynamic temperature conditions. Duan et al. proposed an improved gated recurrent unit network model (GRU-ATL) for lithium-ion battery state-of-charge (SOC) estimation, which solves the SOC estimation problem in the voltage flat region and under noise interference. Song et al. proposed a hybrid model (CNN-LSTM) combining convolutional neural network (CNN) and long short-term memory network (LSTM) for lithium-ion battery state-of-charge (SOC) estimation, which can simultaneously model the spatio-temporal nonlinear dynamic characteristics of the battery.

2. Relevant knowledge

A. Definition of SOC

SOC is used to represent the remaining available power inside the battery and is the main parameter of the battery management system. It is defined by the Advanced Battery Consortium of America as the ratio of the remaining charge to the rated capacity of a battery at a specific discharge multiplier, and is calculated by the formula shown in:

$$SOC = \frac{Q_{remain}}{Q_{rated}} \times 100\% = 1 - \frac{Q}{Q_{rated}}$$

Where: Q_{remain} indicates the remaining charge of the lithium battery, Ah; Q_{rated} indicates the rated capacity of the lithium battery, Ah; Q indicates the discharge of the lithium battery, Ah.

When SOC=100%, it means that the lithium battery is in a fully charged state; when SOC=0, it means that the lithium battery is completely discharged; the range of SOC is between 0 and 100%.

B. SOC evaluation indicators

The evaluation metrics for SOC are generally Mean Absolute Error (MAE) and Root Mean Square Error (RMSE).

$$MAE = \frac{1}{n}\sum_{i=1}^{n} | y_i - x_i |$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_i - x_i\right)^2}$$

Where: n is the number of samples; y_i is the predicted value of the ith sample; x_i is the true value of the i th sample.

MAE is calculated by Eq. The smaller the value of MAE, the better the prediction performance of the model, and when MAE is 0, it means that the prediction result is completely accurate. MAE is explanatory, easy to understand, and has a strong anti-interference ability to the outliers in the data.

RMSE is calculated as shown in Eq. RMSE Since the error of each sample is squared first, it makes the samples with larger errors have a larger impact on the RMSE value, which is an advantage when focusing on large errors

C. TCN definition and calculation formula

Temporal Convolutional Network (TCN) is a temporal modeling architecture based on one-dimensional causal convolution, which consists of three main parts: causal convolution, dilation convolution, and residual connection.

Causal convolution has the two characteristics of not considering future information and the longer the information is traced back in history, the more hidden layers there are, so it can result in a huge convolution kernel and a complex structure. In this regard, dilation convolution is proposed, as shown in Fig. Injecting dilation factors into the standard convolution as a way to increase the sensory field.

Causal dilation convolution can be defined as follows:

$$\left(F * X\right)x_t = \sum_{k=1}^{K} f_k x_t - \left(K - k\right) * d$$

Where $F = (f_1, f_2 \ldots, f_K)$ represents the filter, $X = (x_1, x_2, \ldots, x_K)$ represents the input data and d is the dilation factor.

The input to the residual module undergoes two layers of convolution and nonlinear mapping, with WeightNorm and Dropout also added to each layer to regularize the

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network to prevent gradient explosion and overfitting, and the input uses an additional 1×1 convolution to adjust the width of the residual tensor to ensure that the inputs and outputs have the same shape.

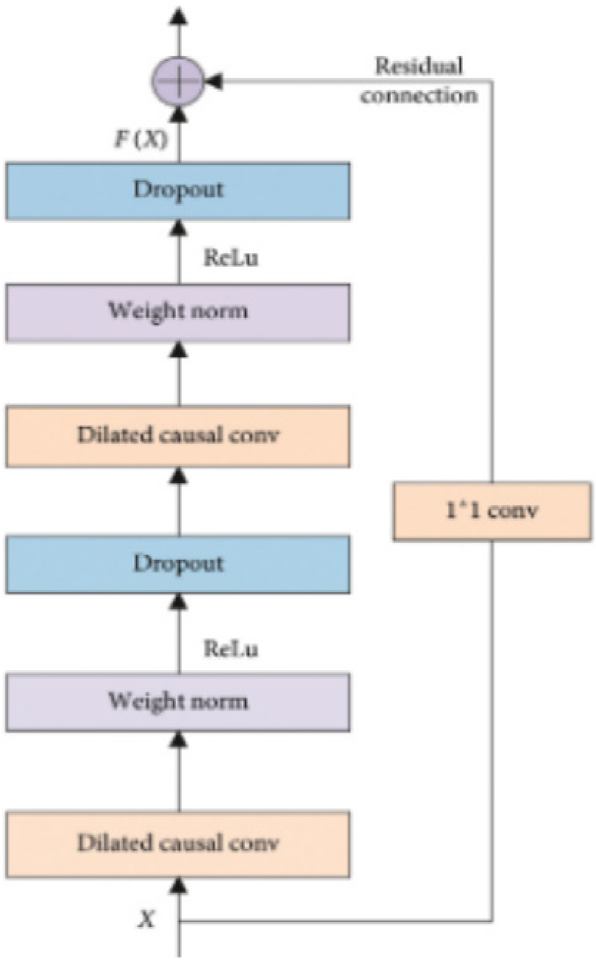

Figure 1. TCN

3. TCN and derivation methods

A. Basic TCN

Yahia et al. first proposed a temporal convolutional network (TCN)-based state-of-charge (SOC) estimation method for lithium-ion batteries, which effectively solves the gradient problem of traditional recurrent neural networks (RNNs) in temporal modeling and achieves high-precision estimation of the SOC under the dynamic operating conditions of the battery. The core structure of the TCN consists of multiple layers of stacked expansion-convolutional modules, each of which exponentially expands the sensory field through the The core structure of TCN consists of multiple layers of expanding convolutional modules, each of which expands the sensory field by exponentially expanding the expansion rate to capture the long and short-term dependencies of different time scales in the input signals, such as battery voltage, current, and temperature, etc. The causal convolution ensures that the prediction at the current moment relies on the historical data only to avoid the leakage of the future information, while the residual module fuses the original inputs and convolutional outputs through jump connections, which strengthens the stability of the information transfer and mitigates the gradient vanishing problem of the deeper network. .

The experimental results show that the model exhibits high robustness under mixed driving cycles and wide temperature range, with the MAE below 2.5% and the RMSE below 3%, which is faster than the traditional LSTM/GRU model in terms of training speed and higher parallel computation efficiency, and does not need to rely on the complex battery model or multi-model fusion strategy, which verifies its application in the practical on-board battery management system (BMS) applications.

B. Integration of TCN with data processing models

1) TCN-LSTM-transfer learning

The main advantage of TCN is that it can flexibly regulate the size of the receptive field as well as effectively manage the memory duration of the model. Moreover, TCN requires less memory during training, especially for long input sequences. This efficiency is attributed to its unique inclusion of dilated causal convolution and residual models. Combining the advantages of TCN and LSTM can optimize the input parameters and reduce the training time.

Zhao et al. proposed a hybrid model TCN-LSTM combining temporal convolutional network (TCN) and long-short-term memory network (LSTM), which improves on the lack of dynamic adaptation and the limited ability of long-term time-dependence capture of the underlying TCN in lithium battery SOC estimation. TCN-LSTM not only retains the TCN's ability to capture multiscale via dilated causal convolutions The TCN-LSTM not only retains the advantage of TCN in capturing multiscale time-dependence through inflated causal convolution, but also introduces LSTM's ability to model complex time-dependent dynamics in a refined way, by connecting the convolutional layers of TCN in series with the cyclic units of LSTM to form a two-stage feature extraction mechanism, as shown in Fig. The former extracts local and global spatial-temporal features from the original signals such as voltage, current, temperature, etc., through the hierarchical inflated convolution, while the latter strengthens the time-dependence of the higher-order features of the output of the TCN. The problem of insufficient sensitivity of a single TCN to nonlinear recession patterns in long-time memory modeling is solved.

The experimental results show that TCN-LSTM significantly outperforms single TCN and other benchmark models in a wide temperature range and under multiple operating conditions, with the average RMSEs of SOC, SOH, and RUL reduced to 1.1%, 0.8%, and 0.9%, respectively, which is about 40-60% lower than that of the single TCN, and the maximal error is always lower than 2.5% in 90 cycle tests, which shows a stronger cross-cycle generalization capability. strong cross-cycle generalization ability.

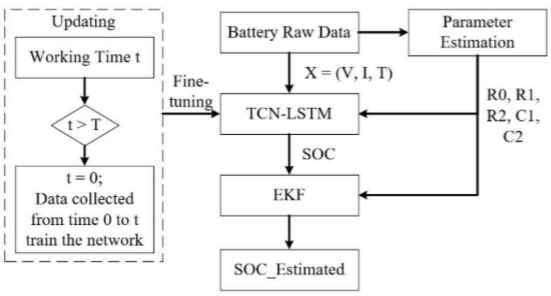

Figure 2. TCN-LSTM-transfer learning

2) TCN-GRU-Transformer

Zhou et al. proposed a three-stage hybrid model TCN-GRU-Transformer (TGT) combining temporal convolutional network (TCN), gated recurrent unit (GRU), and Transformer, to address the poor robustness of missing data and insufficient modeling of global temporal dependence of the base TCN for SOC estimation in the scenario of missing battery data. Improvements were made. By fusing local timing feature extraction, missing data adaptive optimization, and global attention mechanism, multilevel feature cooperative modeling of incomplete battery data is realized for the first time. The model solves the problems of traditional TCN being sensitive to successive missing and LSTM-like model's hidden state being susceptible to interruptions; while the top-level Transformer module captures the effective information at the far-end by using adaptive weight allocation through the multi-head attention mechanism for the context break caused by long-term data missing.

Experiments show that the stability of TGT's estimation of 4000 consecutive missing points is significantly better than that of Longformer and other models under the FUDS conditions of 10°C and 40°C, and its MAE fluctuation range is controlled within ±0.003. Moreover, the residual linkage and hierarchical feature transfer mechanism enable the model to converge quickly within 50 training cycles, which avoids the gradient dispersion problem caused by the coupling of modules in TCN-LSTM. avoiding the gradient dispersion problem caused by the lack of module coupling in TCN-LSTM

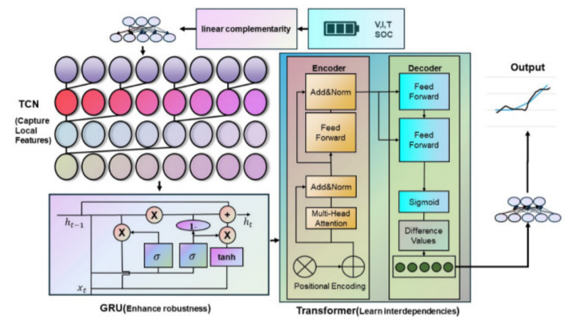

Figure 3. TCN-GRU-Transformer

3) TCRN

Wang et al. proposed a temporal convolutional recombination network (TCRN) that combines a temporal recombination module (TRM) with a non-normalized architecture, which improves on the insufficient dynamic recombination ability of the timing features and the limited adaptability of the normalized architecture of the basic TCN for SOC estimation of lithium batteries. By eliminating the normalization layer in the traditional TCN, the TCRN avoids the destruction of the time-dependence of the battery timing data by the normalization process, and retains the dynamic fluctuation characteristics of the original sequence, thus more accurately capturing the mutation patterns of voltage, current, and other parameters. The TRM module generates temporal recombination weights through the self-attention mechanism to dynamically strengthen the feature contributions of the key time steps, and at the same time imposes a temporal constraint to ensure that the neighboring time-step weights are monotonically increasing, which effectively suppresses the output oscillation problem of the original TCN due to the expansion convolution.

Experiments show that the TCRN reduces the MAE by 23.2% and increases the parameters by only 2.8% compared with the TCN in the SOC estimation of lithium-ion batteries, and the MAE is controlled to be within 1.12% and 2.68% in the prediction of the future SOC for the next 10 and 30 minutes, respectively, which is a reduction of more than 30% compared with the error of the TC.

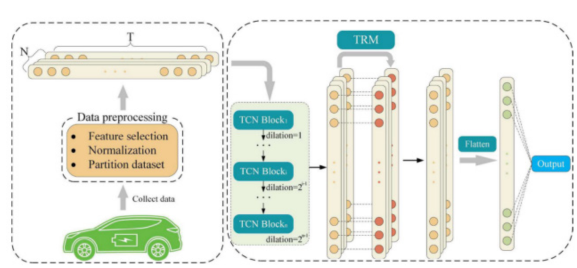

Figure 4. TCRN

C. TCN combined with optimized parameters

1) GA-TCN-UKF

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Huang et al. proposed a hybrid model based on genetic algorithm (GA) optimized TCN and fused with untraceable Kalman filtering (UKF), which addresses the stability problem of the underlying TCN under noise interference. In this study, a genetic algorithm is used to optimize the input time window length, network depth and the number of convolutional kernels of the TCN in a multi-objective manner, and the hyper-parameter search is completed within 20 generations by the selection-crossover-variation operation, which reduces the tuning time by 67% compared with the traditional trial-and-error method. The optimized TCN output is further state-space fused by UKF, and unbiased estimation of nonlinear observation equations is performed by using Sigma point transformation, which effectively suppresses the SOC jump error caused by current sampling noise.

The experimental data show that the MAE of GA-TCN-UKF is 0.227% under the UDDS condition at 0°C, which is 65% lower than that of the base TCN, and the maximum error is reduced from 5.203% to 2.776%.The introduction of UKF reduces the standard deviation of the estimated fluctuation of the model in the charging/discharging plateau period of the battery by 0.12%, and especially in the voltage slowing section of the low SOC interval, the Kalman gain of adaptive adjustment improves the smoothness of the prediction curve by 38%.

2) CGOA-MAM-TCN

Wang proposes an improved TCN model (CGOA-MAM-TCN) that combines the chaotic locust optimization algorithm (CGOA) and the multi-head attention mechanism (MAM) to optimize the base TCN for the insufficient long-range dependence modeling and hyperparameter sensitivity problems in the estimation of the SOC of lithium batteries. The model compensates for the limitation of traditional TCNs that rely only on dilation convolution to extract local features by introducing a multi-head attention mechanism (Fig.), which embeds multiple attention heads in parallel after each TCN stacking layer to capture the dynamic correlation weights among voltage, current, and temperature sequences, respectively.

The experiments show that the RMSE of the CGOA-MAM-TCN reaches 0.069% and 0.013% for the mixed conditions at 10°C and 30°C, respectively, which is a significant reduction of the error compared with the base TCN model. Especially in the low-temperature test, the introduced attention mechanism reduces the prediction error of the voltage-sudden drop section by about 40%, confirming the model's ability to resolve the time-dynamic features of the battery polarization effect.

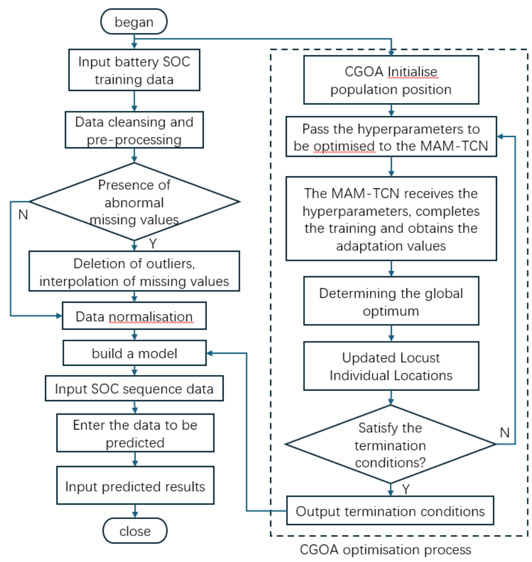

Figure 5. CGOA-MAM-TCN

3) PSO-TCN-Attention

Li et al. proposed a hybrid model PSO-TCN-Attention combining particle swarm optimization algorithm (PSO), temporal convolutional network (TCN) and attention mechanism (Attention), which improves on the hyper-parameter sensitivity of the base TCN with insufficient attention to the key temporal features in the estimation of SOC of lithium battery.

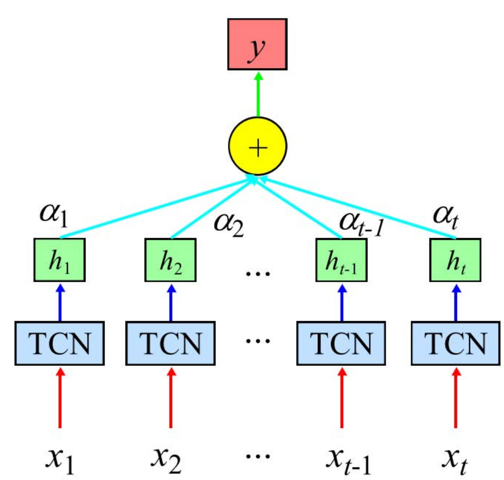

Figure 6. Model of attention mechanism.

Its core innovation lies in the global optimisation of the network structure of the TCN through the PSO algorithm, while embedding the attention mechanism to strengthen the weight allocation of key time steps. Specifically, PSO is used to automatically search for the key hyperparameters of TCN with mean absolute error (MAE) as the fitness function in the iterative process, which improves the tuning efficiency by about 40%. On this basis, the introduced attention mechanism improves the model's feature capture performance during the voltage plateau period in the UDDS dynamic cycle by dynamically calculating the time-step weights of the input sequences.

Experimental results show that the model has an RMSE of less than 1% in multi-temperature tests from 0°C to 40°C, with an RMSE of 0.41% for the LA92 condition at 25°C, and the maximum error is controlled within 5.75%, which is significantly optimized over the base TCN model. In particular, the R^2 coefficient reaches 99.92% in the US06 condition at a high temperature of 40°C, which demonstrates a stronger nonlinear fitting ability than the LSTM model with the TCN model.

Figure 7. Flowchart of the TCN-Attention model for PSO optimization.

4) GWO-LSTM-TCN

Li et al. proposed a hybrid LSTM-TCN model (GWO-LSTM-TCN) based on the Grey Wolf Optimization algorithm, which improves on the problem of incomplete spatio-temporal feature extraction by a traditional single network for SOC estimation of lithium batteries. The model achieves feature complementarity by connecting the LSTM and TCN networks in series: the LSTM layer captures the long time dependence of battery voltage and current using its gating mechanism, while the TCN extracts the voltage-current mutation features within the local time window by inflated causal convolution. To overcome the subjectivity of hyperparameter selection, the grey wolf optimization algorithm is introduced to perform adaptive search on the number of neurons in the LSTM hidden layer, the number of TCN output channels, and the batch size, which shortens the optimization time by mimicking the encircle-and-attack strategy of wolf pack hunting..

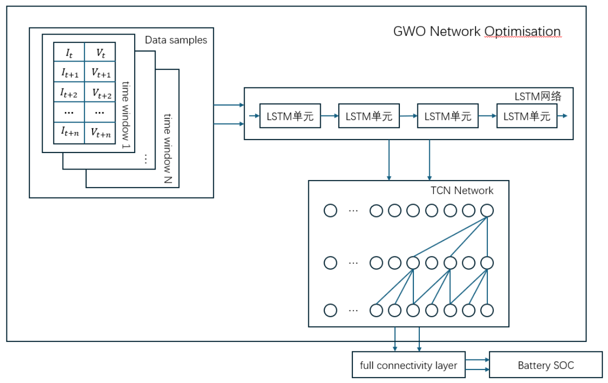

Figure 8. GWO-LSTM-TCN network diagram

The experimental results show that the hybrid model has an RMSE of 1.47% in the FUDS dynamic test at 25°C, which reduces the error by 10% compared to the single TCN model, and the timing memory property of LSTM reduces the maximum error by 22% compared to the pure TCN in the prediction of current transient fluctuations in the low SOC interval (20%-50%).

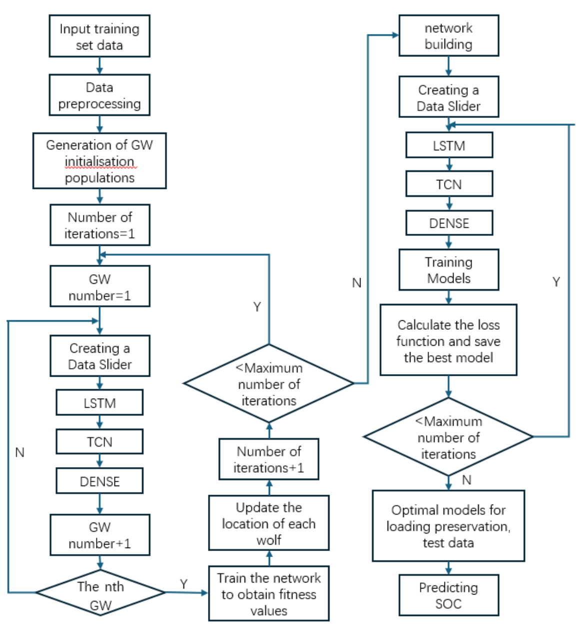

Figure 9. GWO-LSTM-TCN algorithm flow chart

4. Conclusion

Temporal convolutional network opens up an innovative

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technical path for lithium battery SOC estimation through causal convolutional structure and parallel computing characteristics. It utilises inflationary convolution and residual connection to achieve multi-scale feature extraction, and combines attention mechanism, migration learning and other methods to significantly improve the model performance. The study confirms that the deep fusion of TCN and physical model can break through the accuracy limitation of traditional data-driven methods at the late stage of battery aging and under extreme working conditions, while the dynamic structure optimisation technique solves the real-time deployment problem of the model in embedded devices.

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