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Remaining Life Prediction of Lithium-ion Batteries by Integrating VMD-WTC Time-frequency Analysis and Patchtst Block Sequence Modelling

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Abstract. As a core component of energy storage technology, predicting the remaining lifetime of lithium-ion batteries is crucial to guarantee the safety and economy of devices. However, existing methods are difficult to effectively capture non-smooth degradation features due to the cross-scale complexity of battery performance decay and differences in time-frequency resolution of sensor signals. Therefore, this study proposes a three-level joint architecture that incorporates VMD, WTC and PatchTST to address the challenges of noise interference, cross-modal correlation and long-term dependence modeling. The original capacity sequence is adaptively decomposed by VMD, combined with WTC to screen time-frequency strong correlation features, and the chunked-attention mechanism of PatchTST is utilized to enhance the ability of capturing non-smooth trends such as capacity regeneration. This experiment is based on the NASA battery dataset, and the model is obtained to have a cross-dataset MAPE polarity of only 0.0055, which is only about 1/15-1/50 of that of other models, and an MSE polarity of 0.000108, which is reduced by 1-2 orders of magnitude compared with the comparative models, highlighting its strong adaptability to the differences in battery recession patterns. The low relative error and robustness of this model validate its potential in engineering applications and provide new ideas for lithium battery health management.

Keywords: VMD, WTC, PatchTST, battery life prediction

1. Introduction

As a core component of new energy storage technology, lithium-ion batteries play an irreplaceable role in electric vehicles, aerospace equipment and smart grids. With its high energy density, long cycle life and fast charging and discharging capability, Li-ion battery has become a key technology carrier to promote energy transformation [1,2]. In the field of electric vehicles, lithium-ion battery packs account for 30%-40% of the cost of the entire vehicle, which directly determines the range and safety performance of the vehicle; in aerospace applications, their lightweight characteristics can reduce the weight of the aircraft up to 15%-20%, while reducing the dependence on fossil fuels [3]. The International Energy Agency predicts that global demand for lithium batteries will increase tenfold by 2030, with the market size exceeding $300 billion, highlighting the importance of

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lithium-ion batteries. However, lithium-ion batteries undergo capacity degradation during cycling due to mechanisms such as irreversible phase transition of electrode materials, thickening of the SEI film, and decomposition of the electrolyte [4]. When the capacity decreases to 70%-80% of the initial value, the battery enters a critical state of failure, which may lead to thermal runaway or even explosion [5]. Therefore, it is crucial to predict the remaining lifetime of Li-ion battery packs [6,7].

Despite the significant progress of deep learning-based lithium battery residual life prediction technology in recent years, lithium battery performance decay is a complex process involving complex chemical and electrochemical reactions at multiple scales within the lithium battery from materials, interfaces to porous electrodes and devices [8], and there are differences in the temporal resolution of the signals of multiple sensors, such as voltage, temperature, current, etc., and it is difficult to establish an effective cross-scale correlation model by traditional feature fusion methods. The traditional feature fusion method is difficult to establish an effective cross-scale correlation model. Aiming at the above bottlenecks, this study innovatively proposes a three-level joint architecture of VMD-WTC-PatchTST: firstly, a variational modal decomposition is used to separate the adaptive noise from the original capacity sequence, which reduces the end-point effect error compared with the traditional EMD method; and wavelet coherence analysis is introduced to construct the multi-physical field coherence matrix, and the time-frequency coupling strength of the voltage-temperature signal is quantified based on the Torrence coherent spectrum theory (Torrence et al., 1998), so as to enhance the correlation of cross-modal features; finally, based on the temporal attention mechanism, the long-period prediction step size is extended through the synergistic optimization of the local receptive field enhancement and global dependence modeling, which significantly improves the ability to capture the non-smooth features, such as capacity regeneration.

2. Related work

The mainstream approach to monitoring battery packs, on the other hand, is to supervise the charge state and health state of the battery through a battery management system, which is usually represented by the prediction of RUL in academia. Current RUL prediction methods are mainly categorized into three types: physical models, data-driven and hybrid models [9]. Physical model-based methods are based on establishing corresponding analytical formulas according to the lithium battery operation mechanism and decay law. For example, Chu et al. implanted a composite nickel-lithium reference electrode in the battery and simulated the changes in battery voltage characteristics caused by implanting the reference electrode by constructing a two-dimensional electrochemical mechanism model [10].

Data-driven based methods are prediction methods that utilize machine learning, deep learning and other algorithms to mine massive historical data to build regression models or fault prediction models. Common models include Random Forest, SVM, and deep neural networks based on architectures such as LSTM, CNN, and Transformer, etc. Such models rely on a large amount of multi-sensor monitoring data and remaining useful life labels, and can perform well even for semi-supervised learning methods [11]. For example, GUO et al. used SVR to establish the relationship between battery health status and the number of cycles, and optimized the SVR kernel parameters using a particle swarm optimization algorithm to reduce the influence of the feature parameters [12]; Fan et al. proposed a hybrid GRU-CNN network for capturing the physical information of the sensor measurements and learning the time dependence [13]; Yang et al. combined the CNN with Random Forest to better extract and fuse feature variables [14]. There is also a statistical modeling-based approach that mainly models stochastic processes of degraded paths, which usually performs better than machine learning-based approaches with less degraded data. The data-driven approach has

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relatively low mechanistic requirements on the modeling object, and estimates the RUL by learning from the feature data, which often achieves better prediction accuracy when the data quantity is sufficient and of high quality. In addition to this, hybrid modeling is a combination of physical and data-driven models. For example, a physical model is used to estimate the health state of the system a priori, and then a data-driven model is utilized to learn the residuals or deviations to achieve a more accurate and robust prediction.

3. Modeling framework

In lithium-ion battery RUL prediction, this model constructs a hybrid framework based on VMD, WTC and PatchTST. The model first performs VMD on the raw data and screens the health factors by WTC to capture the key features of each mode on different time scales, and subsequently trains the PatchTST predictor for each mode separately to obtain a unified prediction of the global degradation trend.

Specifically, the hybrid framework first uses VMD to adaptively decompose the original capacity degradation sequence into multiple finite bandwidth modal components, separating the trend term, the capacity regeneration term, and the noise term, and then performs the wavelet transform on each of the modal states after the VMD decomposition, and the WTC filters out the local features that are strongly correlated with the lifetime degradation through the time-frequency correlation to construct the set of health factors that are strongly correlated with the RUL, and then calculates and superimposes the predicted values for each of the predicted value of the eigenmodes to obtain the final estimated degradation signal. Finally, the feature sequence is divided into local patches by the PatchTST model, and the long-term dependence capture of the degradation trend is realized by the chunk coding with the multi-head self-attention mechanism, which outputs high-precision capacity prediction values and RUL estimation.

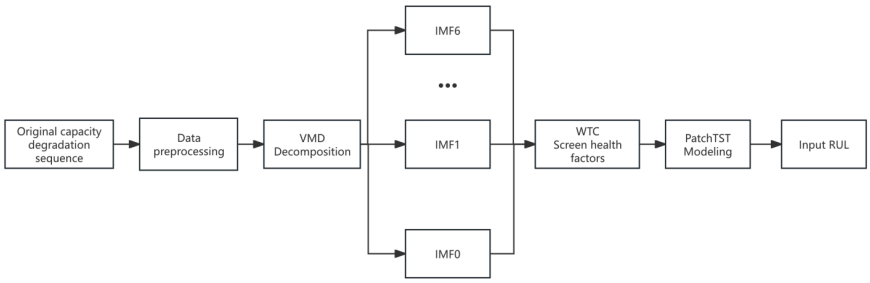

Figure 1: Flowchart of this study

3.1. VMD

Variational modal decomposition is an adaptive signal decomposition method based on the variational optimization framework, which aims to decompose a complex signal into a number of modal components with sparse frequency domain characteristics. The core idea is to force the bandwidth of each modal component to be minimized by constrained variational optimization, and at the same time ensure that the synthesized signals of all modes are consistent with the original signal. Assuming that the original signal is $f(t)$, it needs to be decomposed into K modal components $u_k(t)_{k=1}^{K}$, and each modality corresponds to the center frequency $w_k{}_{k=1}^{K}$. The VMD achieves the decomposition by the following constrained variational problem:

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$$\min_{\{u_k\},\{\omega_k\}} \sum_{k=1}^{K} \left| \left| \partial_t \left[\left(\delta(t) + \frac{j}{\pi t} \right) * u_k(t) \right] e^{-j\omega_k t} \right| \right|_2^2 \quad \text{s.t.} \quad \sum_{k=1}^{K} u_k(t) = f(t) \tag{1}$$

For the objective function, the modal $u_k(t)$ is converted to analytic signal form by the Hilbert transform $\left(\delta(t) + \frac{j}{\pi t}\right) * u_k(t)$, multiplied by $e^{-jw_k t}$ to shift its spectrum to the baseband, and finally the bandwidth is calculated by ∂_t (time derivative). To solve the variational problem with constraints, a quadratic penalty term α and the Lagrange multiplier $\lambda(t)$ are introduced to construct the augmented Lagrange function:

$$\mathcal{L} = \alpha \sum_{k=1}^{K} \left|\left| \partial_t \left[\left(\delta(t) + \frac{j}{\pi t} \right) * u_k \right] e^{-j\omega_k t} \right|\right|_2^2 + \left| f(t) - \sum_{k=1}^{K} u_k(t) \right|_2^2 + \left\langle \lambda(t), f(t) - \sum_{k=1}^{K} u_k(t) \right\rangle \tag{2}$$

ADMM is used to iteratively update u_k, ω_k, λ. Firstly, the modal component u_k is updated and solved in the frequency domain, and the poles of Eq. (2) are solved with respect to u_k. Next, the center frequency ω_k needs to be updated, and the center frequency is updated to be the center of mass of the spectrum of the corresponding modes by minimizing the objective function, and for the Lagrange multiplier the multiplier is updated according to the constrained residuals. Finally, when satisfied $\sum_{k=1}^{K} \frac{\left\| u_k^{n+1} - u_k^n \right\|_2^2}{\left\| u_k^n \right\|_2^2} < \varepsilon$ terminates the iteration.

3.2. WTC

Wavelet transform correlation analysis is a feature screening method that combines time-frequency analysis and statistical correlation, aiming at extracting local frequency band features that are significantly correlated with the target variable from a non-smooth signal. The core logic lies in the following: decompose the signal into multi-scale components in the time-frequency domain by continuous wavelet transform, calculate the correlation coefficient between each component and the target variable, and screen out the high correlation band as the health factor. The continuous wavelet transform maps the signal $f(t)$ to the time-frequency plane through the translation and scaling of the mother wavelet function $\psi(t)$, which is defined as:

$$W(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} f(t) \psi^* \left(\frac{t-b}{a} \right) dt \tag{3}$$

where $a > 0$ is the scale parameter , b is the translation parameter, and $\psi*(t)$ is the complex conjugate of the mother wavelet.

For the modal components obtained from the VMD decomposition $u_k(t)$, a mode-by-mode wavelet transform is performed to obtain the time-frequency coefficients $W_k(a,b)$. The wavelet coefficients corresponding to each scale a are calculated with the Pearson correlation coefficients of RUL. In order to improve the robustness of the features, fusion coefficients are introduced to comprehensively evaluate the energy and correlation of the frequency bands:

$$\mathrm{FIC}_k(a) = \frac{\rho_k(a) \cdot E_k(a)}{\sum_a E_k(a)} \tag{4}$$

The higher the FIC value, the higher the contribution of the band to the lifetime prediction. Finally, the frequency band with the top M FIC ranking is selected as the health factor to suppress the effect of low-energy noise bands.

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3.3. PatchTST

The time series patch transformation model is a time series prediction method based on the Transformer architecture, which divides the time series into local segments by chunking strategy, and captures the long-term dependency by combining with the self-attention mechanism, to solve the problem of gradient disappearance and computational inefficiency of the traditional recurrent neural network in the long sequence modeling. The core idea lies in decoupling the local feature extraction and global dependency modeling of time series, reducing the length of the sequence by chunk coding, and efficiently learning the degradation trend by using the parallel computing capability of Transformer, which is suitable for modeling the non-stationarity and long-term decay characteristics of lithium battery capacity sequences.

Given a time series feature matrix, PatchTST first divides the sequence into N overlapping local patches. Each patch $\mathrm{P_i}$ is mapped into an embedding vector $\mathrm{e_i} = \mathrm{W_e P_i} + \mathrm{b_e}$ by linear projection and a learnable positional encoding is introduced, which is summed with the patch embedding and fed into the Transformer encoder. The encoder consists of a stack of multi-head self-attention and feedforward networks. The self-attention mechanism computes the inter-patch dependency weights via query, key, and value matrices:

$$\mathrm{Attention}\left(Q,K,V\right)=\mathrm{Softmax}\left(\frac{QK^{\top}}{\sqrt{D}}\right)V \tag{5}$$

The feature matrix output from the encoder is spread and fed into the prediction header, which is mapped to the future τ-step capacity prediction through the fully connected layer:

$$\widehat{C}\left(t+1:t+\tau\right)=W_p\cdot\mathrm{Flatten}\left(Z^{'}\right)+b_p\quad\left(W_p\in R^{\tau\times\left(ND\right)},\ b_p\in R^{\tau}\right) \tag{6}$$

The model training adopts the mean square error loss function, and the optimization objective is to minimize the deviation between the predicted capacity and the real capacity, which is combined with the Adam optimizer to adaptively adjust the learning rate to avoid falling into the local optimum. According to the predicted capacity sequence, combined with the preset failure threshold Cend, the remaining service life is calculated.

$$\mathrm{RUL}=\arg\min_{t}\left(\widehat{C}\left(t\right)\le C_{\mathrm{end}}\right)-t_{\mathrm{current}} \tag{7}$$

4. Description of the data set

The dataset used in this experiment is from the NASA Ames Research Center, model 18650 lithium-ion battery aging dataset, including four types of data, B0005, B0006, B0007, and B0018. The variables in this dataset are defined as:

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Table 1: Definitions of variables in the NASA lithium battery dataset

Name	Define
ambient_temperature	Battery operating temperature, 24 degrees Celsius at room temperature
time	Charging and discharging time
Voltage_measured	Measured voltage
Current_measured	Measured current
Temperature_measured	operating temperature
Current_charge	Charger charging current / current measured under load
Voltage_charge	Charging voltage of the charger / voltage measured under load
Capacity	Battery capacity discharged to 2.7V

The capacity decay curves of the B0005 to B0018 batteries were obtained as shown in Fig. 2 when the batteries reached the end-of-life criterion - the rated capacity dropped to 30% of it, i.e., the rated capacity of Batteries 5, 6, 7, and 18 went from 2Ahr to 1.4Ahr at room temperature of 24 degrees Celsius.

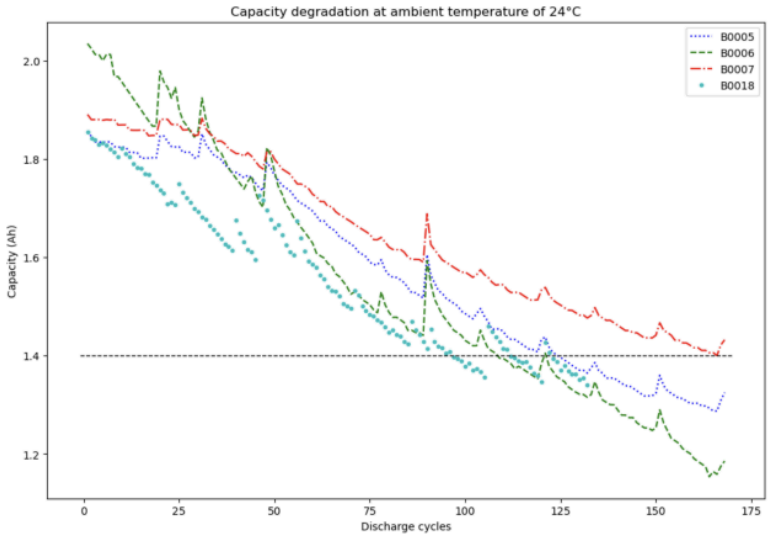

Figure 2: Battery capacity decay curve

5. Model parameter setting

In this study, a hybrid VMD-WTC-PatchTST model is used for time series forecasting, and its core parameters are set as follows: in the VMD module, the number of modes K is set to 6 to extract multiscale degradation features, and the band separation accuracy of the modal decomposition is controlled by the smoothing parameter $\alpha = 2000$; for the PatchTST module, the sequence length is set to 10 to capture local degradation modes For the PatchTST module, the sequence length is set to 10 to capture the local degradation patterns, and the training optimization is performed by combining the batch size of 64 with the learning rate of 0.001, which ensures the model's stable convergence through 200 training cycles. In addition, a dropout rate of 0.1 is introduced into the model to enhance the robustness to noise interference, and ultimately achieve high-accuracy long-term dependence modeling.

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6. Evaluation indicators

In the process of model evaluation, this experiment uses the following metrics to quantify the predictive performance of the model: mean absolute percentage error (MAPE), mean square error (MSE), which are calculated using the following formulas:

$$\mathrm{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i-\hat{y}_i}{y_i}\right| \tag{8}$$

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}\left(y_i-\hat{y}_i\right)^2 \tag{9}$$

7. Analysis of results

In the decomposition using VMD, the whole signal is decomposed into six eigenmode functions, and Fig. 3 demonstrates the results of the VMD decomposition for the battery model B0005. From this figure, it can be seen that IMF0 to IMF2 exhibit significant low-frequency components, which mainly capture the trend of battery performance changes. These low-frequency components are crucial for predicting the health status of the battery as they reflect the possible degradation patterns of the battery during use, while IMF3-IMF5 are high-frequency components that capture noise and short-term fluctuations. The extraction of these IMF components provides multidimensional data inputs for subsequent prediction using the PatchTST model, ensuring that the model captures potential characteristics of battery state changes.

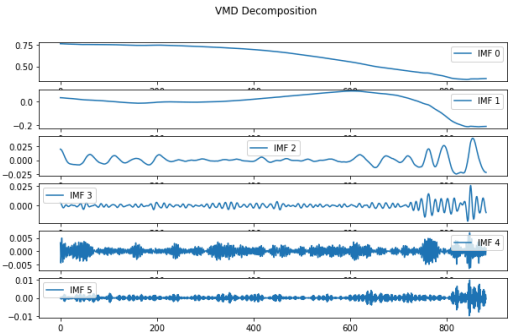

Figure 3: VMD decomposition

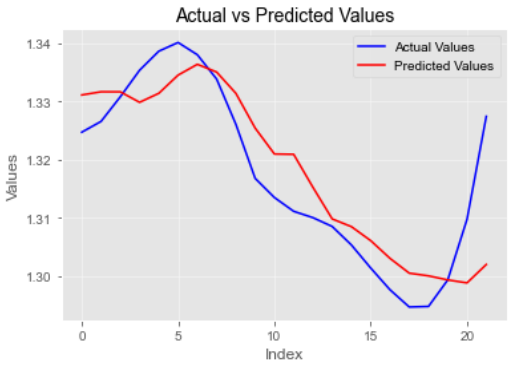

Figure 4: Model prediction results

In order to verify the reliability, stability, and accuracy of the VMD-WTC-PatchTST-based model proposed in this paper, this paper uses batteries B0005, B0006, B0007, and B0018 in the NASA battery dataset for the model training, of which eighty percent is the training set, and twenty percent is the test set, and the prediction results obtained for the battery B0005 are shown in Fig. 4 shows. From the figure, it can be seen that the curves are highly synchronized in the overall fluctuation pattern, indicating that the VMD-WTC-PatchTST model has a strong ability to capture the battery degradation trend, especially at the capacity inflection point can also be predicted accurately.

In order to further examine the performance of the model, this experiment is compared with other deep learning methods that are widely used in the same field, such as TimeNet, NTSformer, iTransformer, and Informer, and all the models use the NASA dataset, and MSE, and MAPE are used as the evaluation metrics, and the results of the comparison of different methods are shown in Table 2.

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Table 2: Comparison results of different models

	B0005		B0006		B0007		B0018	
	MSE	MAPE	MSE	MAPE	MSE	MAPE	MSE	MAPE
Tsmixer	0.000217	0.95336	0.00113	2.57819	0.00017	0.83133	0.00058	1.64533
TimeNet	0.000263	0.84178	0.00102	2.29870	0.00012	0.711257	0.00094	1.90931
NTSformer	0.000202	0.77176	0.00065	1.96647	0.00015	0.693559	0.00077	1.70293
iTransformer	0.000021	0.26927	0.00003	0.33072	0.00002	0.231723	0.00003	0.32409
Informer	0.000216	0.76966	0.00076	2.09827	0.00007	0.544237	0.00075	1.66025
Dlinear	0.000028	0.29899	0.00006	0.51713	0.00005	0.427315	0.00029	1.09548
Crossformer	0.000269	1.11253	0.00085	2.25261	0.00009	0.616845	0.00016	0.77206
VMD-WTC-PatchTCT	0.000062	0.00456	0.00011	0.00804	0.00017	0. 047107	0.00016	0.00763

The VMD-WTC-PatchTST model proposed in this study demonstrates significant advantages in the remaining life prediction task of lithium-ion batteries. The experimental results show that the model achieves the lowest MAPE on all four battery datasets, which are 0.0046, 0.0080, 0.0471, and 0.0076, respectively, indicating that its relative error control capability is significantly better than that of all the compared models, and in particular, it reduces about 90%-98% of MAPE on the B0005, B0006, and B0018 datasets compared with the suboptimal model, iTransformer, to accurately capture the proportional consistency of the degradation trend. is reduced by about 90%-98%, highlighting its ability to accurately capture the proportional consistency of degradation trends. In addition, the MSEs of this model on the four datasets are 0.000062, 0.000113, 0.000170, and 0.00016, respectively, which are significantly better than those of the traditional time-series model and the attention model, suggesting that it effectively mitigates the amplification effect of local mutation on the absolute error in the non-stationary series through multi-stage decomposition and feature screening.

From the side-by-side comparison, it can be seen that the MSEs of models such as iTransformer and Dlinear are maintained at the 10-5level over the four datasets, which show consistent fitting accuracy for different battery aging trajectories, while the VMD-WTC-PatchTCT model has a very low relative error in MAPE that is consistent across the datasets, which suggests that the iTransformer and Dlinear are more concerned with numerical consistency, while the present model emphasizes more on overall curve scale consistency. This phenomenon suggests that iTransformer and Dlinear are more concerned with numerical consistency, whereas the present experimental model emphasizes the scale consistency of the overall curve.

Longitudinal comparison shows that the MAPE extreme difference of VMD-WTC-PatchTCT in the cross-cell dataset is only 0.0055, which is significantly lower than that of iTransformer's 0.10 and Dlinear's 0.77, and its MAPE standard deviation is only about 1/15-1/50 of that of the other models, which highlights the model's strong adaptability to the differences in battery aging patterns. From the model principle, it can be seen that this property stems from the multi-scale decoupling ability of the VMD decomposition for the nonlinear components in the battery capacity decline curves and the precise filtering of the noise signals by the wavelet thresholding process, which enables the model to extract the common features from the complex decline trajectories of different batteries. The MSE of VMD-WTC-PatchTST model is 0.000108, which is 1-2 orders of magnitude lower than that of comparative models such as Tsmixer and TimeNet, indicating that the model's ability to generalize different battery degradation modes is better than that of most baseline methods.

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VMD-WTC-PatchTST achieves a balance between "overall trend accuracy" and "local fluctuation robustness" for the degradation trajectory, which is especially suitable for engineering scenarios that need to balance absolute error control and relative error sensitivity, such as early warning of battery pack life and differentiated maintenance decisions.

8. Conclusion

The VMD-WTC-PatchTST framework proposed in this study significantly improves the accuracy and robustness of the remaining life prediction of lithium-ion batteries through multi-stage collaborative modeling. The experimental results show that the model achieves extremely low MAPE values of 0.0046, 0.0080, 0.0471, and 0.0076 on the cross-cell dataset, respectively, which is about 90%-98% lower than the MAPE of the suboptimal model, iTransformer, and the core advantages of which lie in the VMD decomposition's ability to decouple the nonlinear features at multiple scales, WTC's accurate suppression of noisy signals, and PatchTST's efficient modeling of long-term dependencies. And the MSEs of this model on the four datasets are 0.000062, 0.000113, 0.000170 and 0.00016, which are significantly better than the traditional time-series model and the attention model, indicating that it effectively mitigates the amplification effect of the local mutations in the nonsmooth sequences on the absolute error through the multi-stage decomposition and feature screening.

Therefore, for the sensitivity of the present model to local capacity mutation signals, the dynamic threshold mechanism or adaptive weighting strategy can be explored in the future to balance the conflict between trend capture and outlier suppression, and at the same time, the real-time adjustment of model parameters can be realized by combining with the online learning technology to further enhance the adaptability to the complex degradation patterns. And we can try to embed the a priori knowledge of the degradation path of the electrochemical mechanism model into the feature extraction layer to construct a physical information-driven hybrid architecture, which retains the flexibility of data-driven and enhances the interpretability and mechanism consistency of the model. These directions will promote the leap of lithium battery life prediction from laboratory accuracy to industrial-grade reliability.

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