Remaining-useful-life estimation of solid-state batteries based on convolutional network-long short-term memory method

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Introduction

Global population growth and lifestyle changes have increased energy demand, while fossil fuel reliance has raised atmospheric CO_2, worsening global warming [1]. This has spurred international emission reduction efforts and carbon peaking/neutrality targets , where energy storage technologies—boosting renewable energy utilization by 20–30% [2]—are crucial. Solid-state lithium-ion batteries (SSBs) are transformative but face technical hurdles for large-scale commercialization. Accurate remaining useful life (RUL) prediction is vital for SSB prognostics and health management (PHM) [3], yet AI/data-driven RUL prediction methods for SSBs remain immature , relying on shallow neural networks that fail to capture complex spatiotemporal features and temporal dynamics, hindering battery system design [4]. To address this, this study uses National Science Data Center (NSDC) experimental data to propose novel single/dual-channel hybrid CNN-LSTM models for SSB RUL estimation, outperforming baselines by reducing mean absolute error (MAE) by 16.7%.Given the scarcity of open-source SSB degradation data, this study integrates a P2D electrochemical framework with an aging kinetics model to develop a validated physically data-driven hybrid CNN-LSTM model. Compared to single-physics models, it improves accuracy and generates degradation data to supplement experimental datasets, reducing experimental data reliance. Additionally, based on the model's predictions, factors accelerating SSB degradation are explored to guide application and design optimization.

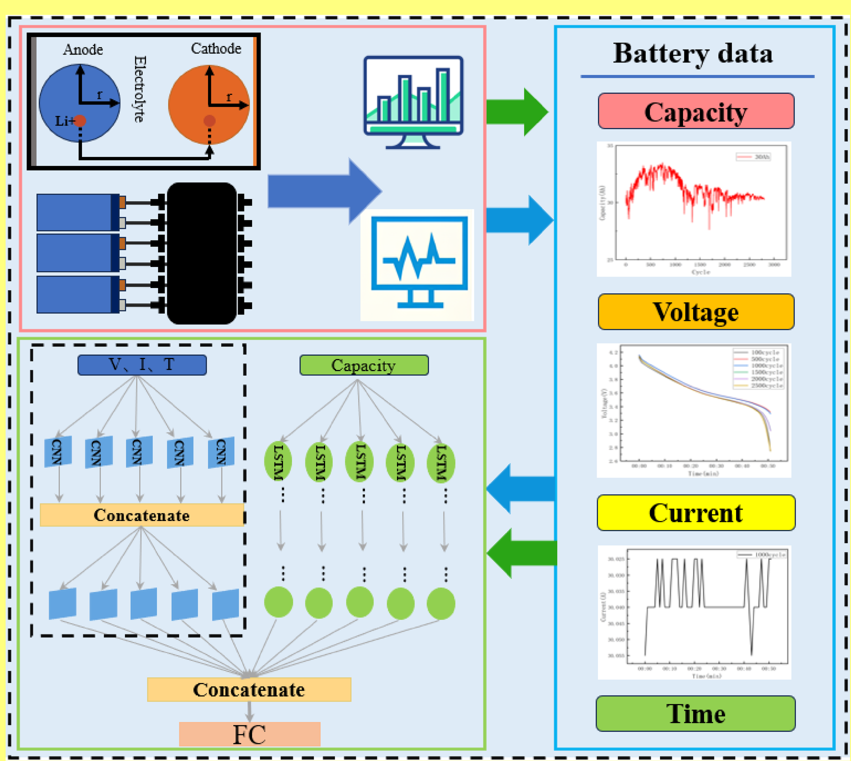

Fig. 1. Forecasting research framework.

Experimental setup

BATTERY SAMPLES

30 Ah energy-type cell & 37 Ah power-type solid-state lithium-ion batteries.

TEST CONDITIONS

25±2°C; 30 Ah cycled at 1 C (2.75 V–4.2 V); 37 Ah charged at 70 W / discharged at 65 W (3.0 V–4.1 V), 1500 cycles.

DATA SOURCE

National Basic Science Data Center (NSDC) cycling aging dataset[5].

MODEL ARCHITECTURE

Single-channel (SCL) & Multi-channel (MCL, MSCL) CNN-LSTM; P2D electrochemical-aging hybrid model for data augmentation.

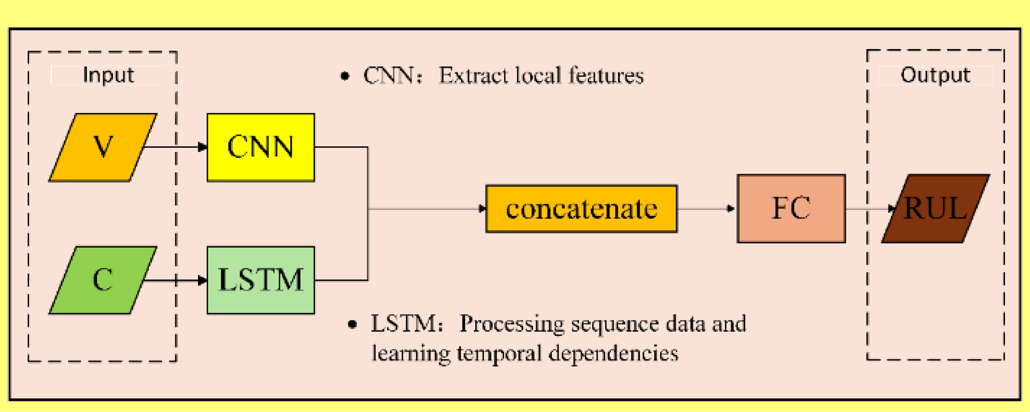

Fig. 2. SCL model.

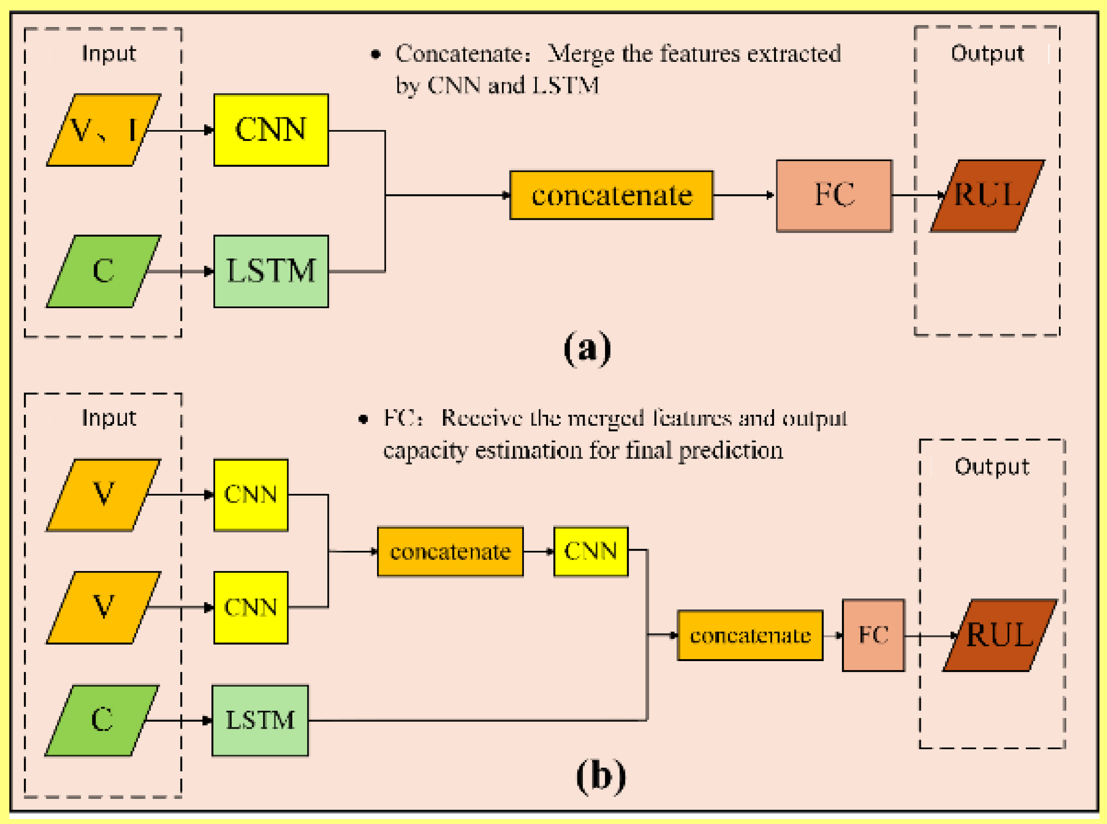

Fig. 3. Multichannel hybrid model (a) MCL (b) MSCL.

Methods

HYBRID CNN-LSTM

CNN : Extract spatial features from voltage/current curves.LSTM : Capture temporal capacity degradation trends.MSCL : Independent voltage/current CNN branches + feature fusion for optimal accuracy.

PHYSIC-DRIVEN ENHANCEMENT

P2D electrochemical model coupled with aging kinetics to generate simulated degradation data.Quartile denoising (IQR) to eliminate experimental outliers.

EVALUATION METRICS

MAE, MAPE, MSE, RMSE, R^2 for RUL prediction accuracy.

METHOD SUMMARY

This study proposes a hybrid physics information deep learning framework based on CNN-LSTM and P2D models, and completes the prediction of its decay state and partial performance optimization with a small amount of solid-state battery experimental data.

Results

Model Accuracy

MSCL model reduces MAE by 16.7% vs. baseline LSTM(SL); $R^2 > 0.98$. Following noise reduction, the enhanced multi-channel model (MSCL) reduces prediction errors by 50% compared to the SL.

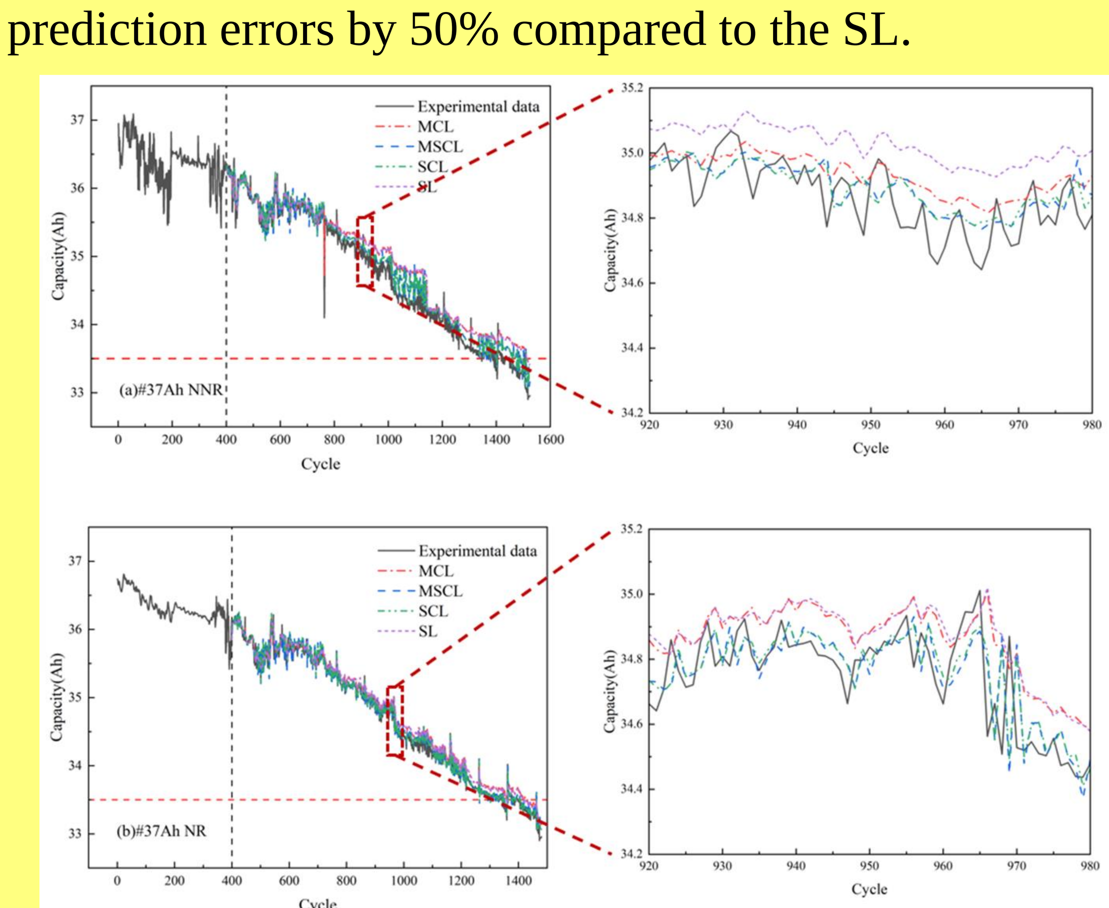

Fig. 4. 37Ah RUL predictions (a) without noise reduction, (b) with noise reduction..

TEMPERATUR AND DISCHARGE EFFECT

As shown in Figures 5 and 6, at 25 ℃, the MSCL model achieved the highest accuracy (error<0.5Ah after 400 cycles), although its initial prediction (first 200 cycles) lagged slightly behind MCL (error difference: 0.3Ah); At one standard discharge rate (65W), which is 1P_rdn, the single channel SCL model initially matched the experimental data very well (with an error of<1Ah), but there was a deviation in the middle of the cycle (for example, the error was about 0.8Ah after 400 cycles). In contrast, MSCL maintained higher accuracy throughout the entire discharge process.

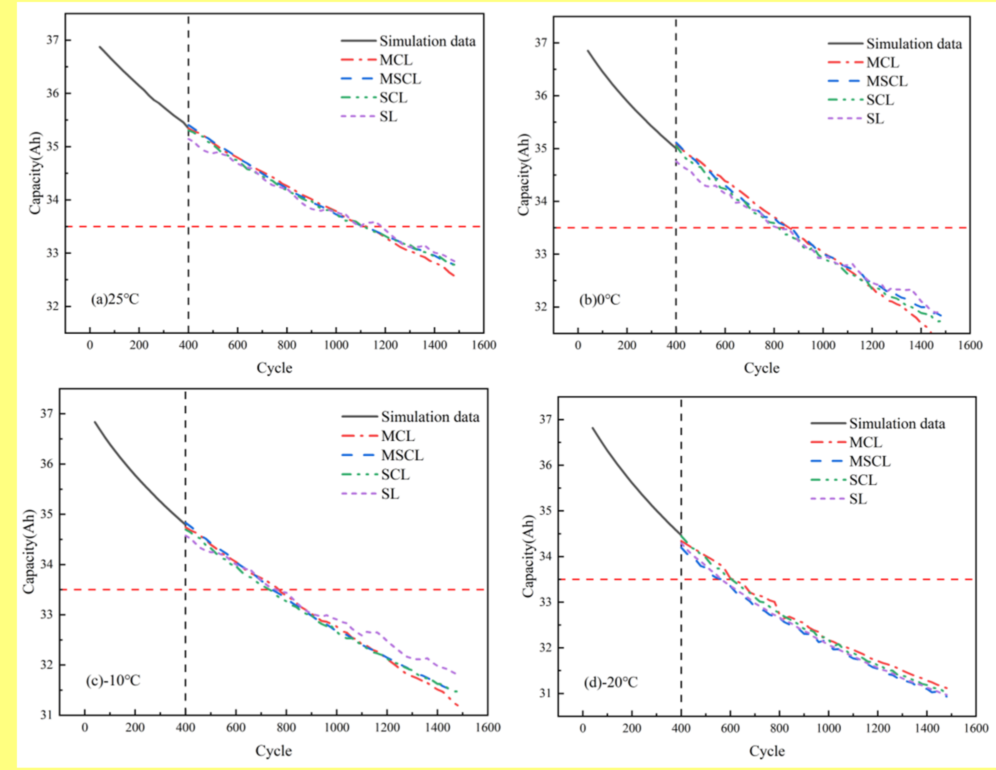

Fig. 5. Performance of RUL estimation for different models at different temperatures.

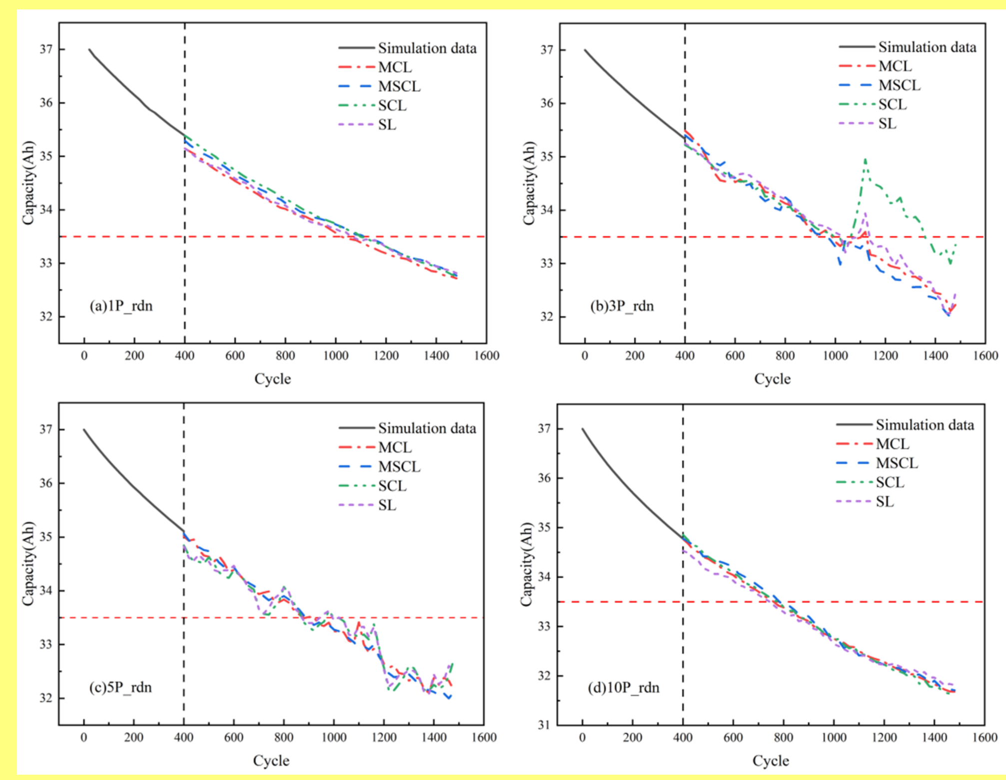

Fig. 6. Performance of RUL estimation for different models at different discharge rates.

STRUCYURE OPTIMIZATION

Estimating battery performance based on capacity decay rate and Coulomb efficiency, the reduction of active material particle size in solid-state batteries can increase the cycle life by 45 cycles. The thickness of solid electrolyte ranges from 30 microns to 5 microns, which can reduce cumulative lithium loss by up to 71%.

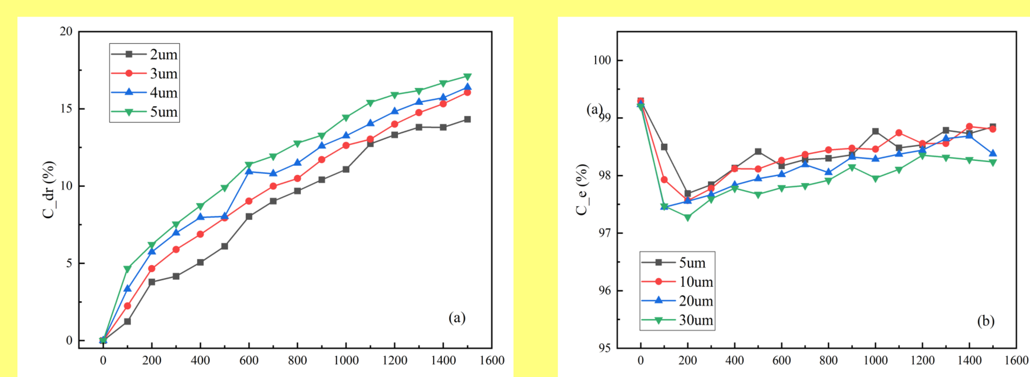

Fig. 7. Battery performance under different particle sizes and electrolyte thicknesses: (a) capacity decay rate (b) Coulombic efficiency.

Conclusions

The main conclusion of this study is:

- The hybrid CNN-LSTM framework achieves high-precision SSB RUL prediction, especially under extreme conditions.
- Physics-data fusion solves sparse experimental data constraints for solid-state battery life estimation.
- Reducing active material particle size and thinning solid electrolyte significantly extend cycle life and reduce degradation.
- This method provides a reliable tool for SSB health management and design optimization.

References

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