Battery prognostics and health management using CNN-BiGRU with temporal attention on CS2 cells

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1. Introduction

WHAT?
- LIBs: Energy Storage Devices
- $LiCoO_2$ (Cathode)
- Graphite(Anode)

WHY?
- High Energy Density
- High Charge/Discharge Cycles
- Highly Efficient

WHERE?
- Portable Electronic Devices,
- Electric Vehicles,
- Grid Energy Storage System,
- More Electric Aircraft (MEA)
- UAV and Space Vehicles

HOW?
- Battery Modelling, Data Training/Testing, Experimentations
- Prognostics and health Management, state of health (SOH) and remaining useful life (RUL) prediction
- Safety and Reliability
- Battery Management System(BMS)

Prognostics and Health Management (PHM)

- **Prognostics** is process of monitoring the health of a product and **predicting its remaining useful life (RUL)** by assessing the extent of deviation or degradation from its expected state of health in its expected usage conditions.
- **Health Management** utilizes prognostic information **to make decision** related to safety, condition-based maintenance, ensuring adequate inventory and product life extension

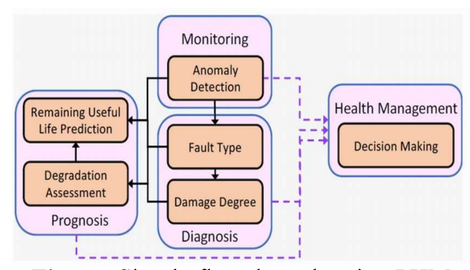
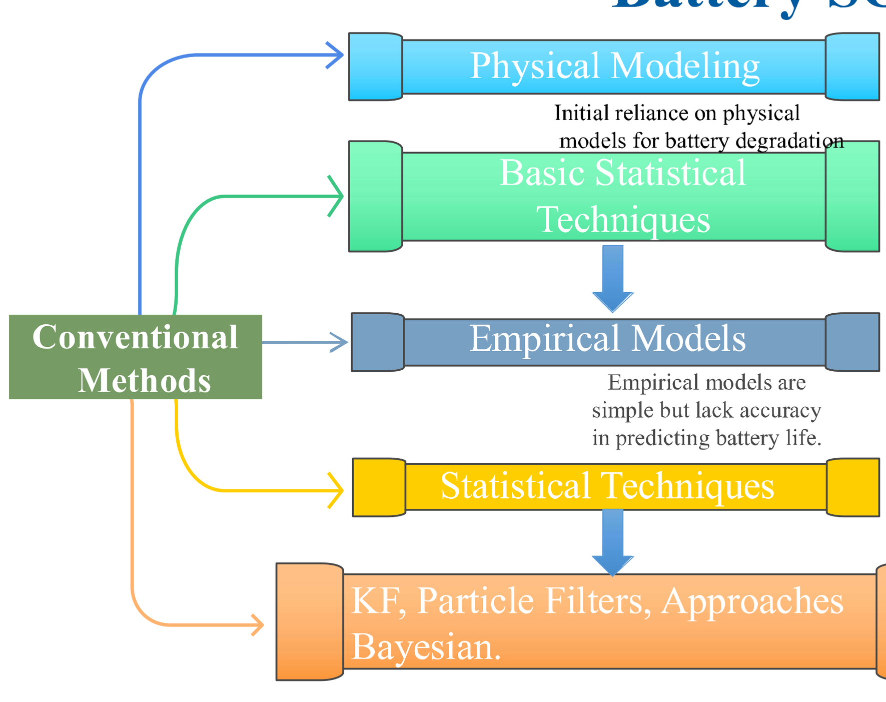


Figure. Simple flowchart showing PHM

Battery SOH & RUL estimation Methods



Machine Learning and Deep Learning Methods

SVMs	GRUs
Random Forests	Attention Based Methods
Gradient Boosting Machines	Autoencoders
ANNs	Hybrid Models
CNNs	Monte Carlo dropout with GRU
LSTMs	BiLSTMs
RNNs	BiGRUs

Figure. Battery SOH and RUL estimation methods conventional and machine learning and Deep learning methods

2. Dataset and Evaluation Metrics

CALCE CS2-type battery dataset

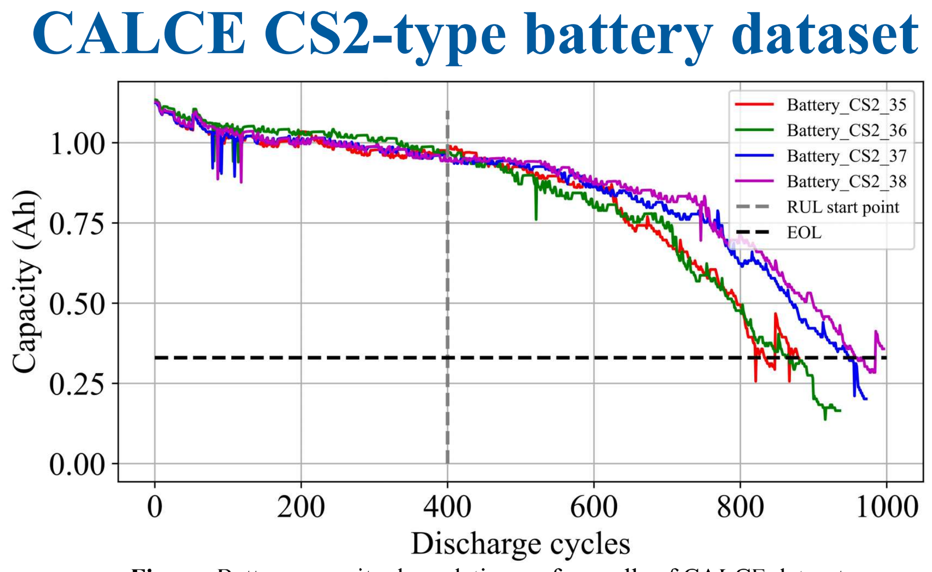


Figure. Battery capacity degradation on four cells of CALCE dataset

Parameters	Values
Dataset	CALCE CS2 (Pouch Cells)
Cells	CS2_35, CS2_36, CS2_37, CS2_38
Cell Chemistry	$LiCoO_2$ cathode,
Dimensions	5.4 x 33.6 x 50.4 mm
Nominal Voltage	4.2 V
Energy Capacity	1.1 Ah
Charging Current	0.55 A or 0.5 C-rate
Discharging Current	1.1 A or 1 C-rate
Voltage Range	4.2 V (charge) to 2.7 V(discharge)

$$SOH = \frac{C_{current}}{C_{rated}} \times 100\%,$$

where $C_{current}$ is the measured capacity of the battery and C_{rated} is the rated or initial capacity

$$RUL_{true} = N_{EOL}^{true} - N_{current},$$
$$RUL_{pred} = N_{EOL}^{pred} - N_{current}$$

where N_{EOL}^{true} and N_{EOL}^{pred} are the true and predicted end-of-life cycles, respectively, and $N_{current}$ is the RUL monitoring cycle

Evaluation Metrics

- Root Mean Square Error(RMSE) $= \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(SOH_{true,i} - SOH_{pred,i}\right)^2}$,
- Mean Absolute Error(MAE) $= \frac{1}{n}\sum_{i=1}^{n}\left|SOH_{true,i} - SOH_{pred,i}\right|$,
- Coefficient of determination $R^2_{SOH} = 1 - \frac{\sum_{i=1}^{n}\left(SOH_{true,i} - SOH_{pred,i}\right)^2}{\sum_{i=1}^{n}\left(SOH_{true,i} - SOH_{true}\right)^2}$,
- Remaining Useful Life (RUL) Error $= |RUL_{true} - RUL_{true}|(in\ cycles)$

3. Research Methodology

Gated Recurrent Unit (GRU)

- Captures long-term temporal dependencies in cycling data
- Efficient for time-series sensor inputs (voltage, current, temperature)
- Hidden state updates directly (no separate memory cell)
- Reset & update gates : prevent gradient dispersion
- Maintains long-term memory capacity with reduced computational load

$Z_t = \sigma(W_z.[h_{t-1}, X_t])$, $\quad h_t = (1 - Z_t) * h_{t-1} + Z_t * \hat{h}_t$,

$R_t = \sigma(W_r.[h_{t-1}, X_t])$, where, $\sigma = \frac{1}{1+e^{-x}}$, $\tanh x = \frac{e^x - e^{-x}}{e^x + e^{-x}}$

$\hat{h}_t = \tanh(W.[R_t * h_{t-1}, X_t])$,

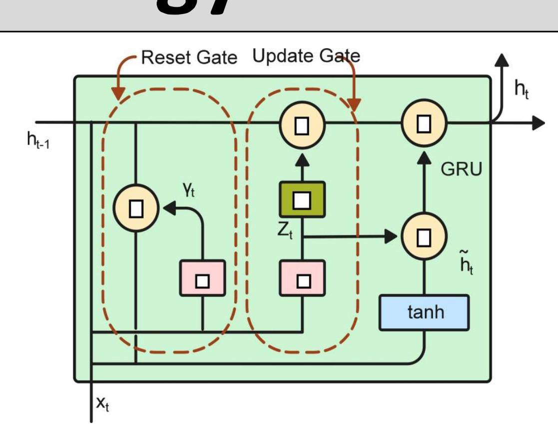


Figure. Gated Recurrent Unit (GRU)

Bidirectional GRU

- Processes data forward & backward
- Learns richer temporal correlations and degradation features
- Improves robustness and accuracy of SOH prediction
- Enhanced feature extraction from cycling data
- Stronger predictive performance for battery health

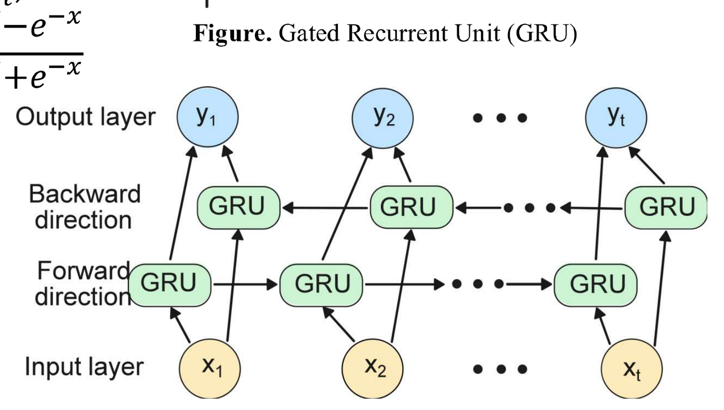


Figure. Bidirectional Gated Recurrent Unit (GRU)

Temporal Attention Mechanism

- **For input sequence** $H = [h_1, h_2, \ldots, h_T] \in \mathbb{R}^{T\times d}$:

$e_t = \tanh(W_a h_t + b_a)$, $\alpha_t = \frac{\exp(e_t^T u_a)}{\sum_{k=1}^{T}\exp(e_k^T u_a)}$,

where, W_a and b_a are the **weight** and the **bias** matrix, u_a is a vector, e_t represents the relevance of the hidden state h_t with respect to overall sequence.

- **The final context vector** c **is :**

$$c = \sum_{t=1}^{T}\alpha_t h_t \text{ and } Y_{SOH} = f(c)$$

Y **is output** of the model, $f(.)$ represent fully connected layer

Model Execution Process

- **Input → Feature Extraction:** Two 1D Convolutional layers for local feature capture
- **BiGRu Modeling**: BiGRU layer to capture forward & backward long term dependencies
- **Attention Mechanism**: To emphasize critical time steps
- **Dimensionality Reduction**: Fully Connected (FC) layers: 1 output node

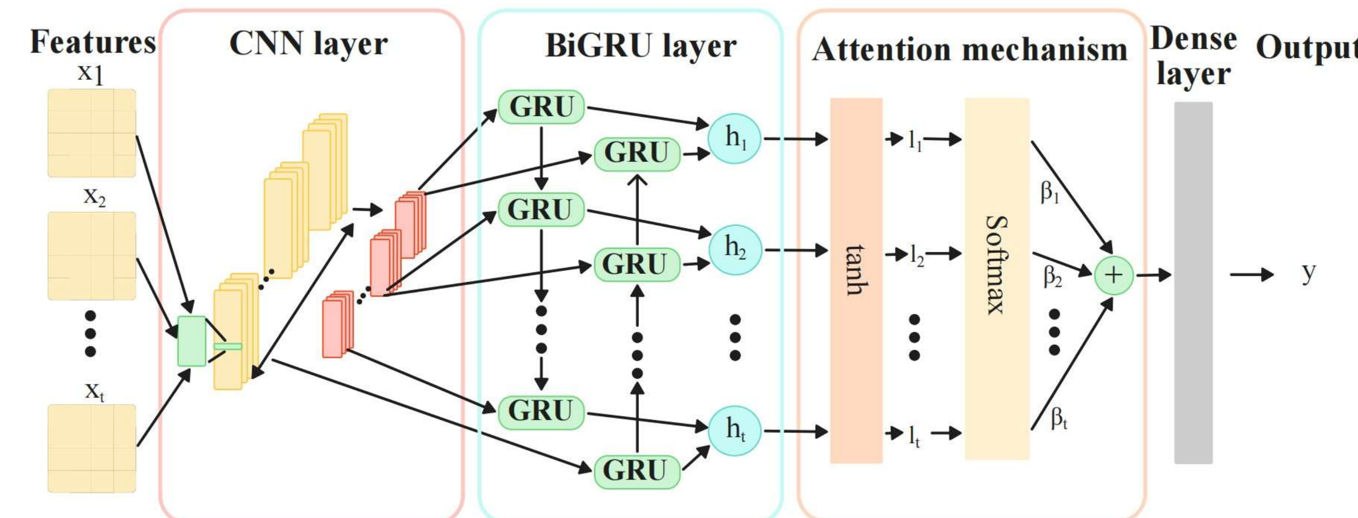


Figure. Full Process showing Execution of the Proposed Model. Feature matrices as input, CNN layer for feature extraction, Bidirectional Gated Recurrent Unit (GRU) followed by temporal attention mechanism and dense layer for final output of SOH

Training and Testing Setup

- Loss Function: Mean Squared Error (MSE)
- Optimizer: AdamW + L2 regularization
- Learning Rate: 0.001
- Dropout: 0.25 (to prevent overfitting)
- Training: 1000 epochs, mini-batch size = 16
- Validation: Leave-One-Out Cross Validation (LOOCV)

Group	Training Cells	Testing Cell
Group I	CS2_36, CS2_37,,CS2_38	CS2_35
Group II	CS2_35, CS2_37, CS2_38	CS2_36
Group III	CS2_35, CS2_36, CS2_38	CS2_37
Group IV	CS2_35, CS2_36, CS2_37	CS2_38

Table. CALCE dataset CS2 cells battery training & testing groups

4. Results

CS2-35

SOH Estimation Error:
MAE: 0.0072,
RMSE: 0.0121,
R^2: 0.9965

RUL Estimation Error:
Cycles: 2

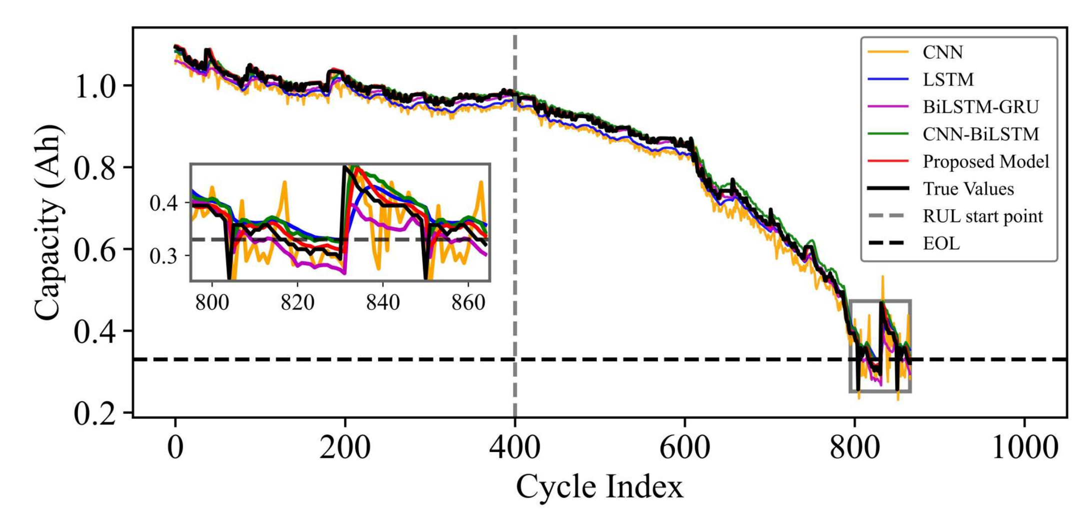


Figure. SOH prediction comparision of different models on CS2-35 cell with failure threshold

CS2-36

RUL Estimation Error:
Cycles: 3

SOH Estimation Error:
MAE: 0.0082,
RMSE: 0.0145,
R^2: 0.9968

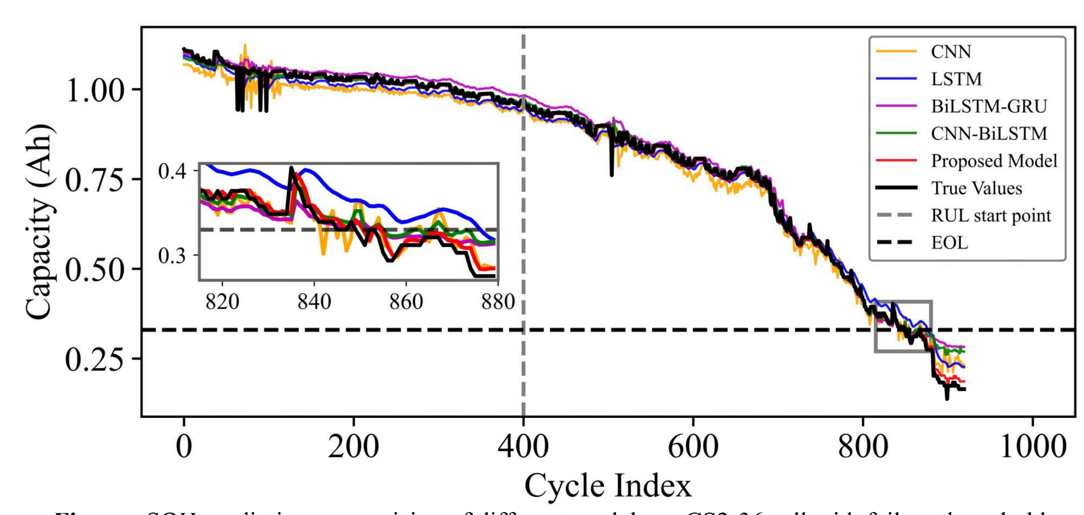


Figure. SOH prediction comparision of different models on CS2-36 cell with failure threshold

CS2-37

SOH Estimation Error:
MAE: 0.0065,
RMSE: 0.0124,
R^2: 0.9963

RUL Estimation Error:
Cycles: 1

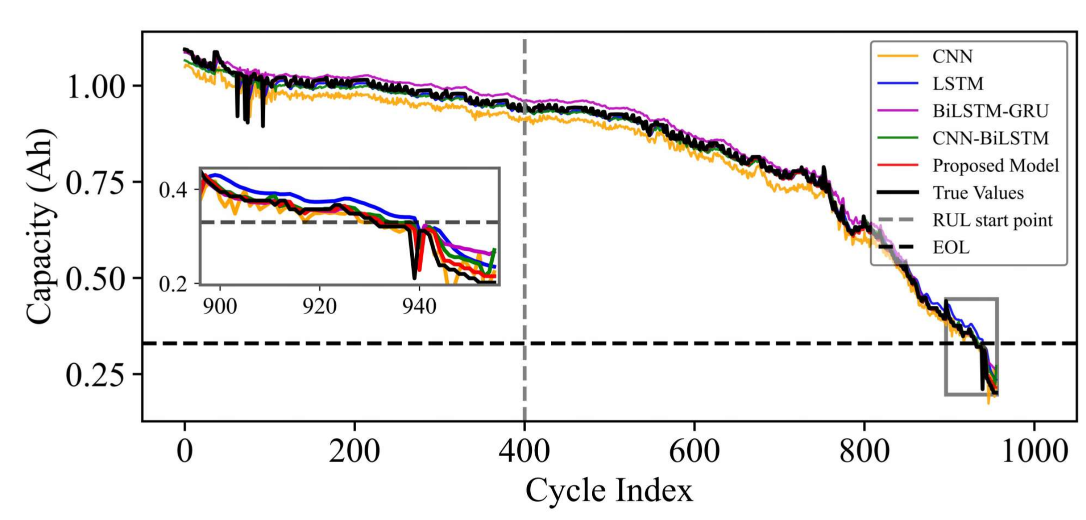


Figure. SOH prediction comparision of different models on CS2-37 cell with failure threshold

CS2-38

SOH Estimation Error:
MAE: 0.0075,
RMSE: 0.0131,
R^2: 0.9958

RUL Estimation Error:
Cycles: 0

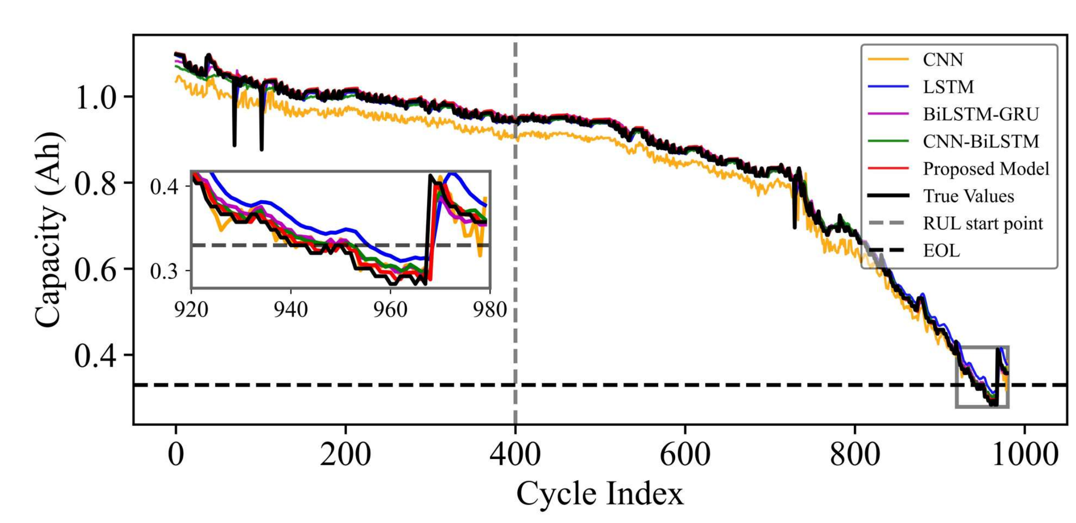


Figure. SOH prediction comparision of different models on CS2-38 cell with failure threshold

5. Conclusions

Accurate SOH & RUL Estimation
- Essential for assessing battery health, degradation, and lifespan
- Optimizes usage, improves safety, and reduces cost

Proposed Framework
- Hybrid CNN-BiGRU with Temporal Attention
- Captures short & long term dependencies
- Sliding window strategy for sequence generation
- Regularization via dropout and weight decay

Performance
- MAE:0.0072, RMSE: 0.0121, R^2: 0.9965
- Robust, reliable, and strong generalization

Impact & Future Work
- Enhances accuracy of SOH & RUL prediction
- Extends data-driven battery prognostics
- Develop lightweight model, real-time model for online BMS in Electric vehicles, Aerospace, Renewable energy storage systems

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