Precise State-of-Health Estimation for Lithium-Ion Batteries Using EGA-Optimized Spatiotemporal Deep Learning

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***Abstract*—Accurately predicting the State-of-Health (SOH) of lithium-ion batteries is a major challenge for electric vehicles because battery aging is complex, nonlinear, and inconsistent across operating cycles. Standard artificial intelligence models often struggle because they require careful manual hyperparameter settings to perform well. In this work, an Enhanced Genetic Algorithm (EGA) is proposed as an automated evolutionary search strategy for identifying the optimal configuration of a spatiotemporal deep learning model. The proposed CNN-LSTM architecture uses convolutional layers to identify patterns in charging, discharging, and temperature data, while the LSTM layer tracks how these patterns evolve across battery cycles. By using the EGA to optimize parameters such as filter count, neuron count, dropout rate, and learning rate, the system achieved a Mean Absolute Error (MAE) of 1.301% and an R^2 score of 0.8770. These results show that combining evolutionary optimization with deep learning can improve the reliability and efficiency of battery management systems.**

***Index Terms*—Lithium-ion batteries, State-of-Health, SOH estimation, CNN-LSTM, Enhanced Genetic Algorithm, battery management system.**

I. Introduction

Lithium-ion batteries play a critical role in modern energy systems, powering applications ranging from portable electronics to electric vehicles (EVs). However, battery degradation is inevitable due to complex electrochemical processes that occur during repeated charge–discharge cycles. This degradation reduces the State-of-Health (SOH), leading to decreased driving range and potential safety concerns in EV applications.

SOH is commonly expressed as the ratio between the current available capacity and the rated capacity of the battery:

$$\text{SOH}_{\text{cap}} = \frac{C_{\text{current}}}{C_{\text{rated}}} \times 100. \tag{1}$$

A. Problem: Complexity and Noise

Accurate prediction of battery health remains challenging because internal degradation processes are not directly observable. Instead, SOH must be inferred from measurable signals such as voltage, current, and temperature. These signals are often noisy and highly nonlinear. Traditional approaches typically treat these inputs independently, failing to capture the underlying spatiotemporal relationships in which present battery behavior is strongly influenced by historical usage patterns.

B. Gap: Trial-and-Error Tuning

Advanced deep learning models, particularly Long Short-Term Memory (LSTM) networks, have been widely adopted for modelling temporal degradation trends. However, their performance is highly sensitive to hyperparameter selection, including learning rate, network depth, and neuron configuration. Existing approaches largely rely on manual tuning through trial and error, which is time-consuming and often suboptimal.

C. Proposed Solution

To address these challenges, this work introduces a hybrid framework that combines deep learning with evolutionary optimization. A Convolutional Neural Network (CNN) extracts spatial features from voltage, current, and temperature data, while an LSTM network captures long-term temporal dependencies across charge–discharge cycles. An Enhanced Genetic Algorithm (EGA) automatically identifies optimal hyperparameters by iteratively evaluating candidate solutions and retaining the most effective configurations.

By integrating spatiotemporal learning with automated hyperparameter optimization, the proposed approach improves prediction accuracy and robustness, contributing to more reliable and efficient battery management systems.

II. Literature Review

The estimation of State-of-Health has been a focal point of battery research for decades. Traditionally, researchers relied on Equivalent Circuit Models (ECM) and Physics-Based Models (PBM). While these models provide deep insight into the internal chemical reactions of a battery, they are computationally expensive and struggle to adapt to the highly nonlinear degradation patterns found in real-world EV usage.

A. Shift to Data-Driven Methods

With the rise of large-scale battery data, research has shifted toward machine learning. Early methods used Support Vector Regression (SVR) and Random Forests to map battery features to health indicators. However, these shallow models often failed to capture long-term dependencies in battery aging, leading to a surge in deep learning applications.

B. Role of Recurrent Neural Networks

Recurrent architectures, especially LSTM networks, have become a common choice for SOH estimation. LSTMs are suited for this task because their memory gates allow the model to retain degradation trends from previous cycles. Despite their success, LSTMs primarily focus on temporal behavior and may miss spatial correlations, such as the relationships among voltage, current, and temperature within a single charging or discharging cycle.

C. Hybrid Spatiotemporal Architectures

Recent studies have proposed hybrid CNN-LSTM models to address this limitation. In these architectures, CNN layers act as spatial feature extractors that identify patterns in charging and discharging curves, while LSTM layers process these extracted patterns over time. Although highly accurate, these hybrid models introduce hyperparameter complexity because performance depends strongly on the number of filters, kernel sizes, hidden units, and learning settings selected.

D. Optimization Using Genetic Algorithms

Standard grid search and random search methods for finding the best model settings are inefficient. Genetic Algorithms (GA) can automate this search process, but standard GA implementations may prematurely converge to a local optimum. This project fills the gap by introducing an Enhanced Genetic Algorithm that incorporates elitism and tournament selection. These mechanisms make the search for the optimal CNN-LSTM architecture more robust and allow the framework to balance spatial and temporal information automatically.

III. Methodology

The proposed methodology follows a structured pipeline consisting of data preprocessing, spatiotemporal feature extraction, and EGA-driven hyperparameter optimization.

A. Data Acquisition and Preprocessing

The raw dataset consists of charging and discharging cycles for lithium-ion batteries. Seven key parameters were selected as degradation-sensitive inputs: charging current (chI), charging voltage (chV), charging temperature (chT), discharging current (disI), discharging voltage (disV), discharging temperature (disT), and battery case temperature (BCt).

Since voltage, current, and temperature operate on different numerical scales, Min-Max scaling was applied to normalize all features into the range $[0, 1]$. This prevents any single feature from dominating the gradient updates during training. A cycle-level sliding window of 10 cycles was used to provide historical context, transforming the data into a spatiotemporal input tensor with multiple sensor features per cycle.

For a measured feature $x^{(m)}$, the normalized value is computed as

$$\tilde{x}^{(m)} = \frac{x^{(m)} - x^{(m)}_{\min}}{x^{(m)}_{\max} - x^{(m)}_{\min}}, \tag{2}$$

where $x^{(m)}_{\min}$ and $x^{(m)}_{\max}$ are the minimum and maximum values of the mth feature in the training data. The cycle-level input sequence is then represented as

$$\mathbf{X}_k = [\mathbf{x}_{k-W+1}, \mathbf{x}_{k-W+2}, \ldots, \mathbf{x}_k]^T \in \mathbb{R}^{W \times F}, \tag{3}$$

where $W = 10$ is the sliding-window length and $F = 7$ is the number of selected sensor features.

B. Spatiotemporal CNN-LSTM Architecture

The core model is designed to handle the multidimensional nature of battery aging. The Conv1D layer scans the features within each cycle and captures spatial patterns, such as how a voltage drop correlates with a temperature rise during high-current discharge. A representative convolutional activation can be written as

$$h_t^{(j)} = \phi\left(\sum_{q=0}^{K-1}\sum_{m=1}^{F} w_{q,m}^{(j)} x_{t+q,m} + b_j\right), \tag{4}$$

where $h_t^{(j)}$ is the activation of the jth convolutional filter at time step t, K is the kernel size, F is the number of input features, $w_{q,m}^{(j)}$ represents the filter weight, b_j is the bias, and ϕ denotes the Rectified Linear Unit (ReLU) activation function.

The output of the CNN is fed into an LSTM layer. With its internal memory cells, the LSTM tracks how the spatial patterns evolve over the input window and identifies the long-term health trend of the battery.

The LSTM update equations are expressed as

$$\mathbf{i}_t = \sigma(\mathbf{W}_i\mathbf{u}_t + \mathbf{U}_i\mathbf{h}_{t-1} + \mathbf{b}_i), \tag{5}$$

$$\mathbf{f}_t = \sigma(\mathbf{W}_f\mathbf{u}_t + \mathbf{U}_f\mathbf{h}_{t-1} + \mathbf{b}_f), \tag{6}$$

$$\mathbf{o}_t = \sigma(\mathbf{W}_o\mathbf{u}_t + \mathbf{U}_o\mathbf{h}_{t-1} + \mathbf{b}_o), \tag{7}$$

$$\tilde{\mathbf{c}}_t = \tanh(\mathbf{W}_c\mathbf{u}_t + \mathbf{U}_c\mathbf{h}_{t-1} + \mathbf{b}_c), \tag{8}$$

$$\mathbf{c}_t = \mathbf{f}_t \odot \mathbf{c}_{t-1} + \mathbf{i}_t \odot \tilde{\mathbf{c}}_t, \tag{9}$$

$$\mathbf{h}_t = \mathbf{o}_t \odot \tanh(\mathbf{c}_t), \tag{10}$$

where $\mathbf{i}_t$, $\mathbf{f}_t$, and $\mathbf{o}_t$ are the input, forget, and output gates, respectively; $\mathbf{u}_t$ is the CNN feature vector at time step t; $\mathbf{c}_t$ is the cell state; and $\mathbf{h}_t$ is the hidden state. The final SOH estimate is obtained through a dense regression layer:

$$\widehat{\mathrm{SOH}}_t = \mathbf{W}_r\mathbf{h}_t + b_r. \tag{11}$$

C. Enhanced Genetic Algorithm Optimization

To avoid suboptimal performance from manual tuning, an Enhanced Genetic Algorithm was developed to evolve the model hyperparameters. First, a population of 12 individuals is initialized, where each individual represents a unique combination of CNN filters, LSTM units, dense units, dropout rate, and

TABLE I
EGA-OPTIMIZED HYPERPARAMETERS FOR THE PROPOSED CNN-LSTM MODEL

Hyperparameter	**Search Space / Range**	**Optimal Value**
CNN filters	$[32, 64, 128, 256]$	256
Kernel size	$[2, 3, 5]$	3
LSTM units	$[32, 64, 128, 256]$	256
Dense units	$[16, 32, 64, 128]$	16
Dropout rate	$[0.1, 0.2, 0.3, 0.4, 0.5]$	0.3
Learning rate	$[0.01, 0.005, 0.001, 0.0005, 0.0001]$	0.005
Window size	10, fixed	10

learning rate. Each individual is trained and evaluated using validation error.

The fitness score is calculated as

$$\mathrm{MSE_{val}}(\boldsymbol{\theta}) = \frac{1}{N_v}\sum_{n=1}^{N_v}\left(y_n - \hat{y}_n(\boldsymbol{\theta})\right)^2, \quad (12)$$

$$\mathrm{Fitness}(\boldsymbol{\theta}) = \frac{1}{\mathrm{MSE_{val}}(\boldsymbol{\theta}) + \epsilon}, \quad (13)$$

where $\boldsymbol{\theta}$ denotes a candidate hyperparameter set, N_v is the number of validation samples, y_n is the measured SOH, $\hat{y}_n$ is the predicted SOH, and ϵ is a small constant used to avoid division by zero. Tournament selection is then used so that individuals compete in small groups, preserving strong traits while maintaining diversity. Crossover exchanges traits between parent configurations to generate child solutions, and mutation randomly adjusts selected parameters with a mutation rate of 0.15. Finally, elitism carries the two best-performing models into the next generation so that the best discovered solution is never lost.

IV. EXPERIMENTAL SETUP

A. Dataset Description

To validate the proposed EGA-CNN-LSTM framework, the NASA Ames Prognostics Center of Excellence (PCoE) battery dataset is used [1]. Specifically, data from 18650-size lithium-ion batteries B0005, B0006, and B0007 are employed. These batteries were subjected to repeated charge and discharge cycles at room temperature, approximately 24°C.

During the charging phase, constant current charging was performed at 1.5 A until the voltage reached 4.2 V, followed by constant voltage charging until the current dropped to 20 mA. During the discharging phase, constant current discharging was performed at 2 A until the voltage reached the specified thresholds of 2.7 V, 2.5 V, and 2.2 V.

B. Feature Engineering

Raw data consisting of terminal voltage V, current I, and temperature T are sampled during the discharge cycles. Min-Max normalization is applied to support stable convergence during EGA optimization. A sliding-window extraction strategy is then used to create time-series segments. For each cycle, a sequence length of $L = 50$ samples is extracted so that the CNN can capture local voltage-drop patterns and the LSTM can learn the long-term degradation trend. The dataset is divided into a 70% training set for EGA-based model evolution and a 30% testing set for final generalization evaluation.

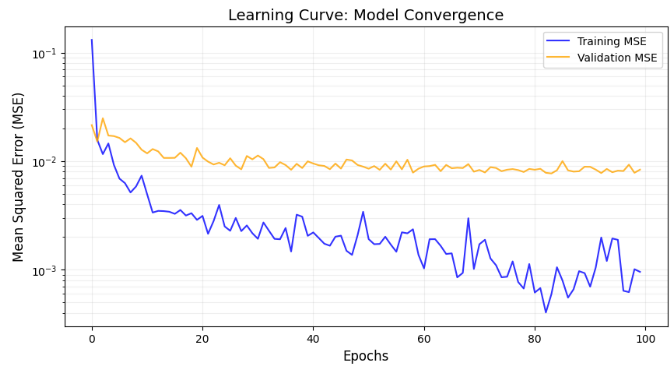

Fig. 1. Model convergence learning curve.

V. RESULTS AND DISCUSSION

The performance of the proposed EGA-CNN-LSTM framework is evaluated through model convergence, feature correlation, SOH tracking accuracy, and statistical error analysis. By leveraging the EGA, the hybrid spatiotemporal architecture was optimized to capture complex nonlinear degradation signatures in lithium-ion batteries.

A. Model Convergence and Learning Stability

The learning curve is the primary indicator of optimization success. As shown in Fig. 1, both training and validation Mean Squared Error exhibit a steep decline and reach stability within 100 epochs. The limited gap between the two curves confirms that the EGA-selected dropout rate of 0.3 and learning rate of 0.005 help prevent overfitting and support generalization to unseen battery cycles.

B. Spatiotemporal Feature Correlation

A critical component of the model's success is its ability to identify relevant spatial features. The feature correlation heatmap in Fig. 2 reveals a dominant linear relationship between battery case temperature and SOH. However, the weak linear correlation of other raw sensor inputs such as voltage and current highlights the need for CNN layers, which can extract nonlinear aging fingerprints from noisy sensor signals before they are mapped onto a temporal sequence by the LSTM.

The feature correlation values are computed using the Pearson correlation coefficient:

$$\rho_{x,y} = \frac{\sum_{n=1}^{N}(x_n - \bar{x})(y_n - \bar{y})}{\sqrt{\sum_{n=1}^{N}(x_n - \bar{x})^2}\sqrt{\sum_{n=1}^{N}(y_n - \bar{y})^2}}, \quad (14)$$

where x is a battery sensor feature, y is the SOH target, and N is the number of samples.

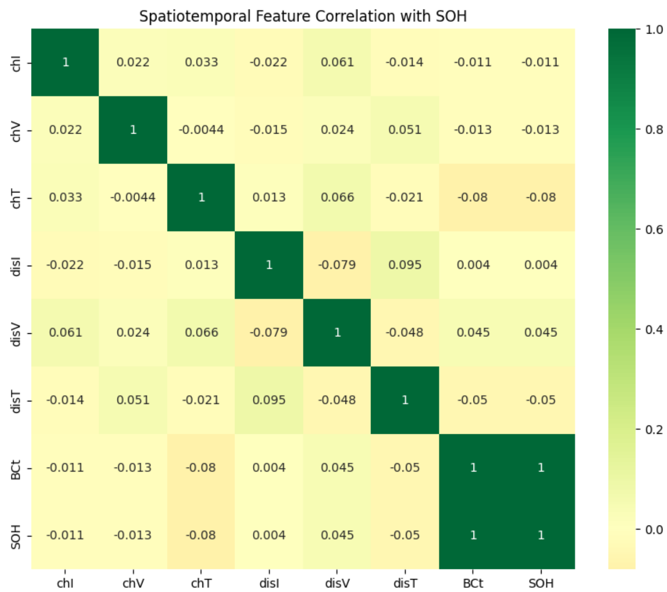

Fig. 2. Feature correlations with SOH.

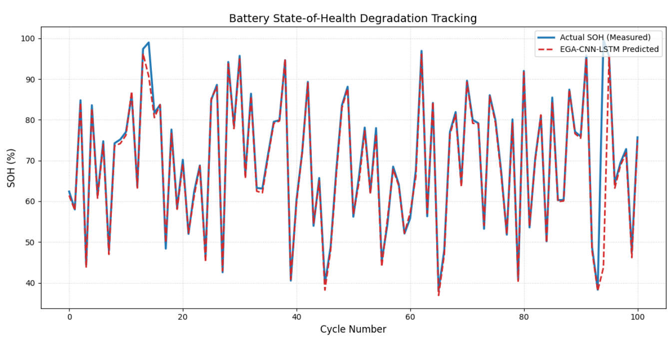

Fig. 3. SOH degradation tracking curve.

C. SOH Estimation and Tracking Accuracy

The degradation tracking results in Fig. 3 demonstrate the predictive strength of the proposed framework. The model achieves a close overlap with the measured SOH values across the testing set. The architecture also tracks the battery aging knee, the region where degradation accelerates, which is important for safety-critical battery management systems.

D. Statistical Validation and Error Analysis

The robustness of the EGA-CNN-LSTM model is quantified using the R^2 score, MAE, and residual distribution. The model achieved an R^2 score of 0.8770, indicating that it captures nearly 88% of the variance in battery aging. The MAE is restricted to 1.301%, demonstrating high prediction precision.

The prediction residual for each test sample is defined as

$$e_n = y_n - \hat{y}_n. \tag{15}$$

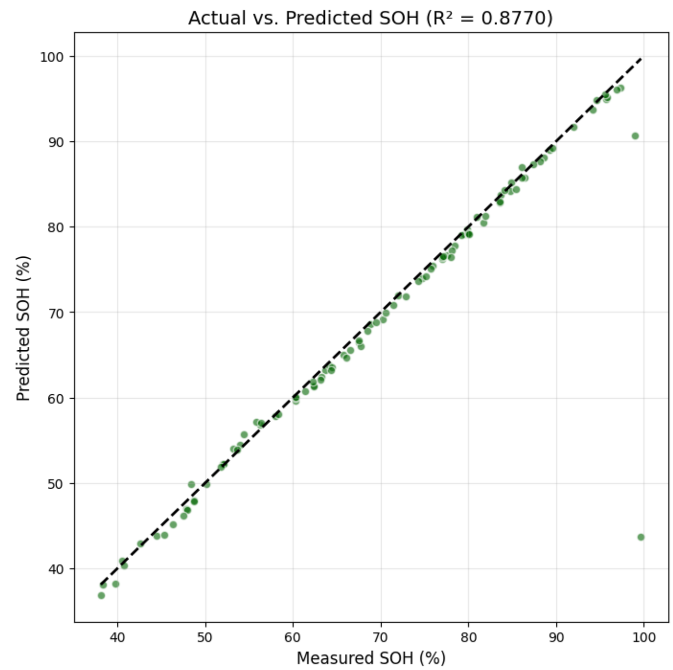

Fig. 4. Actual versus predicted SOH with R^2 score.

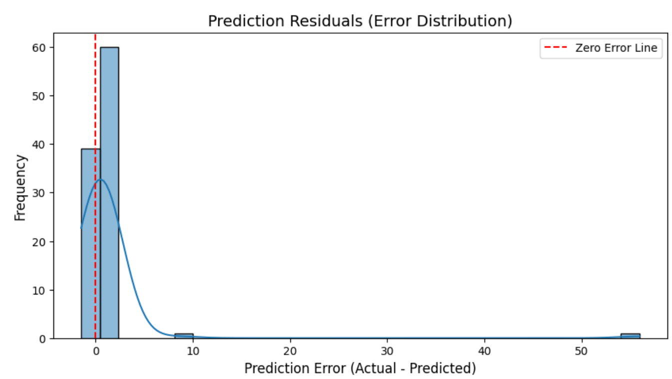

Fig. 5. Prediction residual error distribution.

The main evaluation metrics are then calculated as

$$\mathrm{MAE} = \frac{1}{N}\sum_{n=1}^{N} |y_n - \hat{y}_n|, \tag{16}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{n=1}^{N} (y_n - \hat{y}_n)^2}, \tag{17}$$

$$R^2 = 1 - \frac{\sum_{n=1}^{N} (y_n - \hat{y}_n)^2}{\sum_{n=1}^{N} (y_n - \bar{y})^2}. \tag{18}$$

Fig. 4 shows the alignment between measured and predicted SOH values. Most samples lie close to the ideal diagonal line, confirming strong regression performance. Fig. 5 shows that the residual distribution is centered near zero, suggesting that the model is largely unbiased and that the EGA successfully navigated the hyperparameter search space.

VI. Conclusion

This research presents a high-precision framework for estimating the State-of-Health of lithium-ion batteries by integrating spatiotemporal deep learning with bio-inspired optimization. The proposed EGA-CNN-LSTM model addresses the nonlinear complexity of battery aging by using CNN layers to extract spatial feature correlations and LSTM layers to perform temporal sequence tracking.

The primary innovation is the Enhanced Genetic Algorithm, which automates the selection of architectural hyperparameters. By employing tournament selection and elitism, the EGA identified an optimal configuration with 256 CNN filters and 256 LSTM units. This evolved architecture achieved an MAE of 1.301% and an R^2 score of 0.8770.

Experimental validation using the NASA PCoE dataset confirms that the model accurately captures critical battery degradation behavior, including the aging knee where capacity loss accelerates. This work provides a robust diagnostic tool for next-generation Battery Management Systems to support the safety and longevity of electric vehicle energy storage.

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