

# HYBRID PHYSICS-INFORMED NEURAL NETWORK AND EXTENDED KALMAN FILTER FOR ACCURATE STATE-OF-HEALTH ESTIMATION OF BATTERIES IN ELECTRIC VEHICLES

VIJAYA ANAND NIDUMOLU<sup>1</sup>, HEMANTH SAI MADUPU<sup>2</sup>, PADALA SRIKAVITHA<sup>3</sup>,  
VENKATA ASHOK KALAGA<sup>4</sup>, NIMMAGADDA CHANDRA SEKHAR<sup>5</sup>

<sup>1</sup>Associate Professor, P. V. P. Siddhartha Institute of Technology, Department of EEE, Vijayawada, India

<sup>2</sup>Assistant Professor, P. V. P. Siddhartha Institute of Technology, Department of EEE, Vijayawada, India

<sup>3</sup>Assistant Professor, Department of Electrical and Electronics Engineering, Aditya University,  
Surampalem, Andhra Pradesh, India

<sup>4</sup>Assistant Professor, Department of Electronics and Communication Engineering,  
Lakireddy Bali Reddy College of Engineering, Mylavaram, Andhra Pradesh, India

<sup>5</sup>Assistant Professor, Department of Computer Science and Engineering,  
R.V.R & J.C College of Engineering, Chowdavaram, Andhra Pradesh, India

E-mail: <sup>1</sup>nidumoluvijay@gmail.com, <sup>2</sup>hemanthsai.madupu@gmail.com, <sup>3</sup>srikavithapadala@gmail.com,  
<sup>4</sup>ashok.516m@gmail.com, <sup>5</sup>nimmagadda65@gmail.com

## ABSTRACT

Accurate battery health monitoring is critical for the reliable operation of electric vehicles (EVs). Existing approaches for State-of-Health (SOH) estimation often face challenges such as high computational cost, reliance on large pre-training datasets, sensitivity to irregular operational data, and limited generalizability under diverse real-world conditions. To address these limitations, this work proposes a hybrid framework that integrates a Physics-Informed Neural Network (PINN) with an Extended Kalman Filter (EKF) for real-time, robust SOH estimation. The PINN captures nonlinear relationships between battery operating parameters and SOH while enforcing physical degradation constraints, whereas the EKF enables recursive prediction and correction, mitigating the effects of measurement noise and modeling uncertainties. The proposed PINN–EKF framework achieves accurate, stable, and physically consistent SOH predictions under varying operating conditions. Performance evaluation along with comparative analysis against existing methods, demonstrates that the proposed approach provides superior estimation accuracy, computational efficiency, and robustness, making it highly suitable for practical deployment in resource-constrained EV systems.

**Keywords:** *State of Health, Extended Kalman Filter, Battery Management, Lithium Ion Battery, Useful Life Estimation.*

## 1. INTRODUCTION

Despite the significant advantages of electric vehicles, several challenges persist, particularly in the realm of battery performance and longevity [1-5]. The State of Health (SOH) of EV batteries directly impacts vehicle performance, safety, and longevity. SoH, which refers to a battery's condition relative to its optimal capacity, gradually degrades due to repeated charge-discharge cycles, temperature fluctuations, and aging [6]. When the SOH of a battery falls below, energy storage efficiency declines, resulting in shorter driving range, longer charging periods, and degraded power delivery [7]. These issues highlight the necessity for

accurate SoH prediction models to manage battery life, prevent early degradation, and ensure EVs' long-term viability. Traditional battery management systems, which monitor voltage, current, and temperature, often fall short in providing accurate, long-term SOH predictions due to the complex and gradual nature of battery degradation [8]. To overcome the challenges of accurate and real-time SoH prediction, advanced predictive models integrating both machine learning and electrochemical principles have emerged as promising solutions [9]. These hybrid approaches can leverage large datasets and physical degradation models to predict SoH more accurately across diverse operating conditions [10]. Machine learning

algorithms are capable of learning non-linear relationships between battery parameters and SOH, making them adaptable to varying climates, driving patterns, and battery chemistries [11]. Hybrid models, which combine physics-based insights with data-driven techniques, offer improved interpretability and robustness, capturing the underlying dynamics of battery degradation [12]. Furthermore, these hybrid models can be continuously refined as new data becomes available, improving their predictive accuracy over time [13-14]. As a result, they not only optimize battery management but also contribute to the development of more sustainable and cost-effective electric vehicle technologies [15]. Recent research on battery health monitoring [16-20] in electric vehicles (EVs) indicates that existing approaches face significant limitations, including high computational demands, reliance on large pre-training datasets, sensitivity to irregular or sparse operational data, and reduced generalizability under diverse real-world conditions. Transformer-based models capture temporal dependencies but struggle with unpredictable cycling patterns, CNN and multi-task learning frameworks extract spatial and temporal features effectively but often require extensive pre-processing or operational data, and hybrid methods combining Bayesian filtering, differential modeling, or multiple algorithms improve accuracy at the cost of increased complexity and reduced real-time applicability. Few studies have addressed the simultaneous need for accurate State-of-Health (SOH) prediction while ensuring computational efficiency, robustness to varying battery degradation patterns, and deploy ability on resource-constrained EV systems. These limitations have motivated the development of a proposed framework that is lightweight, interpretable, and capable of capturing both spatial heterogeneity and temporal degradation dynamics for reliable, real-time battery health monitoring.

In this work, a hybrid framework is proposed for battery health monitoring in electric vehicles, focusing on accurate State of Health (SOH) estimation and reliable predictive maintenance. The proposed approach integrates a Physics-Informed Neural Network (PINN) with an Extended Kalman Filter (EKF), enabling the combination of data-driven learning with battery degradation physics to achieve robust SOH estimation under varying operating conditions. Battery aging data are obtained from the NASA lithium-ion battery dataset [21], which includes voltage, current, temperature, and capacity measurements recorded over multiple

charge–discharge cycles. The Physics-Informed Neural Network learns the nonlinear relationship between battery operating parameters and SOH while enforcing physical degradation constraints during training. To facilitate stable and real-time SOH estimation, the trained PINN is integrated with an Extended Kalman Filter, which treats SOH as a system state and performs recursive prediction and correction using real-time measurements. This hybrid PINN–EKF framework effectively reduces the impact of measurement noise and modeling uncertainties. The effectiveness of the proposed framework is further validated through comparative analysis with existing SOH estimation approaches reported in the literature.

## 2. PHYSICS-INFORMED NEURAL NETWORK – EXTENDED KALMAN FILTER (PINN–EKF) BASED SOH ESTIMATION

The block diagram of the proposed Physics-Informed Neural Network and Extended Kalman Filter (PINN–EKF) based State of Health (SOH) estimation framework is illustrated in Figure 1 the sequential steps involved in battery health monitoring. The process begins with the data acquisition block, where battery terminal voltage, current, temperature, and time are collected from experimental setups or a real-time Battery Management System during repeated charge–discharge cycles.

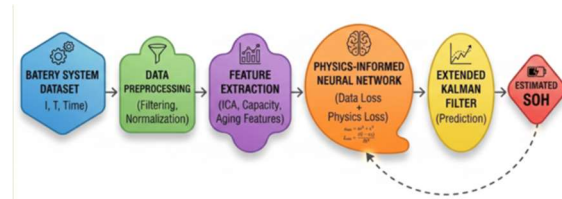


Figure 1: Block diagram of proposed (PINN-EKF) SOH estimation technique.

Raw measurements are cleaned (noise removal, normalization, resampling) to yield consistent signals for analysis. Incremental Capacity Analysis extracts degradation-sensitive features—capturing effects like active-material loss and rising internal resistance—which, together with voltage, current, and temperature, form the SOH input vector. A physics-informed neural network, trained offline with a physics-guided loss, maps these inputs to physically consistent SOH estimates. For real-time use, the PINN output is fused into an Extended Kalman Filter that treats SOH as a state and performs recursive prediction–correction to suppress sensor noise and compensate model uncertainty. The filtered SOH is then provided to the BMS for

monitoring, maintenance planning, and safety, combining physics-based learning with Kalman filtering for robust, real-time performance.

The State of Health (SOH) is defined as the ratio of the available capacity of the battery at a given cycle to its rated capacity and is expressed as

$$\text{SOH}(k) = \frac{Q(k)}{Q_{\text{rated}}} \quad (1)$$

where  $Q(k)$  represents the measured discharge capacity at cycle  $k$ , and  $Q_{\text{rated}}$  denotes the nominal capacity of a fresh battery. The raw datasets often contain noise and non-uniform sampling intervals, which may adversely affect the learning process. Hence, preprocessing steps such as normalization and smoothing are applied to voltage, current, and temperature signals to improve numerical stability and convergence during training. The measured signals are normalized using min-max normalization as

$$x_{\text{norm}} = \frac{x - x_{\text{min}}}{x_{\text{max}} - x_{\text{min}}} \quad (2)$$

where  $x$  denotes the original signal and  $x_{\text{min}}$  and  $x_{\text{max}}$  are the minimum and maximum values of the signal, respectively.

To capture battery degradation characteristics effectively, Incremental Capacity Analysis (ICA) is employed as a feature extraction technique. The ICA curve is obtained by differentiating the battery capacity with respect to voltage:

$$\text{ICA}(V) = \frac{dQ}{dV} \left[ \frac{\text{Ah}}{\text{V}} \right] \quad (3)$$

The ICA curves provide valuable insights into electrochemical aging mechanisms such as loss of active material, lithium plating, and increased polarization. As the battery ages, the intensity of ICA peaks decreases and the peak positions shift, indicating progressive degradation of SOH. These characteristics make ICA a sensitive and reliable feature for battery health estimation.

In addition to ICA, operational features such as temperature variation and current rate are incorporated to reflect real-world battery operating conditions. The combined feature vector used for SOH estimation is defined as

$$X(t) = [V(t), I(t), T(t), \text{ICA}(t)] \quad (4)$$

Since battery degradation is governed by physical laws, physics-based constraints are introduced at the feature extraction stage. The rate of capacity

degradation is assumed to be a function of current magnitude and temperature and is modeled as

$$\frac{d\text{SOH}(t)}{dt} = -\alpha |I(t)|^\beta \exp\left(\frac{-E_a}{RT(t)}\right) \quad (5)$$

where  $\alpha$  and  $\beta$  are empirically determined degradation parameters,  $E_a$  is the activation energy,  $R$  is the universal gas constant, and  $T(t)$  denotes the absolute temperature. This degradation model reflects the physical aging behavior of lithium-ion batteries and serves as prior knowledge for the learning model.

The extracted features and physics-based degradation information are then supplied to the Physics-Informed Neural Network for training. The overall estimation procedure follows a structured pipeline consisting of data acquisition, preprocessing, feature extraction, physics-based modeling, and real-time implementation. This systematic approach ensures that the subsequent learning model operates on physically meaningful and degradation-sensitive inputs, thereby enhancing SOH

### 3. FEATURE EXTRACTION AND ESTIMATION STEPS

Accurate estimation of the State of Health (SOH) of lithium-ion batteries requires a modeling framework that captures both nonlinear degradation behavior and the underlying physical aging mechanisms. To achieve this, a hybrid methodology integrating a Physics-Informed Neural Network (PINN) with an Extended Kalman Filter (EKF) is proposed. The overall framework consists of data preprocessing, physics-guided feature extraction, offline PINN training, and online EKF-based SOH estimation.

The SOH of a battery at cycle  $k$  is defined as the ratio of the available capacity to the rated capacity and is expressed as

$$\text{SOH}(k) = \frac{Q(k)}{Q_{\text{rated}}} \quad (6)$$

where  $Q(k)$  denotes the measured capacity at cycle  $k$ , and  $Q_{\text{rated}}$  represents the nominal capacity of a fresh battery.

The input dataset comprises terminal voltage  $V(t)$ , current  $I(t)$ , temperature  $T(t)$ , and time  $t$ , recorded during repeated charging and discharging cycles.

Since raw battery data often contains noise and irregular sampling, preprocessing techniques such as normalization and filtering are applied to ensure data consistency. In addition to the raw measurements, degradation-sensitive features are extracted using Incremental Capacity Analysis (ICA), which is obtained by differentiating the capacity with respect to voltage:

$$ICA(V) = \frac{dQ}{dV} \quad (7)$$

Variations in the magnitude and position of ICA peaks reflect electrochemical aging phenomena such as loss of active material and increased internal resistance. These extracted features, along with voltage, current, and temperature, form the input vector to the learning model.

To embed physical knowledge into the learning process, simplified battery degradation dynamics are incorporated. The rate of SOH degradation is assumed to depend on current magnitude, temperature, and cycling stress, and is modeled as

$$\frac{dSOH(t)}{dt} = -\alpha |I(t)|^\beta \exp\left(\frac{-E_a}{RT(t)}\right) \quad (8)$$

where  $\alpha$  and  $\beta$  are degradation coefficients,  $E_a$  is the activation energy,  $R$  is the universal gas constant, and  $T(t)$  is the absolute temperature. This equation represents the physical constraint governing capacity fade and serves as prior knowledge for the PINN.

The Physics-Informed Neural Network is designed to approximate the nonlinear mapping between battery measurements and SOH. The network output is given by

$$\widehat{SOH}(t) = \mathcal{N}_\theta(V(t), I(t), T(t), ICA(t)) \quad (9)$$

where  $\mathcal{N}_\theta(\cdot)$  denotes the neural network with trainable parameters  $\theta$ . Unlike conventional neural networks, the PINN is trained using a composite loss function that enforces both data fidelity and physical consistency. The data-driven loss term minimizes the difference between the estimated and measured SOH:

$$\mathcal{L}_{data} = \frac{1}{N} \sum_{i=1}^N \left( SOH_{actual}^{(i)} - \widehat{SOH}^{(i)} \right)^2 \quad (10)$$

To ensure compliance with battery degradation physics, an additional physics-based loss term is introduced:

$$\mathcal{L}_{physics} = \frac{1}{N} \sum_{i=1}^N \left( \frac{d\widehat{SOH}^{(i)}}{dt} + \alpha |I^{(i)}|^\beta \exp\left(\frac{-E_a}{RT^{(i)}}\right) \right)^2 \quad (11)$$

The total loss function minimized during training is expressed as

$$\mathcal{L}_{total} = \lambda_d \mathcal{L}_{data} + \lambda_p \mathcal{L}_{physics} \quad (12)$$

where  $\lambda_d$  and  $\lambda_p$  are weighting coefficients that balance the influence of data accuracy and physical constraints. The PINN is trained offline using historical aging data, and automatic differentiation is employed to compute the time derivatives required in the physics loss term.

For real-time SOH estimation, the trained PINN is integrated with an Extended Kalman Filter. The SOH is treated as a system state evolving over time, and the degradation process is modeled in a nonlinear state-space form. The state transition equation is given by

$$SOH_k = SOH_{k-1} + \Delta t \cdot g(I_k, T_k) + w_k \quad (13)$$

where  $w_k$  represents process noise with covariance  $Q_k$ . The measurement equation uses the PINN as a nonlinear observation model:

$$y_k = \mathcal{N}_\theta(V_k, I_k, T_k, ICA_k) + v_k \quad (14)$$

where  $v_k$  denotes measurement noise with covariance  $R_k$ .

The EKF performs state prediction and correction recursively. During the prediction step, the SOH estimate and error covariance are propagated using the system model. In the update step, the Kalman gain is computed using the Jacobian of the PINN output with respect to SOH, and the predicted SOH is corrected using real-time measurements. This recursive estimation effectively suppresses sensor noise and compensates for modeling uncertainties. By integrating the PINN with EKF, the proposed methodology combines the strong nonlinear approximation capability of neural networks with the stability and real-time adaptability of Kalman filtering. The physics-guided learning ensures physically meaningful SOH predictions, while the EKF enables smooth and reliable online implementation in Battery Management Systems.

### 3.1. Data Collection

The dataset utilized for evaluating the proposed machine-learning framework is obtained from the NASA Ames Prognostics Center of Excellence lithium-ion battery dataset. In this study, three 18650-type lithium-ion batteries, namely Batteries 5, 6, and 7, are selected for analysis. These batteries are widely adopted in battery aging studies due to their well-documented degradation characteristics and long-term cycling data. The data acquisition process involves subjecting the selected batteries to repeated charge–discharge cycling under controlled ambient temperature conditions. During the charging phase, each battery is charged using a constant current (CC) mode at 1.5 A until the terminal voltage reaches 4.2 V. Subsequently, the charging process transitions to constant voltage (CV) mode, which continues until the charging current decreases to approximately 20 mA, ensuring complete charge saturation.

For the discharge process, the batteries are discharged under constant current (CC) mode at a rate of 2 A until their terminal voltage reaches the battery-specific cut-off limits defined in the dataset, namely 2.7 V for Battery 5, 2.5 V for Battery 6, and 2.2 V for Battery 7. These charge–discharge cycles are repeatedly performed until the batteries reach their End-of-Life (EOL) condition. The EOL is defined as the point at which the available capacity degrades to 70% of the rated capacity, corresponding to a 30% capacity fade from the nominal value of 2 Ah to 1.4 Ah.

### 3.2. Evaluation Criteria

To quantitatively evaluate the effectiveness of the proposed battery state-of-health (SOH) estimation framework, multiple statistical performance metrics are employed. These metrics measure the discrepancy between the actual SOH values and the estimated SOH values obtained from the proposed model. Let  $SOH_i$  represent the true SOH at the  $i^{\text{th}}$  sample,  $\widehat{SOH}_i$  denote the corresponding estimated SOH, and  $N$  be the total number of test samples.

#### Mean Absolute Error (MAE)

MAE quantifies the average absolute difference between the estimated and actual SOH values. It provides a direct measure of prediction accuracy without emphasizing larger errors.

$$MAE = \frac{1}{N} \sum_{i=1}^N |SOH_i - \widehat{SOH}_i| \quad (15)$$

#### Mean Squared Error (MSE)

MSE calculates the average of the squared deviations between predicted and true SOH values. Squaring the errors penalizes larger deviations, making MSE sensitive to significant prediction errors.

$$MSE = \frac{1}{N} \sum_{i=1}^N (SOH_i - \widehat{SOH}_i)^2 \quad (16)$$

#### Root Mean Squared Error (RMSE)

RMSE is derived by taking the square root of the MSE, thereby retaining the same unit as SOH. RMSE is widely used due to its interpretability and sensitivity to larger errors.

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (SOH_i - \widehat{SOH}_i)^2} \quad (17)$$

#### Coefficient of Determination ( $R^2$ Score)

$R^2$  evaluates how well the estimated SOH values explain the variance present in the actual SOH data. It indicates the goodness-of-fit of the proposed model, with values closer to 1 representing superior predictive performance.

$$R^2 = 1 - \frac{\sum_{i=1}^N (SOH_i - \widehat{SOH}_i)^2}{\sum_{i=1}^N (SOH_i - \bar{SOH})^2} \quad (18)$$

where  $\bar{SOH}$  is the mean of the actual SOH values.

## 4. RESULT ANALYSIS AND DISCUSSION

This section presents a comprehensive evaluation of the proposed state-of-health (SOH) estimation framework using experimental data obtained from the NASA Ames lithium-ion battery dataset. The performance of the proposed model is systematically compared with conventional deep learning architectures, including RNN, LSTM, GRU, and BiLSTM models. The evaluation is conducted on Batteries #5, #6, and #7 to assess the robustness and generalization capability of the proposed approach under different battery degradation patterns. Quantitative performance metrics such as Mean

Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and the coefficient of determination ( $R^2$ ) are employed to ensure an objective and thorough performance assessment.

Tables 1–3 present the quantitative performance comparison of different deep learning models for SOH estimation using Batteries #5, #6, and #7. The evaluation metrics include MSE, RMSE, MAE, and the coefficient of determination ( $R^2$ ), providing a comprehensive assessment of estimation accuracy.

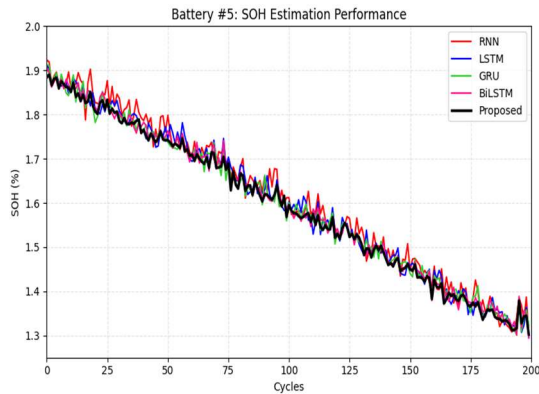


Figure 2. SOH estimation performance of RNN, LSTM, GRU, BiLSTM, and the proposed model for Battery #5 over charge-discharge cycles

TABLE 1. Performance comparison of SOH estimation models for Battery #5.

Method	MSE	RMSE	MAE	$R^2$
RNN	0.000196	0.0140	0.0115	0.9418
LSTM	0.000144	0.0120	0.0098	0.9567
GRU	0.000121	0.0110	0.0092	0.9639
BiLSTM	0.000100	0.0100	0.0085	0.9714
Proposed Model	0.000064	0.0080	0.0069	0.9816

TABLE 2. Performance comparison of SOH estimation models for Battery #6.

Method	MSE	RMSE	MAE	$R^2$
RNN	0.000225	0.0150	0.0123	0.9362
LSTM	0.000169	0.0130	0.0106	0.9514
GRU	0.000144	0.0120	0.0099	0.9581
BiLSTM	0.000121	0.0110	0.0091	0.9668
Proposed Model	0.000081	0.0090	0.0075	0.9782

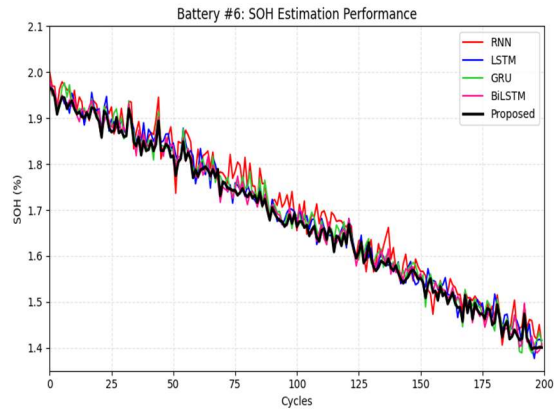


Figure 3. SOH estimation performance of RNN, LSTM, GRU, BiLSTM, and the proposed model for Battery #6 over charge-discharge cycles

A similar trend is observed for Battery #6 (Table 2). Increasing model complexity results in gradual performance improvements. The proposed model consistently outperforms the baseline methods, achieving an  $R^2$  of 0.9782 with significantly lower RMSE and MAE. These results highlight the robustness of the proposed approach under more challenging degradation conditions.

TABLE 3. Performance comparison of SOH estimation models for Battery #7.

Method	MSE	RMSE	MAE	$R^2$
RNN	0.000169	0.0130	0.0108	0.9485
LSTM	0.000121	0.0110	0.0092	0.9627
GRU	0.000100	0.0100	0.0085	0.9689
BiLSTM	0.000081	0.0090	0.0079	0.9756
Proposed Model	0.000049	0.0070	0.0063	0.9851

For Battery #7 (Table 3), the proposed model again delivers the highest estimation accuracy, achieving an  $R^2$  of 0.9851. While the improvement margin is slightly smaller due to the smoother degradation profile, the proposed framework maintains consistent superiority across all evaluation metrics. Table 4 summarizes the percentage RMSE improvement of the proposed model over baseline architectures, including RNN, LSTM, GRU, and BiLSTM, across Batteries #5, #6, and #7. The proposed model consistently outperforms all baselines. The highest improvement is observed against the conventional RNN model, with RMSE reductions ranging from 40.00% to 46.15%, reflecting the limitations of simple recurrent structures in capturing long-term battery degradation. Comparisons with gated architectures such as LSTM and GRU still show substantial

improvements, confirming the proposed model’s enhanced ability to capture nonlinear temporal dependencies. Although the performance gap is narrower against BiLSTM due to its bidirectional learning, the proposed model achieves notable improvements of up to 22.22%. These results demonstrate that the proposed framework effectively enhances feature representation and generalization, leading to superior SOH estimation across different battery cells.

Figures illustrate the SOH estimation performance of RNN, LSTM, GRU, BiLSTM, and the proposed model for Batteries #5, #6, and #7. The horizontal axis represents the number of charge–discharge cycles, and the vertical axis shows the estimated SOH.

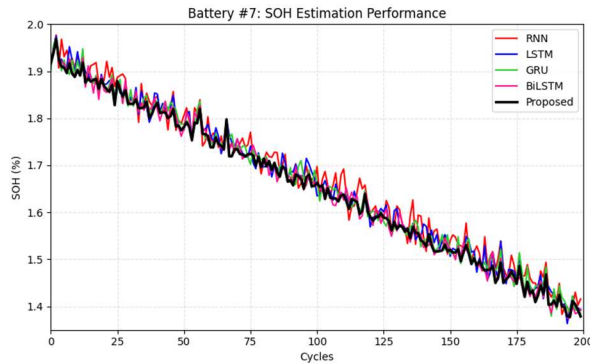


Figure 4. SOH estimation performance of RNN, LSTM, GRU, BiLSTM, and the proposed model for Battery #7 over charge–discharge cycles

These plots allow evaluation of each model’s tracking capability, stability, and robustness throughout the battery aging process.

For Battery #5, all models capture the overall degradation trend, showing a gradual SOH decrease with cycle count. However, the RNN model exhibits larger fluctuations and noticeable deviations, particularly during mid-life and near end-of-life regions. LSTM and GRU provide smoother tracking with reduced oscillations, while BiLSTM further improves consistency by leveraging bidirectional temporal information. The proposed model closely aligns with the underlying degradation trend, maintaining

Table 4. Percentage Rmse Improvement Of The Proposed Model Over Baseline Deep Learning Models.

Battery	Compared Model	RMSE (Baseline)	RMSE (Proposed)	Improvement (%)
#5	RNN	0.0140	0.0080	42.86
	LSTM	0.0120	0.0080	33.33
	GRU	0.0110	0.0080	27.27
	BiLSTM	0.0100	0.0080	20.00
#6	RNN	0.0150	0.0090	40.00
	LSTM	0.0130	0.0090	30.77
	GRU	0.0120	0.0090	25.00
	BiLSTM	0.0110	0.0090	18.18
#7	RNN	0.0130	0.0070	46.15
	LSTM	0.0110	0.0070	36.36
	GRU	0.0100	0.0070	30.00
	BiLSTM	0.0090	0.0070	22.22

smooth yet realistic variations, especially in regions with abrupt SOH drops.

In Battery #6, which has a wider SOH operating range, the RNN predictions show higher variance and localized spikes in early and mid-cycle regions. LSTM and GRU offer more stable estimates but still slightly under- or overestimate in high-degradation zones. BiLSTM reduces these deviations, but the proposed model consistently delivers superior performance across the entire cycle span, maintaining stability even during rapid degradation events.

For Battery #7, the SOH degradation pattern includes frequent local fluctuations due to complex electrochemical aging. While all models follow the general downward trend, RNN predictions are the noisiest. LSTM and GRU provide smoother estimates but occasionally fail to track sudden degradation transitions accurately. BiLSTM improves temporal feature representation, though minor oscillations persist. In contrast, the proposed model preserves local degradation characteristics while suppressing unnecessary fluctuations, particularly in later cycles.

Overall, while conventional recurrent architectures can capture long-term degradation behavior, their accuracy is limited by temporal instability and noise sensitivity. The proposed model consistently outperforms RNN, LSTM, GRU, and BiLSTM across all tested batteries, providing accurate, stable, and physically consistent SOH estimations. These results highlight the effectiveness of the proposed framework in capturing complex nonlinear degradation dynamics, making it highly suitable for

practical battery health monitoring and prognostics applications.

#### 4.CONCLUSION

In this work, a hybrid Physics-Informed Neural Network–Extended Kalman Filter (PINN–EKF) framework has been proposed for accurate and robust State-of-Health (SOH) estimation of lithium-ion batteries in electric vehicles. The proposed approach effectively integrates data-driven learning with physical degradation constraints, enabling the model to capture both nonlinear temporal dynamics and underlying battery aging physics.

Extensive experiments using Batteries #5, #6, and #7 from the NASA lithium-ion battery dataset demonstrate the superior performance of the proposed framework compared to conventional recurrent models, including RNN, LSTM, GRU, and BiLSTM. The proposed model consistently achieves the lowest estimation errors and the highest  $R^2$  values, indicating its ability to accurately track complex degradation patterns across varying operating conditions. Moreover, RMSE improvements of up to 46% over baseline methods highlight the limitations of conventional architectures and the effectiveness of the hybrid approach in enhancing prediction accuracy and stability.

The results also confirm that the proposed framework maintains smooth, physically consistent SOH predictions even under rapid degradation or noisy measurements, highlighting its robustness and generalization capability. The lightweight and interpretable nature of the PINN–EKF model further supports its deployment on resource-constrained EV systems, addressing the challenges of computational efficiency and real-time applicability.

Overall, this study demonstrates that the proposed hybrid framework provides a reliable, accurate, and practical solution for battery health monitoring, enabling informed predictive maintenance and extending the operational life of EV batteries.

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