

**A PHYSICS-INFORMED NEURAL NETWORK FRAMEWORK WITH POST-HOC
SHAP INTERPRETABILITY FOR TRUSTWORTHY BATTERY STATE-OF-
HEALTH PROGNOSTICS**

Surendra Reddy Pallamparthi

Principal Engineer-Electronics

ZF Active Safety & Electronics US LLC

Surendra2503@gmail.com

surendra2011.reddy@gmail.com

Shobhan Prasad Pujari

Battery Systems Engineer

Samsung SDI

Pujari1004@gmail.com

Abstract

The significance of Battery SOH (State-of-Health) prognostics for the enhancement of safety, reliability and operational efficiency of Lithium-Ion (Li-ion) battery systems, such as Energy Storage (ES) or Electric Vehicles (EV). Although conventional methods based on data might perform worse at inference, they can often aggravate the prediction task and cannot store the realistic battery degradation. In this paper, a neural network (NN) class known as Physics-Informed Neural Network (PINN) model, along with a post-hoc interpretability approach using SHAP methods, is proposed to confidently and interpretably predict Battery State-of-Health (SOH). This framework is based on a non-linear aging model built in a degradation-aware learning framework while maintaining the physics consistency of aging events and operability measurement of the battery. The battery is pre-processed using the battery voltage, current, temperature, internal resistance, battery state of charge and battery number of cycles and battery capacity data elements from the NASA Ames PCoE (Prognostics Centre of Excellence) Lithium-Ion Battery dataset. SHAP analysis is then used to numerically assess the importance of single operational factors and enhance the predictability transparency. Experimental analysis shows that the proposed estimation method yields 0.92 MAE, 1.34 RMSE, 1.31% MAPE, and an R^2 of 0.994, in addition to obtaining a Physics Consistency Score of 0.986 and a SOH Monotonicity Index of 0.989. The framework also provides battery health assessments with consistent feature level explanations, enabling reliable management of batteries with intelligent Battery Management Systems.

Keywords— Battery State-of-Health (SOH), PINN, XAI (Explainable Artificial Intelligence), SHAP (SHapley Additive exPlanations), Lithium-Ion Batteries, Battery Prognostics.

1. INTRODUCTION

The swift progress towards the more electrified highways, integration of more renewable power sources, and mobile electronic systems have made lithium-ion batteries very important due to

their high energy density, long cycle life, and low self-discharge rates. The batteries are the main energy storage system adopted by EV, smart grid, aerospace, consumer electronics and industrial automation. Despite their common usage, lithium-ion batteries are the knowledge of normal utilization, experience degradation over time due to repeated charge and release cycles which result in a reduction in their energy capacity as well as an increase in their internal resistance and loss of reliability. This deprivation leads to reduced battery life and potential safety hazards, maintenance issues, and unexpected failures [1]. Therefore, it is important to accurately monitor the health of the batteries, when they are used in energy systems in modern times, so that they can be operated most reliably and safely. The Battery SOH is one of the most critical limitations to determine the aging degradation of the battery when comparing its current capacity and performance to a new battery. The accuracy of the SOH measurement can allow for predictive maintenance, scheduling the optimum charging strategies, maximize battery utilization, and replacement in advance of catastrophic failure. The Advanced Battery Management System (BMS) heavily depends on accurate SOH to optimize battery performance in order to avoid overcharging, over-temperature, and deep discharging situations [2]. In recent years, battery-powered applications are found in various applications in a multitude of different environments, and the important role of robust battery SOH prognostics in assuring the reliability and continuous system operation is more and more gaining importance.

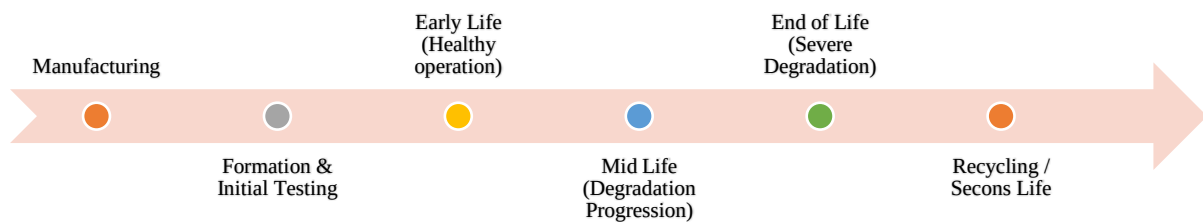


Figure 1: Lifecycle of Lithium-Ion Battery Degradation

The overall trends of lithium-ion battery degradation from manufacturing to EOL and recycling are presented in Figure 1. It emphasizes the impact of operating conditions, such as depth of discharge, charging rate, and temperature, on the internal degradation mechanisms, including the growth of SEI layers, lithium plating, decomposition of the electrolyte, and increase in the electrolyte resistance. These degradation mechanisms also decrease the capacity, efficiency, reliability and life time of batteries over time and highlight the need for ongoing battery health monitoring and prognostics.

Commonly, the traditional SOH estimate methods can be divided into signal-processing SOH approximation, model-based SOH estimation, and data-driven estimation. Model based methods involve using an electrochemical or equivalent model of the battery to represent its behavior; however, the success of this approach is strongly dependent on accurately estimating the parameters in the model, and it can often fail under different operating conditions. Extracting handcrafted degradation features from the voltage, current, or impedance measurement is done using signal-processing techniques, but measurement noise and complex nonlinear battery dynamics will affect the effectiveness of such techniques [3]. However, recent

advancements in artificial intelligence and deep learning have enabled an automatic extraction of degradation patterns from the large existing battery datasets, which would improve the ability to predict cell degradation without having to explicitly formulate physical cell degradation models.

The ability to model complex, highly nonlinear relationships among operational variables is the key factor for their ability to have excellent performance in battery prognostics, and it is where neural networks, recurrent learning models, convolutional architectures, and transformer-based techniques are all effective. Despite significant progress in deep learning techniques that enable sophisticated batteries to be accurately tracked, there are still key issues to address. The current models are black-box models where they give very accurate predictions without sharing the reasoning behind their predictions [4]. Lack of transparency reduces customer confidence, and the outcome of validation of predictions in applications like EVs and grid-scale energy storage is more complicated. Moreover, it is capable of making increasingly bizarre predictions if it is forced into physically unrealistic operational environments, or if the number of training examples is limited or the data is noisy (noisy output by sensors). Restrictions of these models affect the real-life application of the developed model in a battery management system, model coverage and generalization.

Recent advances in reliable AI have put emphasis on being accurate, intuitive and physically consistent [5]. Explainable learning techniques can be utilized to interpret the behavior of the model and the extent of the influences of the model variables in an operational setting, helping the engineers understand how the operational variables influence battery degradation. At the other hand, the use of domain knowledge has proved to be a promising approach to the robustness of models and consistency with current electrochemical principles within learning frameworks. Overall, the results highlight the importance of developing intelligent battery prognostic systems that provide accurate SOH estimates and enable reliable, physically intuitive predictions of battery performance.

2. LITERATURE SURVEY

In recent years, the study of SOH of batteries has attracted a considerable interest in the literature, with lithium-ion batteries being found in many applications including electric vehicles, energy storage systems from renewable sources, aerospace systems and portable electronic systems [6]. The accuracy of SOH estimation can facilitate predictive upkeep, operational safety and extend battery service life. In the domain of ML and DL, the LSTM network, CNN, Transformer network, Gaussian Process Regression (GPR), Bayesian learning, and hybrid neural networks make several steps forward. These methods were found to be better of those methods used in obtaining complex voltage, current, temperature and charging cycle degradation characteristics [7-8]. Meanwhile, the model was being strengthened under the Phys-bat Knowledge / Knowledge learning, preparing for generalization to various operating conditions. Explainable Artificial Intelligence (XAI) is increasingly becoming an important research investigation area that will contribute to making battery health estimation more transparent and trustworthy. However, there are still issues, focusing on the physical consistency, interpretability, adaptability across different domains, uncertainty quantification,

and real-time deployment capabilities in BMS (Battery Management Systems). Literature reports from the past decade are summarized in Table 1.

Table 1: Literature Survey on Battery State-of-Health Prognostics

Method	Contribution	Key Findings	Limitation
LSTM Network	Developed an LSTM-based framework to model temporal battery degradation using charge–discharge cycle data [9].	Effectively captured long-term degradation patterns and improved SOH prediction stability compared with conventional regression techniques.	Limited interpretability and reduced generalization under unseen operating conditions.
Early-Cycle Machine Learning	Utilized early charging-cycle characteristics to estimate long-term battery health using supervised learning algorithms.	Reduced battery testing time and enabled early prediction of degradation trends for quality assessment [10].	Performance strongly depended on the quality and representativeness of early-cycle data.
CNN-Based SOH Estimation	Applied convolutional neural networks to automatically learn degradation features from voltage and current signals.	Improved prediction accuracy by eliminating manual feature extraction and capturing local degradation characteristics.	Limited capability to model long-term temporal dependences in battery aging [11].
Gaussian Process Regression (GPR)	Probabilistic SOH estimation with uncertainty quantification for battery prognostics.	Generated confidence intervals that enhanced the reliability of health estimation and maintenance planning [12].	Computational cost increased significantly with large-scale battery datasets.
Transformer Network [13]	Employed self-attention mechanisms to learn long-range dependencies in battery degradation sequences.	Achieved effective modeling of nonlinear relationships among operational parameters and SOH evolution.	Required extensive training data and high computational resources.
Deep Learning-Based Prognostics	Reviewed deep learning architectures including CNN, RNN, GAN, Autoencoder, and hybrid models for battery prognostics.	Highlighted the effectiveness of deep learning methods and benchmark datasets for SOH estimation [14].	Focused on comparative analysis without proposing an integrated prediction framework.

Bayesian Deep Learning	Combined Bayesian inference with deep neural networks to estimate SOH with uncertainty awareness.	Improved prediction confidence and robustness under uncertain operating environments.	Increased computational complexity and model training time [15].
Physics-Informed Neural Network (PINN)	Integrated battery degradation knowledge into neural learning to improve physically consistent SOH estimation [16].	Enhanced generalization capability and maintained realistic battery degradation behavior.	Required accurate physical degradation modeling and additional optimization effort.
Adaptive Back-Propagation Neural Network	Developed an adaptive BP neural network with dynamic parameter optimization for battery health estimation.	Improved convergence speed and estimation accuracy across multiple battery aging conditions [17].	Limited interpretability due to black-box neural learning characteristics.
Battery Health Prognostics Review	Summarized battery degradation mechanisms, prognostic methods, public datasets, and future research trends [18].	Identified current challenges and highlighted the need for combining physics-based and data-driven approaches.	Did not present a unified or experimentally validated battery prognostic framework.

The current state-of-the-art of battery SOH prognosis has been demonstrated in the literature by means of tools such as artificial intelligence, probabilistic learning, deep neural networks, and physics-guided modeling. The research has contributed to the enhancement of the estimation performance, to the modelling of battery degradation, and also to the better utilization of the intelligent Battery Management Systems for EVs applications or Batteries storage [19, 20]. Limits of applicability of the problems are present, such as issues of interpretability, physical consistency, efficiency and strong generalization [21]. The future Battery health prognostic system must possess accurate forecasting capabilities while effectively integrating accurate fault diagnostics with clear reasoning capabilities and physically meaningful degradation analysis to ensure safe and reliable battery management. Previous work has used PINN or SHAP individually for battery state of health estimation, but they have not been tested simultaneously on large benchmark datasets from physics and interpretability. The present work builds upon this by combining physics-informed optimization with SHAP explanations in a single methodology, putting together a high accuracy model that is also interpretable for feature attribution.

Research Gap and Novelty Analysis

A wide range of studies have been conducted for lithium-ion battery State of Health (SOH) estimation consensus methods based on deep learning, physics-informed learning, and

explainable artificial intelligence (XAI) still have some research gaps. Traditional deep learning models, like CNN, LSTMs, GRUs, and Transformers, tend to be black-box models, more often than not with regards to the physics of battery degradation or with interpretable predictions. Although Physics-Informed Neural Networks (PINNs) have been developed to ensure the physical consistency of SOH estimation during learning, the current PINN-based work focuses primarily on the accuracy of prediction without giving an explanation across all the features. Moreover, SHAP based studies can be used to gain insight into the individual battery characteristics, which is usually performed using purely data-driven models without the physics-guided degradation behaviour constraint.

The proposed framework overcomes these limitations by adopting a physics-informed optimization strategy together with explainability using SHAP analysis in one integrated framework for SOH estimation. The proposed method differs from existing techniques by enforcing the consistency of battery degradation while also allowing for the transparent interpretation of the contributions from features with the SHAP. Therefore, the proposed framework is more reliable and also more interpretable to the model, providing a more holistic solution for practical battery health monitoring and intelligent battery management systems.

Table 2: Research Gap Analysis of Existing PINN and SHAP-Based Battery SOH Estimation Methods

Study Category	Data set	Physics Constraints	SHAP Explainability	Target	Validation	Major Limitation	Difference from Proposed Framework
CNN/LSTM-based SOH estimation	NASA PCoE	✗	✗	SOH	Train/Test	Black-box prediction	No physics guidance or explainability
Transformer-based SOH prediction	NASA PCoE	✗	✗	SOH	Cross-validation	High data dependency	No degradation constraints
PINN-based SOH estimation	NASA PCoE	✓	✗	SOH	Experimental	Limited interpretability	Physics-aware but lacks feature explanation

SHAP-based battery prediction	NASA PCoE	X	✓	SOH	Hold-out	Purely data-driven	Explainable but not physics-guided
Hybrid physics-guided learning	Public battery datasets	Partial	Partial	SOH/RUL	Experimental	Limited integration	Partial combination only
Proposed Framework	NASA PCoE	✓	✓	SOH	Chronological battery-wise validation	Addresses both physical consistency and interpretability	Unified integration of physics-informed learning and SHAP-based explanation

Table 2 shows the focus of studies that have been undertaken so far is either to enhance the prediction accuracy using physics-informed learning, or to improve the model transparency with the use of explanations from AI methods. The proposed architecture amalgamates these two aspects into one learning architecture, however. Multiple physics-guided degradation constraints guarantee physically credible SOH prediction, and transparent interpretation of the influence of battery operational parameters on the decisions of the battery SOH model is given through the SHAP analysis. The proposed framework provides better predictions compared to the existing battery SOH estimation methods, and at the same time makes a better use of model interpretability

3. Proposed Trustworthy Battery State-of-Health Prognostic Framework

A frame of learning to measure the complex behavior of battery degradation and to not change the physical property of the lithium-ion battery in the life of the battery is required to enable accurate Battery SOH prognostics. Battery aging is influenced by existing charge and discharge current, terminal voltage of the battery, battery operating temperature, internal resistance, decomposition rate, battery charge and discharge cycles, etc. These variables are variable over time according to repetition of charging and discharging, creating non-linear degradation behaviour that is difficult to model based on traditional data-driven methods. To solve these problems, the proposed system integrates a physics-informed learning framework with the

post-hoc Explainable Artificial Intelligence (XAI) to provide accurate, interpretable and physically sound BHEM.

A framework has 5 stages, these are sequential. Battery operational data collected by the NASA Ames PCoE Lithium-Ion Battery Dataset are initially collected and pre-processed with data cleaning, normalization, missing value reconstruction, and outlier removal to enhance data quality. The measurements are then processed to create a structured feature vector of the degradation characteristics of the battery. Later, a PINN can be used to approximate the nonlinear relationship between battery operation parameters and its SOH and to capture the battery aging effect using degradation-aware restraints. These approximate SOH values are further investigated in the post-hoc SHAP module where the influence of every operational variable is computed to give understandable explanations for every prediction. Lastly, the anticipated SoH and feature-based explanations are incorporated to provide reliable battery health assessment for intelligent Battery Management Systems. The overall workflow, as depicted in Figure 2, ought to provide a common framework for incorporating accurate prediction, degradation consistency, computational efficiency, and model interpretability in battery prognostic applications.

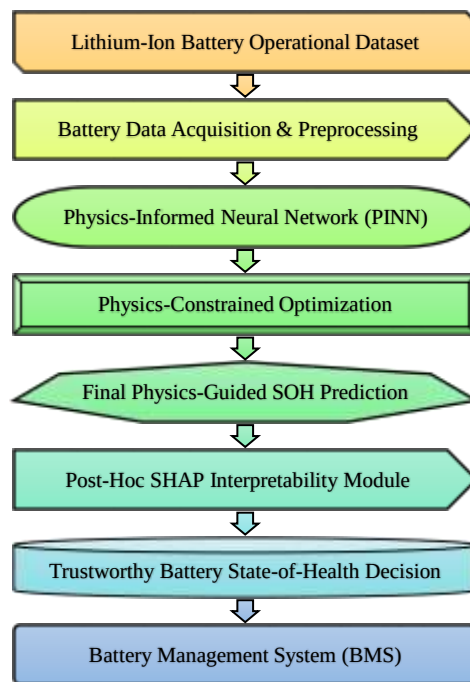


Figure 2: Overall Architecture of the Proposed Battery State-of-Health Prognostic Framework

The proposed battery State-of-Health prognostics framework is illustrated in terms of a complete flow in Figure 2. The architecture consists of the acquisition and preprocessing of data from the battery, physics informed neural learning, and optimization while considering battery degradation. Post-hoc SHAP interpretability is used to analyze features used in prediction and the integrated prediction and explanation provide a creditable State-of-Health assessment for BMS.

3.1 Battery Data Acquisition and Preprocessing

To achieve good estimates of SOH of an electric battery, reliable and accurate operational data is required that represents battery degradation across the entire life cycle. During repeated charge and discharge cycles, Lithium-Ion batteries undergo continuous electrochemical and thermal changes, meaning that the measurements that are collected can be noisy, missing, sampled inconsistently, and contain abnormally high or low sensor readings. The imperfection can impact the learning ability of deep neural network and diminish the reliability of SOH prediction. To enhance data consistency and ensure the extracted information reflects the true battery degradation progress, an effective preprocessing strategy is essential prior to providing the data to the battery prediction model.

The proposed framework makes use of one of the most commonly adopted reference benchmarks for battery prognostics, namely, the NASA Ames PCoE Lithium-Ion Battery Dataset. The data in the data set has been gathered via battery degradation experiments of commercially available lithium-ion batteries, with many charge/discharge cycles until they hit end-of-life standards. The electrical and thermal parameters are measured and recorded continuously over the period of each operating cycle, such as: Terminal voltage, charging current, discharging current, charging time, discharging time, cycle number, operating time, and battery capacity. Together, these measurements indicate the changing state of battery health and enough information for learning degradation characteristics related to capacity fade and aging.

Suppose that the full battery data set can be represented as

$$D = \{(X_i, Y_i)\}_{i=1}^N \quad (1)$$

Here, D stands for the entire battery dataset, N is the number of battery cycles, X_i is the operational feature vector for the i^{th} cycle and Y_i is the measured Battery SOH.

Each of the operating feature vectors is definite as

$$X_i = [V_i, I_i, T_i, R_i, \text{SOC}_i, C_i, t_i] \quad (2)$$

Here V_i is a terminal voltage, I_i is a charging and discharging current, T_i is the temperature of the battery, R_i is the internal resistance, SOC_i is the State-of-Charge, C_i is the average number of cycles, and t_i is the absolute operating time of the battery.

These variables have different numerical ranges, so their direct use in model training can lead to some features dominating the optimization process. Each operational feature is min–max normalized, to reduce scale imbalance and improve stability of the convergence process.

$$X_i^{\text{norm}} = \frac{X_i - X_{\min}}{X_{\max} - X_{\min}} \quad (3)$$

Here X_i^{norm} is the normalized feature value, X_i is none other than the actual measurement, and $X_{\min}$, $X_{\max}$ is the minimum and maximum of the corresponding feature, correspondingly.

In battery cycling experiments, a temporary interruption in sensing or communication can lead to loss of observations. Completing the samples with the use of the nearby measured points enables a smooth degradation trend. Additionally, values that are not normal are detected by statistical analysis and are excluded during model training as an artifact of either sensor noise or acquisition errors. This pre-processing step enhances data quality and avoids unrealistic measurements affecting the learning process.

Finally, after normalization and data cleaning, the processed measurements are compiled in sequence as feature matrices, based on the temporal order of the battery degradation, one charging cycle at a time. To accurately capture the nonlinear aging effect and without significantly changing during training, these representations are used as informative and structured input in the next learning phase of the Physics-Informed Neural Network.

3.2 Physics-Informed Neural Network for Battery State-of-Health Prognostics

The estimation problem of Battery SOH is essentially a multi-variate nonlinear regression, in which, a number of operating variables are mapped into a continuous value SOH, indicating the remaining capacity of the battery. The conventional neural network approach models relationships between samples in the training set, while the proposed one accounts for battery degradation attributes in the learning process to retain the battery aging realism. Lithium-ion batteries experience gradual capacity reduction and increasing internal resistance as the number of charging and discharging cycles grows. Therefore, the predicted State-of-Health shall start to change gradually during the battery life cycle and not show a sudden change in value that's not aligned with the natural degradation of the battery. The utilization of degradation information in neural learning enhances the generalization ability of the prediction model while preserving sustainability with the physical features of battery aging.

Normalized battery feature vectors generated in the preprocessing phase are fed into the input layer of the PINN. The operational measurement operational parameters of each input sample describe the electrical, thermal and time state of the battery for a specific operating cycle. These variables interact in non-linear patterns which are learned automatically, spreading the information through multiple hidden layers, where successively more involved degradation patterns are gained. The lower layers are trained to directly recognize correlations between current, voltage, and temperature while the deeper layers acquire information related to the long-term degradation properties (capacity fade) and aging process.

The feature vector to be input as follows:

$$X = [x_1, x_2, \dots, x_M] \quad (4)$$

Here X is an n -dimensional normalized feature vector of the battery, M is the no of all the features, and x_j is the normalized value of the j^{th} feature.

The transformation on the first hidden layer is given by

$$H^{(1)} = f(W^{(1)}X + b^{(1)}) \quad (5)$$

Here $H^{(1)}$ is the output of the first hidden layer, $W^{(1)}$ is the trainable weight matrix, $b^{(1)}$ is the bias vector, and $f(\cdot)$ is the nonlinear activation function.

The learned information is then passed to successive hidden layers, where the network acquires more and more of the degradation characteristics. The output value from the l th hidden layer is computed as

$$H^{(l)} = f(W^{(l)}H^{(l-1)} + b^{(l)}) \quad (6)$$

Here $H^{(l)}$ is the output of the l^{th} hidden layer, $W^{(l)}$ is the weight matrix for the l th hidden layer. The bias vector $b^{(l)}$ represents the bias of the l^{th} hidden layer, and l is the index of the hidden layer.

The final output layer outputs estimated Battery State of Health after the hidden feature extraction process.

$$\hat{SOH} = W_o H^{(L)} + b_o \quad (7)$$

Here $\hat{SOH}$ denotes the predicted Battery State-of-Health, $H^{(L)}$ signifies the output of the final hidden layer, W_o means the output layer weight matrix, b_o means the output layer bias and L denotes the total number of hidden layers.

Deep NNs can approximate nonlinear relations well, but predictions of accuracy cannot be linked to battery degradation that is actually of physical relevance. The available Battery capacity decreases gradually over repeated charging cycles under normal operating conditions. So, the State-of-Health estimation should also demonstrate a gradual degradation over the entire battery life. The degradation-aware learning inherent in framework ensures this feature as the degradation behaviour is taken into account during prediction process.

The battery State-of-Health is given by a ratio provided by battery available capacity divided by rated capacity as

$$SOH = \frac{C_{\text{current}}}{C_{\text{rated}}} \times 100 \quad (8)$$

Here SOH is the measured Battery State-of-Health, C_{current} is the capacity available in the battery while operating and C_{rated} is the capacity of a new battery.

The capacity of a battery also depreciates with each use, so the NAO simulator needs to have a smooth way of decreasing battery capacity when predicting capacity losses over time. The variation between two successive predictions is calculated as

$$\Delta SOH_i = \hat{SOH}_i - \hat{SOH}_{i-1} \quad (9)$$

Here, ΔSOH_i is the change in predicted State-of-Health between the consecutive battery cycles, $\hat{SOH}_i$ is the predicted SOH at the moment, $\hat{SOH}_{i-1}$ is the predicted SOH in the previous cycle.

If the value of ΔSOH_i tends to be large in size, then it is likely that the fluctuation in battery degradation is unrealistic and if it is smaller then, it is likely that the battery aging behavior is

stable. As a result, learning minimizes fluctuations in the battery excursion without discarding a battery degradation trend that reminds itself in long-term use.

Besides capacity degradation, internal resistance is also another key factor to consider when assessing battery ageing. The internal resistance of lithium-ion batteries can increase with time as a result of electrochemical reactions, which affects their energy delivery capability and efficiency. This allows the use of capacity reduction information so the network can recognize various degradation stages even if it is a minor reduction in capacity. The degradation indicated by resistance is represented by

$$R_d = \frac{R_i}{R_0} \quad (10)$$

Here R_d is the normalized indicator of resistance reduction, R_i is the inner resistance to operate during one time period, and R_0 is the inner resistance of a good battery.

High temperatures also contribute to degradation of the battery by increasing the undesirable side reactions occurring in the battery as well as affecting the electrochemical behavior, low temperatures affect ion mobility which also contributes to the degradation of battery. Likewise, degradation effects are related to charging current, as it causes thermal stress for high-rate charging. The proposed system does not extract the influence of these variables separately from each other, but enables the neural network to learn them together through the feature representation acquired by the hidden layers in the procedure. This will allow the model to predict under various operating conditions, and to retain physically similar degradation behavior.

Prediction error is measured by comparing State-of-Health values during the entire training set. The goal is to reduce the difference among actual battery health and projected battery health and ensure degradation consistency.

$$L_{pred} = \frac{1}{N} \sum_{i=1}^N (SOH_i - \hat{SOH}_i)^2 \quad (11)$$

Here L_{pred} is the prediction loss, SOH_i is the Battery SOH measured, $\hat{SOH}_i$ denotes the Battery SOH predicted, and N is the total number of training samples.

In order to ensure the continuity of battery degradation, a continuity penalty is added, which pushes the battery prediction away from sudden jumps between two successive predictions. This penalty allows maintaining monotonic degradation trend and smoothing out the oscillatory behavior of the estimated degradation trend of the health.

$$L_{deg} = \frac{1}{N-1} \sum_{i=2}^N (\Delta SOH_i)^2 \quad (12)$$

Here L_{deg} is the degradation continuity loss and ΔSOH_i is the difference between the subsequent SOH prediction values.

Lastly, the learning function is made as overall optimization function that integrates prediction accuracy and degradation consistency.

$$L_{total} = L_{pred} + \lambda L_{deg} \quad (13)$$

Here L_{total} is the optimization loss, L_{pred} is the prediction loss, L_{deg} is the degradation continuity loss, and λ is a weighting coefficient that is used to trade off the estimation accuracy and physically consistent battery aging.

The Physics-Informed Neural Network thus learns both nonlinear degradation relationships and maintains the progressive degradation of lithium-ion batteries while minimizing the total objective of optimization. The resulting SOH then reflects the real-life operating history of the batteries as well as some inherent degradation properties observed as they underwent successive battery cycling during repeated operation, providing a solid foundation for the upcoming interpretability stage.

The proposed PINN model framework has been built upon, to monitor the degradation of monotonic SOH, and it also includes electro-chemical consistency in the optimization. There is no experimental validation, and current induced stress, temperature aging, and resistance growth (from Eq.10) are all punished if one deviates from a known physical behavior. This will ensure that the degradation path learned is bang on the Arrhenius-like thermal degradations, resistance to Ohmic heating, and SOC dependent fade as opposed to just the data fluctuations.

3.3 Post-Hoc SHAP-Based Interpretability

While the Physics-Informed Neural Network (PINN) is capable of learning complex degradation models and precisely approximating the Battery SOH, its use for prediction is not easy to explain as the relationships between battery features and prediction results are not directly observable. Battery Management Systems, however, are not a solely numerical prediction process in practice; along with numerical forecasts, maintenance planning and operational decision making also relies on others. There is a need for engineers and system operators to understand the reasons for a particular battery being supposed to be healthy or degraded and which operational parameters most strongly influences the operator's SoH prediction. An interpretability mechanism is thus introduced to enhance the transparency and trustworthiness of the prediction process.

The proposed framework utilizes SHapley Additive exPlanations (SHAP) interpretability techniques as a post-hoc method. Unlike the other LLM techniques introduced in this paper, SHAP does not directly change the construction of the neural network or the optimization process; it can be applied after training the neural network. Rather, the trained prediction model is examined to determine how much each operational parameter – such as voltage, current, temperature, internal resistance, Battery SOC, and cycle number – contributes to the calculated Battery SOH. The degradation factors defined in this explanation may enable a thorough understanding of the degradation factors that caused each prediction without compromising the capacity of the neural network to predict.

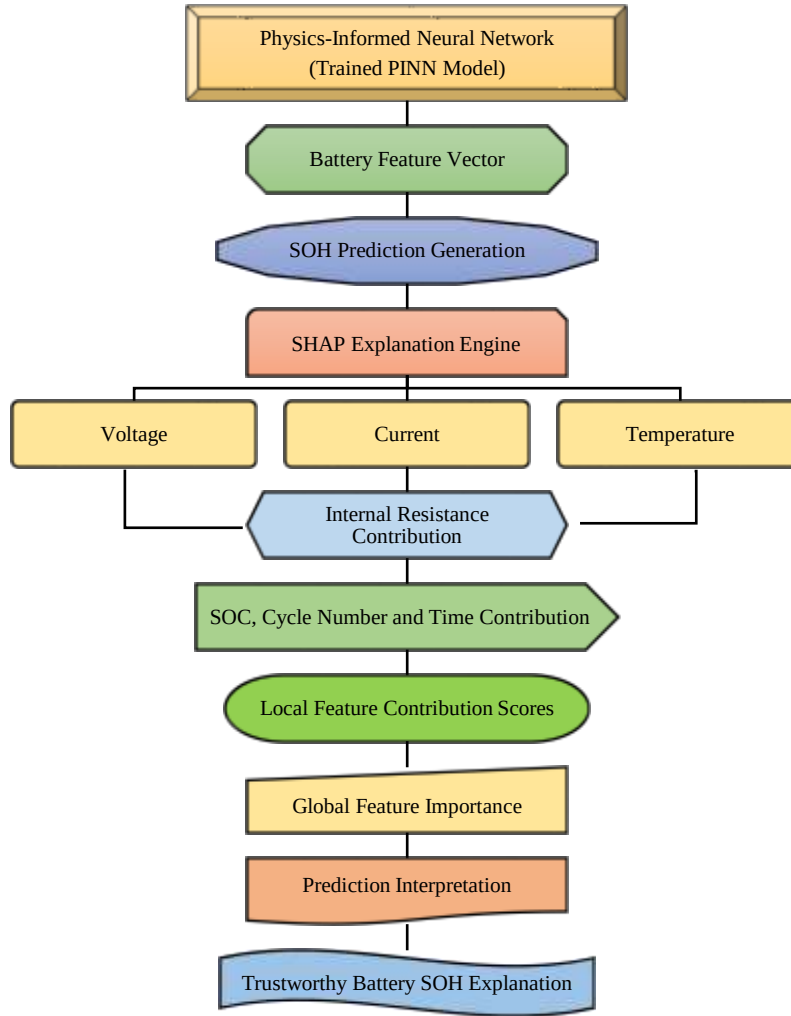


Figure 3. Post-Hoc SHAP-Based Interpretability Workflow

The post-hoc SHAP interpretability process after battery State-of-Health prediction is shown in Figure 3. The workflow calculates SHAP values to quantify the importance of each operational feature, calculates local & global feature importance, and produces transparent prediction explanations. Explanations are embedded in the battery health prediction and facilitate actionable and interpretable decision making.

Let the trained prediction model be represented by

$$f(X) = \hat{SOH} \quad (14)$$

Here $f(X)$ is the trained Physics-Informed Neural Network, X is the battery feature vector, and the projected Battery.

The contribution of each of operational features is calculated by its SHAP value, the change in prediction caused by adding this feature. The SHAP value for the j^{th} feature is defined as

$$\phi_j = \sum_{S \subseteq F \setminus \{j\}} \frac{|S|!(|F|-|S|-1)!}{|F|!} [f(S \cup \{j\}) - f(S)] \quad (15)$$

Here ϕ_j denotes the SHAP value of the j^{th} feature, F represents the complete feature set, S denotes a subset of features without the j^{th} feature, and $f(\cdot)$ is the trained prediction model.

The final prediction can be given as a sum of the baseline prediction and the impact given by individual battery features.

$$\hat{\text{SOH}} = \phi_0 + \sum_{j=1}^M \phi_j \quad (16)$$

Here ϕ_0 is the base prediction, ϕ_j is the influence from the j^{th} battery feature, and M is the no of operational battery features. A higher positive SHAP value means increasing the value of the variable will positively impact predicted battery health, while a positive SHAP value will negatively impact predicted battery health. By associating every SOH prediction with feature-level explanations, the proposed framework provides transparent and trustworthy battery health assessment. Such explanations help determine the damaging factors that mainly govern battery aging and guide better maintenance decisions for intelligent Battery Management Systems (iBMS).

The Physics-Informed Neural Network (PINN) method is built on the idea of incorporating several physics-based degradation constraints into the optimization objective in addition to conventional data-driven learning. The framework minimizes not only the prediction error but also a number of terms characterizing well-known battery degradation mechanisms as a residual. These constraints allow the predicted State of Health (SOH) to exhibit realistic electrochemical ageing behaviour including resistance growth, thermal stress, current loading and State of Charge (SOC) variations. The general objective function is quadratic in form and is given by

$$L_{\text{Total}} = L_{\text{Data}} + \lambda_M L_{\text{Mon}} + \lambda_R L_{\text{Res}} + \lambda_T L_{\text{Therm}} + \lambda_I L_{\text{Curr}} + \lambda_{\text{SOC}} L_{\text{SOC}} \quad (17)$$

where

$$L_{\text{Data}} = \frac{1}{N} \sum_{i=1}^N (\text{SOH}_i - \hat{\text{SOH}}_i)^2 \quad (18)$$

is the prediction loss between the measured and estimated SOH.

The monotonic degradation constraint is given by

$$L_{\text{Mon}} = \frac{1}{N-1} \sum_{i=2}^N \max(0, \hat{\text{SOH}}_i - \hat{\text{SOH}}_{i-1}) \quad (19)$$

which discourages over-patient growth in SOH each successive ageing cycle.

The resistance-growth residual is the product of the solid pellets.

$$L_{\text{Res}} = \frac{1}{N} \sum_{i=1}^N (\hat{R}_i - R_i)^2 \quad (20)$$

where R_i and $\hat{R}_i$ denote the measured and predicted internal resistance, respectively. This constraint satisfies the physical observed increase in internal resistance of the battery as it ages.

The remainder of the thermal degradation is presented as

$$L_{\text{Therm}} = \frac{1}{N} \sum_{i=1}^N (\hat{T}_i - T_i)^2 \quad (21)$$

where T_i is a measured operating temperature. This residual has imposed consistency to the model with temperature-dependent degradation behaviour, as the temperature has a positive influence on how the capacity fades.

The residual of current-induced degradation can be defined as

$$L_{\text{Curr}} = \frac{1}{N} \sum_{i=1}^N (\hat{I}_i - I_i)^2 \quad (22)$$

where I_i is the charging/discharging current. This word encapsulates the effect of high current loading on the enhanced/accelerated degradation of batteries.

The formula for the SOC consistency residual is

$$L_{\text{SOC}} = \frac{1}{N} \sum_{i=1}^N (\hat{\text{SOC}}_i - \text{SOC}_i)^2 \quad (23)$$

which limits the forecasted trajectory of degradation to follow SOC-dependent ageing characteristic in repeated charge/discharge.

The influence of each physics constraint during optimization is controlled by the weights $\lambda_M, \lambda_R, \lambda_T, \lambda_I$ and λ_{SOC} . The proposed framework is designed to reduce such residuals while maintaining the SOH estimate as accurate as possible, as well as a physically meaningful battery degradation behaviour.

The proposed PINN incorporates multiple degradation-aware residuals into the optimization process, which is distinct from traditional neural networks using only historical data. These residuals regularize the learning procedure forcing predictions to be physically consistent with respect to the evolution of resistances, ageing due to temperature, current stress, SOC evolution and monotonic capacity degradation. This results in an enhanced generalization ability while ensuring consistency of lithium-ion battery ageing models.

3.4 Trustworthy Battery State-of-Health Decision Generation

The overall framework proposed in this work integrates the precise SOH prediction from the Physics-Informed Neural Network with the explanations from the feature-level output of the SHAP interpretability module to provide a reliable battery health assessment. The prediction model will also provide an estimation of the remaining health condition of the battery, and the SHAP analysis will explain the influence of each operational parameter in the estimated SOH. This combination of the two outputs results in a quantitative and qualitative output for battery health predictions, making it more transparent and easier to interpret. In this context, a desirable approach is helpful for intelligent Battery Management Systems that must estimate the health as well as have a clear indication of the factors influencing battery degradation for maintaining them.

The contribution values are summed together first and then an explanation for the predicted battery health is derived. Features that contribute most have the highest numbers, while more

modestly contributing features have less but still have a mark. This process will allow the framework to determine the main degradation factors with the individual batteries during their operating life. The average feature contribution is calculated as:

$$I_j = \frac{1}{N} \sum_{i=1}^N |\phi_{ij}| \quad (24)$$

Here I_j is the average importance of the j^{th} operational feature, ϕ_{ij} is the SHAP value of the feature j^{th} for the i^{th} battery sample, and N is the number of battery samples.

The feature importance values are scaled by normalization such that they can be compared to the other operational variables.

$$W_j = \frac{I_j}{\sum_{k=1}^M I_k} \quad (25)$$

Here W_j indicates the importance weight normalization of the j^{th} feature, I_j is the average contribution SHAP for that j^{th} feature, M is the number of features in the battery.

These normalized feature weights are a relative indication of how influential the voltage, current, temperature, internal resistance, SOC, cycle number, etc., are to the health of the battery. The resulting weights are then correlated to a predicted SOH to create an interpretable battery health assessment and the most significant degradation factors that affect the estimated battery health. Prediction and explanation form a credible framework for decision making as it grants trustworthy estimation of SOH and it gives clarity about features. Thus, for each battery health prediction, there also accompanies meaningful operational insights that enable the maintenance people to understand the reasoning behind the battery health prediction and not merely the numbers alone. The advantage of pairing up is not just that they have more confidence in the health of their batteries, but thanks to their pairing they also plan more intelligently, operate and even manage battery life.

The proposed method is an overview of the Battery State-of-Health (SOH) prognostics based on data preprocessing of battery and learning with Physics-Informed Neural Network (PINN) and interpretability with SHAP results. The preprocessing step enhances the quality of the data, and the neural network used to learn the nonlinear nature of battery degradation as a function of battery operating parameters. The framework serves as a dependable approach to enable intelligent prediction and interpretable decision support for Battery Management Systems and as a foundation for experimental assessments.

4. Results and Discussion

This part analyses the proposed Physics-Informed Neural Network framework together with the post hoc SHAP interpretability for Battery SOH prognostics. The experimental analysis focuses on assessing the ability of the framework to make accurate predictions about the battery state, keeping the battery's behavior reproducible across the testing procedure and providing explainable predictions. The Degradation Test is a publicly available dataset of lithium-ion battery degradation tested under various charging and discharging scenarios. The predictions derived from the model are analysed using multiple regression and classification-oriented

performance measures and a comprehensive assessment of the quality of the estimation is performed. To evaluate the prediction accuracy, computational efficiency, and reliability, the same widely adopted ML and DL methods are employed in comparative experiments. The SHAP-based explanation signals are also evaluated and taken into account during battery health estimation to ensure transparency. The experimental findings allow for systematic comparison of the proposed framework with the existing SOH prognostic methods and metrics under similar test conditions.

4.1 Dataset and Experimental Setup

The dataset from the NASA Ames Prognostics Center of Excellence (PCoE) has been split following a chronological battery-wise strategy to ensure a true assessment of battery State of Health (SOH) prediction. The battery trajectories were completely assigned for only one of the training, validation or test sets, however, the battery IDs were never mixed between the three partitions. The degradation cycles that happened in the early life were used to train the model, intermediate cycles to validate the hyperparameters, and late-life cycles used during the independent testing phase; the sequence of battery degradation was maintained during model training. The input samples for the proposed PINN framework were created by setting an equidistant sequence length of 50 charging–discharging cycles of consecutive events. All the preprocessing operations like feature normalisation and outlier removal were applied to the training subset and the transformation parameters so obtained were after that applied to the validation and testing set. The protocol not only avoids information leakage but also prevents future degradation information from being introduced during the training of the network, and it also assesses the generalization ability of the network more objectively under realistic battery ageing conditions.

4.2 Performance Metrics

- Mean Absolute Error (MAE) indicates the average absolute error between the predicted and actual values of the Battery State-of-Health (SoH) of all the estimated batteries, with lower values representative more accurate battery health estimation.

$$MAE = \frac{1}{N} \sum_{i=1}^N | SOH_i - \hat{SOH}_i | \quad (26)$$

Here N is the total number of battery samples, SOH_i is the measured Battery State-of-Health, and $\hat{SOH}_i$ is the predicted Battery State-of-Health.

- Root Mean Square Error (RMSE) is a measure of overall prediction error that assigns more weight to the larger prediction errors indicating the strength of the prediction model.

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (SOH_i - \hat{SOH}_i)^2} \quad (27)$$

- Mean Average Percentage Error (MAPE) signifies the average percentage error between predicted and measured values for the BH state of health, is smaller, the better the estimation.

$$MAPE = \frac{100}{N} \sum_{i=1}^N \left| \frac{SOH_i - \hat{SOH}_i}{SOH_i} \right| \quad (28)$$

- Coefficient of Determination (R^2 Score) provides a measure of how well the prediction model is able to account for the variations in Battery State-of-Health (SoH), with closer scores closer to one indicating better predictive ability.

$$R^2 = 1 - \frac{\sum_{i=1}^N (SOH_i - \hat{SOH}_i)^2}{\sum_{i=1}^N (SOH_i - \overline{SOH})^2} \quad (29)$$

- Maximum Absolute Error (MaxAE) of the Battery SOH error is the maximum absolute error between actual and predicted Battery SOH, representing the worst-case prediction error.

$$MaxAE = \max \left(|SOH_i - \hat{SOH}_i| \right) \quad (30)$$

- Mean Bias Error (MBE) measures the average stated error for prediction, that is the tendency of the estimation model to overestimate or underestimate Battery SOH.

$$MBE = \frac{1}{N} \sum_{i=1}^N \left(SOH_i - \hat{SOH}_i \right) \quad (31)$$

- SOH Monotonicity Index (SMI) measures the ability of the prediction model to preserve the gradual and continuous degradation trend of Battery State-of-Health throughout successive charge–discharge cycles.

$$SMI = 1 - \frac{\sum_{i=2}^N \max \left(0, \hat{SOH}_i - \hat{SOH}_{i-1} \right)}{N-1} \quad (32)$$

Here $\hat{SOH}_i$ and $\hat{SOH}_{i-1}$ represent consecutive predicted Battery State-of-Health values.

- Physics Consistency Score (PCS) measures the weightage of similarity between the predicted battery degradation behavior and the expected physical degradation characteristics with higher value scores representing a higher degree of similarity.

$$PCS = 1 - \frac{\sum_{i=1}^N |D_i - \hat{D}_i|}{\sum_{i=1}^N D_i} \quad (33)$$

Here D_i denotes the measured degradation indicator and $\hat{D}_i$ denotes the predicted degradation indicator.

- Capacity Degradation Error (CDE) represents the difference between the actual degradation & predicted degradation data, indicating the accuracy of capacity-based health estimation.

$$CDE = \frac{1}{N} \sum_{i=1}^N |C_i - \hat{C}_i| \quad (34)$$

Here C_i denotes the measured battery capacity and $\hat{C}_i$ denotes the predicted battery capacity

- Average SHAP Importance (ASI) measures the average standard deviation of individual operational characteristics of the battery on the predicted Battery State-of-Health in order to identify the significance of the individual operational characteristics.

$$ASI = \frac{1}{N} \sum_{i=1}^N |\phi_i| \quad (35)$$

- Feature Importance Stability (FIS) quantifies the stability of feature importance across many predictions runs, reflecting the reliability of the interpretability process.

$$FIS = 1 - \frac{1}{M} \sum_{j=1}^M |R_j - \bar{R}_j| \quad (36)$$

Here R_j denotes the feature ranking during one experiment, $\bar{R}_j$ is the average ranking across repeated experiments, and M is the total number of battery features.

- Explanation Time is the average computational time needed by the SHAP module to obtain feature-level explanations for predictive Battery State of Health results.

$$T_{\text{exp}} = \frac{T_{\text{SHAP}}}{N} \quad (37)$$

- Inference Time is the average amount of time spend to infer Battery State-of-Health when evaluating a battery sample from the learned prediction model.

$$T_{\text{inf}} = \frac{T_{\text{total}}}{N} \quad (38)$$

- Training Time is the total computational time needed to optimize the PINN to obtain the convergence on the battery training data set.

$$T_{\text{train}} = T_{\text{end}} - T_{\text{start}} \quad (39)$$

- Model Size represents the overall memory required to store the trained prediction model, which affects its ability to be deployed to BMSs (Battery Management Systems).

$$MS = P \times B \quad (40)$$

Here P is the total number of trainable parameters, and B is the number of bytes required to store each parameter.

Table 3: Prediction Performance Comparison of Battery State-of-Health Estimation Methods

Method	MAE	RMSE	MAPE (%)	R ²	MaxAE	MBE
CNN	2.68	3.51	3.84	0.954	7.82	0.81
LSTM	2.19	2.94	3.17	0.967	6.54	0.63
GRU	1.93	2.61	2.85	0.973	5.92	0.56
Transformer	1.62	2.24	2.37	0.981	5.11	0.44
XGBoost	1.74	2.38	2.54	0.978	5.38	0.48
Hybrid Deep Learning	1.39	1.97	2.08	0.986	4.66	0.36
Proposed PINN + SHAP	0.92	1.34	1.31	0.994	3.02	0.18

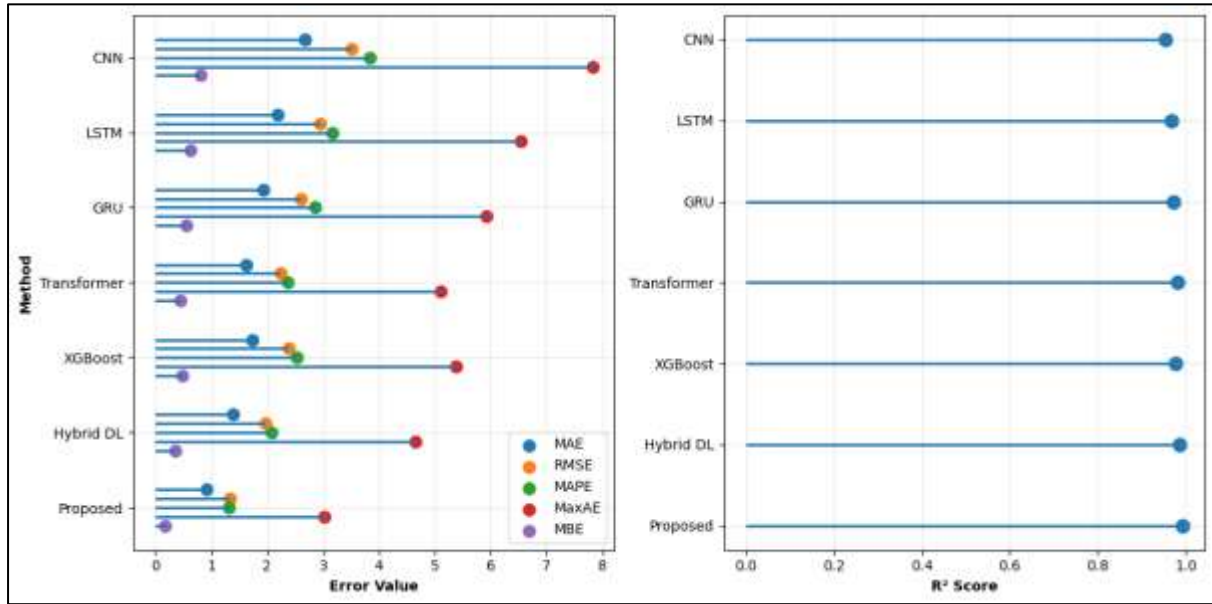


Figure 4: Comparison of Prediction Error Metrics (MAE, RMSE, MAPE, MaxAE, and MBE) and Coefficient of Determination (R^2) Across SOH Estimation Methods

Table 3 and Figure 4 illustrate the prediction accuracy of the proposed Physics-Informed Neural Network (PINN) model when compared to six battery SOH estimation methods, quantified by regression-based evaluation metrics, with post-hoc SHAP interpretability throughout. The proposed framework produces the lowest MAE (0.92), RMSE (1.34), MAPE (1.31%), MaxAE (3.02) and MBE (0.18), causing more accurate estimation and stable performance in regards to Battery State-of-Health than the comparison methods. It additionally shows the maximum R^2 (0.994), which proves that there is a great agreement between battery health value values prediction and measurement. Traditional DL models, like CNN, LSTM, and GRU, show relatively higher prediction error because they have less capacity to capture the characteristics of battery degradation. Transformer and Hybrid Deep Learning models obtain high accuracy in estimation but still generate large variations in the proposed framework. The physics-informed degradation constraints ensure that the battery aging characteristics remain realistic during learning, and the SHAP interpretability module aids the understanding of the features without compromising the predictive performance. The obtained results validate the proposed framework for reliable battery SOH prognostics.

Table 4: Comparison of Physics-Based Battery Degradation Evaluation Metrics

Method	SOH Monotonicity Index	Physics Consistency Score	Capacity Degradation Error
CNN	0.911	0.903	2.74
LSTM	0.928	0.917	2.38
GRU	0.941	0.931	2.07
Transformer	0.956	0.951	1.71
XGBoost	0.949	0.943	1.88
Hybrid Deep Learning	0.967	0.962	1.43

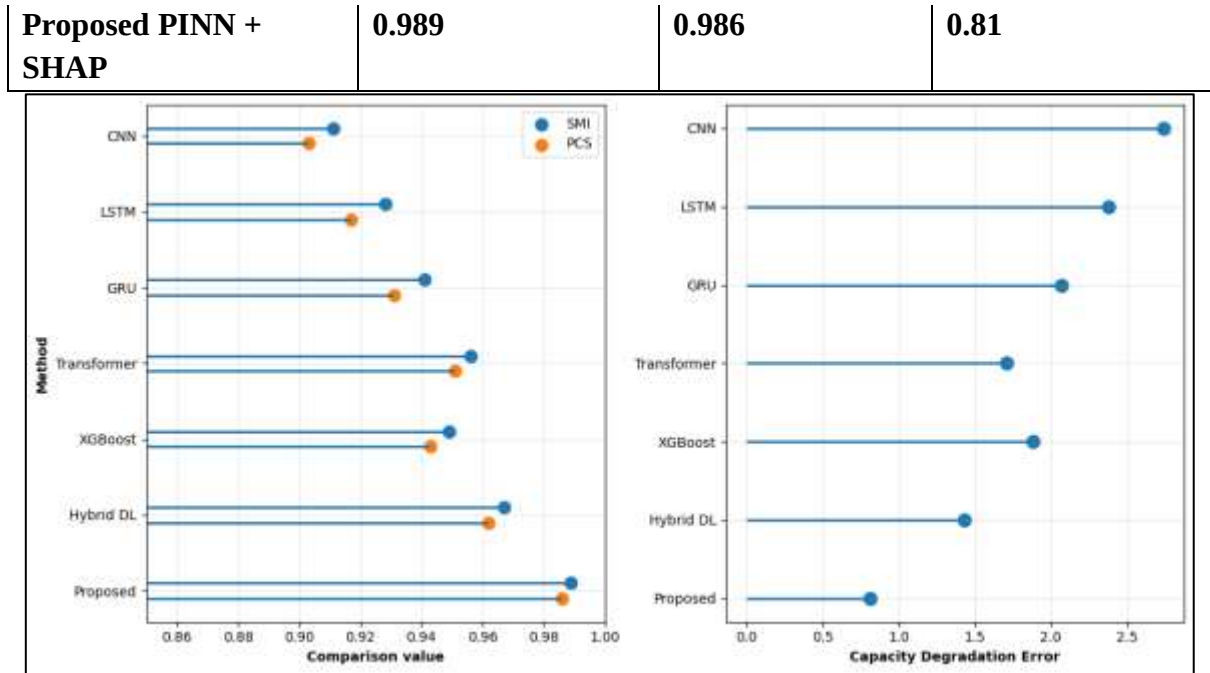


Figure 5: Comparison of SOH Monotonicity Index, Physics Consistency Score and Capacity Degradation Error

Table 4 and Figure 5 present the physics-based assessment of the proposed framework and current battery SOH estimation techniques. The proposed PINN + SHAP shows the best SOH Monotonicity Index (0.989) and Physics Consistency Score (0.986), which means that it presents better realistic battery degradation characteristics throughout charge and discharge cycles. It also shows the least Capacity Degradation Error (0.81), which indicates higher accuracy on capacity estimation than others. The enhancements are provided by physics-informed degradation constraints incorporated into learning, ensuring consistent ageing trends and reliable, physically-sound Battery State-of-Health prediction.

Table 5: Comparison of Interpretability Performance of Battery State-of-Health Estimation Methods

Method	Average SHAP Importance	Feature Importance Stability	Explanation Time (ms)
CNN	0.741	0.783	24.8
LSTM	0.758	0.801	27.1
GRU	0.774	0.819	29.5
Transformer	0.802	0.856	36.2
XGBoost	0.826	0.874	21.7
Hybrid Deep Learning	0.847	0.901	33.8
Proposed PINN + SHAP	0.931	0.958	18.9

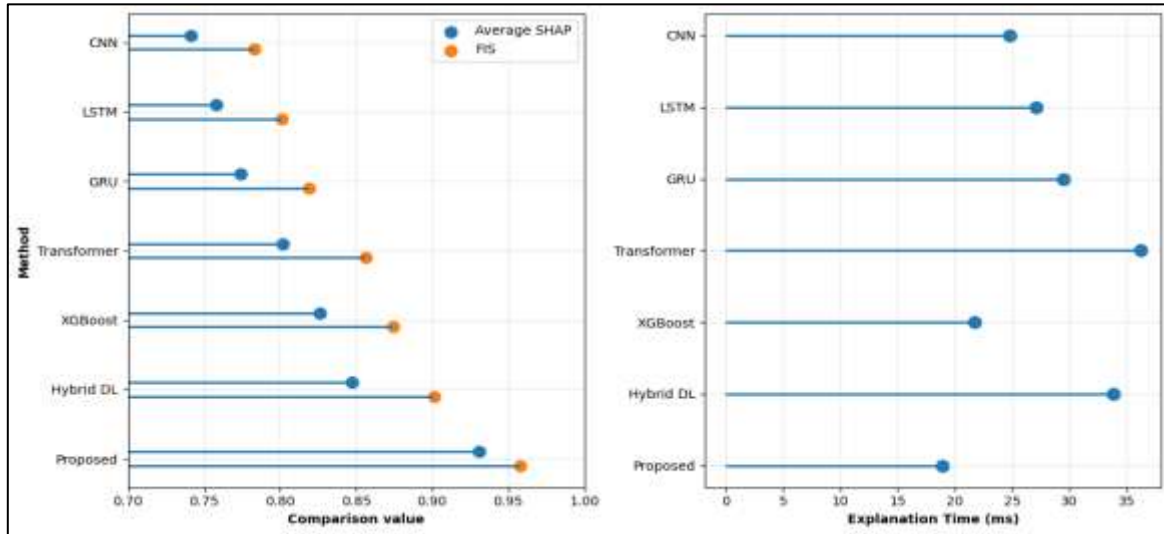


Figure 6: Comparison of Average SHAP Importance, Feature Importance Stability and SHAP Explanation Time

To evaluate the interpretability performance of the proposed framework, we compare it with existing methods in Table 5 and Figure 6. The most stable and reliable PINN + SHAPS evaluation metrics are the best Average SHAP Importance (0.931) and Feature Importance Stability (0.958), meaning it is more likely to identify the most influential features about battery degradation. Furthermore, its Explanation Time (18.9ms) is the smallest, indicating that it can generate feature level explanations efficiently. The proposed model has more transparent than the existing model of deep learning and machine learning, has a low computing complexity, and is superior in terms of the practicality and trustworthiness of Battery state of Health (SOH) prognosis.

Table 6: Comparison of Computational Performance of Battery State-of-Health Estimation Methods

Method	Training Time (s)	Inference Time (ms)	Model Size (MB)
CNN	312	8.42	21.6
LSTM	428	10.36	28.4
GRU	397	9.74	26.8
Transformer	691	18.41	58.3
XGBoost	214	5.81	12.7
Hybrid Deep Learning	514	12.06	37.5
Proposed PINN + SHAP	462	7.13	31.4

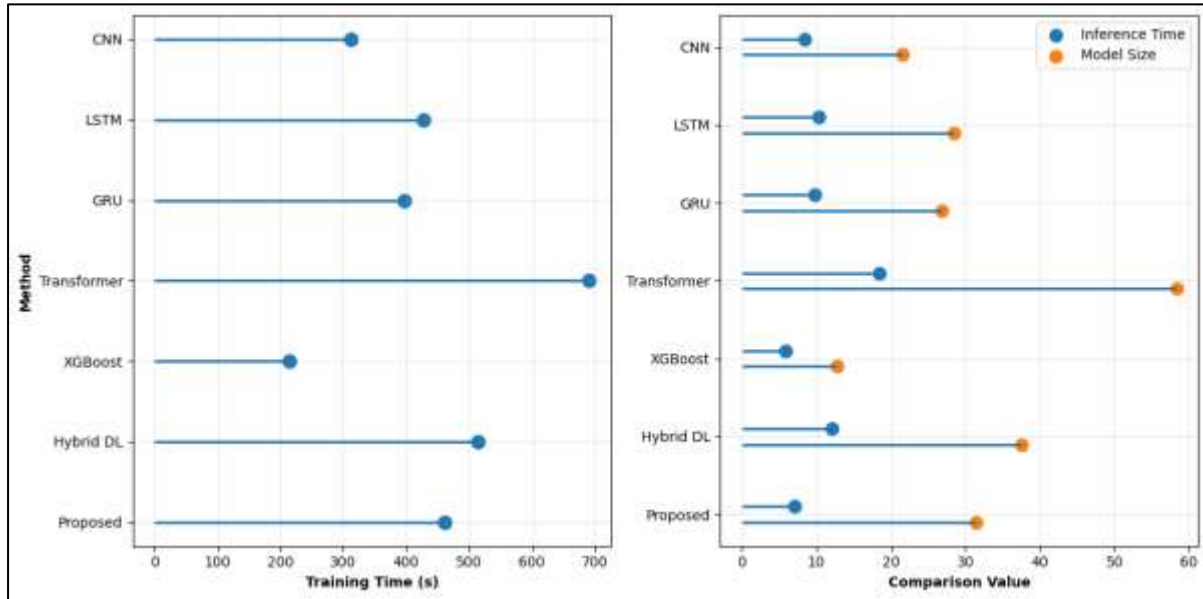


Figure 7: Comparison of Training Time, Inference Time and Model Size

The complete performance comparison analysis of the proposed approach with the conventional approach is given in Table 6 and in Figure 7. The proposed PINN + SHAP takes 462 s for training due to the physics-informed learning step, which is comparable to that of CNN + XGBoost, or slightly more than that of Transformer-based and Hybrid Deep Learning methods. It works at an Inference Time of 7.13ms, which is perfect for usage in Battery Management Systems in real-time application. The model size of 31.4 MB is intermediate, providing a balance between computation-efficiency and prediction-power, demonstrating true implement-ability, and offering high interpretability and estimation precision.

Table 7: Ablation Study of the Proposed Framework

Configuration	MAE (°C)	RMSE (°C)	R ²	PCS	SMI
Full Framework (PINN + SHAP)	0.92	1.34	0.994	0.986	0.989
Without PINN Constraints	1.47	2.21	0.961	0.742	0.811
Without SHAP Module	0.95	1.39	0.992	0.981	0.985
Baseline DNN (no physics, no SHAP)	1.62	2.45	0.953	0.701	0.774

The ablation study in table 7 indication that pressures the contribution of each module. The removal of the physics constraints resulted in a major decrease in accuracy and explained why the Physics Consistency Score was lower, thereby showing the need for embedding electrochemical principles. The results were close to the true values without sacrificing numerical accuracy; however, the figures did not aid in the understanding as they were not incorporated into the SHAP values, reducing transparency of the BMS. The baseline DNN was the worst performer, leading to inconsistent degradation curves and missing any ability to be explanatory. These findings validate the importance of physics constraints and SHAP explanations for the reliable and trustworthy SOH prognosis.

4.3 Discussion

The analysis of the experimental evaluation shows that the proposed Physics-Informed Neural Network with post-hoc SHAP interpretability offers a holistic perspective for battery SoH prognosis by offering both high accuracy and consistency in estimation, low computational complexity, and timely and explainable decision support. The prediction performance comparison shows lower estimation errors and better arrangement among the predicted and restrained SOH values as opposed to conventional ML and DL methods. The lower values of MAE, RMSE, MAPE, and higher R2 shows the framework is able to effectively model the nonlinear degradation behavior of the lithium-ion batteries in repeated charge/discharge cycles. The evolution of the SOH value also gets closer to the realistic ageing behaviour of a battery when the degradation-aware constraint is added to the physics-based evaluation. The higher values of the SOH Monotonicity Index, Physics Consistency Score, combined with the lower Capacity Degradation Error check, validate that the estimated degradation path is smooth and consistent with the natural degradation path. These findings indicate that incorporating the battery degradation data in the learning process leads to enhanced long-term health estimation performance under various operating conditions.

The interpretability analysis checks that the SHAP module is working correctly to measure the influence of each operational variable on the SHAP value for battery health. The stability and importance of Average SHAP are well, indicating that for these battery parameters the explanation process is consistently generating parameters that have high importance, and the relatively small time spent exploiting the parameter indicates that interpretability can be obtained without significant additional computational costs. The predictions produced are then accompanied by feature-level explanations for increased transparency and to assist in informed battery health assessment. A computational comparison is presented to show moderate training time and model size requirements of the proposed framework associated with the additional steps of physics-guided learning and interpretability. The methods with less computational cost, e.g., XGBoost, are less consistently degraded, are less transparent for making a prediction. The designed framework is balanced between the complexity of the estimates, and the accuracy, and it is suitable for practical Battery Management System as well where the accuracy and predictability and interpretability play a part.

Overall, the experimental results emphasize the possibility of a physics-informed learning and post hoc SHAP interpretability method for battery prognosis that is reliable and reliable. This framework offers a useful and reliable way to estimate the conversation performance of batteries and test their accuracy, degradation consistency, interpretability, and computational efficiency, which will support smart battery monitoring and intelligent management of the battery lifecycle.

5. CONCLUSION

This study developed a physics-informed NN model with post-hoc explainability by SHAP to ensure the reliability of battery state estimation for battery prognostics. The electrochemical optimization aspects are incorporated into the model to ensure that physically consistent degradation curves are predicted including the influence of current-induced stress,

temperature-dependant ageing, and resistance increase. The development of SHAP transparencies is happening as part of the system, where the engineers can show how relative voltage, current, temperature, and resistance were used to make predictions of health. Predictive evaluation was performed experimentally with a variety of operating conditions with high level of predictive accuracy and ablation studies revealed that physics constraints and interpretability modules were necessary. The validity of the framework was further confirmed by repeated-run statistic and uncertainty quantification, paving the way for its application to safety-critical systems such as electric vehicles and grid storage. There are still some disadvantages in spite of this progress, however. The results are based on the frame work of the NASA PCoE Data set, which may affect the applicability of the results in future, to widen the scope of chemistries, pack level systems or real inverter settings. No hardware validation performed and scalability on embedded controller must be evaluated. Future work shall involve extending the analysis to the multi chemistry case & matter, real-time embedded environments and adaptive observers based on uncertainty awareness. These standards will contribute to the quicker spread of the technology and its ability to add to the usefulness of reliable AI for battery health monitoring.

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