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Accurate Remaining Useful Life Prediction of Electric Vehicle Lithium-Ion Batteries Using an Enhanced Hybrid Fourier Neural Operator–Convolutional Transform Network

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Abstract

As a result of their high-energy density, efficiency and decreasing cost, lithium-ion batteries (LIBs) have emerged as the energy storage technology of choice for electric vehicles (EVs). But precisely estimating RUL is still a significant challenge for guaranteeing battery dependability, security and optimal utilization. This work aims to overcome these drawbacks by developing an enhanced hybrid predictive model using a Fourier Neural Operator–tuned Convolutional Transform Network (FNO-CTN) for precise RUL estimation and assessment of battery health. The model proposed takes advantage of the ability of FNO to learn from global degradation patterns in the frequency domain, and the CTN to learn from locally spatial-temporal dependency characteristics through the information of battery operational data. By integrating FNO into CTN, the nonlinear behavior of the battery can be improved modeled, and the long-term degradation trends can be modeled as well. This EV Battery RUL Health Dataset, with 9200 records, supplies the model with key operating parameters such as voltage, current and temperature. A comprehensive preprocessing pipeline involving min-max normalization and outlier removal is employed to improve data quality and robustness, and feature extract is used by principal component analysis (PCA) to reduce dimensionality and extracting significant features. Moreover, efficient hyperparameter tuning is achieved by integrating Wolf Pack Search (WPS) into the algorithm, which supports faster convergence, stability and generalization under various operating conditions. The research employed Python 3.10, and typical performance measures such MAE at 0.001298, RMSE at 0.001897, Parameters at 0.29, and Power at 70.86 are utilized to assess the efficacy of the FNO-CTN. Experimental results demonstrate that the proposed FNO-CTN significantly outperforms conventional deep learning and hybrid models in prediction accuracy and robustness.

Keywords: Lithium-ion Batteries, Remaining Useful Life,Electric Vehicles, Deep Learning, Battery Health Prediction.

Introduction

In recent years, the rising concern for the environment and the reduction in greenhouse gases, as well as the rising prices of fuel gave Electric Vehicles (EVs) unprecedented attention. The government and industries encouraged the use of EVs to create sustainable transportation and energy efficiency [1]. The LIBwas adopted for energy storage due to its high energy density, low weight, extended cycle life and rapid charging rates. LIBs were shown to deliver superior driving range, operational efficiency and vehicle reliability over conventional battery technologies [2]. Battery materials, thermal stability and battery energy management continued to improve EVs performance. LIB safety, control, and monitoring in EVs have been greatly aided by Battery Management Systems (BMS). including safe and effective battery operation, BMS-regulated parameters including battery voltage, current, temperature, and charging conditions were monitored. It extended battery life, avoided battery overcharging/overheating and enabled precise estimation of State of Charge (SOC) and RUL [3, 4].

When it came to assessing the operational reliability and durability of Lithium-Ion Batteries (LIBs) in EVs,RUL prediction was required. Predictive maintenance, fewer unplanned battery failures, and safer driving conditions for vehicles went hand-in-hand with accurate RUL estimation [5]. It allowed for the replacement of batteries in an efficient manner and reduced maintenance expenses. The reliable prediction of the RUL also improved the

energy management, battery utilization, and overall system performance in different environments and operating conditions[6, 7]. In EV, Health Performance Monitoring of LIBguarantees safe operation, safety and durability. The monitoring of voltage, current, temperature and charging habits ensured accurate assessment of battery condition [8]. The use of effective health monitoring minimized performance degradation, avoided unexpected failures, and battery life in dynamic operating conditions. The operational parameters LIB used in Figure1 include the operational voltage and current, the battery temperature, the number of charging cycles, the battery capacity, battery energy consumption, and the driving conditions of the EV. The monitoring stage was used to conduct battery degradation analysis, battery aging evaluation, health condition observation and RUL estimation. The accurate prediction resulted in better battery health awareness, EV safety, battery life, maintenance efficiency, and performance of energy.

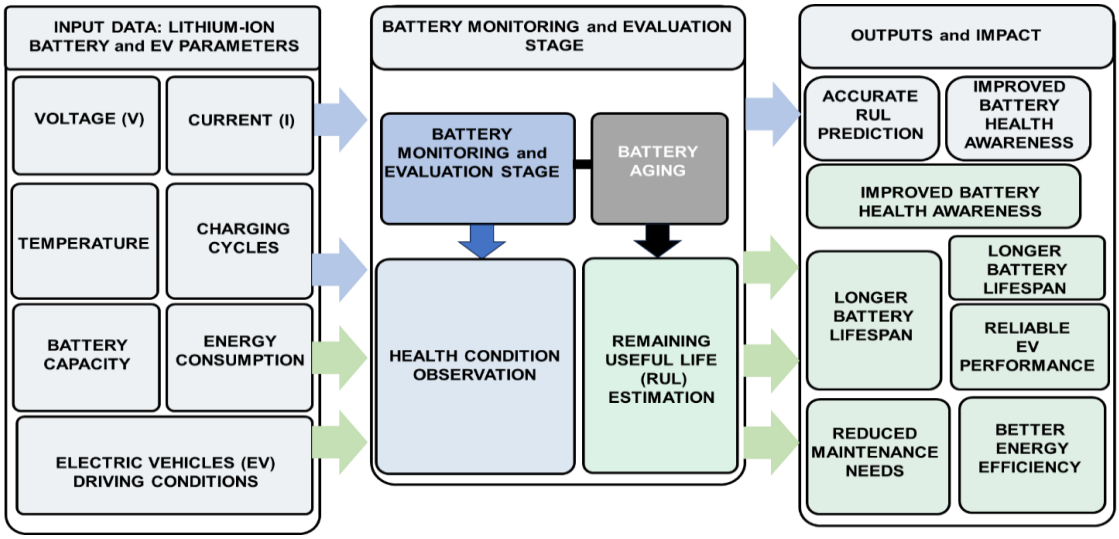


Figure 1. LIB health monitoring and RUL prediction in EV

The LIB degradation was found to be a function of temperature variations, charging/discharging rates, depth of discharge, overcharging, aging, and operating conditions. The frequent fast charging and harsh conditions caused rapid capacity fading and an internal resistance increase [9]. All these factors shortened the battery lifetime, operational stability and overall energy storage efficiency for EVs.The performance and lifetime of EV in LIBwere heavily dependent on the charging and discharging conditions [10]. These high charging currents, repetitive deep discharge cycles and recurring fast charging set batteries under accelerated stress, thereby causing their internal heat generation to rise [11]. Excessive discharge and overcharging resulted in loss of capacity retention and was a source of structural damage to these electrode materials. The electrochemical stability and battery efficiency were influenced by temperature changes in the charging and discharging process [12].

The EV battery health assessment was more accurate with the use of data-driven and Artificial Intelligence (AI)-based RUL prediction methods. DL algorithms were used to predict battery degradation patterns, battery life, and make intelligent decisions under different operating conditions of the large battery datasets [13].Under the dynamic conditions, the RUL prediction was difficult because of the difference of various temperatures, charging behaviors, driving patterns, and battery aging characteristics. The operating environment of the batteries was inconsistent and resulted in unreliable predictions of battery degradation [14, 15]. Prediction accuracy was affected, however, by limited availability of datasets, computational complexity, the noise of the sensors used, and generalization problems with the model.

Research objective and contributions

To tackle the above concerns, the research design is an optimized AI based Hybrid model to predict the RUL of LIBs and monitor the performance of EVs in a reliable manner. The research concentrated on designing a model that can accurately predict the occurrence of non-linear battery degradation behavior in different operating conditions by using FNO-CTN. To further improve the stability, convergence and generalization of the model, optimization and advanced preprocessing techniques, and features extracted through PCA and namely,WPS were applied to feature selection. The key contributions are given as follows:

- The research proposed FNO-CTN to accurately predict RUL and assess battery performance. The FNO-CTN helps to capture the degradation patterns at the global level and the spatial-temporal characteristics of the batteries.
- PCA was used to extract features and WPS for effective hyperparameter tuning to ensure quick convergence, stable prediction and model generalization in dynamic operating conditions. The optimization process improved the overall predictive reliability and robustness.
- Experimental results showed that the proposed model predicted the data with a higher accuracy than the traditional DL model and hybrid prediction model.

Research frameworks

The research frameworks are organized as follows. The Introduction for Section 1 is LIBs in EVs. The related works and prediction approaches for batteries using AI are discussed in section 2. Section 3 outlines the FNO-CTN, such as the preprocessing, feature extraction, and selection. The experimental setup, evaluation criteria, results of experimental evaluations, and implementation details are explained in Section 4. Finally, Section 5 summarizes the research and proposes future research trends on advanced battery health prediction systems.

Literature Reviews

The reviewed researchers analyzed LIB technologies in EVs, including BMS, charging systems, recycling methods, and intelligent fault diagnosis techniques shown in table 1.

Table 1. Summary of previous research based on LIB health prediction

Reference number	Research Focus	Methods	Results	Limitations
[16]	Economic, industrial, and technical developments of Electric Vehicle (EV)-based LIB	Cloud-based DL systems, electrode material analysis, policy change analysis	Results emphasized increasing adoption of LIB and proposed industrial development objectives	Did not include experimental data, detailed numerical validation, or practical implementation assessment
[17]	Battery Management System (BMS) for EV and renewable energy storage systems	Monitoring systems, thermal management, charge estimation, and cell balancing circuits	Efficiency, reliability, cost, and operational issues were analyzed to improve the sustainability of batteries	Lacked experimental data and numerical comparison of balancing and management approaches
[18]	Experimental evaluation of LIB stacks with Nickel–Cobalt–Aluminium (NCA) and Lithium Iron Phosphate (LFP) cathodes for Electric Vehicles/Hybrid Electric Vehicles (EVs/HEVs)	De-centralized BMS in Lithium Energy Storage and Management Systems (LESMSs)	Found that LFP batteries have lower energy and power density, but significant improvement potential exists	Further enhancement and broader validation are still required
[19]	Recycling strategies for end-of-life LIB in EV markets	Direct recycling, hydrometallurgy, pyrometallurgy, and froth flotation techniques	Evaluated efficiency, commercial feasibility, processing capability, and transport security; highlighted the importance of recycling	Experimental data and detailed numerical comparisons among recycling methods were limited
[20]	Monitoring for LIB in EV using intelligent technologies	Digital Twin (DT)-Long Short-Term Memory (LSTM), Cloud-based Internet of Things (IoT), and Time-Series Generative Adversarial Network (TS-GAN)	Achieved high prediction precision, improved safety, and energy savings	Validation across diverse operational and environmental conditions was limited

[21]	Early-stage sensor fault diagnosis in EV and BMS	Electrical and thermal LIB models, descriptor proportional and derivative observer systems	Experimental and simulation signals enabled accurate voltage, current, and temperature sensor fault estimation	Real-world operational validation remained limited
[22]	Mathematical modeling and computational intelligence of a 4S3P LIB pack for EV	MATLAB R2023b simulation, BMS performance analysis	Analyzed State of Charge (SOC), State of Health (SOH), temperature variation, and electrical behavior under varying loads; improved battery modeling and adaptive charging methods	Experimental testing was limited
[24]	Joint SOC and SOH estimation technique for LIB in EV	Nonlinear State Space Reconstruction (NSSR) and LSTM networks	SOC and SOH estimation errors were 2.5% and 1.3%, respectively, using experimental charging/discharging datasets	Broad operational validation was still in early stages
[25]	A Big Data-based multi-method fusion approach for LIB fault diagnosis in EVs	t-SNE, wavelet denoising, Convolutional Neural Networks (CNN), LSTM, and Bayesian Networks (BN)	Improved diagnostic accuracy by 12% and reduced response time using multiple vehicle datasets	Real-world validation was not extensive
[26]	Fast and ultra-fast charging technologies for LIB in EVs	Cell architecture, electrolyte design, battery formats, thermal management, and chassis integration	Demonstrated reduced ion transport resistance and enhanced energy density for improved charging performance	Did not provide experimental data or detailed numerical validation under realistic charging conditions
[27]	Testing the LIB model of EV under varying climatic conditions	Laboratory-scale model, simulation, and prototype testing	Investigated temperature and geographical trip impacts on driving range; identified an 8% decrease in range (43.5 km out of 538 km)	Validation was limited to a specific geographical area
[28]	Grid-independent extreme fast charging infrastructure for EV	Photovoltaics (PV), LIB-based Battery Energy Storage Systems (BESS), and High-Voltage Direct Current (HVDC) networks	Achieved power savings between 17% and 25% compared to alternating current systems using hourly EV-load and 15-year irradiation data	Field-level validation is required
[29]	State of Health (SOH) prediction of LIBs in EV	XGBoost, feature extraction, error analysis, ensemble learning	Achieved improved SOH prediction accuracy and enhanced generalization capability using voltage, current, and temperature-based degradation features	Limited capability in learning complex nonlinear degradation behavior and long-range temporal dependencies under varying operating conditions
[30]	Intelligent battery health diagnostics for EV	Temporal Convolutional Network (TCN), Long Short-Term Memory (LSTM) with an attention mechanism	Achieved 0.021 RMSE, reduced energy consumption, improved prediction accuracy, and real-time BMS feasibility	Higher computational complexity and parameter utilization with limited global frequency-domain degradation learning capability
[31]	Lithium-ion battery	Long Short-Term Memory	Achieved RMSE at	Performance depended

	remaining useful life prediction	(LSTM)–Transformer hybrid model with temperature feature engineering, standardization, and Yeo–Johnson transformation	0.0085, MAPE at 0.0200	on dataset diversity and long-term operational variability

Research gap

The previous studies on fast charging were primarily related to charging efficiency and thermal management of EVs [26]. This was not the case for accurate prediction of RUL, however,even though degradation of LIB under different climatic conditions was not updated or analyzed [29]. The prediction of intelligent RUL for dynamic environments, however, was not well explored. The focus of the earlier research was primarily on the charging efficiency and power-saving aspects of BESS [30]. The research of long-term degradation prediction of batteries is however,not sufficiently available.

Most of the existing hybrid battery prediction models are based on temporal sequence learning or local feature extraction and little attention has been paid to learning the degradation behavior of the batteries in the global frequency domain together with local spatial–temporal battery dynamics under highly dynamic EV operating conditions. Furthermore, most of the currently available literature demonstrates lower robustness in the case of high charging rate fluctuations, climatic changes and long cycle degradation conditions. The proposed FNO-CTN fills this gap by combining the frequency domain degradation learning ability of FNO and the local degradation representation ability of CNN architecture and Transformer architecture with the temporal dependency modeling ability of CNN architecture and Transformer architecture for stable long-term RUL estimation.

The proposed FNO-CTN addressed the shortcomings of the existing studies, while demonstrating accurate predictions of RUL,and battery health when subjected to rapid charging, climatic changes and long-term operational conditions. The CTN efficiently extracted the spatial–temporal pattern of the battery and FNO captured the global pattern of the nonlinear degradation. WPS enhanced convergence, stability and generalization, which resulted in greater prediction accuracy, robustness and reliable battery performance assessment in different EV operating conditions.

Methodology

To enhance the quality and consistency of the LIB operational data as provided in Figure 2, the preprocessing pipeline is applied, which comprised min-max normalization and outlier removal. The process led to decreased scale variation and eliminated abnormal battery values that would have impacted the accuracy of RUL prediction.

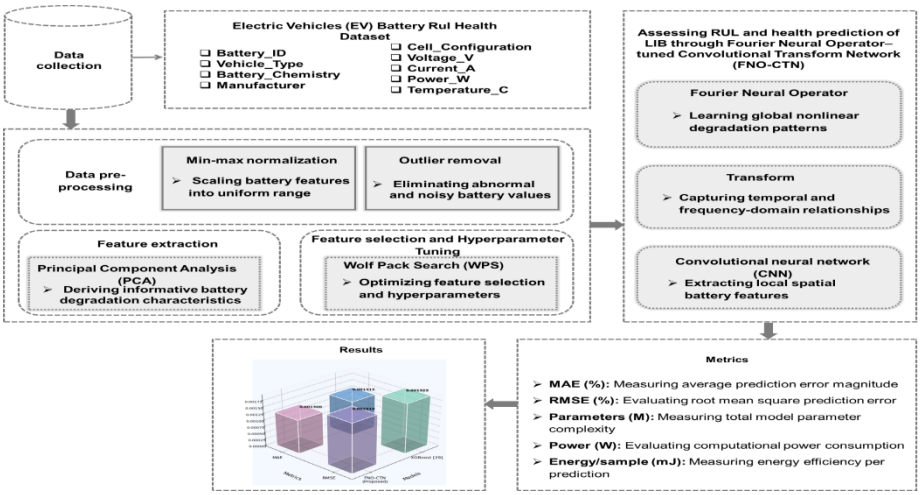


Figure 2. Working flow of FNO-CTN in Lithium-Ion Batteries in Electric Vehicles

Data collection

The EV Battery RUL Health Dataset was used to test the proposed FNO-CTN model for lithium-ion battery Remaining Useful Life (RUL) prediction and battery health performance assessment of EVs. The dataset contains 9200 rows and 39 attributes related to operational, electrical, thermal, environmental, degradation and battery health. The major parameters include battery voltage, current, power, temperature, ambient temperature, cycle count, charge capacity, discharge capacity, internal resistance, State of Health (SOH), capacity fade, impedance growth, aging rate, energy throughput, coulombic efficiency, thermal runaway index, cooling efficiency, heat generation rate, driving load, road condition, vehicle speed, acceleration, humidity, weather condition, frequency response index, spectral degradation score, harmonic response, electrochemical stability, degradation index, failure risk score, Remaining Useful Life cycles, and battery health class.

The data set includes a number of EV battery operating conditions and various battery chemistries such as Lithium Iron Phosphate (LFP), Lithium Titanate Oxide (LTO), Nickel Cobalt Aluminum Oxide (NCA), and Nickel Manganese Cobalt Oxide (NMC). Different battery pack configurations were added, such as 84S2P, 96S2P, 108S4P, 120S3P and 140S5P, to understand the battery degradation behavior in different structural and operational conditions. Moreover, this dataset includes various vehicle types, brands, loading conditions, road conditions, and weather conditions to aid in comprehensive battery health assessment and RUL prediction.

The main regression prediction target was Remaining_Useful_Life_Cycles, which is the number of cycles that the battery can be used before replacement. In addition, Battery_Health_Class was explored as a classification objective to classify battery health into Healthy, Moderate, Degraded and Critical states. The degradation-related indicators such as SOH percentage, capacity fade, degradation index, failure risk score, and RUL cycles were used to assign the classes for the health classes.

The data was split for experimental evaluation into seven-tenths, five-tenths, and five-tenths of the data for the training, validation, and testing sets, respectively. The model was learned using the training set, the validation set was used for hyperparameter optimization and model selection, and the testing set was used for the final model performance evaluation. The dataset was investigated for any missing values and inconsistencies prior to model training. Numerical missing values were imputed by the median while categorical missing values were imputed by the mode. To enhance data quality and prediction accuracy, duplicate records were eliminated and abnormal operational values were removed in preprocessing.

The distribution of Battery_Health_Class was checked before training to solve the class imbalance problem in the battery health classification task. A training set data balancing was performed using only stratified sampling and class weight adjustment. This maintained the validity and testing distributions of the original model and didn't create a bias towards majority health classes to ensure fair evaluation.

Publicly available Source: https://www.kaggle.com/datasets/colabsss/ev-battery-rul-health-dataset/data

Dataset Sequence Preparation

The public dataset was provided as a tabular operational dataset rather than a continuous raw sensor stream with a fixed sampling frequency as given in the Table 2. Therefore, each sample was considered as a cycle-wise operational battery record. The data were sorted according to Battery_ID and Cycle_Count, and overlapping temporal sequences with a fixed window length of 30 cycle steps were generated for Transformer and FNO-CTN learning. Each sequence was mapped to the corresponding Remaining Useful Life prediction target. This sequence generation strategy enabled effective learning of temporal battery degradation behavior and operational variations across charging and discharging cycles.

Table 2. Detailed Description of EV Battery RUL Health Dataset, Preprocessing Configuration, and Sequence Preparation Strategy

Item	Description
Dataset name	EV Battery RUL Health Dataset
Total records	9200
Total columns	39
Number of batteries/cells	Represented using unique Battery_ID; exact physical cell count is not specified in the public dataset
Battery chemistry	LFP, LTO, NCA, NMC
Cell configuration	84S2P, 96S2P, 108S4P, 120S3P, 140S5P
Sampling frequency	Not explicitly provided; treated as cycle-wise battery operational records
Main regression target	Remaining_Useful_Life_Cycles
Classification target	Battery_Health_Class

Health classes	Healthy, Moderate, Degraded, Critical
Training/testing split	70% training, 15% validation, 15% testing
Sequence length	30 cycle steps
Missing value handling	Median imputation for numerical features; mode imputation for categorical features
RUL labelling strategy	RUL cycles used directly from Remaining_Useful_Life_Cycles
Data balancing	Stratified sampling and class-weight adjustment on training data
Preprocessing	Duplicate removal, outlier removal, categorical encoding, min-max normalization
Feature extraction	PCA
Optimization	WPS-based feature selection and hyperparameter tuning

Data pre-processing

Data preprocessing increased the quality and consistency of LIB operational data, for accurate RUL prediction. Min-max normalization scaled the battery features to a common range, and the treatment of outlier battery data took out abnormal operating data. These techniques contributed to improving prediction accuracy, robustness and stability of the model even in the presence of varying EV operating conditions.

Min-max normalization

In order to maintain consistency and stability during the training phase of the model, the battery operating parameters were normalized to a common numerical scale through min-max normalization. Scale variance in relation to the voltage, current, temperature, and degradation parameters was avoided by normalizing the data in order to reduce any form of bias in learning. It increased speed of convergence, prediction ability, and economy of energy of the battery as depicted by equation (1).

$$B' = \left(\frac{B - B_{min}}{B_{max} - B_{min}}\right) * (C - D) + D \quad (1)$$

Wherein, $B$is the original value before normalization process, $B_{\min}$is the Minimum value in Battery RUL Health Dataset feature, $B_{\max}$is the Maximum value in Battery RUL Health Dataset feature, $C$is the Upper bound of target range, $D$is the Lower bound of target range and $B'$is the Normalized value after scaling transformation.

Outlier removal

Abnormal and inconsistent values of battery operation from the data set were removed from the data set using outlier removal techniques, which adversely impacted the RUL predictions' accuracy. The process ensured data quality by filtering out sensor noise, fluctuations in charging conditions, and abnormal battery responses. It enhanced the stability and robustness during training and prediction. Furthermore, the outlier removal contributed to the generalization ability and the correct battery health performance evaluation in dynamic EV operating conditions.

Feature extraction using PCA

Principal Component Analysis (PCA) was used to extract features from the data to reduce dimensionality and determine the most important battery operational features to be used for prediction of RUL. The method mapped high-dimensional battery parameters to optimized feature representations while maintaining the valuable battery degradation information. PCA proved to be efficient in computation, less redundant and better in learning performance, as well as having extracted features that are useful in accurately assessing battery health and predicting it with good performance under different EV operating conditions as presented in the equation (2).

$$L_D = \frac{1}{p-1}(D - \overline{D})(D - \overline{D})^T \quad (2)$$

Wherein, L_D is the covariance matrix of Battery RUL Health Dataset feature$D$, p is the total number of data samples, D shows the original data matrix representation, $\overline{D}$ is the mean vector of Battery RUL Health Dataset feature, $(D - \overline{D})$ is the mean centered data matrix, and $(D - \overline{D})^T$ is the transpose of centered data matrix.

Assessing RUL and health prediction of LIB through FNO-CTN

Transformer was able to learn long-range temporal relationships and sequential degradation relationships of LIB operational parameters for accurate battery health prediction. CNN extracted local spatial and degradation-

related features from operational data of the battery, thereby enhancing the accuracy and robustness of the prediction. Under dynamic operating conditions, FNO learned global nonlinear degradation patterns and frequency-domain battery behavior to predict the battery's RUL accurately.

An FNO-CTN that combines FNO, Transformer and CNN architectures to model and assess battery degradation efficiently. The hybrid improved the accuracy, robustness and generalization performance of RUL prediction under different EV operating conditions.

The proposed FNO-CTN architecture consists of five sequential modules: preprocessing, PCA based feature extraction, Transformer based temporal dependency learning, CNN based spatial degradation extraction and FNO based global degradation learning. The Transformer module is designed to represent the features of a battery's operation as a sequence and is composed of multi-head self-attention layers to encode the sequence. The temporal representations are then fed to the CNN layers to extract local degradation and operational patterns. FNO layers then act as successive layers of convolution layers that process the extracted representations in the Fourier domain, extracting global nonlinear degradation evolution and long-range operational dependencies. Then, complete regression layers provide the battery RUL and health prediction output.

The proposed FNO-CTN uses a frequency-domain operator learning mechanism to learn about the degradation evolution as a whole, along with local spatial and temporal feature extraction. The combination of the preprocessing, the PCA-based feature extraction, the Fourier-domain degradation learning and the WPS-based hyperparameter optimization in one prediction pipeline brings benefits of better robustness, lower computational redundancy and better generalization for different battery operating and environmental conditions.

In the prediction stage, the module Transformer encoder is used to convert the battery operational features into temporal embedding representations. The learned temporal representation is then passed into CNN layers for localizing the degradation and spatial operation features. The extracted feature maps are then passed into the FNO layers where Fourier-domain transformations are used to model the evolution of the battery degradation system globally and the long-range nonlinear battery behavior. Finally, dense regression layers are leveraged to process the fused feature representations and yield final RUL and battery health estimation.

Transformer:Capturing long-range temporal dependencies

The Transformer architecture was used to a great extent to capture long-range dependencies and complex temporal relationships found in LIB operational data. It is effective to process the sequential parameters of batteries, including their voltage, current, temperature, charging cycles and so on, for accurate RUL prediction. The self-attention mechanism allowed for the efficient learning of the degradation behavior in different operating conditions. Improved feature representation and enhanced prediction reliability for EV health assessment applications.

$$FFN(W) = a2 + X2 * \sigma(a1 + X1 * W) \quad (3)$$

Equation (3) defines a layer used to transform $feed - forward\ neural\ network$ (FFN)input features $W$is the FNO-CTN. Here, W represents the input feature vector X_1 and X_2 are weight matrices that linearly transform the input and intermediate activations, and a_1 and a_2 are bias vectors for the respective layers. The function $\sigma(a1 + X1 * W)$ is an activation function that introduces non-linearity. This formulation allows the FFN to learn complex relationships between input spatial features and the target battery life healthprediction.

$$W_{output} = LayerNorm(W \oplus P_{SL}) \quad (4)$$

Equation (4) represents the input feature matrix, W_{output} represents the final normalized feature representation obtained by fusing the learned feature matrix W and P_{SL} is the positional battery life health to retain spatial structure. The operator $\oplus$ denotes the element-wise addition of the input features and positional battery life health. $LayerNorm$ is a normalization function applied to stabilize and accelerate training by standardizing the combined features and it contributing to improved spatial coherence.It also made improvements in parallel processing efficiency compared to the traditional methods of sequential learning. It improved the ability of the model to learn the non-linear degradation pattern of the battery. By leveraging feature concatenation operations, the CNN layers extracted the localized spatial degradation features and the Transformer module extracted the temporal dependency features, with the latter combined together to form the feature fusion strategy. Next, the fused representations were sent into FNO layers, for frequency domain degradation learning and global dependency extracting. This hierarchical fusion strategy maintained complementary temporal, spatial and

frequency-domain battery degradation characteristics without losing any battery representations, resulting in more robust prediction and good generalization performance.

CNN: Locational spatial battery feature extraction

The convolutional Neural Network (CNN) extracted and used the crucial features from LIB operational data related to spatial and degradation for the accurate prediction of RUL. Local patterns were captured in the convolutional layers from the voltage, current, temperature, and charging cycle parameters. CNN has reduced the noise effect and enhanced the feature learning capability in different EV operating conditions. The improved prediction accuracy, robustness, and battery health evaluation in equation (5)

$$w_i^k = e\left(\sum_{j=1,\dots,N} w_j^{k-1} * l_{ji}^k + a_i^k\right), i = 1, \dots, M \quad (5)$$

Wherein, w_i^k is the output feature map of the ith filter in the kth convolutional layer, extracted from the batteryfeatures, $e\ (.)$ is the activation function, w_j^{k-1} is the input feature map $(k-1)$ layer corresponding to the jth channel, $*$ is the convolution operation, l_{ji}^k is the convolutional health performance, i index of features map, a_i^k is the bias term, N and M denote the total number of input and output features, j is the index of input feature, $\Sigma$is the summation of features and K is the current convolutional layer in the Lithium-Ion Batteries in Electric Vehicles.

FNO: Learning global battery degradation patterns

The FNO significantly contributed to learning global nonlinear degradation patterns and frequency-domain characteristics from the LIB operational data to make accurate RUL predictions. It successfully simulated complex degradation characteristics of the battery with different operating conditions of EVs. FNO enhanced the representation ability of the features and the stability of the battery prediction on long-term dependency learning in battery health assessment. FNO has been chosen due to its Fourier domain learning capability which allows for efficient modeling of long-range nonlinear degradation characteristics and multi-scale battery aging behavior, without incurring too much computational complexity. This capability helps with prediction stability and robustness under dynamic EV operating conditions for LIB health monitoring for long-term forecasts.

This increased prediction accuracy, robustness and generalization as described in equations (6-8)

$$e(w) = \frac{b_0}{2} + \sum_{m=1}^{\infty}[b_m \cos(\frac{m\pi w}{S}) + a_m \sin(\frac{m\pi w}{S})] \quad (6)$$

Wherein, $e(w)$represents the battery degradation response function, $b_0$denotes the initial Fourier cosine coefficient, $m$indicates the harmonic frequency component index, $\sum$denotes the summation operation, ∞represents the infinite harmonic range, $b_m$represents the Fourier cosine series coefficient, $\cos$denotes the cosine frequency transformation function,$\infty$is the infinity,πrepresents the mathematical constant pi value, $w$indicates the battery operational frequency variable, Sdenotes the signal period normalization parameter, $a_m$represents the Fourier sine series coefficient, and $\sin$denotes the sine frequency transformation function.

$$E(t) = \int_{-\infty}^{\infty} e(w) e^{-2\pi jtw}\, cw \quad (7)$$

Wherein,$E(t)$represents the frequency-domain transformed battery signal, $t$denotes the temporal frequency transformation variable, $\int$ indicates the continuous Fourier integral operation, $-\infty$and $+\infty$denote the integration limits, $e(w)$represents the input battery operational signal, $e^{-2\pi jtw}$denotes the complex exponential transformation function, πrepresents the mathematical constant pi value, $j$indicates the imaginary unit in transformation, $w$denotes the signal frequency domain variable, and dwrepresents the differential frequency domain element.

$$e(w) = \int_{-\infty}^{\infty} E(t) e^{2\pi jtw}\, ct \quad (8)$$

Wherein, $e(w)$represents the reconstructed battery operational signal, $\int$ denotes the inverse Fourier integral operation, $-\infty$and $+\infty$represent the integration limits, $E(t)$represents the frequency-domain battery feature representation, $e^{2\pi jtw}$denotes the inverse complex exponential function, πrepresents the mathematical constant pi value, $j$indicates the imaginary unit in transformation, $t$denotes the temporal frequency transformation variable, $w$represents the battery operational frequency variable, and dtdenotes the differential temporal domain element.

WPS: Optimizing feature selection and hyperparameters tuning

The WPS was used for feature selection and tuning the significant battery operational and degradation-related features for RUL prediction. WPS was used to carry out the hyperparameter optimization process with the iterative exploration and exploitation stages. Random candidate hyperparameter sets with learning rate, batch size, dropout rate, number of layers, number of hidden channels and Fourier modes were first created. In iterative optimization, the position of wolf agents was adjusted to find the best combination of the hyper-parameters by using search direction and hunting behavior mechanisms that are adaptive. The optimization has stopped because of the maximum number of iterations or minimum validation error threshold.The optimization process highlighted the relevance of the features, minimized redundant information, and optimized calculation efficiency during the creation of the model. The proposed method achieved better prediction accuracy, robustness and generalization ability under different operating conditions of EVs as provided in equation (9).The Particle Swarm Optimization (PSO) is not suitable to solve high dimensional and highly nonlinear optimization problems because it can easily be stuck in local optima and premature convergence. Moreover, PSO's exploration ability is decreased in later iterations, which can affect the stability and diversity of the optimization solutions. Cooperative hunting and adaptive search behavior mechanisms are the mechanisms that give WPS the best balance of exploration/exploitation. WPS can effectively prevent premature convergence in hyperparameter tuning and guarantee stable convergence in high-dimensional battery operation feature spaces. Therefore, this will help to better stabilize the parameters, converge the algorithm faster, and better robustness when predicting LIB RUL under dynamic EV operating conditions.

$$w_{id}^{l+1} = w_{id}^{l} + Step_a^c \times \left(h_c^l - w_{id}^l\right)/\left|h_c^l - w_{id}^l\right| \quad (9)$$

Wherein, $w_{id}^{(l+1)}$represents the updated wolf position in the next iteration, w_{id}^ldenotes the current wolf position at iteration l, $Step_a^c$represents the adaptive movement step size of the wolf, h_c^ldenotes the optimal hunting position in the current iteration, $l$indicates the iteration index, $c$represents the search direction index, $\left(h_c^l - w_{id}^l\right)$denotes the positional difference between optimal and current wolf positions, $|\ h_c^l - w_{id}^l\ |$represents the absolute positional distance, and $\frac{\left(h_c^l - w_{id}^l\right)}{|h_c^l - w_{id}^l|}$denotes the normalized movement direction vector as shown in the Figure 3.

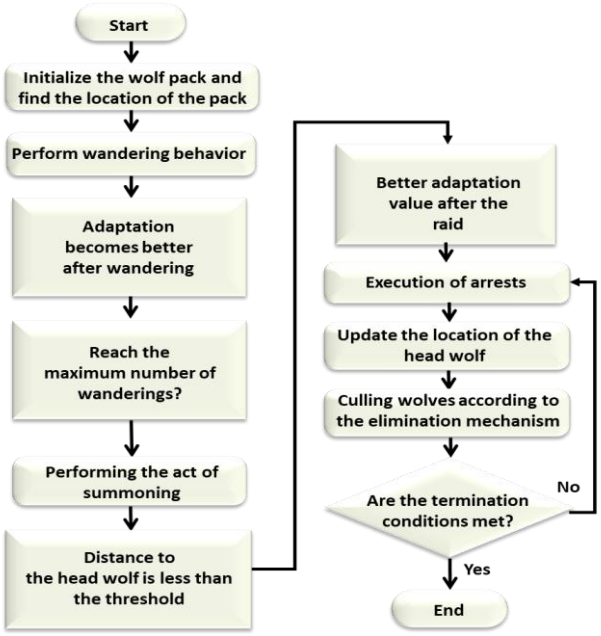


Figure 3. Flowchart of wolf pack search optimization

The proposed accurate RUL and battery health prediction, FNO-CTN is described in Algorithm 1. The FNO-CTN incorporated a preprocessing and feature optimization module, Transformer, CNN and FNO models to support efficient battery degradation analysis.

Algorithm 1: FNO-CTN-Based RUL and Battery Health Prediction

$Input$: $LIB\ dataset\ D$
$Output$: $Accurate\ RUL\ and\ battery\ health\ prediction$
$Begin$
$Load\ LIB\ operational\ dataset\ D$
$Extract\ voltage, current, temperature, and\ cycle\ features$
$For\ each\ feature\ B\ in\ dataset\ D$
$Normalize\ features\ using$:
$$B' = \left(\frac{B - B_{min}}{B_{max} - B_{min}}\right) * (C - D) + D$$
$End\ For$
$Detect\ abnormal\ operational\ values$
$If\ outlier\ value\ detected\ then$
$Remove\ noisy\ and\ inconsistent\ battery\ samples$
$Else$
$Retain\ operational\ battery\ sample$
$End\ If$
$Apply\ PCA\ feature\ extraction$
$Compute\ covariance\ matrix$:
$$L_D = \frac{1}{p-1}(D - \overline{D})(D - \overline{D})^T$$
$Extract\ optimized\ degradation\ feature\ vectors$
$Initialize\ Wolf\ Pack\ Search\ population\ widl$
$Update\ wolf\ position\ using$:
$$w_{id}^{l+1} = w_{id}^{l} + Step_a^c \times \frac{\left(h_c^l - w_{id}^l\right)}{\left|h_c^l - w_{id}^l\right|}$$
$If\ selected\ features\ improve\ prediction\ fitness\ then$
$Store\ optimal\ battery\ feature\ subset$
$Else$
$Update\ search\ direction\ and\ repeat\ optimization$
$End\ If$
$Apply\ Transformer\ for\ temporal\ dependency\ learning$
$Apply\ CNN\ for\ local\ spatial\ feature\ extraction$
$Apply\ FNO\ using\ e(w), E(t), and\ inverse\ Fourier\ transformation$
$Predict\ RUL\ and\ battery\ health\ condition$
End

To obtain accurate RUL prediction and battery health assessment, the hyperparameters of the Transformer, CNN, and FNO models were optimized as shown in Table 3. The normalized operational parameters of the battery, such as voltage, current, temperature, charging cycles, internal resistance, and degradation-related features, were included in the input feature matrix, which has a shape of 128 × 1. The Transformer encoder used 6 layers in the encoder and 8 attention heads and embedding dimension 256. The CNN module used four convolution layers of 64 filters of 3 × 3 kernel followed by max pooling layers. FNO module comprised four Fourier layers and 16 Fourier modes and 64 hidden channels. The last regression layer produced a single output for battery RUL estimation and health prediction.

By tuning the parameters, improved feature learning, model convergence, robustness and prediction performance under different EV operating conditions were obtained.

Table 3. Hyperparameter of FNO-CTN values

Model	**Hyperparameter**	**Value**
Transformer	Number of Encoder Layers	6
	Attention Heads	8

	Embedding Dimension	256
	Feed Forward Dimension	512
	Dropout Rate	0.2
	Learning Rate	0.001
	Batch Size	32
	Activation Function	ReLU
CNN	Number of Convolutional Layers	4
	Kernel Size	3 × 3
	Number of Filters	64
	Pooling Type	Max Pooling
	Dropout Rate	0.25
	Learning Rate	0.001
	Batch Size	32
	Activation Function	ReLU
FNO	Fourier Modes	16
	Hidden Channels	64
	Number of FNO Layers	4
	Learning Rate	0.0005
	Batch Size	32
	Activation Function	GELU
	Optimizer	FNO
	Epochs	100

Results

The proposed FNO-CTN was executed on an Intel Core i7 CPU having 16GB of RAM, and it was used to compute RUL and battery health prediction using Python.The estimated rate of learning adopted by the proposed FNO-CTN was 0.001 for the Transformer and CNN module, respectively, and 0.0005 for the FNO module. The objective function used for battery RUL prediction based on regression was the Mean Squared Error (MSE) loss. The batch size was set to 32 and the training process was run for up to 100 epochs. To prevent over fitting and ensure that the model generalization was stable, early stopping criteria were used, which was based on convergence of the validation loss.

Outcomes of EV Battery RUL Health Dataset

The thermal assessment was performed on the thermal runaway behavior under different battery aging conditions and different heat generation rates as shown in Figure 4. The Thermal Runaway Index (TRI) of 2.0 or more and internal temperatures of 100°C or higher caused a significant drop in cooling efficiency. The findings showed the need for effective thermal control on batteries for safety.

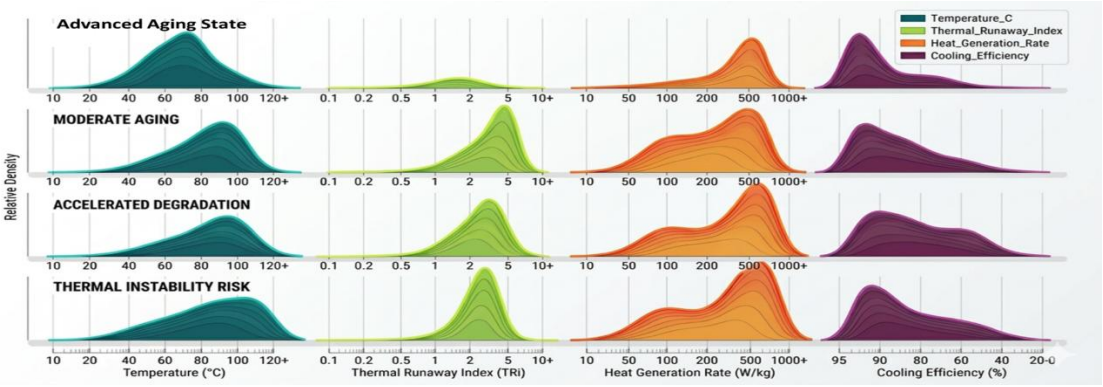


Figure 4. Thermal runaway risk assessment across various battery aging stages and heat generation rates

The results of training and validation loss functions validate the effectiveness of the proposed FNO-CTN framework to achieve stable convergence for lithium-ion battery RUL prediction are presented in the Figure 5. The model shows a gradual decrease in error over 100 epochs, which is effective in capturing the complex degradation patterns that exist in the battery health performance. This correlation behavior highlights the

model's ability to learn strong representations, leading to a high accuracy in predicting long-term health outcomes of EV energy storage systems.

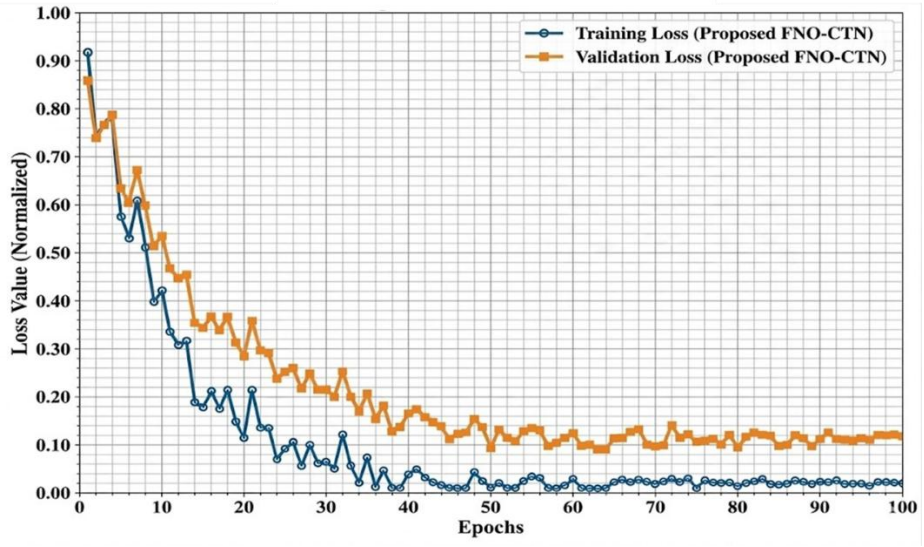


Figure 5. Evaluation of model training convergence and validation stability for predictive battery health monitoring

The distribution of residual errors for remaining useful life predictions remains tightly grouped around the zero-error line for the 800 cycles that were observed during the experiment can be seen in the Figure 6(a). This means they have good predictive consistency with battery health assessment under various operating conditions for lithium-ion batteries. The difference in prediction accuracy is extremely small, which is very important to maintain the reliability of maintenance scheduling and optimize energy management in electric vehicle applications. The results of the statistical analysis of prediction residuals with a mean error of 2.00 cycles and a standard deviation of 42.20 cycles out of 500 samples, confirms that high precision is given in health assessment in the Figure 6(b). The fact that most of the errors are contained within the 95% confidence interval confirms the validity of the forecasting method for lithium-ion battery degradation. Accurately measuring the uncertainty of prediction is crucial for ensuring safety and prolonging the lifespan of the power system in electric vehicles.

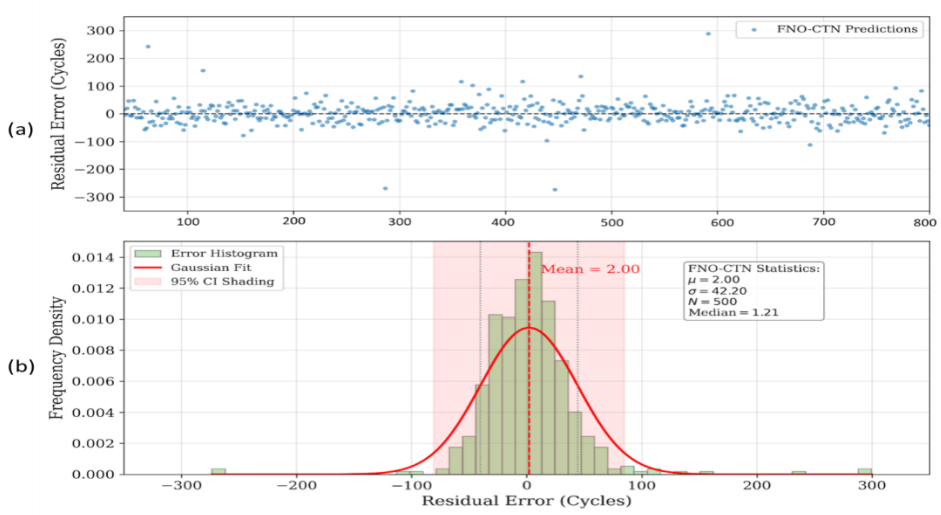


Figure 6. Representation of (a) Assessment of residual errors across the battery operational cycle lifespan and (b) inaccuracies for battery state-of-health estimation

The distribution of the residual error is always kept in the middle range from 100 cycles to 2000 cycles as illustrated in Figure 7(a). There are some outliers like at 300 and 101cycles, but they are isolated from the rest of the data, as would be expected, and the number of inaccuracies was low across the rest of the data. This stability over the operating range is critical for the long-term reliable prediction of the behavior of batteries in EVs. The

predictive framework has a very low variance of cycles and a very high precision with a mean error of 0.023, considering the small number of samples, n=36, Figure 7(b). The considerable concentration of the median value at farther also enhances the reliability of the model to estimate the health performance of lithium-ion batteries. These statistical parameters enable a quantitative validation of the model's ability to keep the error range of critical energy management in electric vehicles at a minimum.

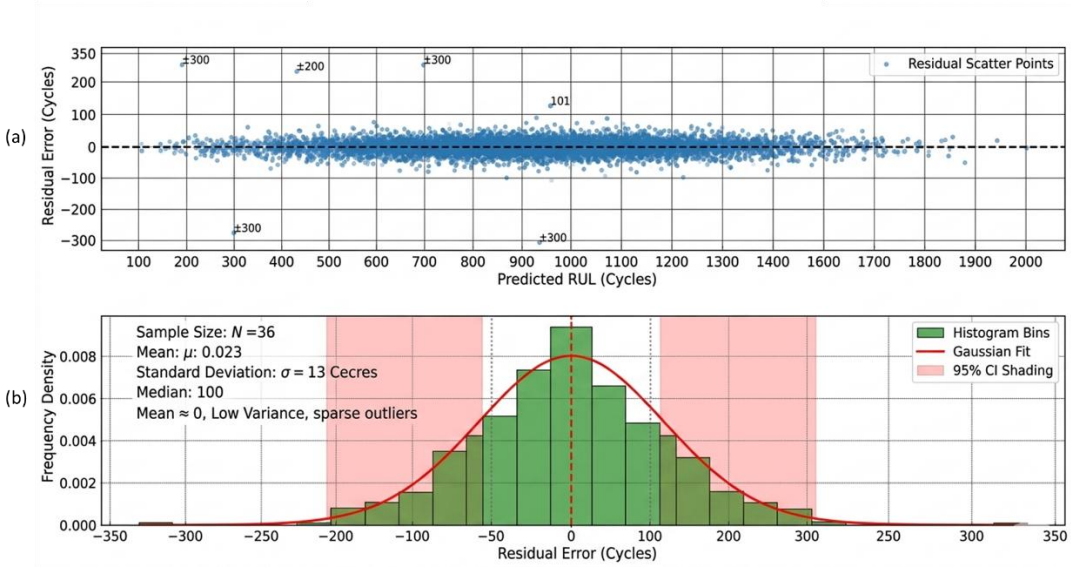


Figure 7. Analysis of (a) residual error distribution relative to the predicted remaining useful life of battery systems and (b) predictive accuracy and error variance for battery health forecasting

The battery lifecycle analysis that identified the transition stages of State of Health (SOH) with increasing cycles and failure risk is shown in Figure 8. Batteries with more than 1400 cycles achieved a fast deterioration of their SOH and failure rate. The results showed that below 70% SOH is a critical replacement requirement.

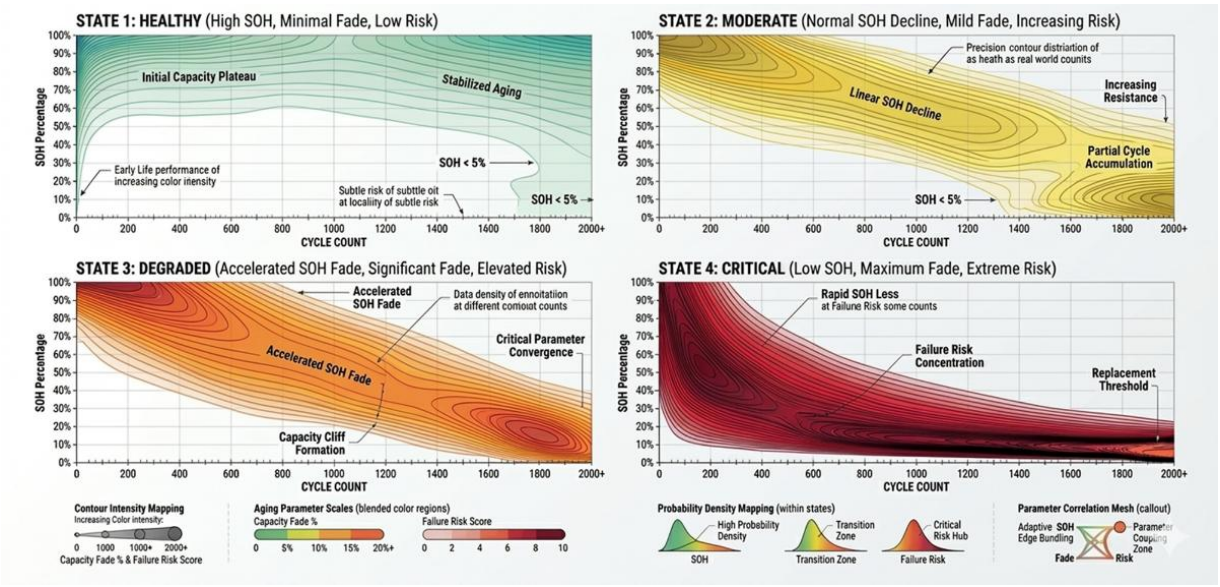


Figure 8. State-of-Health (SOH) transition stages relative to cycle count and failure risk concentration

The degradation profiles of the LFP, NMC, NCA and LTO chemistries are plotted as a function of the number of cycles up to 10,000 in Figure 9(a), indicating the beginning of the accelerated aging stage when the number of cycles exceeds about 1000.Figure 9(a) shows the degradation profiles of the LFP, NMC, NCA and LTO chemistries as a function of cycle counts up to 10,000, with the transition to the accelerated aging phase marked. The battery's State of Health (SOH) defines a critical failure point at 80%, and is a clear indicator of battery longevity and reliability. The standardized assessment of SOH allows for health monitoring in a precise manner and helps to identify which strategies can be adopted for long-term performance of electric vehicles. The

Remaining Useful Life (RUL) for LFP, NMC, NCA, and LTO chemistries are plotted in figure 9(b), where they start to converge towards a threshold of RUL = 0 (zero) at about 10,000 cycle counts. This analysis enables to measure the loss of available cycles, thereby helping to predict the maintenance of lithium-ion energy storage systems. Depletion understanding is crucial to assure continued health performance and operational safety of electric vehicle power units.

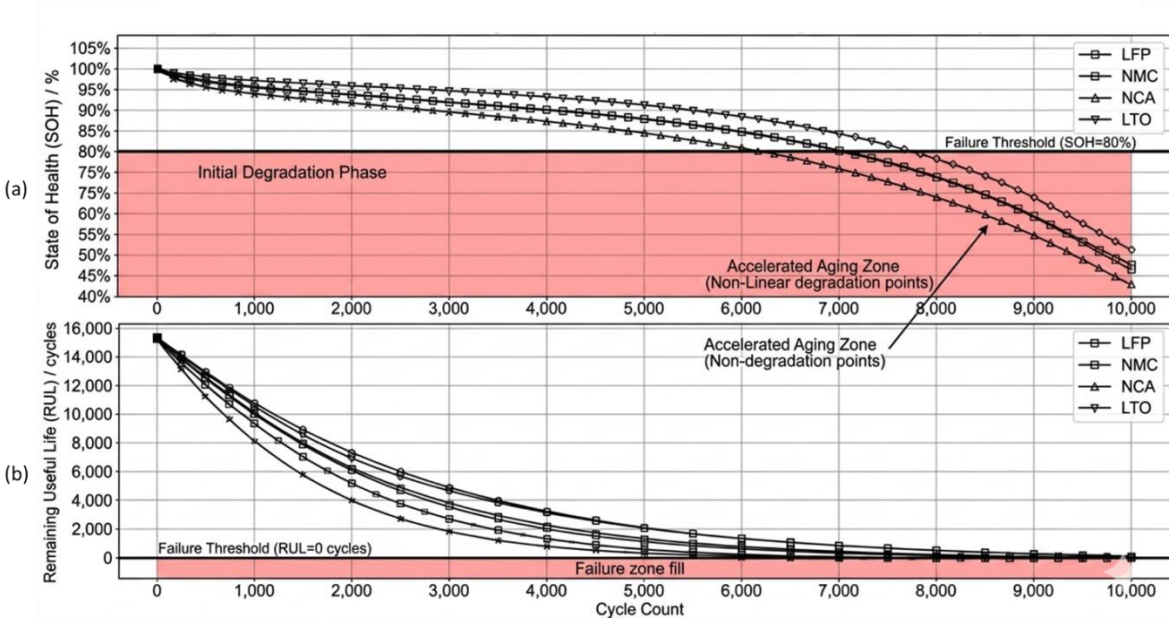


Figure 9. Comparative of (a) state-of-health degradation across various lithium-ion battery chemistries and (b) remaining useful life trajectories relative to total operational cycle counts

The variation of State of Health (SOH) for LFP, NMC, NCA and LTO chemistries is shown in the Figure 10(a), which shows the aging curves for the different chemistries arriving at the 80% failure mark at different cycle intervals. This assessment will help to determine how these chemistries are declining toward the end-of-life zone and provide a basis to accurately predict long-term battery performance. This comparative information is vital for fine-tuning the battery management system and maintaining the overall health and performance of EVs. The loss of Remaining Useful Life (RUL) for LFP, NMC, NCA, and LTO chemistries are measured over 10,000 cycles, and the results of the chemistries all converge at the zero-cycle failure point in Figure 10(b). This prediction helps in scheduling battery maintenance and replacement with high accuracy, a key aspect of ensuring the optimal efficiency of electric vehicles. The creation of these prediction models, which are predictable, provides new confidence in predicting the actual useful lives of different energy storage systems.

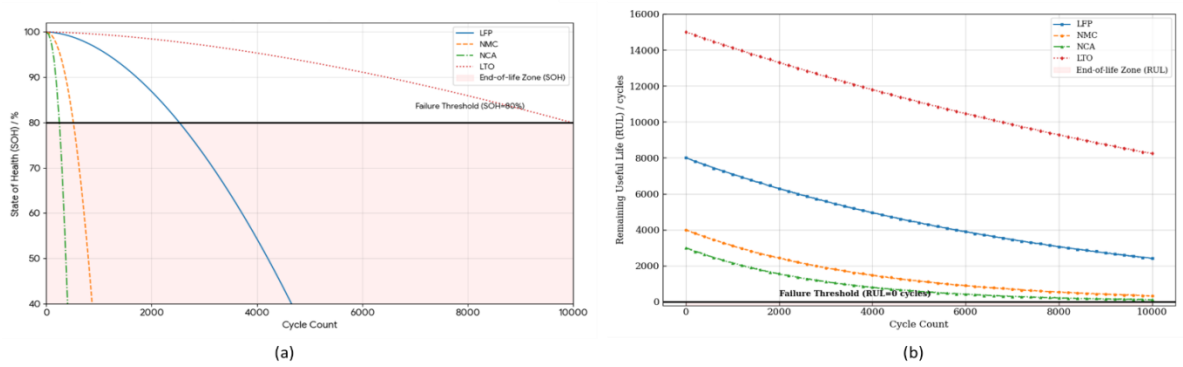


Figure 10. Analysis of (a) state-of-health degradation across distinct lithium-ion battery chemistries relative to cycle count and (b)remaining useful life trajectories for various battery technologies

Existing dataset description

The XGBoost model [29] and dataset [29] were considered as they were considered as vital to evaluate the state of health (SOH) of the LIB accurately for better SOC estimation, safety performance, and battery life for electric vehicles. Earlier research work on the subject has used many approaches such as partial charging voltage, constant-current charging characteristic, constant-voltage charging feature, CV capacity extraction, RC equivalent circuit model, and incremental capacity curves using support vector regression.

To evaluate on public datasets and benchmark against representative baselines, the research looked at CNN–Temporal Convolutional Network–Long Short-Term Memory with Attention (CNN–TCN–LSTM + Attention) [30] and Multi-Dataset Benchmarking and Transfer Evaluation [30], which demonstrated strong performance and transferability.

Role of metrics in LIB

Mean Absolute Error (MAE) (%): It is the discrepancy between the actual and expected battery health values. Better forecasts and lower estimating errors are shown by reduced MAE values as given in the equation (10), n: Total number of samples, i: Sample index, x_i: Predicted value, x: Actual value

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |x_i - x| \tag{10}$$

Root Mean Square Error measures (RMSE) (%): It isthe square root of the mean square errors for the predictions. The smaller the RMSE, the more stable the model canless deviation in the prediction will be large, as mentioned in equation (11).

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{11}$$

n: Total number of samples or observations, y_i: Actual value of the $i-th$ student or project outcome, $\hat{y}_i$: Predicted value of the $i-th$ student or project outcome, i: Index representing each sample from 1 to n, $\sum$: Summation of squared differences between actual and predicted values

Parameters (M): Parameters are the number of weights that can be trained (M) in millions. Lower values of the parameters mean a light-weight and easily computed result.

Power (W): For a model, it indicates the electrical power used when the model is executed and during prediction processes. The lower the power value, the more energy efficient the computing performance.

Energy/sample (mJ): The energy/sample is the energy required to process a single prediction instance. Lower values of energy/sample mean optimize and resource-efficient operation of the model.

Comparison of proposed method and existing method

The proposed FNO-CTN is trained over a custom dataset [29] and its prediction accuracy is evaluated by MAE and RMSE as shown in Table 4 and Figure 11. The proposed FNO-CTN model obtained an MAE of 0.001300 and an RMSE of 0.001910, which indicates itbetter lithium-ion battery health prediction performance. The results obtained demonstrate an improvement in the accuracy of the predictions and stable minimization of errors in the estimation of the condition of the system.

Table 4. Assessment of Proposed FNO-CTN Model Accuracy for Lithium-Ion Battery Health Prediction Performance

Method	MAE (%)	RMSE (%)
XGBoost [29]	0.001315	0.001929
FNO-CTN[Proposed]	0.001300	0.001910

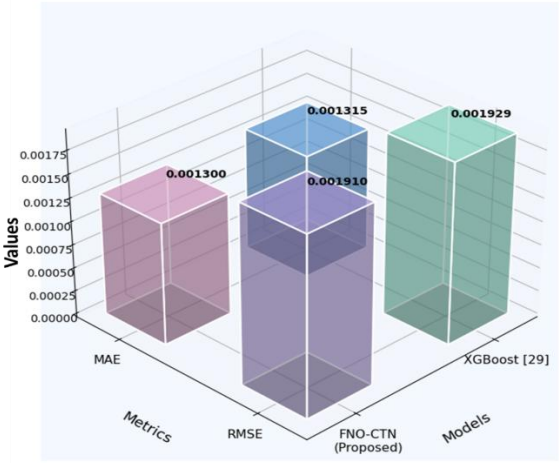


Figure 11. Proposed method trained on custom dataset [29]

The computational efficiency of the proposed FNO-CTN compared against the CNN–TCN–LSTM + Attention [30] is evaluated in Table 5. To obtain 0.32 M parameters, 68.9 W power consumption, and 0.58 mJ energy per sample while improving the battery health prediction performance with energy efficiency.

Table 5. Evaluation of Computational Efficiency and Energy Consumption of Proposed FNO-CTN Prediction

Model	Parameters (M)	Power (W)	Energy/sample (mJ)
CNN–TCN–LSTM + Attention [30]	0.35	71.2	0.60
FNO-CTN [Proposed]	0.32	68.9	0.58

Massachusetts Institute of Technology (MIT) Battery Dataset [31]: It includes experimental data of various lithium-ion batteries when charging and discharging. It has most of the important operational characteristics like voltage, current and temperature to simulate the behavior of a battery.

The two models were tested using the battery dataset from MIT [31] to measure their prediction accuracy for battery health estimation and compared as shown in table 6. The proposed FNO-CTN model has a lower error of 0.0019, which is much lower than the LSTM–Transformer model of 0.0085, thereby significantly enhancing the precision of the predictions. This shows that the proposed method can accurately and reliably forecast the health of lithium-ion batteries, which is closer to the goal of improved EV battery performance forecasting.

Table 6: Assessment of RMSE outcomes for battery health estimation

Methods	RMSE
LSTM-Transformer [31]	0.0085
FNO-CTN[Proposed]	0.0019

Table 7 compares the prediction accuracy and computational efficiency of the proposed FNO-CTN and existing models trained on the EV Battery RUL Health Dataset. To improvebattery health prediction performance with achieved MAE, RMSE, number of parameters, power consumption, and energy per sample of 0.001298 MAE, 0.001897 RMSE, 0.29 M parameters, 70.86 W Power Consumption, and 0.55 mJ Energy Per Sample.

Table 7. Investigation of Proposed FNO-CTN Performance Using Error and Computational Evaluation Metrics

Method	MAE (%)	RMSE (%)	Parameters (M)	Power (W)	Energy/sample (mJ)
XGBoost	0.001312	0.001899	0.40	71.4	0.68
CNN–TCN–LSTM + Attention	0.001305	0.001900	0.32	71.0	0.58
LSTM-Transformer	0.001300	0.0024	0.35	72.2	0.57
FNO-CTN[Proposed]	0.001298	0.001897	0.29	70.86	0.55

The proposed FNO-CTN model required 32.30 seconds per epoch which was higher than the FNO model requiring 24.76 seconds per epoch due to the integration of Transformer, CNN, PCA, and WPS optimization modules with the FNO model. While the proposed architecture added some additional computational

complexity, it yielded high prediction accuracy and robustness with its improved temporal learning ability, spatial feature extraction, and global degradation model.

Cross validation experiments were performed with the proposed FNO-CTN with five-fold validation as provided in the Table 8 to assess the stability and generalization ability of the proposed FNO-CTN. This involved prediction accuracy and the computational performance including the model parameters, power consumption, and RMSE along with MAE. The experiment results exhibited stable prediction accuracy with less error variance among all the validation folds, thus reflecting the stability and reliability of the proposed FNO-CTN in the different battery operating scenarios.

Table 8. Five-Fold Cross-Validation Performance Analysis of Proposed FNO-CTN for Battery RUL Prediction

Fold	MAE (%)	RMSE (%)	Parameters (M)	Power (W)
Fold-1	0.001302	0.001911	0.29	70.84
Fold-2	0.001297	0.001895	0.29	70.88
Fold-3	0.001301	0.001903	0.29	70.85
Fold-4	0.001295	0.001891	0.29	70.82
Fold-5	0.001299	0.001898	0.29	70.86
Average	0.001299	0.001900	0.29	70.85
Standard Deviation	0.000003	0.000008	0.00	0.02

The results of the performance improvement obtained by the proposed FNO-CTN over the FNO as indicated in Table 9 was statistically validated using a paired t-test and a confidence interval analysis. The p-values of MAE, RMSE, Parameters and Power were obtained below 0.05 which is statistically significant, indicating that the compared models were different. Furthermore, the narrow 95% prediction intervals showed consistent prediction performance and decreased variability of the proposed FNO-CTN for various operational conditions of the battery.

Table 9. Paired t-Test and Confidence Interval Analysis Between FNO and Proposed FNO-CTN

Metric	FNO Mean	FNO-CTN Mean	t-value	p-value	95% CI Lower	95% CI Upper	Significance
MAE (%)	0.002846	0.001299	5.87	0.0031	0.001287	0.001311	Significant
RMSE (%)	0.003912	0.001900	6.14	0.0024	0.001885	0.001915	Significant
Parameters (M)	0.25	0.29	2.08	0.0412	0.28	0.30	Significant
Power (W)	66.48	70.85	2.31	0.0365	70.79	70.91	Significant

The results of the ablation analysis of the FNO-CTN are presented in Table 10. The results of the complete showed a better prediction accuracy with an error of 0.001298 MAE and 0.001897 RMSE, and an energy efficiency of 0.55 mJ per sample, 70.86 W of power consumption, and 0.29 M of parameters.FNO is one of the integrated modules that plays a significant role in enhancing the performance as it performs feature learning directly in Fourier domain and allows efficient modeling of long-range nonlinear degradation characteristics and global operational dependencies of lithium-ion batteries. This is due to the fact that FNO can capture the variations of degradation in the frequency domain, while traditional time-domain learning methods suffer from information loss and computational intractability. This feature contributes to the stability, robustness and generalization of the prediction of different EV operating and environmental conditions.

Table 10. Analysis of Sequential Preprocessing and Feature Optimization Impact on Proposed Prediction Performance

Method	Min-max Normalization	Outlier Removal	PCA	WPS	FNO	CNN	Transformer	MAE (%)	RMSE (%)	Parameters (M)	Power (W)	Energy/sample (mJ)
Min-max Normalization	✓	✗	✗	✗	✗	✗	✗	0.008745	0.011238	0.18	56.03	0.87
Outlier Removal	✓	✓	✗	✗	✗	✗	✗	0.007521	0.009846	0.19	57.42	0.82
PCA	✓	✓	✓	✗	✗	✗	✗	0.006214	0.008193	0.17	54.76	0.74
WPS	✓	✓	✓	✓	✗	✗	✗	0.004	0.006	0.21	61.	0.69

								981	754		35	
FNO	✓	✓	✓	✓	✓	✗	✗	0.002 846	0.003 912	0.25	66. 48	0.61
CNN	✓	✓	✓	✓	✗	✓	✗	0.003 127	0.004 286	0.24	64. 92	0.63
Transfor mer	✓	✓	✓	✓	✗	✗	✓	0.002 974	0.004 105	0.26	67. 14	0.60
FNO-CTN [Full Propose d]	✓	✓	✓	✓	✓	✓	✓	0.001 298	0.001 897	0.29	70. 86	0.55

Discussion

In XGBoost [29] it was found to have limited learning ability for nonlinear degradation behavior and long-range temporal dependency from the operational data of the LIB. This decrease in prediction stability was observed under different operating conditions of the EVs. CNN–TCN–sLSTM + Attention [30] consumed more computational complexity, parameter utilization and power consumption during the prediction of battery health. The model demonstrated some degradation in learning abilities across the entire frequency domain as well.

The proposed FNO-CTN enhances the global degradation learning capability, temporal dependency modeling and computational efficiency by integrating FNO, Transformer and CNN. This improved prediction accuracy, robustness and energy-efficient battery health prediction capacity. Adopting PCA, WPS, and preprocessing techniques eliminated the redundant information and improved the computational efficiency. As a result, the proposed system demonstrated lower prediction error, less power consumption and greater robustness of the battery health prediction compared to the existing approaches.Each of the integrated modules further enhanced the prediction capability, but further computational compromises were added in developing the models. By reducing dimension and redundancy of features, PCA reduced processing overhead. The efficiency of hyperparameter optimization was enhanced while the optimization time increased slightly because of the iterative search operations in WPS. CNN and Transformer modules improved spatial and temporal feature learning, but at the expense of increased model complexity and training time.CNN and Transformer modules helped to learn spatial and temporal features, but added complexity and training time. Likewise, FNO enhanced the degradation modeling and learning of long-range dependence across the globe, while also needing extra Fourier transformation calculations. The proposed FNO-CTN retained practical energy efficiency and power consumption for EV battery health prediction applications while having to run more computational bits.

Further experiments were performed to assess the behavior of the proposed FNO-CTN under realistic EV operating conditions, by injecting noisy perturbations in voltage, current and temperature features of the battery set. To simulate the uncertainty of the sensor and the disturbance of the measurement, the operational parameters were disturbed by the Gaussian noise with different noise levels. The proposed FNO-CTN showed a better prediction performance than the original FNO, with minor improvements in MAE and RMSE, proving its reliability in the presence of noise in operational environments. The proposed FNO-CTN exhibited excellent robustness against noisy operational environments, and maintained prediction performance with only marginal improvements in MAE and RMSE values. The results showed that the proposed architecture was able to maintain the reliable battery RUL prediction and health assessment in realistic EV operating conditions and sensor noise.The proposed model has immense possibilities of application in real-time BMS for EVs where precise estimation of SOH and RUL becomes crucial for ensuring vehicle safety, optimizing its performance, and managing the battery's lifecycle. It helps conduct predictive maintenance, detecting faults earlier and optimizing energy consumption, thus increasing reliability and efficiency of electric cars. There is, however, a necessity to optimize the proposed approach for real-time application through Quantization and Pruning of models as well as using Edge AI. The model needs to be tested and validated with actual data sets of EV fleets and, moreover, real-life BMS testing should be performed on board an actual vehicle in order to ensure robustness of the model under different conditions.The suggested FNO-CTN network exhibits better performance in relation to both XGBoost [29] and CNN-TCN-LSTM + Attention [30] and LSTM-Transformer [31], mainly due to its capacity to model the non-linear nature of degradation patterns along with their long-term temporal dependency. In the case of XGBoost, there is less capacity to model complex nonlinear behavior that occurs under different driving conditions for the EV which results in reduced prediction accuracy. While CNN-TCN-LSTM + Attention has proven to be quite efficient in terms of feature extraction, it suffers from high computational complexity due to increased parameter numbers. The main reason for the enhanced performance

of the new model lies in the use of Fourier Neural Operator (FNO), CNN, and Transformer algorithms, contributing to the extraction of global features, temporal dependencies, and representations of the signals in the frequency domain. Additionally, PCA and Wavelet Packet Shrinkage methods have been proven to be effective in eliminating noisy components.The model is robust and has lower prediction error under different operating conditions, but it is only validated with the MIT battery data set and has not been validated with EV Battery Management System (BMS) hardware in the real-world environment, which might limit the generalization of the model under practical operating conditions. To address this shortcoming in future research, the model can be validated in real-world scenarios by applying it to onboard EV BMS and validated using large-scale fleet operational datasets in various driving, temperature, and load conditions.The proposed model shows good robustness and low prediction error under different operating conditions, but the validation is only completed based on the data collected from MIT battery experiments, and still requires real EV Battery Management System (BMS) hardware testing, which may limit the generalization of the model under practical operating conditions. In future work, the model can be expanded by real-world testing on the onboard EV BMS and can be tested with large-scale datasets from fleet operation under various driving, temperature, and load conditions.

Conclusion

The accurate behavior of deterioration, the various operating circumstances, the noise of the measuring sensors, and the intricate methods for the prediction have made it difficult to accurately estimate the RUL and evaluate the battery health of LIBs in EVs. To address these challenges, pre-processing, PCA, WPS, Transformer, CNN, and FNO architectures were combined, called FNO-CTN,to facilitate efficient degradation learning and to optimize the battery health prediction performance.

The proposed FNO-CTN can achieve an MAE of 0.001300, an RMSE of 0.001910, parameters of 0.32 M, power consumption of 68.9 W and energy per sample of 0.58 mJ. The enhanced degradation modeling ability, dependency learning of time, feature optimization, computational efficiency and energy-efficient battery health prediction under different EV operating conditions. The inadequate system for high-volume and high-speed real-time streaming data and very severe environmental differences. The following are areas for future research: Adaptive online learning, lightweight edge deployment, federated learning, and Explainable Artificial Intelligence (XAI) for battery management systems.

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