

Temporal Deep Representation Learning Based Remaining Useful Lifecycle Prediction of Electric Vehicle Lithium-ion Batteries

Pradish Vaidya S¹, Kevin Denzil V¹, Monish S¹, Cloudin S^{1*}, Saradha S²

¹Department of Computer Science and Engineering, Easwari Engineering College, Chennai, India, ²Department of Computer Science and Applications, SRM Institute of Science and Technology, Chennai, India. *Corresponding Author's Email: professorcloudin@gmail.com

Abstract

The recent proliferation of renewable energy systems and electric vehicles has driven a growing need for accurate Remaining Useful Life (RUL) prediction of lithium-ion batteries, which are crucial for effective battery health management and operational safety. AI and deep learning algorithms have proven to be highly promising in data-driven battery degradation modeling and prediction, achieving remarkable accuracy in capturing the intricate dynamics of battery degradation. In this paper, we propose a Temporal Deep Representation Learning-based Remaining Useful Life Prediction (TRDL-RULP) framework for lithium-ion batteries in Electric Vehicles (EVs). The proposed framework proposes to improve the intelligence of the battery management in order to estimate the lifecycle with high accuracy and to support predictive maintenance strategies. Then, a Long Short-Term Memory Autoencoder (LSTM-AE) is used to extract nonlinear temporal degradation features and to learn robust latent representations for a RUL prediction. In addition, the Tuna Swarm Optimization (TSO) algorithm is used to optimize the network hyperparameters, which helps to enhance convergence efficiency and prediction accuracy. A benchmark dataset of lithium-ion battery degradation data from Kaggle is used for the model evaluation. The extensive experimental results show that the TRDL-RULP framework has better prediction accuracy, robustness and generalization ability than other machine learning and deep learning methods. This combination of deep temporal feature learning with intelligent feature selection and metaheuristic hyperparameter optimization offers an effective and scalable method for accurate battery health prognostics, which can effectively guide energy management and enhance the operational lifespan of electric vehicle battery systems.

Keywords: Autoencoder, Deep Learning, Electric Vehicle, Feature Selection, Lithium-ion Batteries, Remaining Useful Lifecycle.

Introduction

In the past few years, the popularity of electric vehicles (EVs) has considerably increased owing to extended cruise range and decreased costs of on-board lithium-ion batteries. Conversely, the higher energy density and intricate manufacturing procedures could generate faulty battery cells, which have short life cycles or lead to fire accidents (1). Nevertheless, healthy batteries and capabilities are evaluated through physical and chemical tests, destructive approaches frequently render the battery ineffective and produce substantial economic loss for automakers and consumers (2). To monitor the discharging and charging procedures of EV batteries and examine the battery performance and its health has become the best option in testing. The performance of the battery declines over time owing to calendar and cycle ageing, resulting in numerous degradation events

(3). Ageing amplifies operational costs, diminishes the lifespan of equipment and impacts safety. Usually, battery can deliberate to achieve its lifecycle once its capability falls to 80% of its initial value. The remaining useful life (RUL) depicts the predicted operational period from the existing state until the battery accomplishes its lifecycle (4). Battery longevity is impacted by its arrangement and the interior chemical variations happens in charge-discharge cycles. This ageing procedure is difficult and non-linear, impacted by aspects such as temperature, discharge or charge rates and environmental factors (5). In industries, accurate RUL predictions could lessen cost of investment and enhance profitability. They also amplify energy storage system, longevity and consistency. The RUL prediction approaches are classified into three major techniques: data-driven, model-based and

This is an Open Access article distributed under the terms of the Creative Commons Attribution CC BY license (<http://creativecommons.org/licenses/by/4.0/>), which permits unrestricted reuse, distribution and reproduction in any medium, provided the original work is properly cited.

(Received 28th February 2026; Accepted 25th August 2026; Published 08th October 2026)

hybrid methods (6). The model-based strategy calculates a mathematical depiction of internal battery and electrochemical outcomes, producing a predictive technique that calculates battery status. Nevertheless, progress in these techniques is statistically intensive and necessitates comprehensive parameterization, forming practical operational challenges (7). On the other hand, data-driven models employ historic information, making them more feasible for lithium-ion battery applications owing to the intricacy of battery behavior. The prediction of EV batteries is vital to enhance both safety and performance. Besides conventional statistical analysis, deep learning (DL) has reached notable performances in the same tasks (8). The prosperity of neural network techniques has revealed the enormous demand for data quality and quantity. In contrast, the obtainability of public large-scale battery data for EVs is inadequate. The current battery datasets usually have constraints like smaller size, absence of diversity, or necessitating synthetic simulations that confine the application of DL to real-world battery systems (9).

This manuscript introduces a Temporal Deep Representation Learning based Remaining Useful Lifecycle Prediction (TRDL-RULP) approach for EV Lithium-Ion Batteries. Primarily, raw battery degradation data can be treated by using data normalization to remove scale variations and enhance model stability. Next, a snake optimization (SO)-based feature selection (FS) process was deployed to allow the extraction of the most useful degradation indicators. For RUL prediction, a long short-term memory autoencoder (LSTM-AE) has exploited to capture non-linear temporal needs and extract robust latent representations. Eventually, the tuna swarm optimization (TSO) algorithm was executed for optimum parameter tuning to improve convergence speed and predictive performance. The simulation analysis of the proposed TRDL-RULP algorithm is conducted utilizing a benchmark lithium-ion battery degradation dataset obtained from the Kaggle repository. The proposed TRDL-RULP approach is a novel combination of metaheuristic feature selection and temporal latent representation learning that is different from the current battery prognostic approaches. The proposed framework is able to predict battery RUL as well as identify

features that are more sensitive to degradation and optimize the parameters of deep learning at the same time, which can make the prediction more reliable and less compute-intensive.

This section summarizes the in-depth studies associated with the prediction of residual useful life (RUL) and the estimation of the state of health (SoH) of Li-ion batteries applicable to electric vehicles (EVs). In order to enhance the battery degradation prediction, an encoder-decoder structure combining with binary attention modules and Bidirectional Gated Recurrent Units (Bi-GRU) has been designed. In the encoding stage, attention-enhanced Bi-GRU modules focus on the salient degradation features while retaining the key temporal information. In the decoding process, the Bi-GRU network reconstructs the battery capacity degradation trajectory, which enables the RUL prediction accuracy to be improved (10). For battery degradation modelling, a deep neural network framework based on Multi-Head Deformable Attention (MHDA) and a Load-Balancing Restriction Mixture of Experts (LBRMOE) has been proposed. The adaptive attention mechanism allows the network to focus on the important degradation patterns and the balanced expert activation enhances feature learning and prevents expert collapse. As a result, better prediction accuracy and generalization performance has been obtained (11). A lightweight dynamic multi-teacher knowledge distillation framework was introduced to better enhance the battery health prediction. Dynamic teacher selection has been done with deep reinforcement learning and Dynamic Attention Fusion with a Mixture-of-Expert's architecture improves feature representation and diversity of learning. Moreover, quantile regression has been embedded to offer an interval-based battery health prediction (12). A novel hybrid prognostics scheme is proposed that integrates the Discrete Wavelet Transform (DWT) with transformer networks with Multi-Head Self-Attention (MHSA) and Extreme Gradient Boosting (XGBoost) to predict the battery lifetime. The optimization routine Chaotic Billiards Optimization in combination with the Adam optimizer has been used to optimize the parameters of the model, thus enhancing the speed of convergence and prediction accuracy (13).

A novel lithium-ion battery RUL prediction model, termed as an enhanced Gated Recurrent Unit–Kolmogorov–Arnold Network–Generalized Cauchy (GRU-KAN-GC) model, has been designed. The GRU architecture has been well known to capture temporal degradation characteristics and the Kolmogorov–Arnold Network to represent the nonlinear features. This has led to increased prediction accuracy and strong degradation modelling (14). To enhance the prediction of battery remaining useful life, a hybrid approach combines a Hierarchical Gated Recurrent Neural Network and Sand Cat Swarm Optimizer has been suggested. The optimization algorithm has been used to find optimized network parameters, which have led to improved convergence properties and overall prediction accuracy (15). Latent representation learning based on an autoencoder has been studied for battery SoH estimation and anomaly detection. Deep autoencoders have been used to learn from the battery degradation data, deriving a compact latent representation to perform accurate health estimation and fault identification. The framework's performance, however, could vary in a variety of operating conditions and large-scale deployment situations (16). This has been achieved by the application of thermoelectric graph learning and interpretable temporal decomposition for the estimation of the battery State-of-Health. Graph-based feature learning benefits in terms of accurate estimation and model interpretability by effectively capturing the complex degradation relationships. However, learning graphs is computationally complex and makes it impractical in limited resources (17). The developed Physics Guided Spatio-Temporal Graph Neural Network (PG-STGNN) enables the prediction of battery life at the fleet level. The physical degradation knowledge has been fused into the graph neural networks for better long-term battery health prediction and

battery lifecycle estimation. While better prediction accuracy has been obtained, the necessity of using huge amounts of historical data and powerful computing capacity limits its use in large-scale industrial applications (18). While significant advancements have been made in lithium-ion battery RUL prediction using recurrent neural networks (RNNs), transformer-based models, graph neural networks (GNNs) and hybrid optimization techniques, there are still challenges to be addressed. The reliability of prediction is still hampered by high computational complexity, redundant representation of features, lack of generalization for different operating conditions and suboptimal hyperparameter selection. To enhance the accuracy of prediction, computational efficiency and battery lifecycle management for electric vehicles, an efficient framework for Remaining Useful Life Prediction (RULP) based on Temporal Deep Representation Learning (TDRL) is proposed, which combines intelligent feature selection, deep temporal representation learning and metaheuristic optimization.

Methodology

In this paper, we have introduced a novel TRDL-RULP methodology for EV Lithium-Ion Batteries. The major objective of the presented TRDL-RULP is to maintain intelligent battery management methods and assist in improving the safety of operation and life cycle strategy of EV energy storage systems. Figure 1 depicts the entire process flow of the TRDL-RULP approach. As shown in Figure 1, the framework contains four stages: data pre-processing, SO-based feature reduction strategy is utilized to reduce dimensionality, RUL prediction using a hybrid LSTM with AE network and TSO algorithm-based fine-tuned optimizer process.

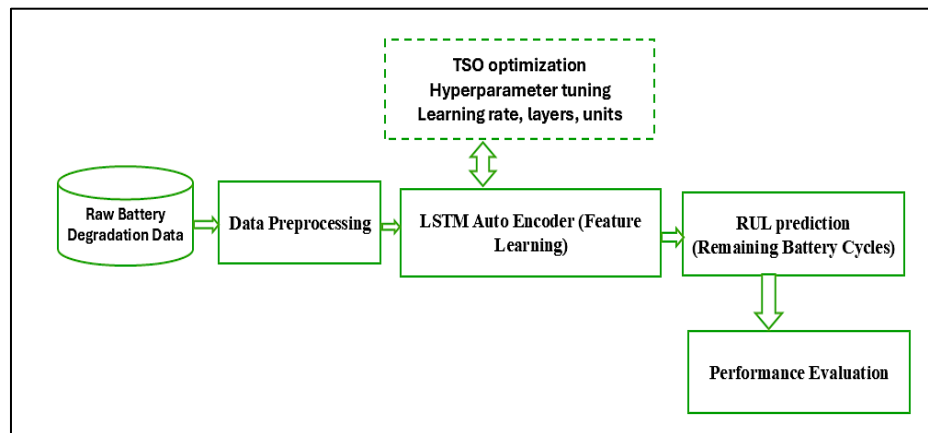


Figure 1: Overall Flow of TRDL-RULP Approach

To test the proposed TRDL-RULP framework, the Lithium-Ion Battery Degradation Dataset from the Kaggle repository was used. The dataset was created using the NASA Ames Prognostics Center of Excellence battery datasets, which provide information about the degradation characteristics of the batteries, along with some operational data collected through multiple charge-discharge cycles. The dataset consists of lithium-ion batteries that are widely employed in EVs for energy storage and also contain battery health metrics related to battery capacity reduction and aging characteristics. These are 11 attributes of the dataset: battery identification number, cycle count, battery capacity trend (BCt), State of Health (SOH), Remaining Useful Life (RUL), charging current (chI), charging voltage (chV), charging temperature (chT), discharging current (disI), discharging voltage (disV) and discharging temperature (disT). To develop the models, all the following attributes were used, except for the battery identification field of the score: 10 attributes related to the degradation.

The battery degradation was measured during repeated cycling operations and the degradation of battery capacity and health was seen as the cycle number increased. SOR gradually decreased over the battery life and the RUL showed a decreasing trend. The following measurements were taken as part of the charging and discharging process and were deemed to be operational indicators that impact on degradation behavior: temperature, voltage, current. Typically, when battery capacity drops 20% from the nominal rated capacity, the battery is considered to be at the end-of-life. In line with the literature, the capacity decrease criterion

used in this study is 80% capacity. The prediction target is the number of cycles that the battery is expected to last after it has reached the defined end-of-life condition. The data set contains full degradation data but lacks detailed metadata on the individual cell chemistry, actual operating conditions in the environment and cell manufacturing specifications. The source for the publicly available data set does not explicitly report this detailed information. However, this dataset has been widely used for benchmarking data-driven battery prognostics techniques, due to its realistic degradation paths and representative battery ageing characteristics.

Data Normalization

In the beginning stage, raw battery degradation data are processed utilizing data normalization to eradicate scale differences and enhance model consistency. The data pre-processing is carried out using Z-score normalization to enhance the performance of model (19). This effectively lessens the impacts of differing scales and hinders the features with greater values by dominating the process of learning. The performance and convergence are also enhanced by the model and it can be minimal exposed to outliers. Categorical aspects are encoded by employing a one-hot encoder or label encoder depend on the requirements of the model and consequently transform them into number notation suited for model. Assuring that both numeric and categorical data can efficiently be employed through Z-score normalization by converting data into units with 0 mean and unit variance.

It changes each data point. $x_{i,n}$ in data into its normalized value $x'_{i,n}$ depend on Equation [1] showed below,

$$x'_{i,n} = \frac{x_{i,n} - \mu_i}{\sigma_i} \quad [1]$$

Here, μ and σ refers the mean and standard deviation (SD), respectively. It lowers the effects of outliers. Although the mean and SD values are changed by time, their effectiveness to maintain constant normalization over data with related units diminishes.

Feature Reduction Process

In this section, an SO-based FS approach was utilized to improve feature relevance and reduce dimensionality. SO is a model that depends upon the optimum simulation of a snake (20). The population of snakes has been divided into 50

percent of males and 50 percent of females that pretend amount of food, temperature and move toward food, search for food, mating, fight and egg-laying socio-sexual habits. SO partitioning the iterations into local exploitation and global exploration that effectively balances the path ranges.

The calculation model for diverse techniques is specified and showed in Equation [2].

$$\begin{cases} Temp = \exp\left(-\frac{z}{Z}\right) \\ Q = c_1 \left(-\frac{z}{Z}\right) \end{cases} \quad [2]$$

Here, Z represents the maximal iteration number, $c_1 = 0.5$, z indicates the existing iteration number, $Temp$ represents temperature and Q signifies the quantity of food. While $Q < 0.25$, they enter the food-searching way is shown in Equations [3, 4].

$$\begin{cases} A_m = \exp\left(\frac{-f_{randm,m}}{f_{i,m}}\right) \\ V_{i,m}(z+1) = \\ V_{randm,m}(z) \pm c_2 \times A_m \times ((V_{\max} - V_{\min}) \times randm + V_{\min}) \end{cases} \quad [3]$$

$$\begin{cases} A_f = \exp\left(\frac{-f_{randm,f}}{f_{i,f}}\right) \\ V_{i,f}(z+1) = \\ V_{rand,f}(z) \pm c_2 \times A_m \times ((V_{\max} - V_{\min}) \times randm + V_{\min}) \end{cases} \quad [4]$$

Here, $V_{randm,f}$, $V_{randm,m}$, indicates arbitrarily generated positions of female and male snakes, A_f , A_m refers to the capability of female and male snakes to find food; $V_{i,m}$, $V_{i,f}$ signifies the location of i^{th} male and female snakes; $V_{\max}$, $V_{\min}$ refers to the upper and lower bounds and $rand$ signifies an arbitrary value from zero to one. $c_2 = 0.05$. While $Q \geq 0.25$ and $Temp > 0.6$, they move towards the nutrition phase is modelled in Equation [5].

$$\begin{cases} V_{i,m}(z+1) = \\ v_{food} \pm c_3 \times Temp \times randm \times (v_{food} - V_{i,m}(z)) \\ V_{j,f}(z+1) = \\ v_{food} \pm c_3 \times Temp \times randm \times (v_{food} - V_{j,f}(z)) \end{cases} \quad [5]$$

Now, v_{food} represents the location of the optimum individual, $c_3 = 2$ and an arbitrary number from zero to one has been created by $randm$. In contrast, a likelihood threshold of 0.6 permits the choice of mating or fighting modes. While $randm < 0.6$, they enter combat, is modelled in Equations [6, 7].

$$\begin{cases} F_m = \exp\left(-\frac{f_{best,m}}{f_i}\right) \\ V_{i,m}(z+1) = \\ V_{i,m}(z) \pm c_3 \times F_m \times randm \times (Q \times v_{best,f} - V_{i,m}(z)) \end{cases} \quad [6]$$

$$\begin{cases} F_f = \exp\left(-\frac{f_{best,f}}{f_i}\right) \\ V_{i,f}(z+1) = \\ V_{i,f}(z) \pm c_3 \times F_m \times randm \times (Q \times V_{besti,m} - V_{i,f}(z)) \end{cases} \quad [7]$$

Here, $f_{best,m}, f_{best,f}$ refers to fitness value of optimum individuals between male and female snakes; f_i signifies fitness value of individual i and F_f, F_m refers to the fighting capability of female and male snakes; While $randm \geq 0.6$, the snake model enters the mating is shown in Equations [8, 9].

$$\begin{cases} M_m = \exp\left(-\frac{f_{i,f}}{f_{i,m}}\right) \\ V_{i,m}(z+1) = \\ V_{i,m}(z) \pm c_3 \times M_m \times randm \times (Q \times V_{i,f} - V_{i,m}(z)) \end{cases} \quad [8]$$

$$\begin{cases} M_f = \exp\left(-\frac{f_{i,m}}{f_{i,f}}\right) \\ V_{j,f}(z+1) = \\ V_{j,f}(z) \pm c_3 \times M_f \times randm \times (Q \times V_{i,m} - V_{j,f}(z)) \end{cases} \quad [9]$$

Now, $f_i, f, f_{i,m}$ refers to value of fitness of male and female snakes and M_f, M_m represent mating capability of female and male snakes. While the snake model goes into the mode of spawning is modelled in Equation [10].

$$\begin{cases} V_{worst,m} = V_{\min} + randm \times (V_{\max} - V_{\min}) \\ V_{worst,m} = V_{\min} + randm \times (V_{\max} - V_{\min}) \end{cases} \quad [10]$$

Here, $V_{worst,f}, V_{worst, and m}$ indicate the poor individuals with a population of female and male snakes. The fitness function (FF) employed in the presented methodology is intended to have a balance amongst the chosen feature counts in all solutions (minimum) and the classification precision (maximum) is shown in Equation [11].

$$Fitness = \alpha \gamma_R(D) + \beta \frac{|R|}{|C|} \quad [11]$$

Now, $\gamma_R(D)$ depicts the classification rate of error of a stated classifier. $|R|$ signifies the cardinality of the chosen subset and $|C|$ indicates the overall number of features in the database, α and β refer to 2 parameters.

Hybrid LSTM-AE Prediction

For RUL prediction, an LSTM-AE has been exploited to capture non-linear temporal dependencies and extract robust latent representations. The LSTM-AE model can be utilized for the classification method (21). This technique efficiently gains the consecutive and temporal dependency. In contrast with traditional classifiers, long-range patterns and latent correlation have been successfully demonstrated in this method to increase the forecast accuracy for time-dependent or sequential data. The flattened representation of input data can

be appropriately acquired through the AE model, reducing noise and highlighting vital classification forms. It increases robustness and deals with complex non-linear correlations and lessens overfitting through learning a useful latent space. The architecture is deemed more suitable with greater accuracy and better generalization when compared to standard classification techniques. An LSTM-AE is a specialized technique precisely developed for consecutive data processing. This can be utilized as an encoder-decoder model composed of LSTM. This framework compresses the input orders into a vector of regular size,

incessantly employed for recreating the new data, therefore ensuring the keeping of significant time-related data. Such configurations have been extremely efficient for tasks which can be required the comprehension of how data is developed with respect to time, often exceeding the outcomes of traditional AEs in these domains.

The LSTM networks are determined to be a normal class of DL techniques that were especially developed for alleviating the complex problem of

vanishing gradient, a main task came across standard RNN. This memory cell is performed under 3 major gates. The first one is the input gate that works on the integration of new data. The second one is the forget gate that possesses the accountability to find what to continue or remove. Finally, the third one is output gate that can control the transmitted data to the outcome over the network.

The mathematical form is represented for all gates as denoted in Equations [12-17]. To gain the input order $= (x_1, x_2, \dots, x_z)$, the LSTM cell executes the following progression at each time step z and mathematical model is shown in Equations [12-17],

$$i_z = \sigma(W_i \cdot [h_{z-1}, x_z] + b_i) \quad [12]$$

$$\tilde{C}_z = \tanh(W_c \cdot [h_{z-1}, x_z] + b_c) \quad [13]$$

$$C_z = f_z \odot C_{z-1} + i_z \odot \tilde{C}_z \quad [14]$$

$$f_z = \sigma(W_f \cdot [h_{z-1}, x_z] + b_f) \quad [15]$$

$$o_z = \sigma(W_o \cdot [h_{z-1}, x_z] + b_o) \quad [16]$$

$$h_z = o_z \odot \tanh(C) \quad [17]$$

Here, the parameter o_z defines the output gate, i_z indicates the input gate, f_z specifies the forget gate. The term $\tilde{C}_z$ The candidate memory cell vector is specified. C_z denotes the vector of cell layer. h_z represents the vector of hidden layer (HL). The symbol σ signifies the activation sigmoid function. The symbol $\odot$ represents element-wise multiplication. The parameter W_f, W_i, W_c, W_o denote the weight matrices. The terms b_f, b_i, b_c and b_o remains biased vectors.

The LSTM-AE is generally useful and can identify longer-range patterns with respect to time-sequences data. It can enhance the dependability and working efficiency. This can be included in dual units: an encoded transforms the input orders into certain size vectors and the decoded that reforms the order from those vectors. The architecture of the LSTM-AE is explained how these models are performed for providing strong effectiveness corresponding with time-series.

Fine-tuned Model via TSO

At last, the TSO algorithm can be executed for better parameter tuning to improve convergence speed and predictive results. Tunas are marine predator fish that eat either surface or midwater fish. The ability of the tunas to constantly swim is either

effective or exceptional. They utilize the group travel tactic for predatory behavior. To find and hunt their prey, they utilize its intelligence (22). In addition, tunas have developed a type of intellectual and efficient hunting tactics, comprising spiral and parabolic hunting. To relocate their target across the shallow water and attack without effort, they utilize the spiral pattern they generate while swimming within their hunting strategy. Snake Optimization was chosen due to its adaptive exploration and exploitation properties. When choosing degradation sensitive features in high-dimensional features, such as battery characteristics, SO is more capable than PSO, GA, GWO and ACO in avoiding premature convergence and keeping the population diversity.

Initialization

The primary populations in the searching region are randomly generated by the TSO model to begin the optimizer procedure is showed in Equation [18].

$$G_e^{adv} = \mathcal{R} \cdot (Upp_{bo} - Low_{bo}) + Low_{bo}, = 1, 2, \dots, num_{po} \quad [18]$$

The searching regions' maximum and minimum are indicated by Upp_{bo} and Low_{bo} , the arbitrary vector in the interval of zero and one is stated as $\mathfrak{R}$, the entire tuna populations can portray as num_{po} and the e^{th} The first individual is symbolized by G_e^{div} .

Spiral Foraging

While the smallest schooling fish meet predators, they all generate a dense formation, which continually alters their swimming route. Therefore, the predators find it challenging to surround the target. To hunt their victim, the tuna troop generates closed spiral structures. Like the

gathering of fish that swim dynamically along the selected path, nearby fish change their route one by one, create a larger group with a common objective and begin foraging. Each tuna follows the prior fish and the schools of tuna interconnect with one another (23). Spiral Foraging is modelled in Equations [19-23].

$$G_e^{f+1} = \begin{cases} \gamma_1 \cdot (G_{best}^f + \mu \cdot |G_{best}^f - G_e^f|) + \gamma_2 \cdot G_e^f, e = 1 \\ \gamma_1 \cdot (G_{best}^f + \mu \cdot |G_{best}^f - G_e^f|) + \gamma_2 \cdot G_{e-1}^f, e = 2, 3, \dots, num_{po} \end{cases} \quad [19]$$

$$\gamma_1 = j + (1 - j) \cdot \frac{f}{f_{max}} \quad [20]$$

$$\gamma_2 = (1 - j) - (1 - j) \cdot \frac{f}{f_{max}} \quad [21]$$

$$\mu = \exp(qr) \cdot \cos(2\pi q) \quad [22]$$

$$r = \exp\left(3\cos\left(\left(\left(f_{max} + \frac{1}{f}\right) - 1\right)\pi\right)\right) \quad [23]$$

Whereas, f_{max} characterizes the iteration boundary, the provided constant can be specified by j , the e^{th} An individual for iteration $f + 1$ is represented by G_e^{f+1} . The weight coefficients are specified by γ_1 and γ_2 , the number selected at random among zero and one is stated as q , the present top individual is represented by G_{best}^f and the present iteration is characterized by f . Every tuna can use the area near its prey. In addition, the searching region creates stochastic coordinates for spiral hunting that aid all individuals in looking for the largest region and give the TSO the capability of discovering the complete world is shown in Equation [24].

$$G_e^{f+1} = \begin{cases} \gamma_1 \cdot (G_{\mathfrak{R}}^f + \mu \cdot |G_{\mathfrak{R}}^f - G_e^f|) + \gamma_2 \cdot G_e^f, e = 1 \\ \gamma_1 \cdot (G_{\mathfrak{R}}^f + \mu \cdot |G_{\mathfrak{R}}^f - G_e^f|) + \gamma_2 \cdot G_{e-1}^f, e = 2, 3, \dots, num_{po} \end{cases} \quad [24]$$

Whereas, $G_{\mathfrak{R}}^f$ displays the randomly established reference point within the possible area. The last developed formulation for the spiral searching tactic is formulated in Equation [25]:

$$G_e^{f+1} = \begin{cases} \begin{cases} \gamma_1 \cdot (G_{\mathfrak{R}}^f + \mu \cdot |G_{\mathfrak{R}}^f - G_e^f|) + \gamma_2 \cdot G_e^f, e = 1 \\ \gamma_1 \cdot (G_{\mathfrak{R}}^f + \mu \cdot |G_{\mathfrak{R}}^f - G_e^f|) + \gamma_2 \cdot G_{e-1}^f, e = 2, 3, \dots, num_{po} \end{cases} & \text{if } \mathfrak{R} < \frac{f}{f_{max}} \\ \begin{cases} \gamma_1 \cdot (G_{best}^f + \mu \cdot |G_{best}^f - G_e^f|) + \gamma_2 \cdot G_e^f, e = 1 \\ \gamma_1 \cdot (G_{best}^f + \mu \cdot |G_{best}^f - G_e^f|) + \gamma_2 \cdot G_{e-1}^f, e = 2, 3, \dots, num_{po} \end{cases} & \text{if } \mathfrak{R} < \frac{f}{f_{max}} \end{cases} \quad [25]$$

Parabolic Foraging

They improve the parabolic formation from the selected point, i.e., food. Additionally, they discover their environments. As a result, either of these approaches is utilized simultaneously and a 50% probability selection is used for either method (24). Parabolic Foraging is shown in Equations [26, 27].

$$G_e^{f+1} = \begin{cases} G_{best}^f + \mathfrak{R} \cdot (G_{best}^f - G_e^f) + XC \cdot a^2 \cdot (G_{best}^f - G_e^f), & \text{if } \mathfrak{R} < 0.5 \\ XC \cdot a^2 \cdot G_e^f, & \text{if } \mathfrak{R} \geq 0.5 \end{cases} \quad [26]$$

$$a = \left(1 - \frac{f}{f_{\max}}\right)^{\left(\frac{f}{f_{\max}}\right)} \quad [27]$$

An arbitrary number in this sample drops in the interval[1, 1] specified by XC . Till the end condition is fulfilled, every TSO will be upgraded and constantly calculated in the procedure of the complete optimization. The fitness choice is a major

feature prompting the performance of the TSO methodology. The parameter selection method comprises the solution encoding methodology to evaluate the efficacy of candidate performances.

The TSO reflects precision as the major standard to strategy the FF, which is represented as in Equations [28, 29].

$$Fitness = \max(P) \quad [28]$$

$$P = \frac{TP}{TP + FP} \quad [29]$$

Now, TP and FP epitomize the true and the false positive values.

Performance Validation

In this part, the experimental result of the TRDL-RULP method could be inspected employing the Lithium-Ion Battery Degradation Dataset (20). This database is modelled after the NASA Ames Prognostics Center of Excellence lithium-ion battery degraded databases. It suggests the charge-discharge behaviour and aging procedure of lithium-ion batteries through many cycles, taking real tendency in battery health in time. The database involves 11 attributes: BCt and RUL, SOH, chl, disI, disV, chV, disT, ch and battery_id, cycle. For

analysis purposes, 10 attributes are chosen: BCt, SOH, RUL, disI, chl, disV, chV, disT, chT and cycle.

Figure 2 shows the correlation matrix of the TRDL-RULP method between battery attributes, where values near 1 and -1 specify stronger positive and negative correlations. It is noted that SOH and BCt reveal a robust positive correlation with RUL, emphasizing their significance in predicting the battery life. However, the cycle shows a robust negative correlation with RUL, implying that battery life reduces with growing cycles. In addition, disI, disV, disT, chl, chV and chT display weaker correlations, signifying their restricted influence on RUL approximation.

Attributes	cycle	chl	chV	chT	disI	disV	disT	BCt	SOH	RUL
	1.00	0.01	0.01	0.08	-0.00	-0.05	0.05	-1.00	-1.00	-0.97
	0.01	1.00	0.02	0.03	-0.02	0.06	-0.01	-0.01	-0.01	-0.01
	0.01	0.02	1.00	-0.00	-0.02	0.02	0.05	-0.01	-0.01	0.00
	0.08	0.03	-0.00	1.00	0.01	0.07	-0.02	-0.08	-0.08	-0.08
	-0.00	-0.02	-0.02	0.01	1.00	-0.08	0.10	0.00	0.00	0.02
	-0.05	0.06	0.02	0.07	-0.08	1.00	-0.05	0.05	0.05	0.04
	0.05	-0.01	0.05	-0.02	0.10	-0.05	1.00	-0.05	-0.05	-0.04
	-1.00	-0.01	-0.01	-0.08	0.00	0.05	-0.05	1.00	1.00	0.97
	-1.00	-0.01	-0.01	-0.08	0.00	0.05	-0.05	1.00	1.00	0.97
	-0.97	-0.01	0.00	-0.08	0.02	0.04	-0.04	0.97	0.97	1.00
Attributes	cycle	chl	chV	chT	disI	disV	disT	BCt	SOH	RUL

Figure 2: Correlation Matrix of the TRDL-RULP Method

Results and Discussion

Figure 3 represents the feature distribution of the TRDL-RULP method between disI and RUL. It is noted that the data points are randomly distributed without any clear growing or declining tendency. This specifies that disI has a weaker correlation with RUL and has minimum influence on battery life prediction.

Figure 4 depicts the prediction performance of the

TRDL-RULP system at various epochs (20, 30, 40 and 50) for both testing and training datasets. It is monitored that at lesser epochs, there is a long gap between the actual and predicted values, representing minimal prediction accuracy. As the epochs rise, the predicted outcomes are closer to actual outcomes, exhibiting enhanced learning ability. At epoch 50, the technique attains best alignment and steadiness, indicating efficient and precise RUL prediction.

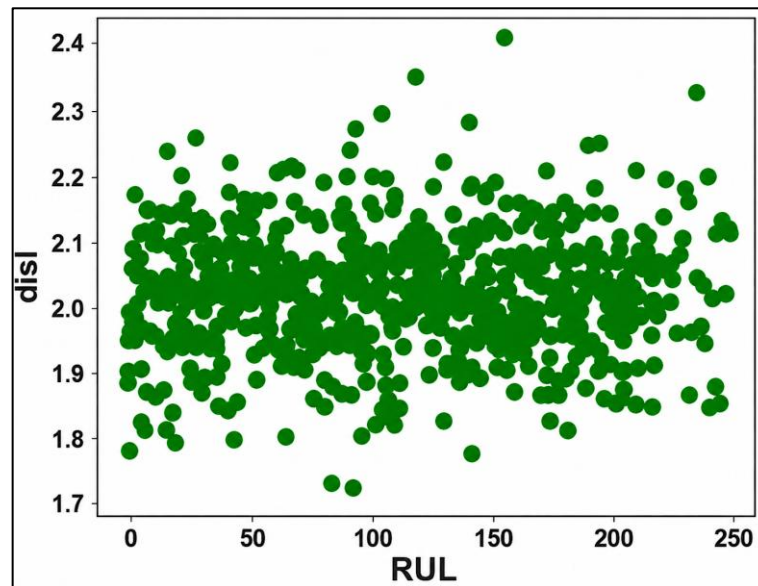


Figure 3: Feature Distribution with disI and RUL

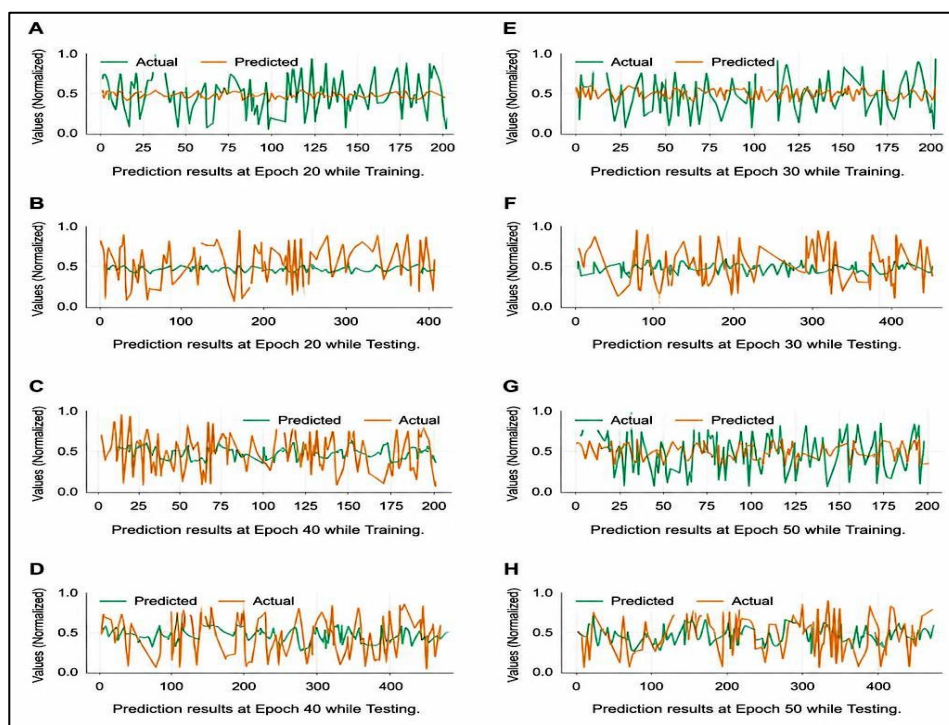


Figure 4: Comparison Between the Actual and Predicted Normalized Values for the Testing and Training Datasets. (A, B) Prediction Results at Epoch 20, (C, D) Prediction Results at Epoch 40, (E, F) Prediction Results at Epoch 30 and (G, H) Prediction Results at Epoch 50

Table 1 portrays the RUL prediction result of the TRDL-RULP approach with several metrics using training and testing sets. The outcome indicates that the TRDL-RULP approach exactly identified the samples. Under training set, the proposed TRDL-RULP technique provides results with MSE of

0.0242, RMSE of 0.1557, MAE of 0.1319, MAPE of 7.3191 and R2 Score of 0.6562, correspondingly. In the meantime, under testing set, the proposed TRDL-RULP model gives outcomes with MSE of 0.0257, RMSE of 0.1603, MAE of 0.1363, MAPE of 1.8496 and R2 Score of 0.6503, correspondingly.

Table 1: RUL Prediction Outcomes of the Temporal Deep Representation Learning-based Remaining Useful Life Prediction (TRDL-RULP) Model with Metrics

Metrics	Training Set	Testing Set
MSE	0.0242	0.0257
RMSE	0.1557	0.1603
MAE	0.1319	0.1363
MAPE	7.3191	1.8496
R2 Score	0.6562	0.6503

Note: MSE = Mean Squared Error, RMSE = Root Mean Squared Error, MAE = Mean Absolute Error, MAPE = Mean Absolute Percentage Error, R² Score = Coefficient of Determination.

Figure 5 illustrates the loss curves of the TRDL-RULP model using different performance metrics like MSE, RMSE, MAE, MAPE and R² score for both training and testing datasets. It is observed that the MSE, RMSE and MAE values decrease steadily with increasing epochs, indicating improved prediction

accuracy and effective learning. The R² score increases gradually, showing enhanced model performance and better fit to the data. Additionally, the training and testing curves follow a similar trend, indicating good generalization without significant overfitting.

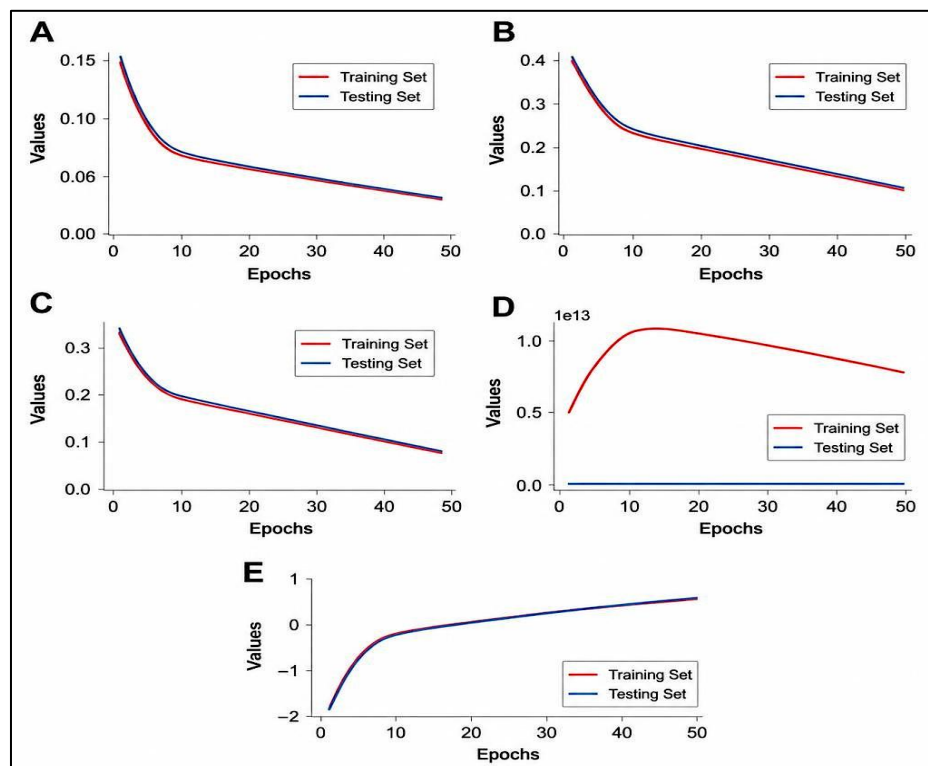


Figure 5: Training and Testing Performance of the Proposed TRDL-RULP Model Over 50 Training Epochs Using Different Regression Evaluation Metrics. (A) Mean Squared Error (MSE), (B) Root Mean Squared Error (RMSE), (C) Mean Absolute Error (MAE), (D) Mean Absolute Percentage Error (MAPE), (E) Coefficient of Determination (R² Score)

In addition to average performance metrics, the reliability of the proposed TRDL-RULP model was

also explored using error distribution analysis. The similarity of training and testing performance

metrics suggests good generalization ability and low overfitting. The small RMSE and MAE values indicate that forecast errors across various degradation levels are kept low. Moreover, the learning behaviour is seen to be stable as the loss curves start to converge over time, showcasing accurate model optimisation. In the present work, residual plots and confidence interval estimation were not discussed explicitly, but the results

achieved indicate that the proposed framework is able to provide a consistent and robust RUL prediction performance under different degradation conditions. Future research will explore the use of uncertainty-aware prognostic models that include residual analysis, prediction intervals and prediction confidence bounds to provide better reliability assessment.

Table 2: Comparison Result of the Temporal Deep Representation Learning-Based Remaining Useful Life Prediction (TRDL-RULP) Technique with Existing Systems

Algorithms	MSE	RMSE	MAE	R2 Score
NN	0.293	2.360	3.280	2.911
SVR	0.236	2.920	7.700	1.002
LSTM-DSSN	0.242	2.670	6.850	1.044
SVM	0.192	2.130	1.830	2.784
DCNN-TL	0.369	1.560	7.720	0.887
FCNN	0.252	0.630	5.420	1.110
LSTM	0.258	2.060	6.160	2.970
TRDL-RULP	0.024	0.156	0.132	0.656

Note: MSE = Mean Squared Error, RMSE = Root Mean Squared Error, MAE = Mean Absolute Error, R^2 Score = Coefficient of Determination.

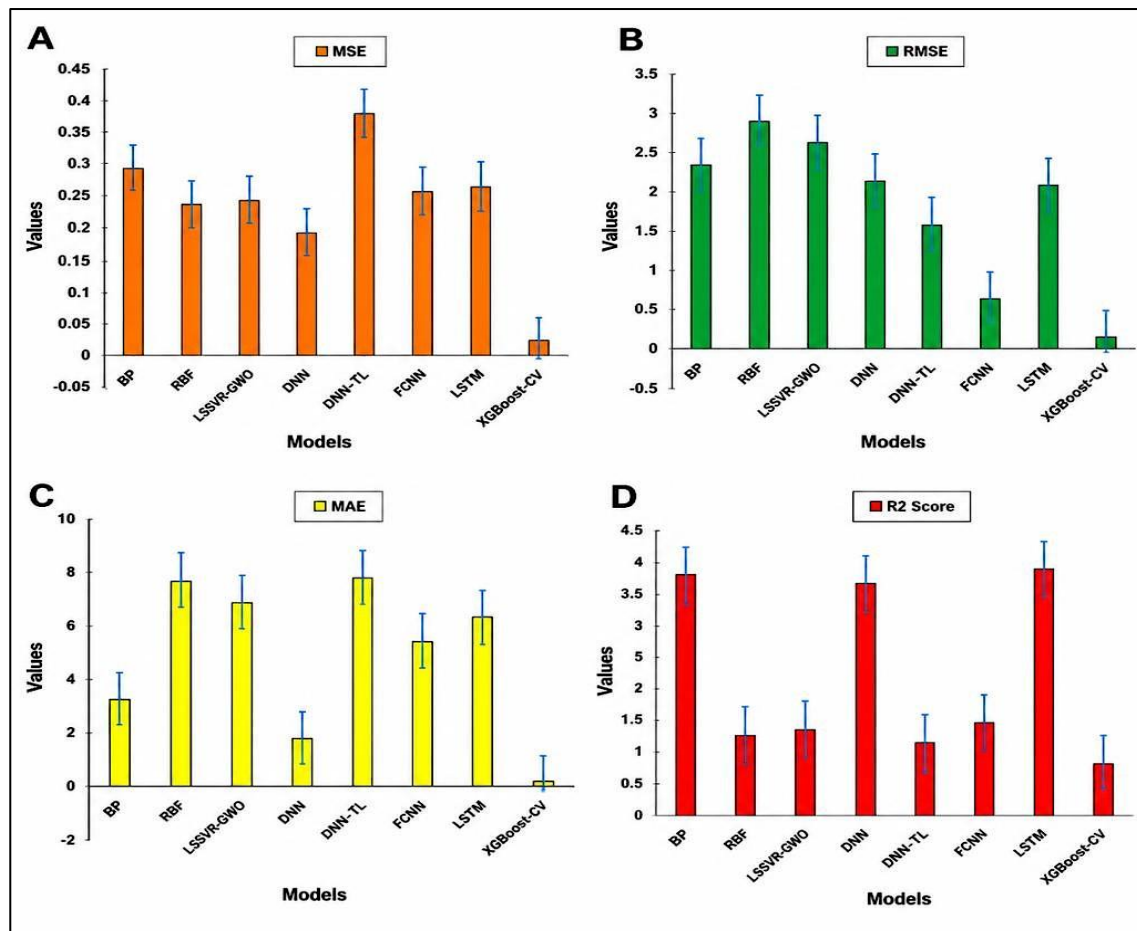


Figure 6: Performance Comparison of the Evaluated Prediction Models Using Regression Error Metrics. (A) Mean Squared Error (MSE), (B) Root Mean Squared Error (RMSE), (C) Mean Absolute Error (MAE), (D) Coefficient of Determination (R^2 Score)

The comparative investigation of the TRDL-RULP method with other existing approaches is shown in Table 2 and Figure 6 (21, 22). The performance evaluation implied that the TRDL-RULP system has revealed the best outcomes. The proposed TRDL-RULP model has reached the lowest outcomes with MSE of 0.024, RMSE of 0.156, MAE of 0.132 and R2 Score of 0.656, whereas the SVM method has slightly higher results with MSE of 0.192, RMSE of 2.130, MAE of 1.830 and R2 Score of 2.784. In addition, NN, SVR, LSTM-DSSN, FCNN and LSTM methodologies have achieved maximal performance. At last, the DCNN-TL method has obtained greater outcomes with an MSE of 0.369, RMSE of 1.560, MAE of 7.720 and R2 Score of 0.887. The performance reveals that the TRDL-RULP model gives the most precise and strong outcomes amongst all the techniques assessed. The TRDL-RULP model can be taken up in the cloud supported Battery Management Systems. The inference phase is performed by only doing a forward pass through the trained network, which could allow for real-time deployment (25). The compression and edge-AI techniques could be further applied to reduce the computational cost of embedded EV controllers.

Conclusion

In this manuscript, we have introduced a novel TRDL-RULP system for EV Lithium-Ion Batteries. The main goal of the proposed TRDL-RULP framework is to assist intelligent battery management methods and help to increase the effective safety and life cycle strategy of the EV energy storage method. At first, raw battery degradation data can be processed via data normalization to eradicate scale variants and increase model consistency. To develop feature relevance and reduce complexity, SO-based FS method can be deployed to allow the extraction of the most useful degradation indicators. For RUL prediction, an LSTM-AE has been employed to capture non-linear temporal dependencies and extract robust latent representations. Lastly, the TSO algorithm is performed for optimum parameter tuning to improve convergence speed and predictive solution. The simulation examination of the proposed TRDL-RULP system is conducted utilizing a benchmark lithium-ion battery degradation dataset obtained from the Kaggle repository. Widespread comparative outcomes validate the higher performance of the

TRDL-RULP method over recent methodologies. The proposed TRDL-RULP framework has several limitations, however, based on its great potential. First, it utilizes a benchmark data set of lithium-ion batteries provided by Kaggle, which means it needs to be tested further with other batteries, battery manufacturers, battery ageing conditions, driving patterns and the environmental temperatures. Secondly, the feature selection and hyperparameter tuning of the online processing has increased the computational cost of the corresponding offline process including Snake Optimization and Tuna Swarm Optimization. Moreover, the current approach does not explicitly give the magnitude of the uncertainty in the prediction, which is important for safety critical battery management decisions. The methodology will be tested in the future with multi-source experimental and real-world EV battery datasets. In addition, lightweight model compression and online learning strategies will be proposed to enable real-time deployment and adaptation in resource-limited environment for EV battery management systems.

Abbreviations

CNN: Convolutional Neural Network, DL: Deep Learning, EV: Electric Vehicle, FS: Feature Selection, ML: Machine Learning, RNN: Recurrent Neural Network, RUL: Remaining Useful Life, SOH: State of Health, TRDL-RULP: Temporal Deep Representation Learning-based Remaining Useful Life Prediction, TSO: Tuna Swarm Optimization.

Acknowledgement

We would like to acknowledge the contributions of all those who supported this research. Our sincere thanks go to the participants who took part in the study, as well as to all individuals and institutions whose support made this research possible.

Author Contributions

Pradish Vaidya S: Data Interpretation, Writing – Original Draft, Review and Editing, Kevin Denzil V: Data Interpretation, Writing – Original Draft, Review and Editing, Monish S: Result Analysis, Cloudin S: Result Analysis, Saradha S: Conceptualization, Conducted the Study, Data Collection. All authors critically reviewed the final manuscript.

Conflict of Interest

The authors have expressed no conflict of interest.

Data Availability

Data is available in the following link,
<https://www.kaggle.com/datasets/programmer3/lithium-ion-battery-degradation-dataset>

Declaration of Artificial Intelligence (AI) Assistance

The authors confirm that they have not used generative AI or AI-assisted technology in the preparation of this manuscript, either during writing or editing. The authors take full responsibility for the content's originality, interpretation and accuracy.

Ethics Approval

Not applicable

Funding

The authors did not receive support from any organization for the submitted work.

References

- Cheng H, Zhang L. A physics-informed deep learning framework for remaining useful life prediction of lithium-ion batteries with feature subset construction. *Energy*. 2026;140288. <https://doi.org/10.1016/j.energy.2026.140288>
- Shu X, Yang W, Wei K, Zhang B, Yan R, Cattley R. Remaining useful life prediction of lithium-ion batteries by leveraging end-of-charge characteristics. *Journal of Energy Storage*. 2025;134:118135. <https://doi.org/10.1016/j.est.2025.118135>
- Huang W, Zhou T, Ma J, Chen X. An ensemble model based on fusion of multiple machine learning algorithms for remaining useful life prediction of lithium battery in electric vehicles. *Innovations in Applied Engineering and Technology*. 2025;4(1):1-12. <https://doi.org/10.62836/iaet.v4i1.319>
- Li F, Feng H, Min Y, Zhang Y, Zuo H, Bai F, Zhang Y. Prediction of lithium-ion battery degradation trajectory in electric vehicles under real-world scenarios. *Energy*. 2025;317:134663. <https://doi.org/10.1016/j.energy.2025.134663>
- Huang X, Liang C, Tao S, Che Y, Bian N, Zhang J, Wang R, Zhang Y, Xia B, Zhang X. IC2ML: Unified battery state-of-health, degradation trajectory and remaining useful life prediction via intra-cycle and inter-cycle enhanced machine learning. *Journal of Power Sources*. 2026;666:239148. <https://doi.org/10.1016/j.jpowsour.2025.239148>
- Josephin JS F, Sonthalia A, Subramanian T, Aloui F, Bhatt D, Varuvel EG. Early Prediction of the Remaining Useful Life of Lithium-Ion Cells Using Ensemble and Non-Ensemble Algorithms. *Energy Storage*. 2025;7(1):e70133. <https://doi.org/10.1002/est2.70133>
- Sravanthi CL, Chandra sekhar JN. Predicting remaining useful life of lithium-ion batteries for electric vehicles using machine learning regression models. *ITEGAM-JETIA*. 2025;11(51):143-50. <https://doi.org/10.5935/jetia.v11i51.1267>
- Rajabzadeh M, Ghadimi P, Hargaden V, Papakostas N. A Hybrid Exponential Smoothing and LSTM Approach With Double Lightning Search for Enhanced Prediction of Lithium-Ion Battery Remaining Useful Life. *Battery Energy*. 2026;5(1):e70056. <https://doi.org/10.1002/bte2.20250052>
- Wang S, Zhou R, Ren Y, Jiao M, Liu H, Lian C. Advanced data-driven techniques in AI for predicting lithium-ion battery remaining useful life: a comprehensive review. *Green Chemical Engineering*. 2025;6(2):139-53. <https://doi.org/10.1016/j.gce.2024.09.001>
- Shi Z, Ibrahim AW, Xu J, Zeng L, Farh HM, Al-Shamma'a AA, Ameer K. Enhanced remaining useful life prediction of lithium-ion battery based on a dual attention hybrid data-driven method. *Scientific Reports*. 2026;16(1):1303. <https://doi.org/10.1038/s41598-025-30849-x>
- Dong X, Yao M, Xiang S. A load-balanced deformable expert network for lithium-ion battery remaining useful life prediction. *Journal of Energy Storage*. 2026;141:119587. <https://doi.org/10.1016/j.est.2025.119587>
- Hu J, He J, Wu L. A lightweight and dynamic multi-teacher knowledge distillation framework for remaining useful life prediction of lithium-ion batteries. *Journal of Energy Storage*. 2026;152:120738. <https://doi.org/10.1016/j.est.2026.120738>
- Mchara W, Raissi M. Hybrid Wavelet-Transformer-XGBoost Framework Optimized via Chaotic Billiards for Accurate Lithium-ion Battery Remaining Useful Life Prediction in Electric Vehicles. *Clean Energy*. 2026;10(2). <https://doi.org/10.1093/ce/zkag004>
- He J, Ma Z, Liu Y, Ma C, Gao W. Remaining useful life prediction of lithium-ion battery based on improved gated recurrent unit-generalized Cauchy process. *Journal of Energy Storage*. 2025;126:117086. <https://doi.org/10.1016/j.est.2025.117086>
- Pratheeba C, Sukumar P. Hybrid HGRN-SCSO technique for enhanced prediction of remaining useful life in EV batteries. *Electrical Engineering*. 2025;107(4):5311-23. <https://doi.org/10.1007/s00202-024-02913-8>
- Kumar N, Agrawal A, Kumar R, Badoni M. Autoencoder-Based Latent Representation Learning, SoH Estimation and Anomaly Detection in Electric Vehicle Battery Energy Storage Systems. *Vehicles*. 2026;8(4):81. <https://doi.org/10.3390/vehicles8040081>
- Lv Z, Ou SS, Jing H, Dong H, Shi D, Zhao J. Battery state-of-health estimation via thermoelectric graph learning and interpretable temporal decomposition for real-world electric vehicles. *Journal of Energy Storage*. 2026;153:120956. <https://doi.org/10.1016/j.est.2026.120956>
- Hussain A, Hussain T. Fleet-level network lifetime prediction for electric vehicle batteries: physics-guided spatio-temporal graph neural networks with interaction effects. *Discover Electronics*.

- 2026;3(1):2.
<https://doi.org/10.1007/s44291-025-00152-0>
1. Altalhi AH, Ragab M. Modelling of enhanced predictive analytics and decision-making approach using recurrent autoencoder with attribute subset reduction for students' academic performance. *Ain Shams Engineering Journal*. 2026;17(3):103999. <https://doi.org/10.1016/j.asej.2026.103999>
 2. Jiang H, Kuang X. Improved Snake Optimization and Particle Swarm Fusion Algorithm Based on AUV Global Path Planning. *Journal of Marine Science and Engineering*. 2025;13(4):796. <https://doi.org/10.3390/jmse13040796>
 3. Safavi V, Vaniar AM, Bazmohammadi N, Vasquez JC, Keysan O, Guerrero JM. Early prediction of battery remaining useful life using CNN-XGBoost model and Coati optimization algorithm. *Journal of Energy Storage*. 2024;98:113176. <https://doi.org/10.1016/j.est.2024.113176>
 4. Govindharajalu Kaliyaperumal V, Gopalan PA. A Deep Neural Network Framework for Dynamic Two-Handed Indian Sign Language Recognition in Hearing and Speech-Impaired Communities. *Sensors*. 2025;25(12):3652. <https://doi.org/10.3390/s25123652>
 5. Vilsen SB, Stroe DI. Lithium-ion battery degradation dataset based on a realistic forklift operation profile. *Mendeley Data*. 2023;2. doi:10.17632/yz4pttm73n.2.
 6. Shan C, Chin CS, Mohan V, Zhang C. Review of various machine learning approaches for predicting parameters of lithium-ion batteries in electric vehicles. *Batteries*. 2024;10(6):181. <https://doi.org/10.3390/batteries10060181>
 7. Al-Meer MH. A deep learning method for the health state prediction of lithium-ion batteries based on LUT-Memory and Quantization. *World Electric Vehicle Journal*. 2024;15(2):38. <https://doi.org/10.3390/wevj15020038>

How to Cite: Vaidya PS, Denzil KV, Monish S, Cloudin S, Saradha S. Temporal Deep Representation Learning Based Remaining Useful Lifecycle Prediction of Electric Vehicle Lithium-ion Batteries. *Int Res J Multidiscip Scope*. 2026;7(4):552-566. DOI: 10.47857/irjms.2026.v07i04.010890