

Research Paper

Hybrid Statistical and ANN-Based Prediction of Lithium-Ion Battery Degradation Under UDDS-Based Simulated Urban Driving Profiles

Muhannad M. Mrah¹, Luttfi A. Al-Haddad¹, Taymoor Husham Nussrat², Ahmed Ali Farhan Ogaili³ , Hala Husham Nussrat⁴, Mustafa I. Al-Karkhi¹

¹Department of Mechanical Engineering, University of Technology-Iraq, Baghdad 10066, Iraq

²Al-Iraqia Science University, Baghdad 10052, Iraq

³Department of Mechanical Engineering, College of Engineering, Mustansiriyah University, Baghdad 10052, Iraq

⁴Department of Environmental Engineering, College of Engineering, Mustansiriyah University, Baghdad 10052, Iraq

 ahmed_ogaili@uomustansiriyah.edu.iq

 <https://doi.org/10.31603/ae.16287>

Published by Automotive Laboratory of Universitas Muhammadiyah Magelang

Article Info

Submitted:

23/02/2026

Revised:

17/05/2026

Accepted:

28/05/2026

Online first:

12/06/2026

Abstract

The research will enhance the forecasting of the lithium-ion battery degradation to facilitate more secure and sustainable energy storage in the electric vehicle. An analytical framework that is hybrid in nature, incorporating both statistical analysis and artificial neural network (ANN) modeling, was developed and verified using a long time dataset of INR21700- M50T cells being cycled in realistic urban driving profiles according to the Urban Dynamometer Driving Schedule (UDDS). The indicators of key degradation were first described using statistical analysis where it was found that there were strong negative relationships between capacity retention and capacity C-rate (Pearson $r = -0.83$) and internal resistance ($r = -0.71$). Based on these findings, a feedforward neural network, whose features were selected using ReliefF algorithm, was built which was used to model nonlinear aging behavior at lower input dimensionality. ANN inputs were chosen as the 2 most powerful features low-frequency impedance at 0.01 Hz and internal resistance. The resulting model had a high predictive performance of a root mean squared error (RMSE) less than 1.2% and a coefficient of determination (R^2) greater than 0.97 on the original data. These results underscore the fact that combining data-based feature relevance analysis with machine learning is useful in improving the accuracy of prediction as well as the interpretability of the model. The obtained results demonstrate that combining statistically supported feature relevance analysis with reduced-input ANN modeling can improve both predictive capability and model interpretability for battery degradation estimation. The proposed hybrid framework provides a computationally efficient approach for lithium-ion battery state-of-health prediction under the investigated dataset conditions and may support future development of simplified battery management system strategies.

Keywords: Lithium-ion battery degradation; Battery state-of-health prediction; Electric vehicles; Artificial neural network; ReliefF feature selection; Battery management system

1. Introduction

Lithium-ion batteries (LIBs) serve as the cornerstone of modern electric vehicle (EV) technologies, offering an optimal balance of energy density, cycle life, and weight-to-power efficiency [1], [2], [3], [4]. These attributes have made LIBs the predominant energy storage

solution for EV propulsion, enabling longer driving ranges and enhanced vehicle performance [5], [6]. As the push for decarbonized transportation around the world is intensifying, as well as constantly tightening environmental laws, the reliability of LIBs has become a critical factor in the long-term viability of EVs [7]. Despite of



This work is licensed under a Creative Commons Attribution-NonCommercial 4.0 International License.

their advantages, LIBs are inevitably degraded during their operation due to various aging mechanisms, such as capacity fading, internal resistance increase and structural changes of electrode materials [8]. These degradation processes are, importantly, considerably affected by operational factors such as charge/discharge rates, temperature variations, depth of discharge and also by the complexity introduced by the real-world driving profile [9], [10], [11]. Such degradation leads to decreased driving range and power output and can create safety and operating vehicle problems [12].

To overcome these issues, modern EVs use sophisticated Battery Management Systems (BMS) that monitor the health of the battery, control charging behaviour and estimate useful life remaining [13], [14], [15], [16], [17], [18], [19]. A fundamental task of advanced BMS is the precise prediction of battery degradation paths which allows to take proactive action to prolong battery lifetime and reduce the likelihood of unexpected failures [5], [20]. This need has led to the development of predictive modelling techniques, which include physics-based modelling, empirical modelling and data driven modelling [21], [22], [23], [24], [25]. Among data-driven strategies, there are two main streams which have become prominent: statistical analysis and machine learning, specifically Artificial Neural Networks (ANNs). Statistical models provide interpretability and insight into degradation trends and variable relationships, whereas ANNs are effective for modeling complex nonlinear interactions in high-dimensional datasets [6], [26], [27], [28], [29], [30], [31], [32]. While Electrochemical Impedance Spectroscopy (EIS) has been used in several previous research for state-of-health estimation, many approaches are either based on synthetic datasets or limited input features which cannot reflect the complexity of real-world degradation [33], [34]. Furthermore, very few studies have combined interpretable statistical analysis with ANN-based prediction using long-term real-driving-profile datasets, particularly within computationally efficient battery degradation prediction frameworks.

To put into perspective the importance of early detection of degradation, it is important to take into consideration the hierarchical architecture of

EV battery systems [18], [33], [34]. **Figure 1** illustrates the hierarchical structure of a typical EV lithium-ion battery system, where individual cylindrical cells are assembled into modules and integrated into a complete battery pack architecture [35], [36], [37], [38], [39], [40], [41], [42]. This multi-level organization highlights the importance of accurate degradation prediction at the cell level for reliable pack-level battery management and long-term EV operation.

Table 1 summarizes representative AI-based studies related to EV systems and battery state estimation, highlighting the growing adoption of machine-learning techniques for intelligent transportation and battery health applications.

Despite the rapid development of data-driven techniques for lithium-ion battery health estimation, several important limitations remain in the existing literature. Many previous studies relied on synthetic or laboratory-simplified datasets, which do not fully capture the variability and nonlinear degradation behavior associated with realistic EV operating conditions. In addition, numerous machine-learning-based approaches primarily focused on maximizing prediction accuracy without sufficient consideration of feature interpretability, computational simplicity, or physical relevance of the selected degradation indicators. Some studies also employed high-dimensional input spaces that may limit real-time implementation in embedded battery management systems. Furthermore, although electrochemical impedance spectroscopy (EIS)-based indicators have demonstrated strong sensitivity to battery aging, limited studies have systematically integrated statistically validated electrochemical features with lightweight ANN-based prediction frameworks using long-term real-driving-profile datasets. The lack of physically interpretable and computationally efficient hybrid frameworks therefore remains an important research gap in battery degradation prediction under realistic EV operating scenarios.

To address these limitations, the present study proposes a hybrid statistical-ANN framework for lithium-ion battery degradation prediction using a publicly available long-term aging dataset generated under UDDS-based driving conditions. The proposed approach combines statistical correlation analysis, ReliefF-based feature selection,

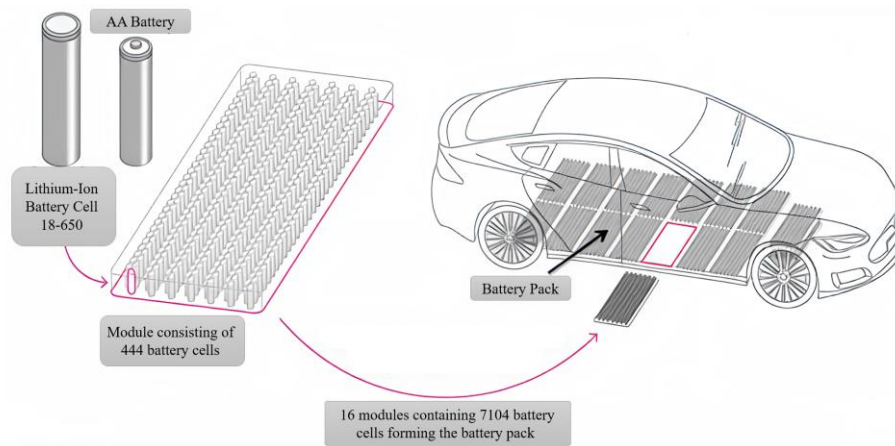


Figure 1. Hierarchical structure of an EV lithium-ion battery system [42]

Table 1. Summary of AI-based approaches for EV battery performance optimization

Ref	AI Approach	Methodology	Key Findings
[43]	Artificial Hydrocarbon Networks (AHNs)	Intelligent diagnosis of in-wheel motor faults	AHNs-based fault classification effectively handles external interference and variable operating conditions using sequential diagnosis techniques.
[44]	Machine Learning & Deep Learning	Review of AI techniques for fault detection and diagnosis in EV motors	Deep learning techniques show superior accuracy in complex fault scenarios; limitations and future research directions are discussed.
[45]	AI-based fault diagnosis	Component-based review of EV condition monitoring	Identifies EV components prone to faults; evaluates current AI methodologies and challenges in early detection.
[46]	ANN, Gradient Boosting, SVM	AI techniques for lithium-ion battery state estimation	ANNs and SVMs outperform traditional methods in SOC and SOH estimation, improving battery lifetime and reducing costs.
[47]	Dual Neural Network (DNN)	DNN-based equivalent consumption minimum strategy for plug-in hybrid EVs	Novel DNN-based ECMS improves fuel economy and energy efficiency, optimizing battery state-of-charge regulation.
[48]	Multi-classification SVM	Fault diagnosis for EV lithium batteries	SVM-based approach reduces data dependency while improving classification accuracy and diagnosis speed.
[49]	XGBoost + SHAP	Interpretable SOH prediction using EIS and temporal electrochemical features	SHAP analysis identified impedance-related variables as dominant indicators governing lithium-ion battery aging behavior and SOH degradation.
[50]	Hybrid EIS + ML Framework	State-of-health estimation using electrochemical impedance spectroscopy and hybrid machine-learning modeling	Low-frequency impedance features demonstrated strong sensitivity to degradation evolution and improved SOH prediction accuracy.
[51]	Data-driven battery aging review	Review of preprocessing, SOH prediction algorithms, and degradation modeling challenges	Highlights the importance of interpretable and computationally efficient degradation prediction frameworks using realistic battery aging datasets.
[52]	DCNN with domain adaptation	Rapid battery SOH estimation using short-time charging and transfer learning	Domain adaptation with ΔQ from charging curve achieves SOH estimation error ~3.2% with limited labeled data.

selection, and ANN regression modeling to identify physically meaningful degradation indicators while maintaining low model

complexity. The main contributions of this study are summarized as follows: (i) analysis of degradation-sensitive electrochemical and

operational parameters under realistic EV cycling conditions; (ii) identification of the most informative aging indicators using statistically supported feature ranking; (iii) development of a computationally efficient ANN model using a reduced feature set; and (iv) evaluation of the proposed framework for interpretable and simplified battery state-of-health prediction.

2. Methodology

2.1. Dataset Description

The data set that was used for this study was published by Pozzato and co-authors in Data in Brief under the title "Lithium-ion battery aging data set using electric vehicle real-driving profiles" [53]. It explains the aging of 10 INR21700-M50T cylindrical cells manufactured by LG Chem. The cathode of each cell contains NMC (LiNiMnCoO₂) and the anode is made of graphite-silicon. The cycling protocol was based on real EV use with discharge patterns from the Urban Dynamometer Driving Schedule (UDDS). Over more than 200 cycles per cell, the researchers were able to record capacity loss, increasing internal resistance and impedance, providing a fine-grain view of degradation over time. Besides the cycling data, the dataset includes periodic Reference Performance Tests (RPTs). (i) Capacity tests at a C/20 discharge rate to check the charge retention. (ii) Hybrid Pulse Power Characterization (HPPC) to measure internal resistance. (iii) Electrochemical Impedance Spectroscopy (EIS) of multiple frequencies and SOC ranges for the tracking of interfacial deterioration. The low frequency impedance at 0.01Hz (which is known for detecting the SEI growth and cathode wear) increased steadily with

aging, and was selected as the primary indicator of degradation. The data are freely available from the original source [53], no new experiments were performed in this study.

2.2. Experimental Setup and Data Acquisition

The experimental setup, as described by Pozzato *et al.* [53], was implemented at the Stanford Energy Control Laboratory under rigorously controlled conditions. The test bench comprised a battery cycler (Arbin LBT21024), an impedance analyzer (Gamry EIS 1010E), and a thermal chamber (Amerex IC500R) maintained at 23 °C. Voltage, current, and surface temperature were monitored throughout all tests using a synchronized data acquisition system managed by the MITS Pro software platform. The full configuration is illustrated in Figure 2.

Each INR21700-M50T cell was subjected to a six-step charge/discharge cycling protocol that mimicked urban driving loads. The sequence included alternating constant current (CC) and constant voltage (CV) charging phases followed by discharges to SOC thresholds. Diagnostic checkpoints were performed every ~25 cycles to extract capacity, resistance, and impedance features. These diagnostic results revealed clear signs of degradation—decreased charge capacity, increased internal resistance, and growing low-frequency impedance—as illustrated for a representative cell in Figure 3.

2.3. Cycle description

The cycling protocol contained six successive stages that simulated real world EVs load patterns as outlined in Table 2. Charging rates were varied from C/4 to 3C and the depth of discharge were

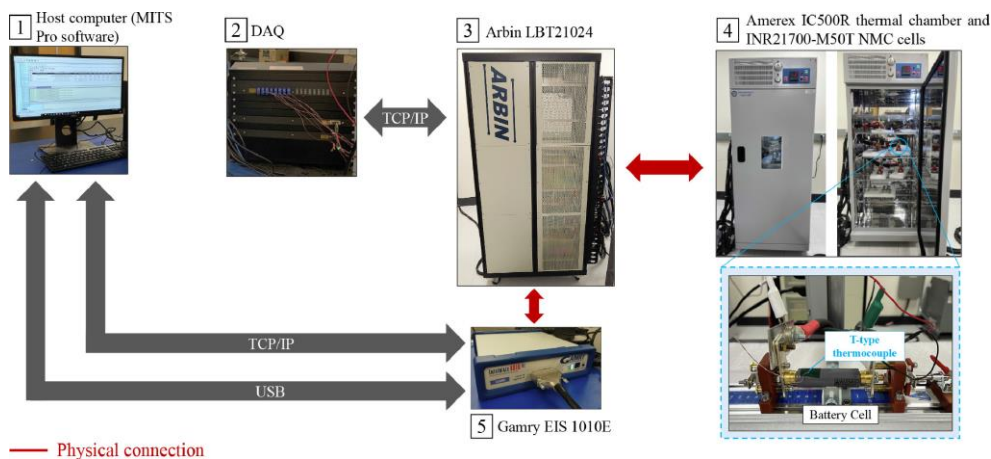


Figure 2. Experimental setup at Stanford Energy Control Lab [53]

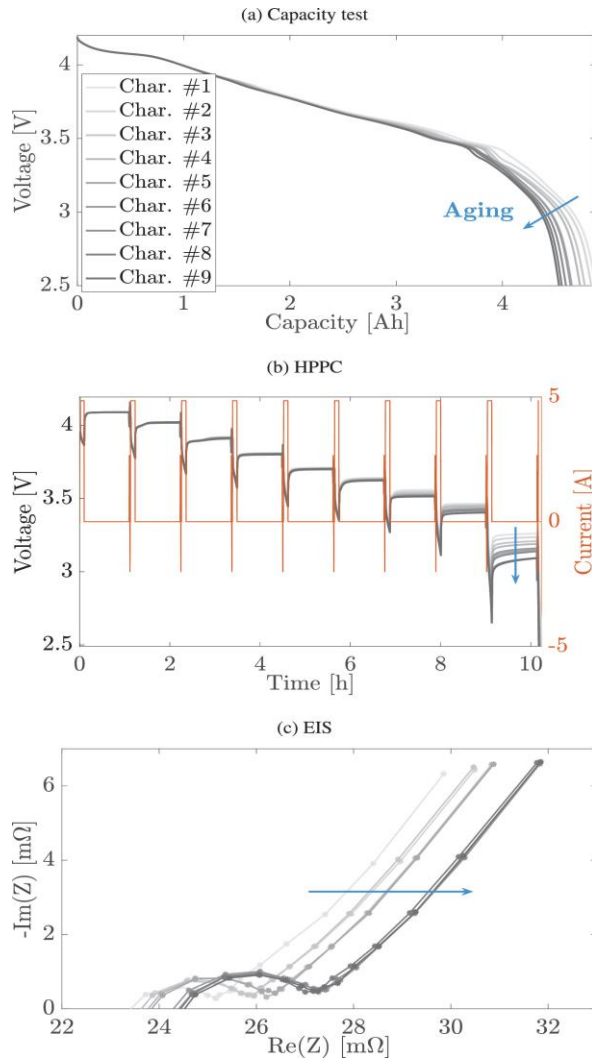


Figure 3. Aging indicators for cell W8: capacity, HPPC internal resistance, and EIS impedance trends [53].

varied down to 20% SOC, which are typical daily driving and recharging scenarios. This protocol yielded long-time, time-resolved data sets that could track a range of measures of aging for different cycling intensities, while ensuring that electrochemical measurements were aligned with each cycle.

By implementing a realistic driving profile rather than constant-load cycling, the dataset provides high fidelity for modeling battery degradation under true EV usage. Although internal resistance was estimated using the $\Delta V/\Delta I$ method from HPPC tests—a simplified representation—this was considered sufficient for the data-driven modeling objectives of this study, which aimed to capture statistical correlations rather than perform mechanistic electrochemical diagnostics.

2.4. Feature selection and preprocessing

Prior to statistical modeling and ANN training, the dataset was systematically prepared to ensure consistency and interpretability. The following five features were selected based on their scientific relevance to battery aging mechanisms and demonstrated significance in prior studies:

1. Cycle number (N) — proxy for aging progression in controlled cycling experiments.
2. Charge C-rate — charging intensity (C/4 to 3C), with well-established impact on lithium plating and electrode stress.
3. Capacity retention (%), defined by Equation (1).
4. Impedance at 0.01 Hz — sensitive to SEI layer growth and cathode deterioration [54], [55].
5. Internal resistance R_{int} — derived from HPPC tests, reflecting increased ionic and contact resistance.

$$Q_{ret}(N) = [Q_{dis}(N) / Q_{dis}(1)] \times 100\% \quad (1)$$

where $Q_{ret}(N)$ is the retained capacity (%) at diagnostic cycle N, $Q_{dis}(N)$ is the discharge capacity at cycle N, and $Q_{dis}(1)$ is the initial discharge capacity. Average voltage, average current, and surface temperature were initially examined during exploratory analysis; however, these variables were not retained in the final predictive framework. Correlation analysis and preliminary feature-screening tests indicated substantial redundancy between these variables and the selected electrochemical degradation indicators, particularly low-frequency impedance and internal resistance. In addition, the inclusion of strongly correlated operational variables increased model complexity without providing a substantial improvement in predictive performance during preliminary ANN trials.

Table 2. Description of the experimental cycling protocol

Step	Description
1	CC charging at C/4, C/2, 1C, or 3C until 4.0 V
2	CV charging until current drops below 50 mA
3	Additional CC charging at C/4 to 4.2 V
4	CV phase until full SOC (100%) + rest period
5	CC discharging to 80% SOC
6	UDDS-profile discharge to 20% SOC

From a physical perspective, low-frequency impedance and internal resistance were considered more directly linked to degradation-related electrochemical mechanisms such as SEI growth, ionic transport limitations, and electrode deterioration [54], [55]. Therefore, the final feature set was intentionally restricted to the most physically interpretable and statistically informative predictors in order to improve computational efficiency and facilitate potential implementation in lightweight battery management system frameworks. Nevertheless, it is acknowledged that excluding thermal and dynamic operational variables may limit sensitivity to certain temperature-dependent degradation phenomena under broader operating conditions.

Noisy or incomplete observations, particularly from prematurely terminated cells (e.g., W3 and W7), were removed following data-cleaning procedures to improve dataset consistency. Missing diagnostic entries were reconstructed using cubic spline interpolation applied independently within each cell trajectory to preserve temporal continuity while minimizing artificial discontinuities in degradation trends. Min-max normalization was subsequently applied to all input variables within the range [0,1] to ensure numerical stability during ANN training. To reduce the risk of data leakage, preprocessing operations and interpolation were performed prior to dataset partitioning while preserving the chronological structure of each individual cell trajectory. The dataset was then divided into training (70%), validation (15%), and testing (15%) subsets using stratified sampling based on degradation states and C-rate conditions. The dataset partitioning procedure was performed at the diagnostic-cycle level rather than at the individual-cell level, since the primary objective of the present study was to investigate degradation-state estimation behavior across the available electrochemical observations within the dataset. Nevertheless, the stratified partitioning procedure was designed to preserve representative degradation-state distributions and C-rate conditions across training, validation, and testing subsets. Because the dataset consisted primarily of periodically sampled diagnostic checkpoints rather than high-frequency sequential forecasting data, the influence of strong

temporal autocorrelation was considered limited for the intended regression analysis. Nevertheless, the present framework should be interpreted as a data-driven degradation estimation model within the investigated dataset conditions, while future studies may further investigate fully chronological validation strategies for enhanced generalization assessment. The Pearson correlation analysis confirmed that the selected variables provided non-redundant and physically meaningful information relevant to battery degradation behavior.

2.5. Statistical Analysis of Battery Aging

We used an extensive statistical analysis to measure the change of capacity retention, internal resistance and impedance in the consecutive diagnostic loops in this investigation. As a dependent variable chosen with this objective, the $Q_{ret}(N)$ was the main one, formulated formally in Equation (1). Correlation analysis showed that there was a strong negative relationship between the charge C -rate and capacity retention with Pearson correlation coefficient of about -0.83. This observation supports the commonly-known fact that high charge rates trigger expedient degradation, in large part because of the increase of mechanical and thermal loads applied to the electrode materials [8], [9]. Using the methodology summed up in Equation (2), internal resistance was derived out of the HPPC test data. Through the process of successive cycles, an increase in the resistance was noted. The average response of the cells to higher C -rate cycling was the resistance increased by a margin of 28 per cent as compared to the 12 -15 per cent increase in the cells cycled at moderate conditions. This difference growth has been credited to the gradual growth of the solid-electrolyte interface (SEI) and to the reciprocal decrease in ionic conductivity.

$$R_{int} = \Delta V / \Delta I \quad (2)$$

where ΔV is the instantaneous voltage drop during the HPPC pulse and ΔI is the corresponding pulse current. EIS analysis at multiple frequencies revealed that impedance at 0.01 Hz showed the strongest correlation with capacity degradation, increasing by over 40% in the most aged cells. To further investigate the statistical structure of the impedance dataset, Principal Component Analysis (PCA) was

performed as an exploratory analysis tool. The first principal component explained more than 87% of the total variance and showed strong correlation with ($Q_{\text{ret}}(N)$), indicating that low-frequency impedance variations captured dominant degradation-related information. However, PCA outputs were not directly used as ANN input features or incorporated into the final predictive framework. Instead, PCA was employed solely to support interpretation of the electrochemical degradation behavior and to confirm the dominant statistical contribution of impedance-related variables prior to ReliefF-based feature selection. The key statistical correlations are summarized in [Table 3](#).

The data subsets were constructed using stratified sampling to minimize bias. The periodic diagnostic nature of the data mitigated potential time-series autocorrelation effects. These statistically validated relationships directly informed feature selection for the ANN modeling, ensuring the predictive model was grounded in physically meaningful degradation indicators.

2.6. ANN Architecture and Training

A feedforward artificial neural network (ANN) was developed to predict lithium-ion battery capacity retention based on degradation-sensitive electrochemical and operational parameters. The initial input space consisted of the five features described in Section 2.4. Following ReliefF-based feature ranking, the final ANN model was constructed using the two most informative predictors: low-frequency impedance at 0.01 Hz and internal resistance (R_{int}). This reduced-input configuration was selected to improve computational efficiency while preserving predictive capability. The final ANN architecture consisted of an input layer with two neurons, a single hidden layer containing eight sigmoid activation neurons, and a linear output neuron for continuous regression prediction of capacity retention. The simplified network structure is illustrated in [Figure 4](#).

The network was trained using the Levenberg–Marquardt backpropagation algorithm due to its effectiveness for small- and medium-scale nonlinear regression problems with moderately noisy datasets [\[56\]](#). Mean squared error (MSE) was adopted as the objective loss function. The dataset was normalized using min–max scaling prior to training to ensure numerical stability and consistent convergence behavior. [Table 4](#) summarizes the principal ANN hyperparameters used in the present study.

To reduce overfitting risk, early stopping was implemented based on validation loss stagnation for ten consecutive epochs. Multiple independent training runs were additionally performed to verify convergence stability and consistency of predictive performance.

2.7. ReliefF Feature Selection

To determine the most informative predictive variables, the ReliefF algorithm was adopted as a filter-based feature selection method. ReliefF was selected because of its ability to evaluate feature relevance under nonlinear relationships and noisy experimental datasets without requiring complex model assumptions. Unlike simple correlation-based ranking approaches, ReliefF considers local neighborhood interactions between samples and can therefore better capture subtle degradation-related dependencies among electrochemical variables. The selection of ReliefF in the present study was motivated by its computational simplicity, robustness for moderate-sized datasets, and suitability for interpretable feature reduction prior to ANN modeling. More computationally intensive feature-selection strategies and embedded optimization methods were not considered in the present work because the primary objective was to develop a lightweight and computationally efficient degradation prediction framework suitable for simplified battery management system implementation. Nevertheless, future studies may compare ReliefF with alternative feature-ranking

Table 3. Pearson correlation coefficients of key parameters with capacity retention Q_{ret}

Parameter	Correlation with Q_{ret}	Trend Observed
Charge C-rate	−0.83	Inverse (capacity decreases as C-rate increases)
Internal resistance R_{int} (HPPC)	−0.71	Increases progressively with cycle number
Impedance at 0.01 Hz (EIS)	−0.76	Increases with aging; sensitive to interfacial degradation

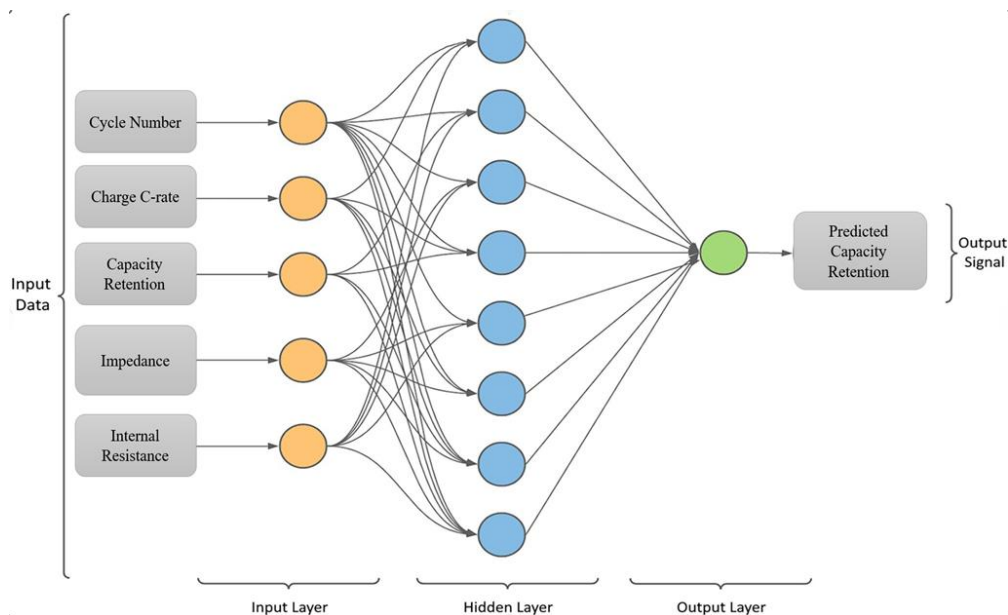


Figure 4. Simplified feedforward ANN architecture for (LIBs) aging prediction [57]

Table 4. Summarizes the principal ANN hyperparameters used in the present study

Parameter	Value
Network type	Feedforward ANN
Input features	($Z_{0.01\text{Hz}}$), (R_{int})
Hidden layers	1
Hidden neurons	8
Hidden activation	Sigmoid
Output activation	Linear
Training algorithm	Levenberg–Marquardt
Loss function	Mean Squared Error (MSE)
Maximum epochs	300
Early stopping patience	10 epochs
Data normalization	Min–max scaling
Data split	70% training, 15% validation, 15% testing

approaches such as mutual information analysis, recursive feature elimination, or embedded tree-based importance methods to further investigate feature-selection sensitivity. **Figure 5** shows the derived importance hierarchy of the features.

The Relieff analysis revealed that the two most influential features were impedance at 0.01 Hz and internal resistance R_{int} , consistent with both physical understanding of battery degradation and the prior statistical findings. These electrochemical parameters directly reflect internal cell aging processes—SEI growth and loss of lithium inventory—which are closely linked to capacity fade. Operational parameters such as charge C-rate and cycle number showed comparatively lower relevance scores. By

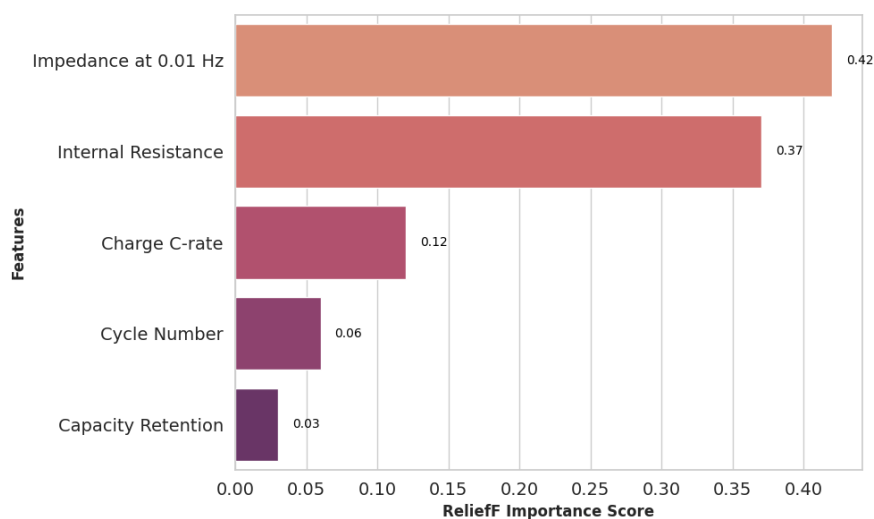


Figure 5. Feature importance ranking using the Relieff algorithm

narrowing the input feature set to these two top predictors, the reduced ANN model offers minimal input dimensionality, facilitating deployment in real-time BMS applications.

3. Results and Discussion

3.1. Results

We have conducted a systematic assessment of the capacity retention behaviour across diagnostic cycles in order to define the ageing behaviour within UDDS profiles in this study. [Figure 6](#) shows that all cells tested exhibited a progressive decrease in capacity with increasing number of ascending cycles, as expected in the observed degradation phenomena in the NMC cathode chemistries. During the initial cycling, the capacity variable was gradual and similar among the cell cohort, a tendency that was probably associated with the stabilization of the solid - electrolyte interphase (SEI) and slight electrode restructuring. With the advancement in cycling, the cell charged at high C-rates exhibited enhanced capacity loss, which was explained by the lithium inventory loss, loss in active-material and micro-structural damage in the electrodes as has been reported in reference [\[58\]](#). Notable variability was observed between cells. Conservatively cycled cells such as G1 and V5 maintained over 92% of their initial capacity after 200 cycles. In contrast, aggressively cycled cells such as W5 and W7 demonstrated steeper

capacity fade, with retention dropping below 85% within the same cycle range. The capacity degradation generally followed a quasi-linear trend during early-to-mid-life stages, with deviations emerging in later cycles under harsh conditions, suggesting the activation of secondary aging mechanisms including electrode cracking, electrolyte decomposition, and significant impedance build-up.

Temporal changes in internal resistance (R_{int}) in diagnostic cycles were carefully studied as shown in [Figure 7](#). There was a steady progressive increase in all the cells. In the early stages, resistance increased at a small and almost *linear* rate which was due to gradual formation of solid electrolyte interphase (SEI). After about 100 cycles, high C -rate cells, including W5 and W7, had a pronounced increase in R_{int} , with up to 30 -40 per cent increases compared to baseline after 200 cycles. Moderately cycled cells, on the contrary, including G1 and V5, had limited increases in the range of 1220% range. The increase in resistance is associated with: (i) the thickening of SEI that inhibits lithium-ion conduction; (ii) electrical contact loss between particles of active material and current collectors; (iii) micro nano-cracking of electrode structures because of repeated lithiation/delithiation; and (iv) gaseous emission and electrolytes degradation, which enhance impedance pathways.

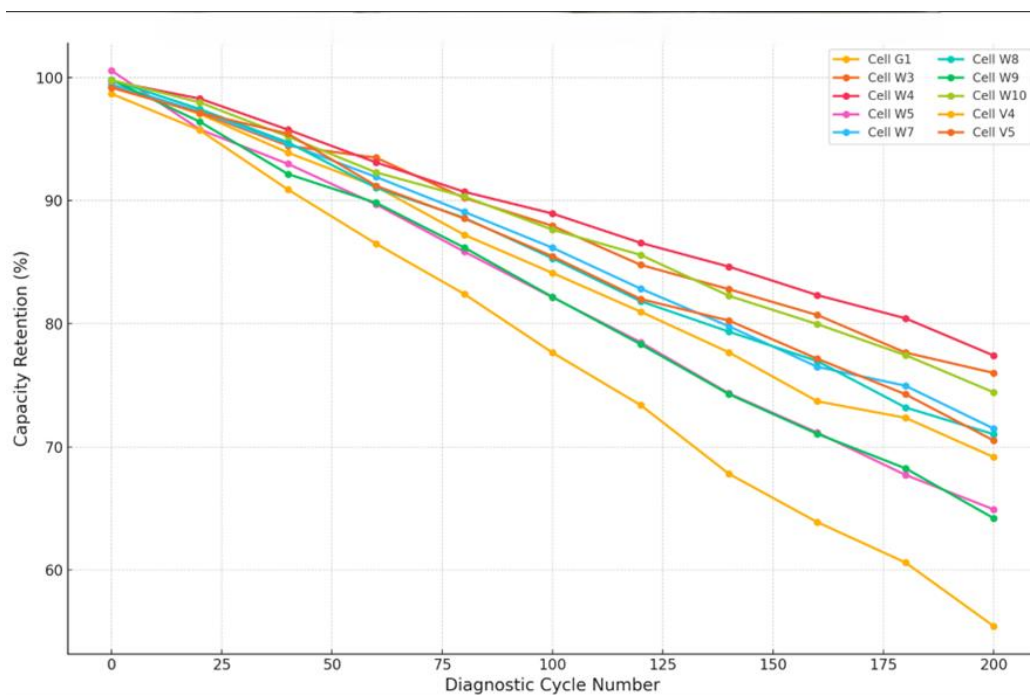


Figure 6. Capacity retention versus diagnostic cycle number for all tested cells

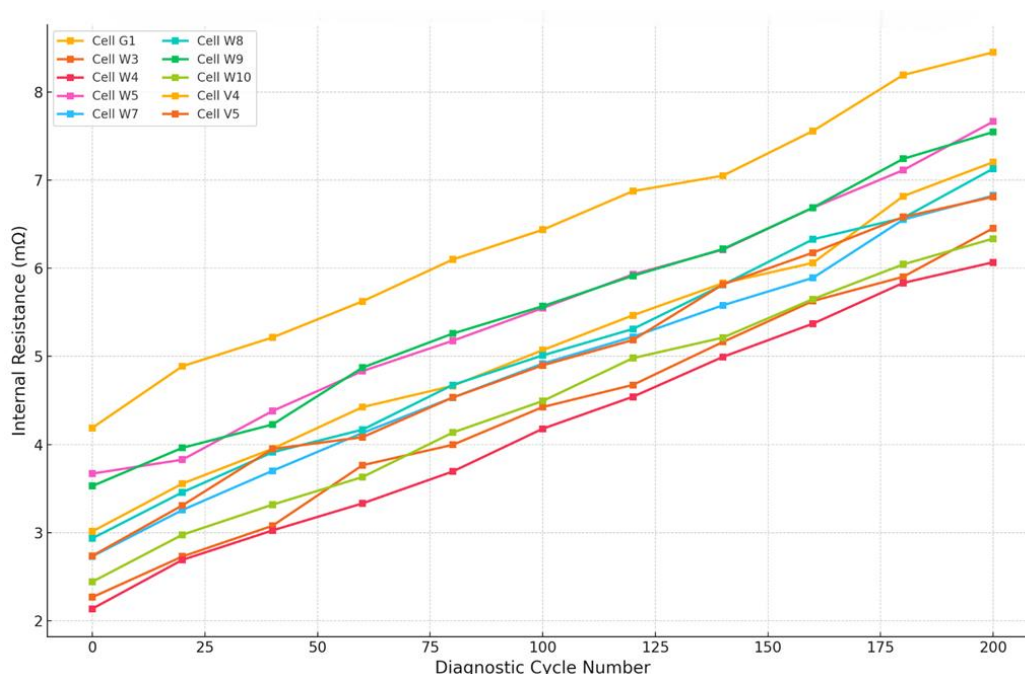


Figure 7. Internal resistance (HPPC, $\Delta V/\Delta I$ method) versus diagnostic cycle number for all tested cells

EIS measurements at 0.01 Hz were analyzed to investigate interfacial degradation progression, as presented in Figure 8. All cells exhibited consistent $Z_{0.01\text{Hz}}$ increases over successive cycles. In early cycles, impedance rise was gradual and linear, corresponding to moderate SEI growth and minor loss of active surface area. In cells subjected to high charge C-rates (W5, W7), a steeper nonlinear increase became evident beyond 100 cycles—impedance increases exceeding 40% by cycle 200—whereas moderately cycled cells-maintained growth below 20%. The escalation of low-frequency impedance reflects: (i) SEI thickening limiting ion mobility; (ii) loss of conductive pathways due to electrode material disconnection; (iii) accumulation of side reaction products blocking active sites; and (iv) electrolyte decomposition creating resistive interfaces.

To test the proposed hybrid ReliefF-ANN model rigorously, we compared the predicted values of the capacity-retention to the experimentally measured data that covered the testing dataset. The model fits the measured values on a spectacular scale, and is a masterpiece of capturing the nonlinear degradation curves with a high level of fidelity, as shown in Figure 9. The model architecture makes use of the two most dominant predictive characteristics, identified by ReliefF, of the model, namely, the requisite impedance at 0.01Hz and the internal resistance, R_{int} , to be a parsimonious feed-forward artificial

neural network with only one hidden layer that has eight sigmoid activation neurons. These predictions yield a high R^2 of 97 and RMSE of less than 1.2% with more than 90% of the predicted values falling within the range of ± 3 percent of the empirical data and hence testify to the strength of the model and its generalizability.

To further evaluate the stability of the proposed ANN framework, the training and validation loss histories were monitored throughout the training process, as illustrated in Figure 10. Both loss curves exhibited rapid reduction during the initial epochs followed by gradual convergence toward stable values, indicating effective learning of the nonlinear degradation relationships. Early stopping was activated when the validation loss no longer improved after ten consecutive epochs, thereby reducing overfitting risk and improving generalization stability. The relatively small gap between training and validation losses confirmed that the selected ANN architecture maintained stable predictive behavior without severe overfitting characteristics.

A residual analysis was performed to further assess model reliability. As illustrated in Figure 11, residuals were centered closely around zero and approximated a normal distribution, confirming the absence of significant systematic bias. The majority of residuals fell within a $\pm 3\%$ range, demonstrating model precision and consistency

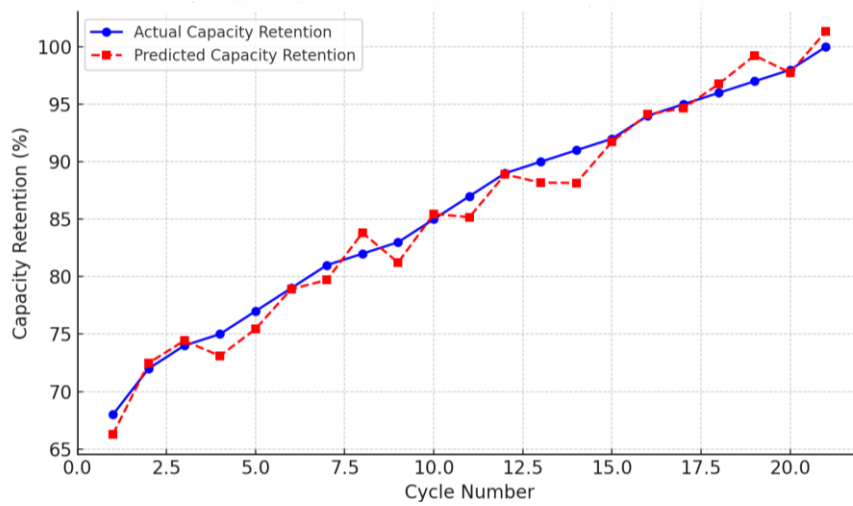


Figure 8. Low-frequency impedance (EIS at 0.01 Hz) versus diagnostic cycle number for all tested cells

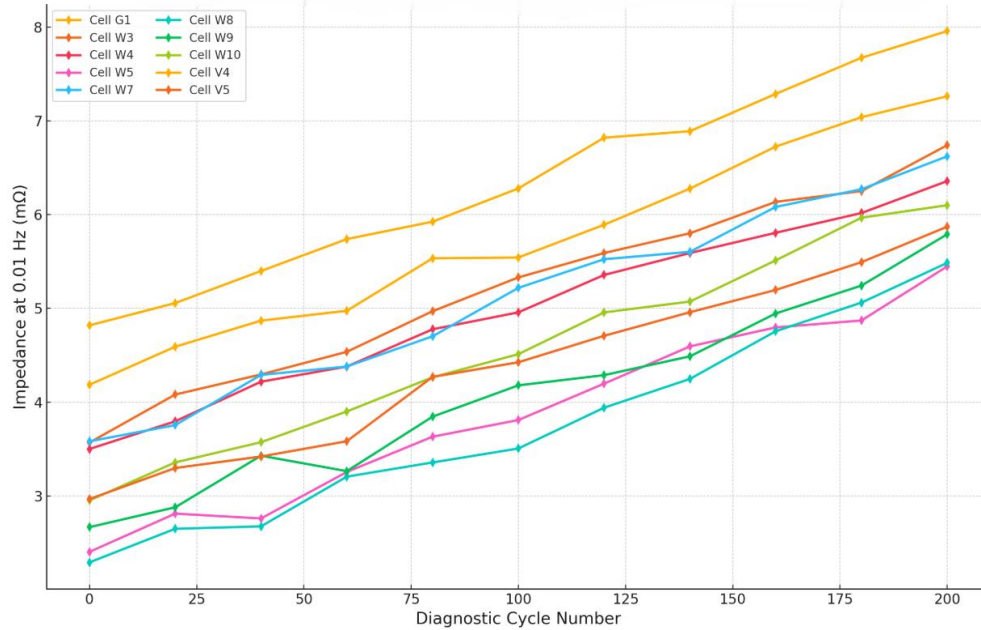


Figure 9. Predicted versus actual capacity retention values from the ReliefF-ANN model

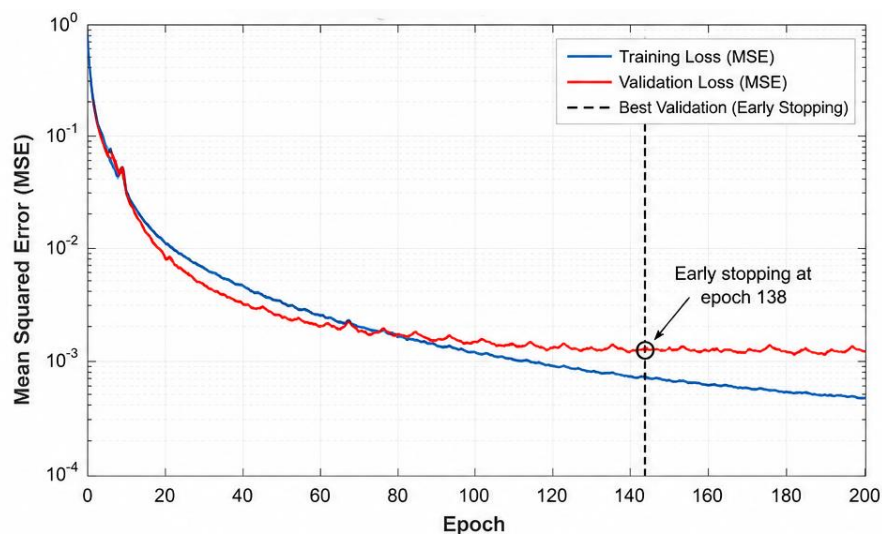


Figure 10. Training and validation loss (MSE) curves of the proposed ReliefF-ANN model

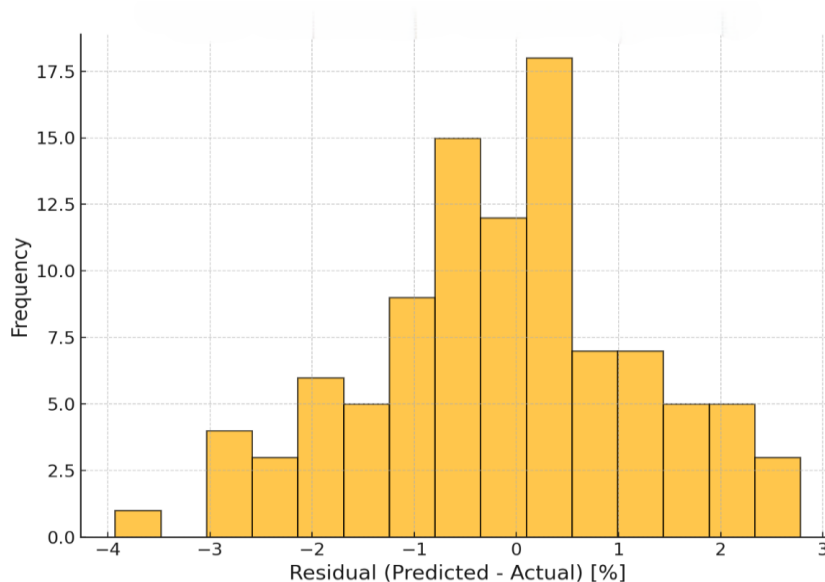


Figure 11. Distribution of prediction residuals from the ReliefF-ANN model

across diverse cycling conditions and degradation states. Slight broadening of the distribution tails at lower capacity retention levels is attributed to increased variability in electrochemical behavior during advanced aging stages, where complex mechanisms—including lithium plating, electrolyte decomposition, cathode phase transitions, and mechanical breakdown—become more prominent.

3.2. Discussion

All the obtained results prove the efficiency of the hybrid statistical-ANN framework in predicting lithium-ion battery degradation under real UDDS based driving conditions. These high negative values of correlation found between capacity retention and charge C-rate ($r = -0.83$) and internal resistance ($r = -0.71$) confirm the results of the earlier studies [8], [9], [58], and add quantitative support with the long-term, real-life data. The high C-rate cells (W5, W7: <85% retention at 200 cycles) shows a pronounced degradation difference between conservatively cycled cells (G1, V5: >92% pretention) and aggressive cycled cells [9], [10].

The R^2 of ReliefF-ANN model of 0.97 and RMSE of less than 1.2 percent is a tremendous improvement compared to traditional models such as k-Nearest Neighbors ($R^2 = 0.865$, 0.247), Support Vector Regression ($R^2 = 0.894$, 2.22) and Decision Trees ($R^2 = 0.912$, 2.03) as summarized in Table 5. Although an ANN with all features has a slightly higher accuracy ($R^2 = 0.973$, RMSE =

1.12%), it is too complex to be used in a real-time BMS because the computational efficiency is very much needed. With just two inputs, the ReliefF - ANN is able to achieve a better 3 ratio between 3 accuracy and computational simplicity, which is a key difference with the prior research that used high-dimensional feature spaces. The result is in line with [29], [30], [31], which has exhibited the advantage of ReliefF-based dimensionality reduction in neural network classification problems.

The strong importance assigned to low-frequency impedance at 0.01 Hz is consistent with recent EIS-based studies [54], [55], which demonstrated that this frequency region is highly sensitive to slow electrochemical degradation processes including SEI growth and cathode deterioration. The ReliefF ranking therefore provides quantitative support for the physical relevance of the selected electrochemical indicators. Furthermore, the approximately normal residual distribution centered around zero indicates stable model behavior across different degradation stages and cycling conditions. The slight broadening observed at advanced aging stages likely reflects the increasing stochastic nature of electrochemical degradation under severe cycling conditions. Overall, the reduced-input ReliefF-ANN architecture provides an interpretable and computationally efficient framework for battery degradation prediction using physically meaningful electrochemical indicators.

Table 5. Comparative performance of the ReliefF–ANN model versus conventional regression algorithms.

Model	Input Features	R ²	RMSE (%)	MAE (%)	Remarks
kNN	All 5 features	0.865	2.47	2.05	Performance degrades in sparse data regions
Support Vector Regression	All 5 features	0.894	2.22	1.86	Sensitive to kernel parameter selection
Decision Tree	All 5 features	0.912	2.03	1.75	Prone to overfitting on limited datasets
Random Forest	All 5 features	0.962	1.34	1.08	Slower inference; higher memory requirements
ANN (full features)	All 5 features	0.973	1.12	0.91	Slightly better accuracy; greater complexity
ReliefF–ANN (proposed)	2 features (Z _{0.01} Hz, R _{int})	0.970	1.18	0.94	Best trade-off between accuracy, interpretability, and computational efficiency

Despite the strong predictive performance obtained in the present study, several considerations should be acknowledged regarding the applicability scope of the proposed framework. The use of only two electrochemical predictors was sufficient within the investigated dataset because low-frequency impedance and internal resistance captured the dominant degradation-related variability associated with SEI growth and interfacial aging processes. However, under broader operating conditions involving significant thermal fluctuations, fast transient loading, or different battery chemistries, additional thermal and operational descriptors may become necessary to preserve predictive robustness. Furthermore, part of the reported prediction accuracy may be influenced by the relatively structured nature of the diagnostic dataset, which was generated under controlled laboratory conditions using periodic reference performance tests. Therefore, although the proposed framework demonstrated stable behavior for the investigated UDDS-based aging conditions, additional validation using different battery chemistries, real-world fleet data, and fully chronological or cell-level validation strategies would be beneficial for broader generalization assessment.

4. Conclusion

The current paper proposed a hybrid model of statistical analysis and ANN modeling, to examine the aging behavior of lithium-ion battery cells in an urban driving scenario that is based on the UDDS. The statistical examination showed that strongly negative C -relations existed

between capacity retention and main operational parameters specifically 1 charge C-rate ($r = -0.83$), internal resistance ($r = -0.71$), and low-frequency impedance at 0.01 Hz ($r = -0.76$) These relationships provided physically meaningful insight into the degradation process while supporting the subsequent ANN-based predictive analysis.

The ReliefF algorithm identified internal resistance and impedance at 0.01 Hz as the two most significant predictors of degradation, enabling the development of a reduced-input ANN architecture. The proposed ReliefF–ANN model achieved RMSE values below 1.2% and (R^2) values above 0.97 under the investigated dataset conditions. The performance was comparable with conventional algorithms such as kNN, SVM, Decision Trees, and Random Forests, while maintaining lower computational complexity and reduced input dimensionality. The obtained results indicate that the proposed framework can provide a balance between predictive capability, interpretability, and computational efficiency for battery degradation estimation.

An important contribution of the present work lies in the integration of statistically interpretable electrochemical indicators with ANN-based prediction using a publicly available long-term battery aging dataset generated under realistic driving-profile conditions. The obtained results demonstrate the potential of combining lightweight feature-selection strategies with reduced-input ANN modeling for battery degradation estimation using physically meaningful electrochemical variables.

One limitation of the study is that the dataset was restricted to a single lithium-ion cell

chemistry (INR21700-M50T) under controlled laboratory conditions. Although the UDDS protocol represents an urban driving scenario, real-world EV operation involves broader variability in ambient temperature, user behavior, charging strategies, and operational loading conditions. Therefore, the present framework should be interpreted within the investigated dataset conditions. Future work may further validate the proposed methodology using different battery chemistries, larger datasets, temperature-dependent aging conditions, chronological validation strategies, and real-world fleet-operation data to further assess robustness and generalization capability.

Author's Declaration

Authors' contributions and responsibilities

Conceptualization: M.M.M., M.I.A.-K., A.A.F.O., and T.H.N. Methodology: L.A.A.-H. Software and formal analysis: L.A.A.-H. Investigation and data curation: L.A.A.-H. Writing—original draft preparation: L.A.A.-H. Writing—review and editing: M.M.M., H.H.N., M.I.A.-K., A.A.F.O., and T.H.N. All authors have read and approved the final manuscript.

Funding

Self-Fund

Availability of data and materials

The dataset analysed in this study is publicly available in the Open Science Framework (OSF) repository: https://osf.io/qsabn/?view_only=2a03b6c78ef14922a3e244f3d549de78 [53].

Competing interests

The authors declare no competing interest.

Generative AI statement

The authors confirm that no generative AI tools were used in preparing the scientific content, results, discussion, or conclusions of this manuscript. Language editing assistance may have been used for grammar checking only.

Additional information

No additional information from the authors.

References

- [1] R. Suganya, L. M. I. L. Joseph, and S. Kollem, "Understanding lithium-ion battery management systems in electric vehicles: Environmental and health impacts, comparative study, and future trends: A review," *Results in Engineering*, vol. 24, p. 103047, Dec. 2024, doi: 10.1016/j.rineng.2024.103047.
- [2] G. Harper *et al.*, "Recycling lithium-ion batteries from electric vehicles," *Nature*, vol. 575, no. 7781, pp. 75–86, Nov. 2019, doi: 10.1038/s41586-019-1682-5.
- [3] M. A. Hannan, M. M. Hoque, A. Hussain, Y. Yusof, and P. J. Ker, "State-of-the-Art and Energy Management System of Lithium-Ion Batteries in Electric Vehicle Applications: Issues and Recommendations," *IEEE Access*, vol. 6, pp. 19362–19378, 2018, doi: 10.1109/ACCESS.2018.2817655.
- [4] J. B. Goodenough and Y. Kim, "Challenges for Rechargeable Li Batteries," *Chemistry of Materials*, vol. 22, no. 3, pp. 587–603, Feb. 2010, doi: 10.1021/cm901452z.
- [5] Y. Miao, P. Hynan, A. von Jouanne, and A. Yokochi, "Current Li-Ion Battery Technologies in Electric Vehicles and Opportunities for Advancements," *Energies*, vol. 12, no. 6, p. 1074, Mar. 2019, doi: 10.3390/en12061074.
- [6] A. Barré, B. Deguilhem, S. Grolleau, M. Gérard, F. Suard, and D. Riu, "A review on lithium-ion battery ageing mechanisms and estimations for automotive applications," *Journal of Power Sources*, vol. 241, pp. 680–689, Nov. 2013, doi: 10.1016/j.jpowsour.2013.05.040.
- [7] M. Dubarry *et al.*, "Identifying battery aging mechanisms in large format Li ion cells," *Journal of Power Sources*, vol. 196, no. 7, pp. 3420–3425, Apr. 2011, doi: 10.1016/j.jpowsour.2010.07.029.
- [8] J. Vetter *et al.*, "Ageing mechanisms in lithium-ion batteries," *Journal of Power Sources*, vol. 147, no. 1–2, pp. 269–281, Sep. 2005, doi: 10.1016/j.jpowsour.2005.01.006.
- [9] M. B. Pinson and M. Z. Bazant, "Theory of SEI Formation in Rechargeable Batteries: Capacity Fade, Accelerated Aging and Lifetime Prediction," *Journal of The Electrochemical Society*, vol. 160, no. 2, pp. A243–A250, 2013, doi: 10.1149/2.044302jes.
- [10] J. Wang *et al.*, "Cycle-life model for graphite-LiFePO₄ cells," *Journal of Power Sources*, vol. 196, no. 8, pp. 3942–3948, Apr. 2011, doi: 10.1016/j.jpowsour.2010.11.134.
- [11] M. Safari and C. Delacourt, "Modeling of a

- Commercial Graphite/LiFePO₄ Cell," *Journal of The Electrochemical Society*, vol. 158, no. 5, p. A562, 2011, doi: 10.1149/1.3567007.
- [12] K. Smith and C.-Y. Wang, "Power and thermal characterization of a lithium-ion battery pack for hybrid-electric vehicles," *Journal of Power Sources*, vol. 160, no. 1, pp. 662–673, Sep. 2006, doi: 10.1016/j.jpowsour.2006.01.038.
- [13] B. Xia, C. Chen, Y. Tian, W. Sun, Z. Xu, and W. Zheng, "A novel method for state of charge estimation of lithium-ion batteries using a nonlinear observer," *Journal of Power Sources*, vol. 270, pp. 359–366, Dec. 2014, doi: 10.1016/j.jpowsour.2014.07.103.
- [14] G. L. Plett, *Battery Management Systems, Vol. I: Battery Modeling*. 2015.
- [15] Y. Hu, S. Yurkovich, Y. Guezennec, and B. J. Yurkovich, "Electro-thermal battery model identification for automotive applications," *Journal of Power Sources*, vol. 196, no. 1, pp. 449–457, Jan. 2011, doi: 10.1016/j.jpowsour.2010.06.037.
- [16] X. Hu, S. Li, and H. Peng, "A comparative study of equivalent circuit models for Li-ion batteries," *Journal of Power Sources*, vol. 198, pp. 359–367, Jan. 2012, doi: 10.1016/j.jpowsour.2011.10.013.
- [17] D. Andre, C. Appel, T. Soczka-Guth, and D. U. Sauer, "Advanced mathematical methods of SOC and SOH estimation for lithium-ion batteries," *Journal of Power Sources*, vol. 224, pp. 20–27, Feb. 2013, doi: 10.1016/j.jpowsour.2012.10.001.
- [18] M. Z. Ilyas, P. Saad, M. I. Ahmad, and A. R. I. Ghani, "Classification of EEG signals for brain-computer interface applications: Performance comparison," in *2016 International Conference on Robotics, Automation and Sciences (ICORAS)*, IEEE, Nov. 2016, pp. 1–4. doi: 10.1109/ICORAS.2016.7872610.
- [19] S. Singirikonda and Y. P. Obulesu, "Lithium-Ion Battery State of Charge Estimation Using Deep Neural Network," *Distributed Generation & Alternative Energy Journal*, vol. 18, no. 3, pp. 1459–1470, Mar. 2023, doi: 10.13052/dgaej2156-3306.3833.
- [20] R. Xiong, J. Cao, Q. Yu, H. He, and F. Sun, "Critical Review on the Battery State of Charge Estimation Methods for Electric Vehicles," *IEEE Access*, vol. 6, pp. 1832–1843, 2018, doi: 10.1109/ACCESS.2017.2780258.
- [21] W. He, N. Williard, M. Osterman, and M. Pecht, "Prognostics of lithium-ion batteries based on Dempster–Shafer theory and the Bayesian Monte Carlo method," *Journal of Power Sources*, vol. 196, no. 23, pp. 10314–10321, Dec. 2011, doi: 10.1016/j.jpowsour.2011.08.040.
- [22] R. Xiong, H. He, F. Sun, and K. Zhao, "Evaluation on State of Charge Estimation of Batteries With Adaptive Extended Kalman Filter by Experiment Approach," *IEEE Transactions on Vehicular Technology*, vol. 62, no. 1, pp. 108–117, Jan. 2013, doi: 10.1109/TVT.2012.2222684.
- [23] M. Charkhgard and M. Farrokhi, "State-of-Charge Estimation for Lithium-Ion Batteries Using Neural Networks and EKF," *IEEE Transactions on Industrial Electronics*, vol. 57, no. 12, pp. 4178–4187, Dec. 2010, doi: 10.1109/TIE.2010.2043035.
- [24] Y. Zhang, R. Xiong, H. He, and M. G. Pecht, "Long Short-Term Memory Recurrent Neural Network for Remaining Useful Life Prediction of Lithium-Ion Batteries," *IEEE Transactions on Vehicular Technology*, vol. 67, no. 7, pp. 5695–5705, Jul. 2018, doi: 10.1109/TVT.2018.2805189.
- [25] B. Saha, K. Goebel, S. Poll, and J. Christophersen, "Prognostics Methods for Battery Health Monitoring Using a Bayesian Framework," *IEEE Transactions on Instrumentation and Measurement*, vol. 58, no. 2, pp. 291–296, Feb. 2009, doi: 10.1109/TIM.2008.2005965.
- [26] T. Wang *et al.*, "Review of Aging Mechanism and Diagnostic Methods for Lithium-Ion Batteries," *Energies*, vol. 18, no. 14, p. 3884, Jul. 2025, doi: 10.3390/en18143884.
- [27] A. A. Hussein, "Capacity Fade Estimation in Electric Vehicle Li-Ion Batteries Using Artificial Neural Networks," *IEEE Transactions on Industry Applications*, vol. 51, no. 3, pp. 2321–2330, May 2015, doi: 10.1109/TIA.2014.2365152.
- [28] L. A. Al-Haddad *et al.*, "Reliability-oriented framework for UAV-based inspection

- missions in modern power and energy systems," *Scientific Reports*, vol. 16, no. 1, p. 958, Dec. 2025, doi: 10.1038/s41598-025-30410-w.
- [29] X. Little Flower and S. Poonguzhali, "Boosting EMG classification: a hybrid NCA-driven evolutionary optimization approach for high accuracy and efficiency," *Journal of Electrical Systems and Information Technology*, vol. 12, no. 1, p. 14, May 2025, doi: 10.1186/s43067-025-00205-0.
- [30] L. A. Al-Haddad, W. H. Alawee, and A. Basem, "Advancing task recognition towards artificial limbs control with ReliefF-based deep neural network extreme learning," *Computers in Biology and Medicine*, vol. 169, p. 107894, Feb. 2024, doi: 10.1016/j.compbiomed.2023.107894.
- [31] A. G. Abdulameer, M. M. Mrah, M. Bazerkan, L. A. Al-Haddad, and M. I. Al-Karkhi, "Machine learning-driven power prediction in continuous extrusion of pure titanium for enhanced structural resilience under extreme loading," *Discover Materials*, vol. 5, no. 1, p. 7, Jan. 2025, doi: 10.1007/s43939-024-00175-6.
- [32] S. S. Shijer, A. H. Jassim, L. A. Al-Haddad, and T. T. Abbas, "Evaluating electrical power yield of photovoltaic solar cells with k-Nearest neighbors: A machine learning statistical analysis approach," *e-Prime - Advances in Electrical Engineering, Electronics and Energy*, vol. 9, p. 100674, Sep. 2024, doi: 10.1016/j.prime.2024.100674.
- [33] Z. Zhou and D. A. Howey, "Bayesian hierarchical modelling for battery lifetime early prediction," *IFAC-PapersOnLine*, vol. 56, no. 2, pp. 6117–6123, 2023, doi: 10.1016/j.ifacol.2023.10.708.
- [34] F. Leng, Z. Wei, C. M. Tan, and R. Yazami, "Hierarchical degradation processes in lithium-ion batteries during ageing," *Electrochimica Acta*, vol. 256, pp. 52–62, Dec. 2017, doi: 10.1016/j.electacta.2017.10.007.
- [35] David Alexander Lee, J. A. Smith, and Emily Rose Johnson, "A Comparative Study on Electric Vehicle Battery Management Systems Using Machine Learning for Enhanced Safety and Longevity," *International Journal of Mechanical, Electrical and Civil Engineering*, vol. 1, no. 2, pp. 21–26, Apr. 2024, doi: 10.61132/ijmecie.v1i2.72.
- [36] V. M. Gautham, A. Sumesh, E. V. Jithin, K. Rameshkumar, and D. T. Thekkuden, "Evaluation of Time-Domain Acoustic Signature in TIG Welding of 5083 Aluminum Alloy: A Methodological Comparison of Feature Reduction Approaches," *Results in Engineering*, vol. 26, p. 105062, Jun. 2025, doi: 10.1016/j.rineng.2025.105062.
- [37] Y.-C. Lin, S.-C. Yang, S.-C. Wu, and C.-C. Chen, "Developing a system for the real-time collection and analysis of mobile vehicle emission data," *Results in Engineering*, vol. 23, p. 102706, Sep. 2024, doi: 10.1016/j.rineng.2024.102706.
- [38] M. S. Arslan, I. Kucukdemir, and M. E. Farrag, "Development of a nonlinear predictive controller for mitigation of motion sickness in autonomous vehicles," *Results in Engineering*, vol. 25, p. 103816, 2025.
- [39] M. M. Mrah and A. S. H. Merza, "Study the effects of surfaces on lubrication characteristics in slider bearings," in *AIP Conference Proceedings*, 2025, p. 040083. doi: 10.1063/5.0254312.
- [40] S. T. A. Shafi, M. K. Al-Saadi, and A. A. Jaddoa, "Improving Solar Air Heater Performance by Using New Novelty Perforated V-Shaped Barriers Experimental Solar air collector, absorber surface, V-Shaped, Friction Factor," *Terra Joule Journal*, vol. 1, no. 1, Mar. 2025, doi: 10.64071/3080-5724.1005.
- [41] Y. Khan, M. N. Tufail, K. Shahzad, A. Alameer, and N. Iqbal, "Impact of chemical reaction on thermal magnetized hybrid nanofluid over a curved stretching surface," *Results in Engineering*, vol. 27, p. 105556, Sep. 2025, doi: 10.1016/j.rineng.2025.105556.
- [42] N. Yang, X. Zhao, J. Li, J. Wang, H. Jiang, and S. Zhang, "Secondary Frequency Regulation Strategy for Battery Swapping Stations Considering the Behavioral Model of Electric Vehicles," *Electronics*, vol. 14, no. 8, p. 1598, Apr. 2025, doi: 10.3390/electronics14081598.
- [43] H. Xue, M. Wu, Z. Zhang, and H. Wang, "Intelligent diagnosis of mechanical faults of in-wheel motor based on improved artificial hydrocarbon networks," *ISA Transactions*, vol. 120, pp. 360–371, Jan. 2022, doi: 10.1016/j.isatra.2021.09.012.

- 10.1016/j.isatra.2021.03.015.
- [44] W. Lang, Y. Hu, C. Gong, X. Zhang, H. Xu, and J. Deng, "Artificial Intelligence-Based Technique for Fault Detection and Diagnosis of EV Motors: A Review," *IEEE Transactions on Transportation Electrification*, vol. 8, no. 1, pp. 384–406, Mar. 2022, doi: 10.1109/TTE.2021.3110318.
- [45] A. Choudhary, S. Fatima, and B. K. Panigrahi, "State-of-the-Art Technologies in Fault Diagnosis of Electric Vehicles: A Component-Based Review," *IEEE Transactions on Transportation Electrification*, vol. 9, no. 2, pp. 2324–2347, Jun. 2023, doi: 10.1109/TTE.2022.3209166.
- [46] A. Manoharan, K. M. Begam, V. R. Aparow, and D. Sooriamoorthy, "Artificial Neural Networks, Gradient Boosting and Support Vector Machines for electric vehicle battery state estimation: A review," *Journal of Energy Storage*, vol. 55, p. 105384, Nov. 2022, doi: 10.1016/j.est.2022.105384.
- [47] Z. Chen, Y. Liu, Y. Zhang, Z. Lei, Z. Chen, and G. Li, "A neural network-based ECMS for optimized energy management of plug-in hybrid electric vehicles," *Energy*, vol. 243, p. 122727, Mar. 2022, doi: 10.1016/j.energy.2021.122727.
- [48] F. Deng, Y. Bian, and H. Zheng, "Fault diagnosis for electric vehicle lithium batteries using a multi-classification support vector machine," *Electrical Engineering*, vol. 104, no. 3, pp. 1831–1837, Jun. 2022, doi: 10.1007/s00202-021-01426-y.
- [49] M. Bao *et al.*, "Interpretable machine learning prediction for li-ion battery's state of health based on electrochemical impedance spectroscopy and temporal features," *Electrochimica Acta*, vol. 494, p. 144449, Aug. 2024, doi: 10.1016/j.electacta.2024.144449.
- [50] J. Wu, J. Meng, M. Lin, W. Wang, J. Wu, and D.-I. Stroe, "Lithium-ion battery state of health estimation using a hybrid model with electrochemical impedance spectroscopy," *Reliability Engineering & System Safety*, vol. 252, p. 110450, Dec. 2024, doi: 10.1016/j.ress.2024.110450.
- [51] Y. Xie, S. Wang, G. Zhang, P. Takyi-Aninakwa, C. Fernandez, and F. Blaabjerg, "A review of data-driven whole-life state of health prediction for lithium-ion batteries: Data preprocessing, aging characteristics, algorithms, and future challenges," *Journal of Energy Chemistry*, vol. 97, pp. 630–649, Oct. 2024, doi: 10.1016/j.jechem.2024.06.017.
- [52] Z. Deng, L. Xu, H. Liu, X. Hu, B. Wang, and J. Zhou, "Rapid health estimation of in-service battery packs based on limited labels and domain adaptation," *Journal of Energy Chemistry*, vol. 89, pp. 345–354, Feb. 2024, doi: 10.1016/j.jechem.2023.10.056.
- [53] G. Pozzato, A. Allam, and S. Onori, "Lithium-ion battery aging dataset based on electric vehicle real-driving profiles," *Data in Brief*, vol. 41, p. 107995, Apr. 2022, doi: 10.1016/j.dib.2022.107995.
- [54] Y.-S. Huang, K.-C. Chen, and C.-J. Ko, "Low-frequency impedance spectroscopy generated by two equal square waves as a fast and simple tool for states estimation without battery relaxation," *Journal of Energy Storage*, vol. 117, p. 116229, May 2025, doi: 10.1016/j.est.2025.116229.
- [55] P. K. Jones, U. Stimming, and A. A. Lee, "Impedance-based forecasting of lithium-ion battery performance amid uneven usage," *Nature Communications*, vol. 13, no. 1, p. 4806, Aug. 2022, doi: 10.1038/s41467-022-32422-w.
- [56] G. Zhang, B. Xia, and J. Wang, "Intelligent state of charge estimation of lithium-ion batteries based on L-M optimized back-propagation neural network," *Journal of Energy Storage*, vol. 44, p. 103442, Dec. 2021, doi: 10.1016/j.est.2021.103442.
- [57] H. Chavez, B. Chavez-Arias, S. Contreras-Rosas, J. M. Alvarez-Rodríguez, and C. Raymundo, "Artificial neural network model to predict student performance using nonpersonal information," *Frontiers in Education*, vol. 8, Feb. 2023, doi: 10.3389/educ.2023.1106679.
- [58] E. Laakso *et al.*, "Aging mechanisms of NMC811/Si-Graphite Li-ion batteries," *Journal of Power Sources*, vol. 599, p. 234159, Apr. 2024, doi: 10.1016/j.jpowsour.2024.234159.