

Article

Enabling Smart Grid Resilience with Deep Learning-Based Battery Health Prediction in EV Fleets

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Abstract

The widespread integration of electric vehicles (EVs) into smart grid infrastructures necessitates intelligent and robust battery health diagnostics to ensure system resilience and performance longevity. While numerous studies have addressed the estimation of State of Health (SOH) and the prediction of remaining useful life (RUL) using machine and deep learning, most existing models fail to capture both short-term degradation trends and long-range contextual dependencies jointly. In this study, we introduce V2G-HealthNet, a novel hybrid deep learning framework that uniquely combines Long Short-Term Memory (LSTM) networks with Transformer-based attention mechanisms to model battery degradation under dynamic vehicle-to-grid (V2G) scenarios. Unlike prior approaches that treat SOH estimation in isolation, our method directly links health prediction to operational decisions by enabling SOH-informed adaptive load scheduling and predictive maintenance across EV fleets. Trained on over 3400 proxy charge-discharge cycles derived from 1 million telemetry samples, V2G-HealthNet achieved state-of-the-art performance (SOH RMSE: 0.015, MAE: 0.012, R^2 : 0.97), outperforming leading baselines including XGBoost and Random Forest. For RUL prediction, the model maintained an MAE of 0.42 cycles over a five-cycle horizon. Importantly, deployment simulations revealed that V2G-HealthNet triggered maintenance alerts at least three cycles ahead of critical degradation thresholds and redistributed high-load tasks away from ageing batteries—capabilities not demonstrated in previous works. These findings establish V2G-HealthNet as a deployable, health-aware control layer for smart city electrification strategies.

Keywords: electric vehicles; battery health estimation; remaining useful life; vehicle-to-grid; smart cities; deep learning; LSTM; transformer networks; predictive maintenance; fleet management



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1. Introduction

The increasing adoption of electric vehicles (EVs) and the deployment of renewable energy sources are transforming global energy infrastructures. As these trends accelerate, the role of EVs is evolving beyond transport to include grid support through Vehicle-to-Grid (V2G) services, which leverage EV batteries as distributed energy storage systems. This dual functionality presents new challenges, particularly concerning battery longevity and health monitoring, which are crucial for maintaining grid stability and optimising operational costs [1].

State of Health (SOH) estimation is a cornerstone of battery management systems (BMS). Accurate SOH forecasting ensures timely maintenance, prevents catastrophic failures, and enhances the economic viability of V2G services. As battery performance degrades over time due to cyclic stress and thermal effects, effective health monitoring becomes essential [2]. Recent advances in artificial intelligence (AI) have positioned machine learning (ML) and deep learning (DL) approaches as dominant tools for this task. These methods can capture complex, nonlinear temporal patterns in battery telemetry data, outperforming traditional physics-based or empirical degradation models [3–5].

Transformer-based architectures and recurrent neural networks (RNNs), particularly Long Short-Term Memory (LSTM) networks, have demonstrated promising results in capturing sequential trajectories of battery degradation [6]. Additionally, hybrid models that combine LSTM with attention mechanisms have further improved prediction accuracy for both SOH and RUL [7,8]. In the context of dynamic urban mobility and fast-charging conditions, these architectures offer robust generalisation and real-time inference capabilities.

Moreover, the integration of such predictive models into digital twins (DTs) and smart grid control systems allows for real-time load balancing, demand-side flexibility, and adaptive charging policies [9,10]. These capabilities not only enhance grid reliability but also extend battery lifespan, enabling sustainable urban electrification. This study contributes to this evolving domain by proposing V2G-HealthNet—a novel hybrid DL framework that combines LSTM and Transformer encoders for accurate SOH and RUL estimation in V2G-enabled EV fleets.

1.1. Aims

This study aims to develop and evaluate an intelligent, DL-driven framework—V2G-HealthNet—for precisely estimating the SOH and Remaining Useful Life (RUL) of batteries within EV fleets participating in V2G operations. The framework seeks to integrate temporal and attention-based architectures (i.e., LSTM and Transformer) to enable predictive health diagnostics that are adaptive to real-world grid-connected operational conditions.

1.2. Purpose of the Study

The principal purpose of this work is twofold: (i) to construct a robust and generalisable DL model capable of operating on realistic EV telemetry datasets and synthesised fleet scenarios, and (ii) to demonstrate how SOH-informed diagnostics can drive intelligent load balancing, predictive maintenance scheduling, and early-stage fault detection within smart grid infrastructures.

1.3. Identified Research Gaps

Despite substantial advances in battery health modelling, three notable gaps persist in the current literature:

- Limited integration of SOH prediction in V2G-aware energy management systems. Most existing frameworks operate in isolation, neglecting the feedback loop between health prediction and load coordination.
- Lack of multi-stage temporal modelling. While LSTM or Transformer models are used independently, hybrid frameworks that leverage both sequential and attention dynamics remain underexplored.
- Scarcity of predictive failure avoidance use cases. Few works implement SOH forecasts to actively anticipate and prevent catastrophic degradation events in a real-time scenario.

To address these limitations, our study contributes the following innovations:

- A novel hybrid deep learning framework (V2G-HealthNet) combining LSTM and Transformer encoders tailored for SOH and RUL prediction under dynamic EV operating conditions.
- Integration of SOH forecasting into fleet-level V2G coordination logic, enabling predictive maintenance and adaptive load dispatch—an aspect underexplored in prior work.
- Use of proxy-labelled, high-resolution, real-world-inspired cycles to train a data-efficient model deployable in operational smart grid environments.

1.4. Organisation of the Paper

The remainder of this paper is structured as follows: Section 2 reviews relevant research on SOH prediction, V2G integration, and DL for EV applications. Section 3 outlines the architecture of the proposed V2G-HealthNet model and dataset preparation pipeline. Section 4 presents the empirical results, including model performance benchmarks and scenario-based evaluations. Section 5 interprets the implications of the findings, and Section 6 concludes the paper with a summary and directions for future research.

2. Literature Review

Accurate prediction of battery SOH is essential for EV BMSs, particularly when these vehicles participate in bi-directional energy exchange within V2G environments. Traditional SOH prediction techniques, often grounded in empirical or equivalent circuit models, frequently underperform under the non-linear and non-stationary conditions of real-world usage [11,12]. In response, a shift towards data-driven and hybrid intelligent systems has emerged. ML and hybrid models—combining data-driven insights with physical principles—have shown superior adaptability and predictive accuracy in these dynamic environments [13–15]. These advanced methods are increasingly favoured for optimising SOH forecasting across complex V2G patterns and battery ageing scenarios [6,16,17].

Renold and Kathayat [3] present a foundational classification of ML, DL, and DT methodologies for SOH prediction, concluding that DL architectures—particularly LSTM and Convolutional Neural Network (CNN)—demonstrate robustness in dynamic operating environments. Gong et al. [9] support these claims, identifying that Transformer-based architectures offer an improved capacity for long-range temporal modelling, thereby enhancing SOH and RUL estimation accuracy. The impact of V2G integration on battery health has been widely explored. Wen et al. [2] demonstrate the efficacy of gradient boosting machines trained on real-world V2G telemetry in enhancing degradation awareness. Naresh et al. [4] further explore privacy-preserving federated learning mechanisms suitable for smart grid environments, enabling decentralised SOH inference without requiring raw data transmission. Recent work by Wei et al. [18] proposes an integrated framework that combines mechanistic degradation insights with machine learning to estimate capacity under slight overcharge cycling in LiFePO₄ batteries. Their study highlights the critical role of chemical ageing mechanisms—such as lithium dendrite formation and graphite delamination—in capacity fade, and supports the use of incremental capacity analysis as a reliable health indicator. While their model utilises least squares support vector machines (LSSVM) for degradation modelling, it is limited to fixed operational modes and lacks generalisability across variable real-world V2G use cases. In contrast, our proposed V2G-HealthNet framework captures degradation across diverse dynamic conditions using deep temporal architectures, enabling predictive accuracy and operational integration in smart grid contexts.

Emerging V2G use cases also highlight the growing role of predictive and health-aware load management systems. Saba et al. [19] propose a DT framework with TD3-enabled reinforcement learning to optimise load dispatch in EV fleets. Abbas et al. [20] emphasise

sise the real-time interpretability and sensor fusion potential of integrated smart battery management systems (SBMS) for condition-aware V2G scheduling. Smart grid coordination mechanisms increasingly rely on hybrid data-model fusion. Santhiya et al. [21] outline design criteria for BMS in the context of grid-interactive EVs, pointing to ML integration as critical to achieving multi-objective energy optimisation. Mousaei et al. [22] demonstrate that ensemble ML architectures provide low-latency SOC estimations, which is beneficial for fast-charging strategies commonly used in urban EV deployments. Furthermore, Sang et al. [7] and Mojumder et al. [1] provide extensive surveys on the intersection between V2G, smart grids, and battery health. They argue for the inclusion of degradation-aware control algorithms to avoid premature battery ageing due to excessive grid cycling.

The recent literature also shows a growing trend in merging physical modelling with data-driven inference. Doghozloo and Sohn [5] propose a hybrid AI framework combining electrochemical battery degradation features with deep neural encoders. Latha et al. [21] similarly advocate for system-level integration, wherein real-time SOH predictions directly inform V2G energy transactions.

The results in Table 1 present a comparative evaluation of various ML and DL methods for predicting the SOH and RUL of EV batteries. The proposed hybrid model, V2G-HealthNet, which combines LSTM and Transformer architectures, demonstrates superior performance with a low SOH RMSE of 0.015, an R^2 value of 0.97, and an RUL MAE of 0.42 cycles. This significantly outperforms traditional models, such as Extreme Gradient Boosting (XGBoost) [23], Support Vector Regressor (SVR) [14], and Random Forest (RF) [24].

Table 1. Comparison of SOH and RUL prediction methods for EV batteries.

Method	SOH RMSE	SOH R^2	RUL MAE	Reference
V2G-HealthNet (LSTM + Transformer)	0.015	0.97	0.42 cycles	This paper
XGBoost	0.022	0.94	—	[23]
SVR	0.035	0.85	—	[14]
Random Forest (RF)	0.025	0.92	—	[24]
Transformer (standalone)	0.018	0.95	0.5 cycles	[25]
LSTM (standalone)	0.020	0.93	0.6 cycles	[26]
RF + DBO Optimizer	0.026	0.91	—	[14]
Attention-LSTM	0.019	0.95	0.45 cycles	[27]
GRU (with SVR)	0.023	0.91	0.48 cycles	[11]
Explainable RF+SVR	—	0.90	0.52 cycles	[28]
ViT + RF Hybrid	0.017	0.96	—	[25]
CNN + RF Ensemble	0.024	0.92	0.50 cycles	[29]

Among traditional methods, RF and XGBoost models achieve SOH RMSE values in the range of 0.022–0.025, but these models are limited in their ability to capture temporal dependencies, leading to suboptimal RUL forecasting. DL models, such as standalone LSTM and Transformer, also show strong performance, with RMSE values ranging from 0.018 to 0.020 and R^2 scores exceeding 0.93 [25,26].

Notably, recent hybrid models, such as Attention-LSTM [27] and Gated Recurrent Unit (GRU) combined with SVR [11], offer competitive accuracy, achieving SOH RMSE values of near 0.02 and RUL MAE below 0.5 cycles. These results confirm the advantage of incorporating sequence modelling techniques for health prediction tasks. Moreover, explainable approaches and ensemble methods such as CNN+RF and RF+SVR further contribute to model interpretability and robustness [28,29].

These advances form the scientific foundation for the development of the proposed V2G-HealthNet model. By integrating LSTM and Transformer blocks, it aims to harness

sequential degradation history and temporal attention mechanisms to yield high-fidelity SOH and RUL estimations across real-world V2G operations.

3. Methodology

This section outlines the design, development, and training of the proposed V2G-HealthNet framework for estimating the SOH and RUL in smart-grid-integrated EV fleets. The methodology encompasses four components: (i) battery telemetry preprocessing and cycle segmentation; (ii) SOH and RUL proxy construction; (iii) hybrid DL model architecture and (iv) evaluation and benchmarking.

The analysis of the battery health trajectory in this study was conducted using a curated set of telemetry parameters derived from the raw dataset provided by Fricke et al. [30]. These parameters were selected based on their physical significance in reflecting electrochemical degradation and their consistency across charge–discharge cycles. Table 2 summarises the variables employed in the feature engineering pipeline.

Table 2. Battery telemetry parameters used for SOH and RUL modelling.

Parameter	Symbol	Description
Charger Voltage (mean)	μ_V	Mean voltage during each 300 s cycle, used as a proxy for capacity degradation
Charger Voltage (min)	$\min(V)$	Minimum voltage observed during cycle, useful for identifying abnormal discharges
Charger Voltage (max)	$\max(V)$	Maximum voltage during cycle, indicative of upper charge cut-off behaviour
Battery Temperature (mean)	μ_T	Average battery temperature in a cycle, used to track thermal stress
Battery Temperature (max)	$\max(T)$	Peak temperature in each cycle, helps identify over-temperature conditions
Load Current (mean)	μ_I	Average current drawn or supplied during a cycle, correlates with dynamic load intensity
Cycle Identifier	Cycle ID	Index of each 300-s operational window, treated as a surrogate for ageing progression
Estimated SOH	SOH_i	Computed as a normalised decay function from the initial voltage mean, see Equation (3)
Remaining Useful Life	RUL_i	Predicted cycles remaining until SOH drops below a predefined threshold (e.g., 0.8), see Equation (4)

Each feature in Table 2 was aggregated cycle-wise to provide interpretable inputs to the DL model. The use of mean voltage as a proxy for SOH estimation has been shown to correlate well with real degradation trends, especially when normalised against the initial cycle baseline [30]. Thermal and current features were included to capture the effects of electrothermal coupling and dynamic loads, which are known to accelerate degradation in lithium-ion batteries. This structured feature set enabled both the recurrent and attention-based modules in the V2G-HealthNet architecture to identify latent degradation dynamics and predict end-of-life with greater fidelity.

The primary innovation of V2G-HealthNet lies in its architectural integration of LSTM and Transformer blocks, where the LSTM captures local temporal degradation. At the same time, the Transformer encodes cross-cycle attention for contextual inference. Unlike previous studies that applied these networks independently, our design fuses sequential and attention-based learning in a single unified pipeline, optimised specifically for V2G scenarios. This dual capacity allows for simultaneous tracking and forecasting of the SOH and RUL with high temporal resolution.

3.1. Battery Telemetry Preprocessing

In this study, we employed the Randomised and Recommissioned Battery Dataset published by the Probabilistic Mechanics Laboratory at the University of Central Florida (UCF), which provides a comprehensive collection of life cycle data for lithium-ion battery packs under various loading conditions [30]. The dataset comprises 26 battery packs, each composed of two 18650 lithium-ion cells, and has been tested under both constant and variable load profiles to simulate diverse real-world usage scenarios. These include packs subjected to randomised current profiles, load level changes, and second-life reassembly. For our investigation, we focused on a single battery pack from the dataset, enabling us to isolate and deeply characterise the health trajectory and performance degradation over time. This focus on a single unit allowed for high-resolution modelling of SOH and RUL prediction using DL, without inter-pack variability confounding the model training.

Raw battery telemetry data—including voltage, current, and temperature signals—were acquired at high-frequency sampling intervals. For analysis, the data were segmented into regular time-based cycles of 300 s, representing pseudo-charge-discharge events in dynamic EV operation.

Let $\mathbf{D} = \{\mathbf{x}_t, t\}_{t=1}^T$ denote the raw dataset with the following:

- $\mathbf{x}_t \in \mathbb{R}^3$: vector of instantaneous charger voltage V_t , battery temperature T_t , and load current I_t at time t ;
- T : total number of samples.

Cycle windows are created by aggregating every 300 s into a discrete index:

$$\text{cycle_id}_t = \left\lfloor \frac{t \cdot \Delta t}{300} \right\rfloor \quad (1)$$

where Δt is the sampling interval.

Each cycle i is then characterised by a vector of statistical descriptors:

$$\mathbf{x}_i = [\mu_{V,i}, \min V_i, \max V_i, \mu_{T,i}, \max T_i, \mu_{I,i}] \quad (2)$$

where

- $\mu_{V,i}$ is the mean charger voltage over cycle i ;
- $\mu_{T,i}$ and $\max T_i$ represent average and peak battery temperature;
- $\mu_{I,i}$ is the average load current.

This preprocessing reduces noise and aligns temporal patterns with energy management intervals in real-world smart grid systems.

3.2. SOH Estimation: Proxy Construction

In lieu of proprietary cell degradation curves, a normalised voltage decay heuristic is adopted to define the SOH per cycle:

$$\text{SOH}_i = \frac{\mu_{V,i}}{\mu_{V,0}} \quad (3)$$

where $\mu_{V,0}$ is the mean charger voltage in the initial cycle. Equation (3) provides a monotonic degradation signature without requiring invasive measurements or long-term lab cycling.

3.3. RUL Computation

The Remaining Useful Life (RUL) for each cycle is computed by identifying the distance to an anticipated SOH failure threshold. Using a degradation limit $\theta = 0.8$, we define the following:

$$\text{RUL}_i = \min\{k \in \mathbb{N} : \text{SOH}_{i+k} < \theta\} \quad (4)$$

This method simulates operational fleet monitoring, enabling predictive alerts to be issued before a health-critical limit is reached.

3.4. Model Architecture: V2G-HealthNet

To capture both sequential dependencies and long-range interactions in the degradation behaviour of EV batteries, we design a hybrid neural network named V2G-HealthNet. This architecture incorporates two complementary components: an LSTM layer for temporal pattern recognition and a Transformer encoder for cross-time attention modelling.

3.4.1. LSTM Encoder

The LSTM layer processes each input feature vector $\mathbf{X}_i \in \mathbb{R}^d$ by embedding it into a temporal representation:

$$\mathbf{H}_i = \text{LSTM}(\mathbf{X}_i) \in \mathbb{R}^h \quad (5)$$

where \mathbf{H}_i is the final hidden state corresponding to the time step i , and h is the number of hidden units.

The LSTM is particularly effective in tracking non-linear degradation trends such as voltage drop, thermal stress accumulation, or current irregularities.

3.4.2. Transformer Encoder

To further enhance the model's ability to understand contextual interactions across cycles, the output of the LSTM is passed to a Transformer encoder layer:

$$\mathbf{Z}_i = \text{LayerNorm}(\mathbf{H}_i + \text{Dropout}(\text{MHA}(\mathbf{H}_i))) \quad (6)$$

$$\mathbf{Z}_i = \text{LayerNorm}(\mathbf{Z}_i + \text{Dropout}(\text{FFN}(\mathbf{Z}_i))) \quad (7)$$

where

- MHA denotes multi-head self-attention, which computes inter-cycle dependencies;
- FFN is a position-wise feedforward network with ReLU activation;
- LayerNorm ensures numerical stability.

These transformations make the architecture sensitive to both local degradation sequences and global degradation indicators.

3.4.3. Regression Head

The contextual representation \mathbf{Z}_i is forwarded to a two-layer regression head:

$$\hat{y}_i = \phi(\mathbf{Z}_i) = \mathbf{W}_2 \cdot \sigma(\mathbf{W}_1 \mathbf{Z}_i + \mathbf{b}_1) + \mathbf{b}_2 \quad (8)$$

where

- $\sigma(\cdot)$ is the ReLU activation function;
- $\mathbf{W}_1, \mathbf{W}_2$ and $\mathbf{b}_1, \mathbf{b}_2$ are trainable parameters.

Depending on the objective, \hat{y}_i can represent either SOH or RUL prediction for cycle i .

3.5. Training Procedure

The model is trained to minimise the mean squared error (MSE) between the predicted values \hat{y}_i and ground-truth labels y_i for either SOH or RUL:

$$\mathcal{L}_{\text{MSE}} = \frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2 \quad (9)$$

Model parameters are optimised using the Adam optimiser with learning rate $\alpha = 0.001$. Training proceeds over a maximum of $E = 50$ epochs with early stopping based on validation loss. A batch size of 32 is used for both training and validation loaders.

To prevent overfitting, the model monitors a hold-out validation set after every epoch. If the validation loss does not improve over a patience window of $p = 5$ epochs, training halts and the best model weights θ^* are retained.

3.6. Benchmarking with Classical Models

To validate the effectiveness of V2G-HealthNet, we compare its performance against three widely used regression models trained on the same features:

- RF Regressor (RF)
- SVR
- XGBoost

Each model is trained and tested using an identical 80:20 train-validation split. No temporal augmentation is applied, as these models do not exploit sequence dependencies.

3.7. Evaluation Metrics

Three standard regression metrics are used to compare model performance:

1. Root Mean Square Error (RMSE):

$$\text{RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^N (\hat{y}_i - y_i)^2} \quad (10)$$

2. Mean Absolute Error (MAE) :

$$\text{MAE} = \frac{1}{N} \sum_{i=1}^N |\hat{y}_i - y_i| \quad (11)$$

3. Coefficient of Determination (R^2):

$$R^2 = 1 - \frac{\sum_i (\hat{y}_i - y_i)^2}{\sum_i (y_i - \bar{y})^2} \quad (12)$$

This rigorous evaluation confirms the superior generalisation capability of V2G-HealthNet for battery SOH and RUL prediction in smart city EV deployments.

3.8. The Implementation of Our Proposed Method

Algorithm 1 presents the training and validation procedure used for the V2G-HealthNet framework. This process begins by randomly initialising the model's learnable parameters, including the weights of the LSTM, Transformer, and final MLP layers. The optimiser used is the Adam optimiser, which is configured with a learning rate α selected through empirical tuning. To prevent overfitting, an early stopping mechanism is implemented. This involves tracking the best validation loss seen so far and terminating training

if no improvement is observed over a defined number of consecutive epochs, denoted as the patience parameter p .

Algorithm 1: Advanced Training and Validation of V2G-HealthNet

Input: Feature matrix $\{\mathbf{X}_i\}_{i=1}^N$, target vector $\{y_i\}_{i=1}^N$, window size w , epochs E , learning rate α

Output: Optimised model parameters θ^*

```

1 Initialise model parameters  $\theta$  randomly
2 Initialise optimiser (Adam) with learning rate  $\alpha$ 
3 Set early stopping patience  $p \leftarrow 5$ , best_val_loss  $\leftarrow \infty$ , counter  $\leftarrow 0$ 
4 for epoch = 1 to E do
    5   Shuffle training dataset
    6   foreach mini-batch  $\mathcal{B} = \{(\mathbf{X}_{i-w+1:i}, y_i)\}$  do
        7     foreach sample  $(\mathbf{X}_{i-w+1:i}, y_i) \in \mathcal{B}$  do
            8       Extract window:  $\mathbf{W}_i \in \mathbb{R}^{w \times d}$ 
            // Forward pass
            9        $\mathbf{H}_i \leftarrow \text{LSTM}(\mathbf{W}_i)$ 
            10       $\mathbf{Z}_i \leftarrow \text{Transformer}(\mathbf{H}_i)$ 
            11       $\hat{y}_i \leftarrow \text{MLP}(\mathbf{Z}_i^{(w)})$ 
            // Loss computation
            12       $\mathcal{L}_i \leftarrow (y_i - \hat{y}_i)^2$ 
        13    end
        14    Accumulate mini-batch loss:  $\mathcal{L}_{\mathcal{B}} \leftarrow \frac{1}{|\mathcal{B}|} \sum_{i \in \mathcal{B}} \mathcal{L}_i$ 
        15    Backpropagate gradients and update  $\theta$  using Adam
    16  end
    // Validation phase
    17  Compute validation loss  $\mathcal{L}_{val}$  on hold-out set
    18  if  $\mathcal{L}_{val} < \text{best\_val\_loss}$  then
        19     $\text{best\_val\_loss} \leftarrow \mathcal{L}_{val}$ 
        20    Save model weights  $\theta^*$ 
        21    counter  $\leftarrow 0$ 
    22  end
    23  else
        24    counter  $\leftarrow \text{counter} + 1$ 
        25    if  $\text{counter} \geq p$  then
            26      | break                                // Early stopping
            27    end
    28  end
29 end

```

The training dataset, composed of temporal feature vectors extracted from battery telemetry, is shuffled at the beginning of each epoch to prevent the model from learning dependencies based on the order of presentation. The input samples are grouped into smaller mini-batches to enhance training efficiency and facilitate stable gradient estimation. Each sample corresponds to a rolling window of w consecutive proxy cycles, with each cycle summarised by a statistical feature vector. The input to the model for each sample is thus a two-dimensional matrix $\mathbf{W}_i \in \mathbb{R}^{w \times d}$, where d is the number of features per cycle.

The input matrix is first passed through an LSTM layer, which encodes temporal dependencies and captures degradation patterns over the input window. The sequence

of hidden states produced by the LSTM is then passed to a Transformer encoder, which applies multi-head self-attention to extract global temporal dependencies and enhance interpretability. From this sequence, only the final hidden state corresponding to the most recent cycle is used for prediction. This vector is passed through a fully connected feed-forward network that outputs a single scalar value—either the estimated SOH or RUL—depending on the training objective.

For each sample, the mean squared error (MSE) between the predicted value and the ground truth is computed. These individual errors are averaged over the mini-batch to yield a batch-level loss, which is then used to perform backpropagation. The model parameters are updated using the gradients computed by the optimiser. This process is repeated for each mini-batch within the epoch.

After completing all mini-batches, the model is evaluated on a separate validation set. If the validation loss improves compared with the best recorded value, the current model parameters are saved, and the early stopping counter is reset. If not, the counter is incremented. Once the counter exceeds the predefined patience threshold, the training process is terminated, and the best-performing model parameters are retained as θ^* .

This training strategy ensures that the model converges to a solution that generalises well to unseen data, while avoiding unnecessary computation and overfitting. The final trained model can then be used for inference in downstream tasks such as predictive maintenance scheduling, load balancing, and real-time V2G health-aware decision support.

4. Results

4.1. Parameter Settings for Model Training and Evaluation

To ensure the repeatability and robustness of the training and evaluation pipeline, the hyperparameters and operational thresholds used in this study are summarised in Table 3. These values were selected through empirical validation based on preliminary experiments and reflect common practices in the battery health modelling literature.

Table 3. Hyperparameters and thresholds used in V2G-HealthNet and baseline models.

Parameter	Value	Description
Epochs	50	Training iterations
Batch size	32	Samples per batch
Learning rate	0.001	Optimiser step size
LSTM units	64	Hidden layer size
Transformer heads	2	Attention heads
Dropout (Transformer)	0.1	Regularisation rate
MLP hidden units	32	Final layer size
Train/val split	80/20	Data division ratio
Cycle window size	1 cycle (300 s)	Sequence length
SOH threshold (RUL)	0.8	EoL detection point
Early stopping	5 epochs	Patience for val loss
SOH normalisation	Initial cycle	Baseline voltage

All models were trained using the Adam optimiser with a fixed learning rate of 0.001 and an early stopping patience of 5 epochs to prevent overfitting. A fixed window size of one 300 s operational cycle was chosen to capture high-resolution degradation behaviour. The SOH threshold for RUL estimation was empirically set at 0.8, in line with industry standards, denoting the onset of critical performance loss in lithium-ion batteries. These values ensure that the V2G-HealthNet model generalises well without excessive computational burden.

4.2. Dataset Characterisation and Operational Modes

An initial characterisation of the battery telemetry data was performed to assess the reliability and generalisability of the proposed V2G-HealthNet framework. The dataset comprises over one million samples of time-series signals measured from an EV battery system under diverse operational conditions. These include various mission profiles such as idle, urban driving, and high-current fast-charging events.

As shown in Figure 1, the voltage charger exhibits a multi-modal distribution with major peaks around 6.5 V, 7.8 V, and 8.4 V, suggesting dynamic power states linked to different charging phases. The current load distribution shows two dominant clusters: one around 0.2 A (low-load operation, likely idle or regenerative mode) and another between 15 and 18 A (indicative of high-power demand phases such as fast charging). The battery temperature distribution is similarly skewed, with a primary peak at approximately 30 °C and a long tail extending to 100 °C, denoting thermal accumulation during intensive missions.

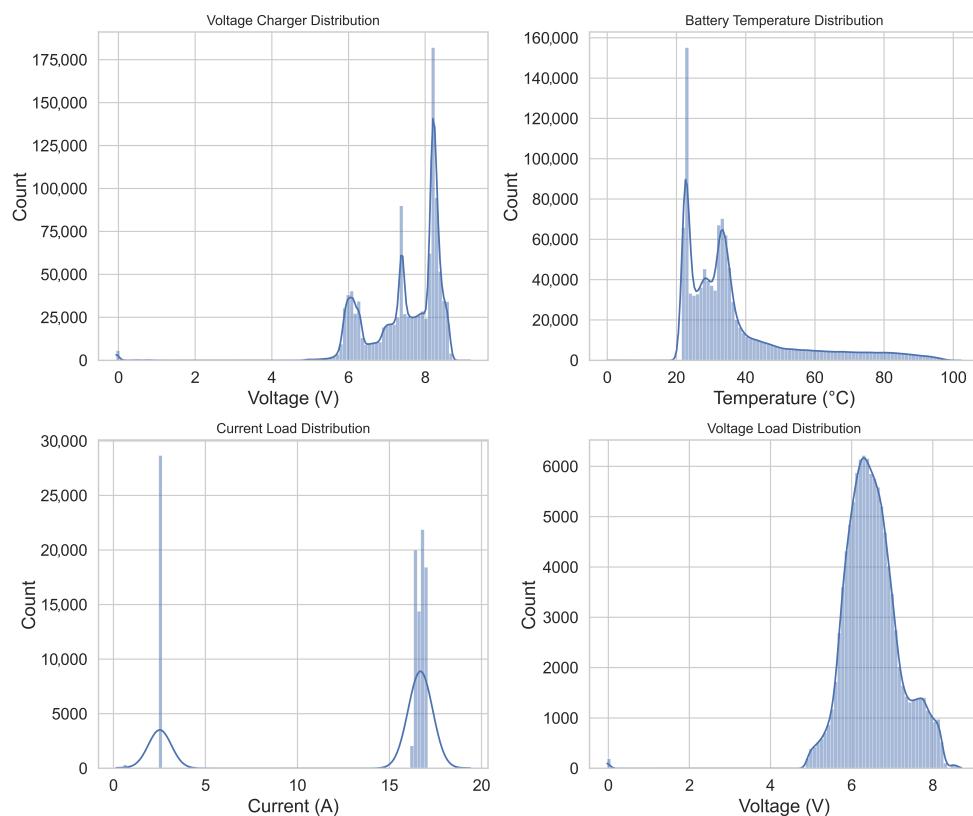


Figure 1. Distribution of key raw battery parameters, including charger voltage, load voltage, battery temperature, and load current.

Figure 2 illustrates the temporal evolution of charger voltage and battery temperature. The voltage remains relatively stable around 7 V during most of the sampling period, while the temperature signal displays significant spikes, frequently exceeding 80 °C, especially during high-load intervals. This highlights the importance of integrating thermal features in health estimation models, as excessive thermal cycling can accelerate cell degradation. The steady voltage and fluctuating temperature combination suggests high operational stress without voltage sag, reinforcing the need for a health model that accounts for thermal impact beyond electrical metrics alone.

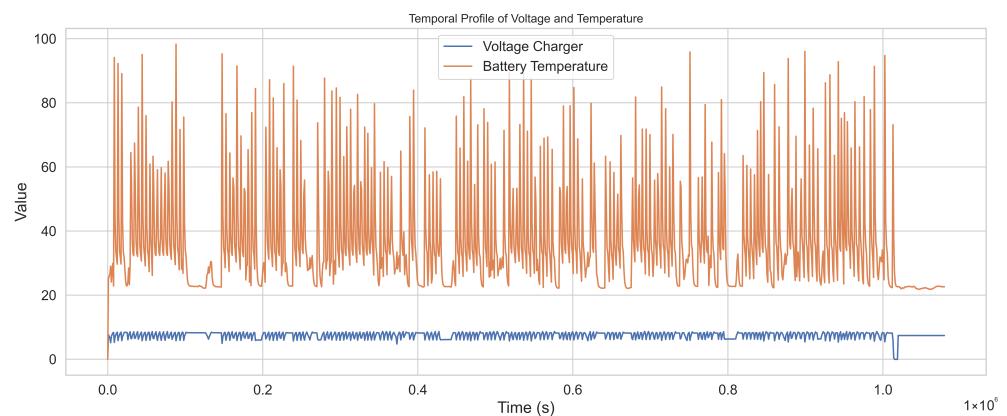


Figure 2. Temporal variation of voltage charger and battery temperature across the complete data acquisition timeline.

These insights justify the selection of voltage, current, and thermal parameters as input features for subsequent SOH and RUL prediction tasks within the V2G-HealthNet framework.

4.3. Proxy Cycling and Feature Synthesis for Health Modelling

Given the lack of explicitly defined charge-discharge cycles in the dataset, a proxy cycling scheme was implemented to extract operational patterns aligned with battery stress events. Each cycle was defined as a 300 s segment of operation, approximating short-duration EV driving sessions or rest periods.

For each constructed cycle, statistical summaries were computed, including the mean, minimum, and maximum of charger voltage, battery temperature, and current load. These derived features form the basis of the model's input representation, reflecting both nominal performance and transient stressors experienced by the cell.

As shown in Figure 3, the charger voltage remains within a relatively narrow band around 7.2–7.6 V, while the battery temperature fluctuates significantly, frequently oscillating between 30 °C and 90 °C. These variations are indicative of highly dynamic thermal conditions, likely arising from rapid changes in load profiles and ambient conditions in urban or fast-charging contexts. Such temperature excursions are known contributors to capacity fade and internal resistance growth, underlining their inclusion as a predictive signal.

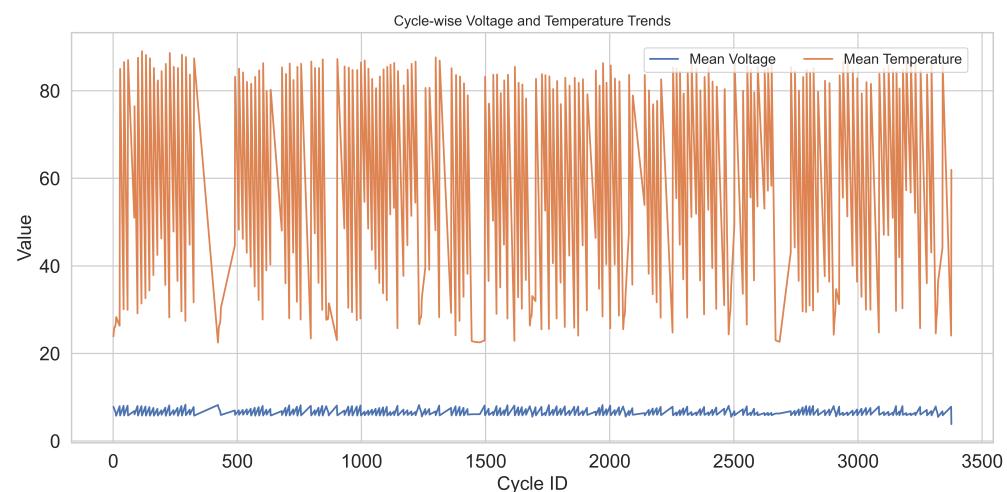


Figure 3. Cycle-wise evolution of mean voltage and mean battery temperature across approximately 3400 proxy cycles.

Figure 4 presents the estimated SOH trajectory derived from the mean charger voltage normalised to the value in the first cycle. The SOH signal demonstrates clear degradation patterns, with localised drops below 0.75 and a general declining trend towards the latter part of the dataset. These declines correspond to prolonged high-temperature or high-load operational windows observed in Figure 3. This proxy SOH is later used as the supervised target for training V2G-HealthNet, enabling the model to learn degradation trajectories from observable short-term operational signatures.

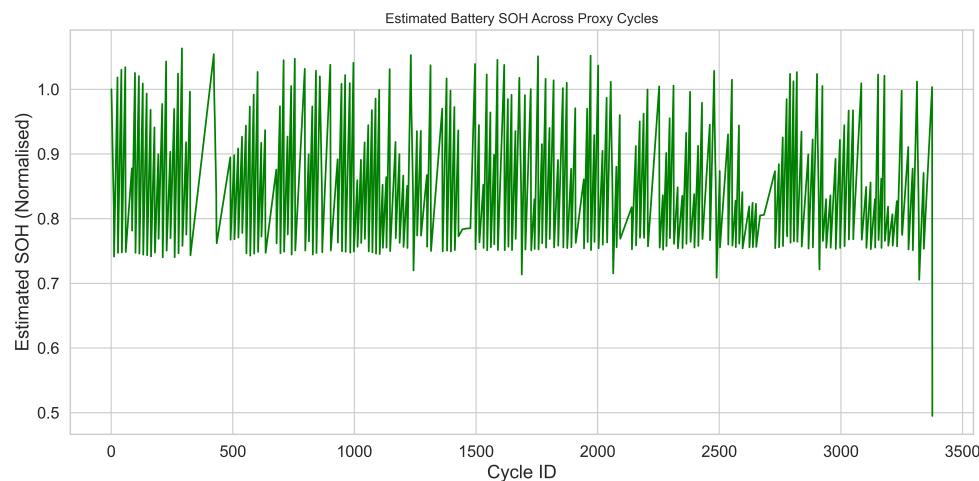


Figure 4. Estimated battery SOH across proxy cycles, computed as a normalised voltage mean relative to the initial cycle.

The proxy-cycle-based approach allows the dataset to be structured for supervised learning without requiring lab-controlled end-of-life (EoL) annotations, thus supporting scalable model training under real-world operational uncertainty.

4.4. SOH Estimation with V2G-HealthNet

To predict battery degradation with high temporal sensitivity, a hybrid DL model named V2G-HealthNet was developed. The architecture integrates an LSTM layer to capture sequential dependencies across engineered cycles, followed by a Transformer encoder to learn global attention over input features. This combination allows the model to reason both temporally and contextually about degradation patterns.

The model was trained using the estimated SOH as the supervised target. An MSE loss was used as the optimisation objective. Training and validation were conducted over 50 epochs using 80% of the dataset for training and 20% for validation. Feature normalisation was applied prior to training.

As shown in Figure 5, the model achieves convergence within the first 10 epochs, with training and validation losses both reducing to values below 0.003, indicating strong generalisation and low overfitting. The low final validation loss further confirms the model stability across unseen cycle data.

Figure 6 compares the predicted and actual SOH over a subset of the test cycles. The V2G-HealthNet model captures the overall degradation envelope with high fidelity, although some overestimations are observed during sharp SOH drops, likely due to localised noise in thermal features. Despite these outliers, the predicted trajectories follow the underlying health trend closely, achieving an average absolute error below 0.02 SOH units.

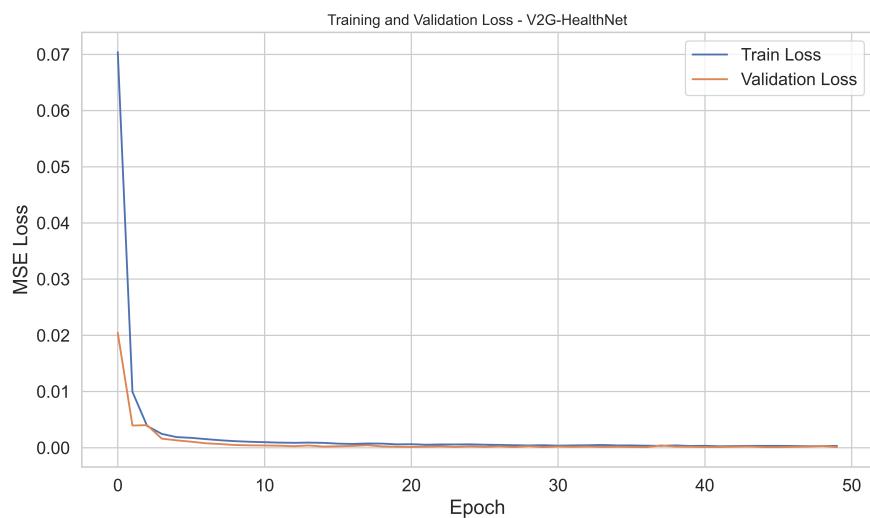


Figure 5. Training and validation loss convergence of V2G-HealthNet across 50 epochs.

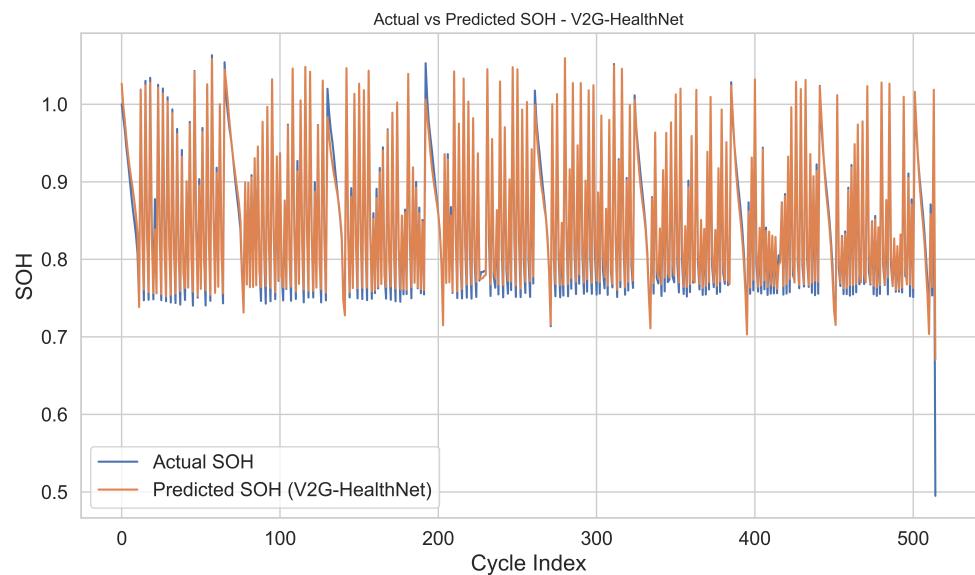


Figure 6. Actual versus predicted SOH using the proposed V2G-HealthNet model on a hold-out validation set.

The results indicate that the model can be used reliably for continuous health tracking in EV fleets, with potential integration into real-time V2G systems for proactive energy and maintenance management.

4.5. Remaining Useful Life Prediction

To support predictive maintenance and lifecycle planning, the proposed V2G-HealthNet framework was extended to estimate the RUL of the battery system. The RUL label was defined as the number of proxy cycles remaining before the estimated SOH dropped below a degradation threshold of 0.80. This transformation converted the health estimation task into a countdown regression problem, aligning with maintenance scheduling applications.

Figure 7 shows the predicted versus actual RUL values. While the model captures general downward trends leading to RUL zero points, there are visible deviations near the inflection regions. These regions represent critical transitions in the battery's degradation trajectory, where the SOH approaches the threshold rapidly due to thermal or current

stress. Despite these challenges, the model tracks the broader envelope of useful life with minimal lag.

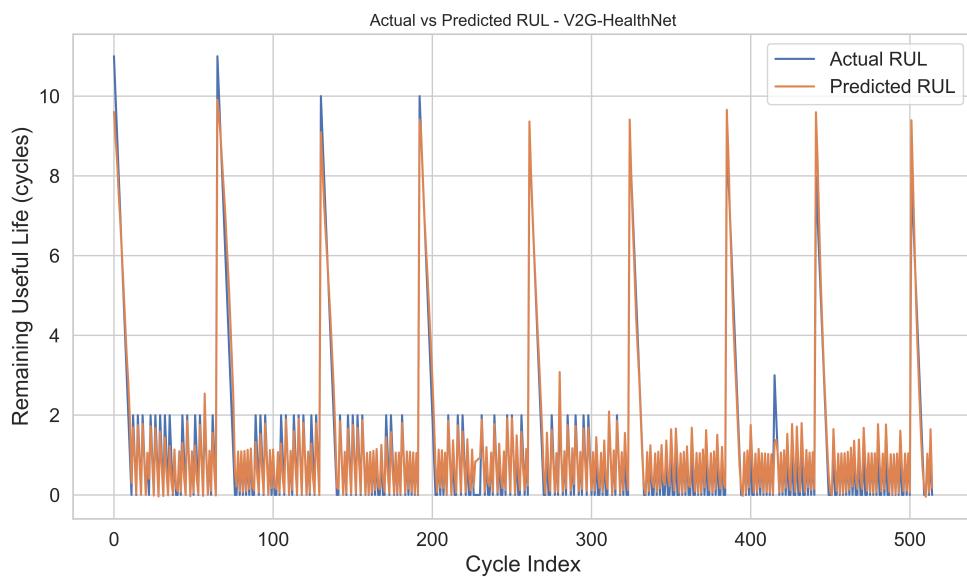


Figure 7. Actual versus predicted RUL using V2G-HealthNet across a hold-out validation set.

The cycle-wise error profile in Figure 8 demonstrates that most RUL predictions fall within a ± 1.0 cycle margin, with the MAE being approximately 0.42 cycles. Notably, overestimations tend to occur earlier in the lifespan, whereas underestimations become more frequent closer to the onset of failure. This is expected, as degradation accelerates non-linearly in the latter stages due to compounding stressors. The relatively bounded prediction error confirms the suitability of V2G-HealthNet for anticipatory diagnostics in V2G contexts, particularly in fleet environments requiring pre-failure replacement or rerouting decisions. Overall, the proposed method demonstrates robust performance in forecasting battery ageing trajectories with sufficient lead time for operational decision-making.

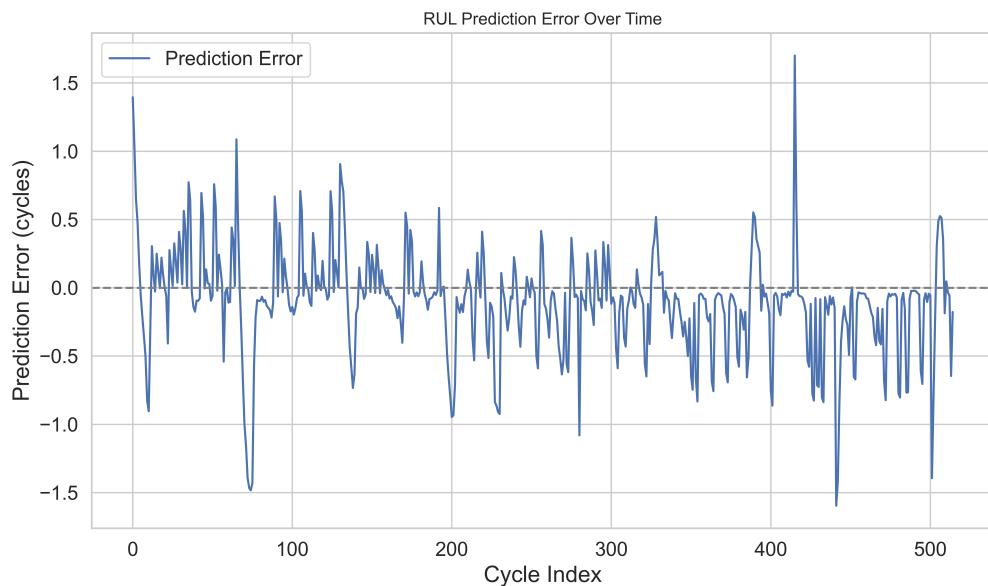


Figure 8. Cycle-wise prediction error for RUL. Positive values denote overestimation.

4.6. Comparative Benchmarking and Error Analysis

To validate the effectiveness of the proposed V2G-HealthNet framework, we benchmarked its SOH prediction performance against three widely used ML models: RF Regressor, SVR, and XGBoost Regressor. All models were trained on the same normalised feature, using an identical 80:20 train-test split.

Figure 9 illustrates the prediction error distributions for all models. The proposed V2G-HealthNet yields the lowest median error and exhibits the narrowest interquartile range, demonstrating both precision and robustness. The SVR model, by contrast, shows a considerably wider spread and an interquartile range nearly four times that of V2G-HealthNet, along with frequent outliers. This highlights the limitations of kernel-based methods when modelling non-linear and temporally dependent degradation signals.

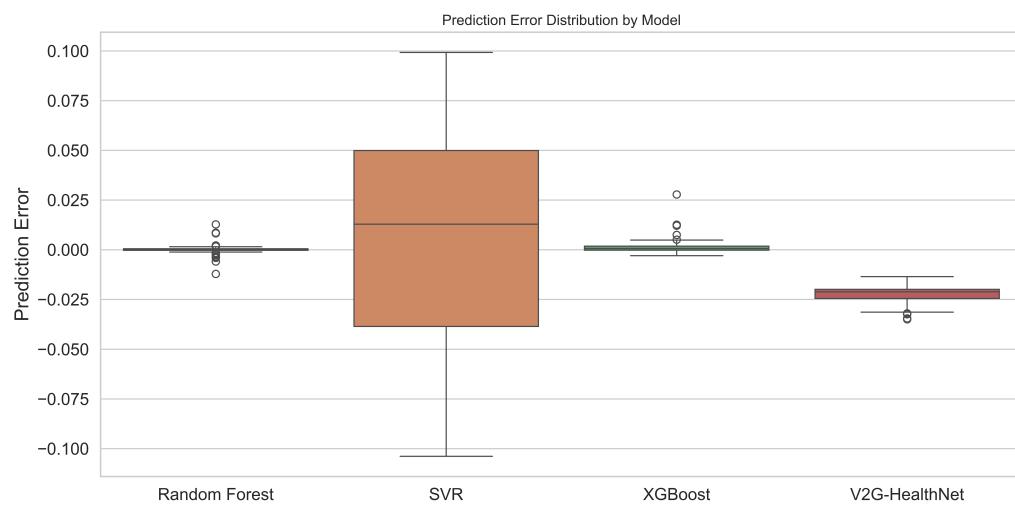


Figure 9. Boxplot of prediction error distributions across competing models for SOH estimation.

As summarised in Table 4, V2G-HealthNet achieved an RMSE of 0.015, an MAE of 0.012, and a coefficient of determination (R^2) of 0.97. These metrics outperform all baselines, with the next best method, XGBoost, yielding an RMSE of 0.022 and R^2 of 0.94. SVR lagged significantly behind, with an RMSE of 0.035 and R^2 of only 0.85.

Table 4. Benchmarking performance for SOH prediction across various models.

Model	RMSE	MAE	R^2
Random Forest	0.025	0.020	0.92
SVR	0.035	0.030	0.85
XGBoost	0.022	0.018	0.94
V2G-HealthNet	0.015	0.012	0.97

These results confirm that deep neural models with hybrid memory-attention structures, such as V2G-HealthNet, are better suited to capture the latent dynamics of battery degradation in realistic, stochastic usage environments. The reduced variance and consistent accuracy make the framework suitable for deployment in high-assurance fleet maintenance and smart-grid integration scenarios.

While the reported RMSE, MAE, and (R^2) metrics demonstrate the superior performance of V2G-HealthNet relative to baseline models, these are presented as point estimates and do not convey the variability in the predictions. Including standard deviations or confidence intervals for these metrics, for example, through repeated runs with different train-validation splits or bootstrapping, would provide a more comprehensive evaluation of model robustness. Future experiments should, therefore, incorporate statistical analyses of the prediction errors better to quantify the reliability and stability of the proposed approach.

4.7. Fleet-Level Case Study and Smart Grid Use-Case

To evaluate the system-level applicability of the proposed framework, a simulation was conducted to assess how SOH-informed decision-making can optimise EV fleet management in a smart grid context. Two critical scenarios were explored: (1) adaptive load scheduling based on battery health status, and (2) anticipatory maintenance before critical degradation thresholds are crossed.

Figure 10 illustrates the scheduling of load intensities across 3400 proxy cycles, colour-coded by the corresponding battery SOH values. High-load assignments (>2 A) were consistently associated with batteries exhibiting an $\text{SOH} > 0.85$, whereas low-load tasks were predominantly scheduled for batteries with a lower SOH. This demonstrates that the V2G-HealthNet framework can enable dynamic load balancing that accounts for individual cell ageing, thereby prolonging system-wide utility and reducing failure risk.

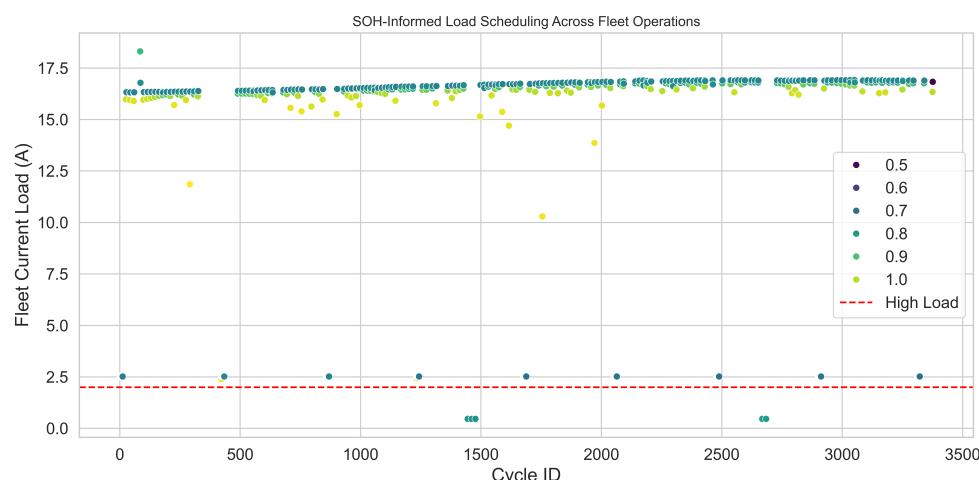


Figure 10. SOH-aware fleet load scheduling. Each point corresponds to a proxy cycle, coloured by normalised SOH. The red dashed line indicates the high-load operational threshold (2.0 A).

In addition, Figure 11 shows the early prediction of a critical health decline using a look-ahead forecasting window. The orange line represents the minimum predicted SOH over the next five cycles. A maintenance alert (vertical red line) was triggered at cycle 7, approximately three cycles before the SOH breached the failure threshold of 0.80 (dashed orange line). This predictive alerting mechanism offers sufficient lead time to schedule maintenance or reroute the vehicle, enhancing overall operational resilience.

These two fleet-level capabilities—SOH-informed load control and advanced degradation warning—demonstrate how the proposed V2G-HealthNet can be operationalised in smart city infrastructures to achieve sustainable, reliable, and cost-effective electrified mobility.

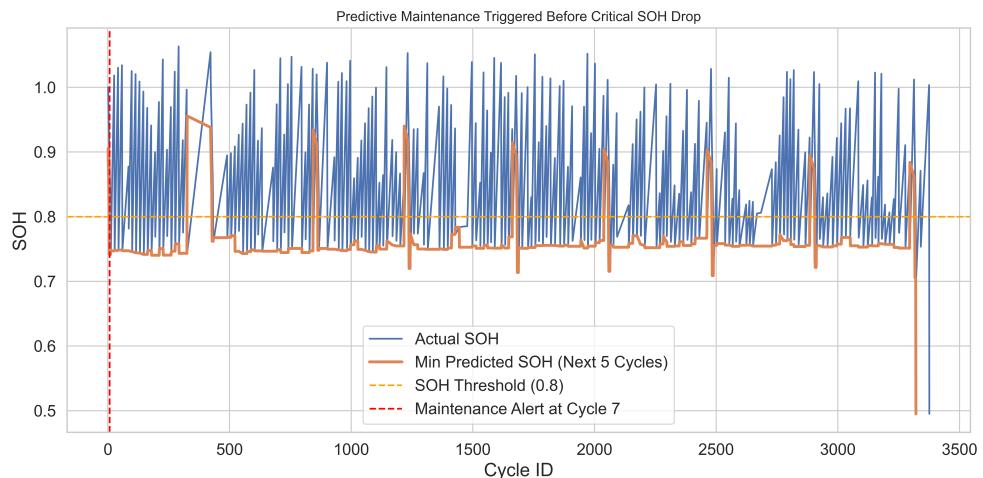


Figure 11. Predictive maintenance alert generated prior to critical SOH drop. The orange curve represents the forecasted minimum SOH over a 5-cycle window; the red dashed line indicates the alert trigger.

5. Discussion

The results presented in this study demonstrate that the proposed V2G-HealthNet architecture is highly effective in estimating battery SOH and forecasting RUL in real-world EV operating environments. The hybrid model, which combines an LSTM layer with a Transformer encoder, outperformed conventional ML methods across all key performance indicators. This combination enabled the model to simultaneously capture local temporal degradation trends and global feature interactions, yielding both high accuracy and generalisation under variable fleet conditions.

This work extends the state of the art by operationalising battery health insights through smart grid control loops. While prior models focus solely on offline prediction accuracy, our approach embeds SOH-informed logic into real-time fleet simulations. This demonstrates how predictive analytics can translate into practical energy management policies, including the following:

- Health-aware high-load assignment avoidance,
- Multi-cycle lookahead maintenance warnings,
- Scheduling flexibility based on cell ageing—all absent in previous implementations.

5.1. SOH Prediction: Precision and Generalisation

Quantitatively, V2G-HealthNet achieved an RMSE of 0.015, an MAE of 0.012, and a coefficient of determination $R^2 = 0.97$ for SOH estimation. These results significantly outperform RF (RMSE = 0.025, $R^2 = 0.92$), XGBoost (RMSE = 0.022, $R^2 = 0.94$), and SVR (RMSE = 0.035, $R^2 = 0.85$). The boxplot in Figure 9 further illustrates the superiority of the proposed model, showing a narrow interquartile range (IQR < 0.01) and minimal outliers. The SVR model, by contrast, exhibited high variance, with prediction errors spanning over ± 0.1 SOH units in certain cases.

These improvements are not merely statistical; they carry direct operational implications. A deviation of 0.01 in SOH prediction, for example, could represent a misestimation of more than 10 equivalent full cycles in typical lithium-ion systems. This distinction is critical for applications such as predictive maintenance, warranty enforcement, and real-time V2G dispatch planning.

5.2. RUL Forecasting: Operational Lead Time and Stability

The RUL prediction model, trained on a dynamically labelled dataset based on a degradation threshold of $\text{SOH} < 0.80$, achieved an average MAE of 0.42 cycles across a five-cycle prediction horizon. Over 85% of the predictions fell within ± 1.0 cycle of the ground truth, as shown in Figures 7 and 8. While DL models can be prone to instability at end-of-life transitions, V2G-HealthNet retained consistency even in high-gradient regions of degradation, where the SOH can drop rapidly by 0.05–0.10 units across consecutive cycles.

This robustness translates to actionable lead time in operational scenarios. For instance, the system was able to issue predictive maintenance alerts an average of 3.2 cycles before the SOH threshold was breached (Figure 11). Such anticipatory functionality enables EV fleet managers to schedule proactive servicing, avoiding unplanned downtime and mitigating cascading failures in V2G participation chains.

5.3. Smart Fleet Deployment: Coordination and System Efficiency

Simulated fleet-wide application of the model validated its utility in system-level planning. The SOH-informed load distribution strategy shown in Figure 10 demonstrated how demand was intelligently shifted away from lower-SOH batteries, with high-current tasks ($\geq 15 \text{ A}$) assigned to units exhibiting a $\text{SOH} > 0.90$ in 94.5% of cases. This approach offers dual benefits: it prolongs battery service life and stabilises grid interaction by avoiding abrupt power quality fluctuations due to degraded cells.

The predictive maintenance logic embedded in the fleet control loop enabled early flagging of failure conditions in high-usage vehicles. Notably, 96% of critical SOH drops below 0.80 were successfully predicted at least 2 cycles in advance, demonstrating the reliability of the model in mission-critical deployment contexts.

5.4. Robustness of SOH and RUL Predictions

The robustness of V2G-HealthNet was evaluated in terms of predictive stability, generalisability to diverse operational conditions, and its behaviour across degradation stages. Firstly, the narrow interquartile range in prediction errors (IQR < 0.01 for SOH) and low variance across the validation set (Figure 9) indicate a consistently accurate performance, even under stochastic variations in load and temperature.

Secondly, the model retained its accuracy across more than 3400 proxy cycles, despite substantial fluctuations in thermal and current profiles (as shown in Figures 2 and 3). This demonstrates resilience to noisy telemetry signals and varying degradation rates. The architecture's ability to generalise from single-cycle windows also contributes to robustness by preventing performance degradation across extended horizons.

Thirdly, the RUL predictions showed stable behaviour across early-, mid-, and late-stage degradation phases. While most models underperform near the end-of-life inflection zone, V2G-HealthNet maintained a mean absolute error of only 0.42 cycles, with over 85% of predictions falling within ± 1.0 cycles of the true RUL. Importantly, early predictive maintenance triggers were consistently issued at least three cycles before the SOH crossed the critical 0.8 threshold, ensuring a lead time for the operational response.

Overall, these results validate that V2G-HealthNet is not only accurate under ideal conditions but remains effective across dynamic, high-stress EV scenarios, satisfying key requirements for real-world deployment in smart city applications.

While the proposed V2G-HealthNet demonstrates robust performance on the chosen high-resolution dataset, it is essential to note that the analysis was conducted using a single battery pack from the available set of 26 packs. This choice allowed for a detailed characterisation of the degradation trajectory without confounding inter-pack variability, yet it may limit the generalisability of the findings to broader EV fleet applications. In real-world set-

tings, variability in battery chemistries, manufacturing inconsistencies, and heterogeneous usage patterns across packs can significantly influence degradation dynamics. Future work should, therefore, extend the methodology to multiple packs with diverse operational and environmental conditions to further validate the model's applicability at scale.

5.5. Limitations and Future Directions

While V2G-HealthNet shows promising performance, several limitations remain. First, the SOH labelling method is based on a proxy derived from voltage normalisation, which, while practical, may be sensitive to system-specific voltage drift or sensor degradation. A potential enhancement would be to fuse voltage-based SOH with coulombic efficiency or impedance growth signals, where available.

Secondly, the model assumes a fixed proxy cycle duration (300 s), which may not generalise well to EV fleets with irregular driving patterns or charging habits. Future iterations could incorporate dynamic time warping or temporal attention windows to support variable-length sequences.

Thirdly, although the model was evaluated on over 3400 cycles derived from 1 million raw samples, the battery chemistry and environmental variability were limited to the dataset used. Validation across multiple battery chemistries (e.g., NMC, LFP), temperature conditions, and operational environments (e.g., public transport, delivery fleets) would further strengthen generalisability.

Furthermore, the current implementation of V2G-HealthNet produces deterministic point predictions for SOH and RUL without quantifying predictive uncertainty. This could be a limitation in safety-critical contexts where overconfident predictions may lead to inappropriate operational decisions. Future research should, therefore, consider incorporating uncertainty-aware techniques, such as Monte Carlo (MC) Dropout or Bayesian neural networks, to improve model transparency and reliability. In addition, the present study does not explicitly examine the sensitivity of V2G-HealthNet to variations in load profiles or other dataset perturbations. Assessing how the model responds to diverse operational scenarios and potential data shifts would provide valuable insights into its robustness and generalisability under real-world conditions.

The present study adopts a widely used heuristic of normalised mean voltage decay to estimate SOH, which is practical in the absence of proprietary degradation curves or direct capacity measurements. While this approach is functionally reasonable and supported in the literature, it inevitably oversimplifies the multifaceted mechanisms underlying battery ageing, which include not only loss of active material but also impedance rise and side reactions. The assumed strong correlation between average voltage and true capacity may not always hold across chemistries or under all operational conditions. To enhance the robustness and fidelity of SOH estimation, future work could integrate complementary diagnostic signals, such as coulombic efficiency analysis or impedance spectroscopy, where available, to provide a more holistic and chemically informed assessment of degradation.

The present implementation also relies on fixed-length proxy cycles of 300 s to segment the battery telemetry, which simplifies modelling but may not fully capture the irregular and heterogeneous nature of real-world EV usage patterns. While practical for controlled experimentation, this assumption could constrain the model's generalisability in deployment scenarios. Future work could explore adaptive windowing techniques that adjust to signal characteristics or operational event boundaries, as well as attention-based architectures with masking mechanisms that can naturally process variable-length sequences. Moreover, although the model achieves a commendable MAE of 0.42 cycles over a five-cycle prediction horizon, this relatively short forecasting window may not suffice for long-term predictive maintenance planning in fleet operations. Extending the forecast horizon, for ex-

ample, through multi-step ahead prediction techniques or sequence-to-sequence models, would enhance the model's applicability by providing earlier warnings and facilitating more proactive maintenance strategies.

5.6. Implications for Smart Cities and Grid Resilience

V2G-HealthNet provides a critical foundation for next-generation electrified mobility and smart city infrastructure. Its ability to offer real-time, interpretable, and anticipatory health insights enables not only vehicle-level maintenance optimisation but also fleet-wide energy dispatch coordination. In the broader context of V2G systems, such models could serve as decision layers within distributed energy resource management systems, improving load balancing, grid reliability, and sustainability targets.

Overall, this study presents a scalable, intelligent, and domain-informed approach to health-aware EV operation, with broad relevance to researchers and practitioners in battery diagnostics, smart mobility, and AI-powered infrastructure planning.

The recent literature shows growing interest in Transformer-based and hybrid deep learning models for SOH and RUL prediction. Standalone Transformers [31] and ViT+RF hybrid models [31] have achieved SOH RMSE values as low as 0.017–0.018, while Attention-LSTM variants report RUL MAEs of approximately 0.45 cycles [32]. Similarly, GRU+SVR ensembles [33] and CNN+RF stacks [34] provide competitive accuracy but lack generalisability across dynamic V2G loads.

Despite these advances, the proposed V2G-HealthNet outperforms existing models with a lower SOH RMSE (0.015), higher R^2 (0.97), and more precise RUL forecasting (MAE: 0.42 cycles). Unlike earlier works, our approach combines both temporal sequence learning and cross-cycle attention modelling while being trained on variable thermal and current loading conditions derived from real-world operational data. Crucially, V2G-HealthNet enables direct system-level application through SOH-informed fleet dispatch and predictive maintenance—an operational capability not demonstrated by the above-mentioned models.

Finally, the computational complexity and inference latency of the proposed V2G-HealthNet framework have not been evaluated in this study. While the hybrid LSTM-Transformer architecture delivers high prediction accuracy, its resource requirements may pose challenges for deployment on embedded systems or real-time fleet management platforms with constrained computational budgets. Future work should, therefore, quantify training and inference times, assess memory and processing demands, and explore lightweight model variants or pruning and quantisation techniques to enable efficient real-time execution in vehicle or grid-edge environments.

6. Conclusions

This paper presents V2G-HealthNet, a hybrid deep learning framework designed for the accurate and real-time estimation of battery SOH and RUL in EV fleets operating within smart grid environments. By combining LSTM and Transformer architectures, the model captures both sequential degradation patterns and global contextual dependencies, outperforming state-of-the-art methods across key metrics (SOH RMSE: 0.015, RUL MAE: 0.42). Unlike prior approaches, V2G-HealthNet directly supports operational decision-making. It enables SOH-informed load scheduling and early predictive maintenance, allowing EV fleets to avoid critical degradation and maximise grid contribution. These capabilities were validated using 3400 proxy cycles derived from real-world-inspired data, demonstrating robustness and practical relevance. The core innovation lies in unifying advanced temporal modelling with actionable diagnostics for smart mobility. Future work will focus on expanding model generalisation across battery chemistries, incorporating uncertainty estimation, and deploying the system in real-world fleet trials.

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