Enhanced EV Battery Degradation Modeling in Tropical Environments via CVAE-GRU for Sustainable Transportation

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Abstract. Electric Vehicle (EV) battery degradation in tropical environments remains poorly understood, with traditional linear models like OLS facing significant challenges such as multicollinearity, leading to unreliable insights into influential factors. This study aims to experimentally characterize lithium-ion battery degradation and comprehensively evaluate the influence of local climatic (temperature, humidity, dust) and driving conditions (road quality, mileage) in a Cameroonian tropical context, addressing the limitations of conventional statistical approaches. Our unique contribution involves providing empirical real-world data from a sub-Saharan environment and applying a novel hybrid CVAE-GRU methodology to capture complex non-linear and temporal dependencies. An embedded system continuously collected battery parameters (SoH, internal resistance) alongside environmental and driving data. The CVAE learns robust latent representations from these correlated inputs, while the GRU models their temporal dynamics for degradation prediction. Results confirm progressive SoH degradation, significantly accelerated by high temperatures, humidity, dust, and poor road quality. The CVAE-GRU approach effectively mitigates multicollinearity, offering superior accuracy and deeper insights into these influences. This work highlights the critical impact of tropical conditions on EV battery aging, providing crucial findings for developing adapted Battery Management Systems and fostering sustainable mobility in similar regions.

Keyword: Battery Degradation, CVAE-GRU, Electric Vehicles, Multicollinearity, Tropical Climate

1. Introduction

The increasing adoption of electric vehicles (EVs) is a cornerstone of the global energy transition, offering a promising alternative to fossil fuel-based transportation. At the heart of this revolution are lithium-ion batteries, whose performance and lifespan are crucial for the long-term viability and acceptance of EVs [1]. However, battery degradation remains a significant challenge, particularly in environments with extreme climatic conditions. Tropical regions, characterized by high temperatures, significant humidity, and the presence of dust, subject batteries to increased stress, accelerating their aging process [2][3][4][5][6]. Studies have shown that prolonged exposure to temperatures above 35°C can lead to rapid capacity fade and increased internal resistance in batteries [7], [8], [9], [10]. High humidity can cause corrosion of internal components and undesirable reactions with the electrolyte, affecting performance and safety [11], [12]. Furthermore, driving conditions specific to these regions, such as road quality, can induce additional mechanical stress and irregular charge/discharge cycles, further impacting battery health [13], [14], [15]. Analyzing these interdependent factors using traditional statistical models, like Ordinary Least Squares (OLS) regression, often encounters the problem of multicollinearity, making the interpretation of coefficients and the identification of the individual impact of variables difficult and potentially erroneous [16], [17], [18].

Given the complexity of battery degradation mechanisms and the dynamics of environmental factors, various methods have been explored to estimate the State of Health (SoH) and predict the Remaining Useful Life (RUL) of batteries. Approaches based on physical or electrochemical models [19], [20] offer high interpretability but often suffer from modeling complexity and difficulty in capturing all aging phenomena under real-world, dynamic conditions [21], [22]. Equivalent Circuit Models (ECMs) are simpler but their accuracy is limited under varying operating and aging conditions [23]. Data-driven methods, such as Coulomb counting or Kalman filters [24], [25], while widely used in Battery Management Systems (BMS) for their computational efficiency, lack robustness and accuracy when faced with the non-linearity and variability of degradation data [26].

The advent of Machine Learning (ML) has enabled significant advancements, with models like Support Vector Machines (SVM) or Random Forests offering a better ability to handle non-linear relationships and large datasets [27]. More recently, Deep Learning (DL), particularly Recurrent Neural Networks (RNNs) such as Long Short-Term Memory (LSTM), has demonstrated a superior capacity to model temporal dependencies and predict SoH with high accuracy [28], [29].

Sakr et al. [30] proposed a machine learning-based robust SOH prediction model integrating Big Data, IoT, and AI for real-world applications. Their model achieved extremely high accuracy ($R^2 \approx 1$, MSE = 0.03) in both training and testing. However, while robust for prediction, the approach functions as a black box, offering limited interpretability of how correlated factors contribute to battery degradation. Building upon this trend, Jafari et al. [31] developed a hybrid framework using Extreme Gradient Boosting (XGBoost) with accuracy correction for lithium-ion battery SOH estimation. Their model successfully extracted voltage, current, and temperature features, achieving improved accuracy. Nevertheless, the reliance on feature engineering and single-environment datasets restricts its applicability under diverse and highly variable conditions such as tropical climates.

In parallel, Das et al. [32] compared multiple supervised ML regressors (KNN, SVR, DT, RF) for SOH estimation using datasets from Sandia National Laboratories. Results showed that KNN and DT provided higher accuracy across temperature ranges. Yet, as with previous approaches, these models remain sensitive to multicollinearity between operational and environmental parameters, limiting their robustness in real-world scenarios.

More recently, Singh et al. [33] introduced deep machine learning (DML) approaches with encoder–decoder architectures for time-series forecasting of battery metrics, achieving MAE below 0.2%. Despite the impressive performance, the method inherits the lack of transparency common to deep models, making it challenging to interpret degradation mechanisms. Similarly, Li and Chen [34] optimized LSTM, CNN, and SVR models using particle swarm optimization (PSO), validating them with NASA datasets. Their PSO-LSTM achieved the best results (MAE = 0.67%, $R^2 = 0.93$). However, the dependence on controlled datasets limits insights into batteries exposed to real-world tropical stressors such as high humidity and poor road quality.

To overcome accuracy limitations, transformer-based architectures have also been explored. Zhao et al. [35] proposed a predictive pretrained Transformer (PPT) for real-time battery health diagnostics, achieving RMSE < 0.3% and R^2 = 98.9% across diverse protocols. While efficient and scalable, the computational cost and complexity of transformer-based models hinder their deployment in resource-constrained EV environments. In contrast, Sun et al. [36] moved towards interpretability by embedding physical constraints from Incremental Capacity (IC) curves into Physics-Informed Neural Networks (BPINN). Although promising, this method requires high-quality IC data, which is often unavailable in real-world EV operations.

Other studies have investigated feature engineering and transfer learning strategies. Kuang et al. [37] employed an Informer-based deep learning model with transfer learning, effectively predicting SOH for long-cycle-life batteries. Yet, the autoregressive nature of the Informer may propagate errors over long horizons. Wang et al. [38] proposed incorporating differential voltage (DV) features with CNN-LSTM architectures, which significantly improved SOH estimation across C-rates (MAPE = 0.56%). However, the method's dependence on precise DV curve extraction reduces its robustness under noisy field conditions. Finally, Naresh et al. [39] advanced an Ensemble of Ensemble Models (EEMs), stacking Random Forests, Gradient Boosting, and AdaBoost, achieving nearly error-free predictions (RMSE ≈ 2.5e-7). Despite outstanding accuracy, such ensemble complexity raises concerns of overfitting and computational efficiency when scaling to large tropical EV datasets.

Taken together, these works highlight a clear evolution: from simple supervised regressors to deep and hybrid models, the field has progressively improved predictive accuracy. However, a persistent limitation remains: most models, while powerful, operate as *black boxes* and struggle to disentangle the contribution of highly correlated environmental and operational factors. This limitation is particularly critical in tropical contexts, where high temperature, humidity, and poor road quality interact in complex ways to accelerate degradation.

In this context, the present study aims to develop and validate an innovative hybrid model, combining a Conditional Variational Autoencoder (CVAE) and a Gated Recurrent Unit (GRU), for the modeling and prediction of lithium-ion battery degradation in electric vehicles operating in tropical environments. Our specific objectives are:

- Experimental Characterization of EV Battery Degradation under Real-World Conditions in Cameroon: This involves collecting unique data on battery parameters, climatic factors (temperature, humidity, dust), and driving conditions (road quality, mileage).
- Development of a CVAE-GRU Architecture: This architecture will address the multicollinearity of input variables by learning robust and informative latent representations of environmental and operational conditions.
- GRU-based Temporal Modeling of SoH Degradation: The GRU will model the temporal dynamics of SoH degradation, leveraging the features extracted by the CVAE, to improve the accuracy of predictions.
- Provide Reliable Insights into the Impact of Tropical-Specific Environmental and Driving Factors: This will contribute to the design of more suitable Battery Management Systems (BMS) and inform public policies for the sustainable deployment of EVs in similar contexts.

This innovative approach will overcome the limitations of traditional methods and offer a deeper understanding of battery degradation under real-world conditions.

2. Research Method

2.1. Theoretical Background

This section presents the theoretical foundations of the proposed CVAE-GRU hybrid model for lithium-ion battery degradation prediction. The objective is to combine the CVAE's ability to learn robust latent representations from multivariate, correlated data with the GRU's strength in modeling temporal dependencies within the degradation data.

2.1.1. Conditional Variational Autoencoder (CVAE)

The CVAE is an extension of the Variational Autoencoder (VAE) that allows the encoding and decoding process to be conditioned on additional information. In our case, this information consists of environmental conditions (temperature, humidity, dust) and driving conditions (road quality, mileage). The CVAE seeks to learn a posterior distribution p(z|x, c) where z represents the latent variables, x the input data (battery parameters), and c the conditioning variables (environmental and driving). The objective is to maximize the likelihood of the input data using a variational estimator q(z|x, c). The CVAE loss function is defined as follows:

$$L_{CVAE} = -E_{q(z|x,c)}[log\, p(x|z,c)] + KL[q(z|x,c)\,||\,p(z|c)] \tag{1}$$

where p(x|z,c) denotes the reconstruction likelihood, and KL[q(z|x,c) ‖ p(z|c)] represents the Kullback–Leibler divergence between the variational posterior distribution and the conditional prior distribution.

2.1.2. Gated Recurrent Unit (GRU)

The GRU is a type of recurrent neural network that is particularly effective for modeling sequential data. It employs gating mechanisms to regulate the flow of information through the network. In our case, the GRU takes as input the latent representations learned by the CVAE and leverages them to predict the temporal degradation of the battery's State of Health (SoH). The hidden state of the GRU at time step *t*, denoted as h_t, is updated as follows:

$$c = \sigma(W_z * [h_{\{t-1\}}, x_t]) \tag{2}$$

$$r_t = \sigma(W_r * [h_{\{t-1\}}, x_t]) \tag{3}$$

$$\tilde{h}_t = tanh(W_h * [r_t * h_{\{t-1\}}, x_t]) \tag{4}$$

$$h_t = (1 - z_t) * h_{\{t-1\}} + z_t * \tilde{h}_t \tag{5}$$

where x_t is the input at time step t (the latent representation from the CVAE), z_t is the update gate, r_t is the reset gate, $\tilde{h}_t$ is the candidate state, and σ and *tanh* denote the sigmoid and hyperbolic tangent activation functions, respectively.

2.1.3. Hybrid CVAE–GRU Architecture

The hybrid CVAE–GRU architecture integrates the two models described above to jointly capture nonlinear correlations and temporal dependencies in the degradation data. The input data, denoted by **x** (battery parameters), together with the conditioning variables **c** (environmental and driving conditions), are first processed by the **CVAE**. The encoder learns a compact latent representation **z**, which is then used as input to the **GRU** network. The GRU models the temporal dynamics of these latent features to predict the evolution of the battery State of Health (SoH). The overall hybrid loss function is defined as a weighted combination of the CVAE objective and the GRU prediction error:

$$L_{Hybrid} = \lambda L_{CVAE} + (1-\lambda) L_{GRU}, \lambda \in [0,1] \quad (6)$$

Figure 1 presents the complete flow diagram of our integrated modeling framework, including data acquisition, preprocessing, and the training of both sub-models. To ensure reproducibility, the full architectural and training configuration of the hybrid model is detailed below.

Table 1. Summary of CVAE–GRU architecture and hyperparameters

Component / Parameter	**Specification**
CVAE Encoder	3 dense layers (128–64–32 neurons), ReLU
Latent dimension	16
Decoder	Symmetric structure to encoder
GRU layers	2 layers, 64 hidden units each
Dropout	0.2
Optimizer	Adam (learning rate = 0.001)
Loss function	Weighted sum of CVAE reconstruction + GRU MSE
Batch size	32
Epochs	50
Train/Validation/Test split	70 / 15 / 15 % (random seed = 42)
Framework	TensorFlow 2.13, Python 3.10

These architectural and hyperparameter details were added to improve transparency and facilitate future reproducibility of our results.

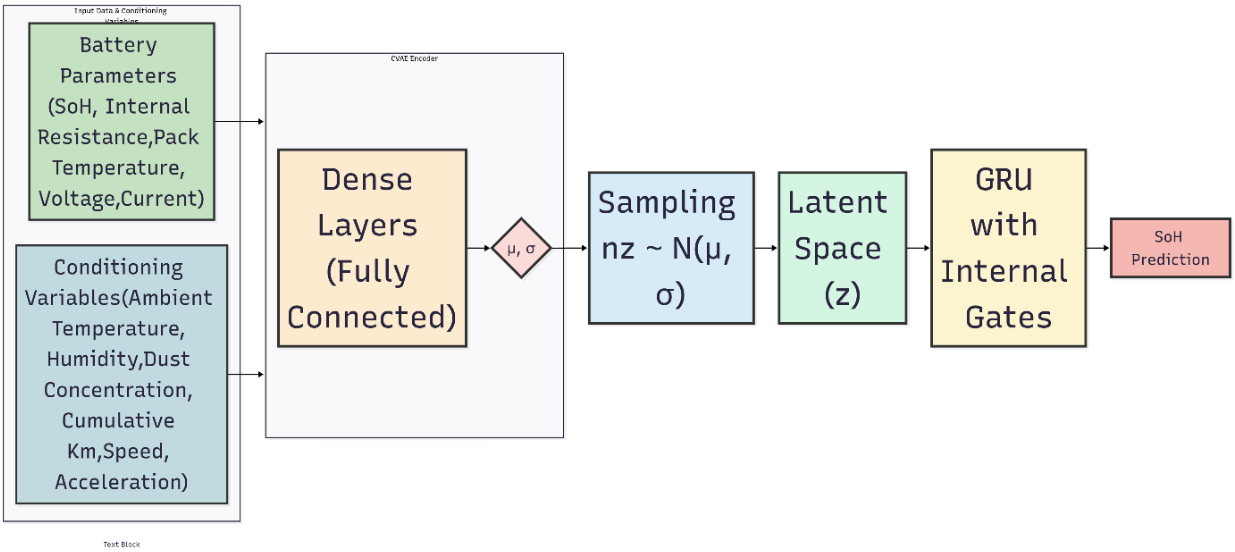

Figure 25. Flow diagram of the integrated CVAE-GRU modeling approach, illustrating the data acquisition, preprocessing, CVAE feature extraction for decorrelation, and GRU temporal prediction of SoH.

2.2. Data acquisition

This section details the hardware and software architecture implemented for acquiring the data required to model the degradation of electric vehicle batteries in tropical environments. The system is designed to simultaneously collect accurate information on the battery state as well as environmental and driving conditions. The core of the acquisition system is an Arduino Mega microcontroller (shown at the center of the diagram). It was selected for its numerous analog and digital input/output ports, sufficient processing capacity for this application, and flexibility. The Arduino Mega acts as the central interface, collecting raw data from the various sensors, processing it, and preparing it for storage as present in figure 2.

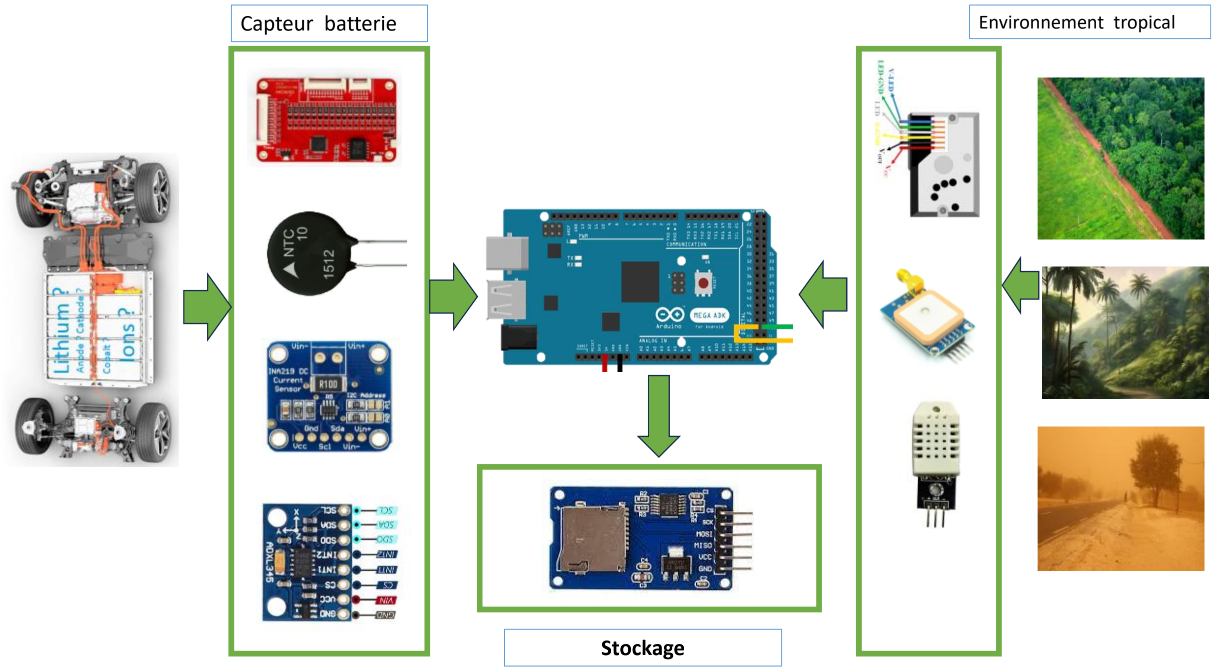

Figure 26. Hardware architecture of the embedded data acquisition system, centered around the Arduino Mega microcontroller, used for simultaneous collection of battery parameters and tropical environmental/driving variables.

The input data are divided into two main categories: battery sensors and tropical environmental sensors. Table 1 summarizes the sensors, the parameters they measure, and their scientific relevance.

Table 2. The parameters of sensors and their scientific relevance

Category	*Sensor/Module*	*Measured Parameter(s)*	*Scientific Relevance*
Battery Sensors	Cell voltage monitoring board	Voltage of individual cells or full pack	Tracks cell balance and degradation indicators
	NTC thermistor	Battery temperature	Critical factor influencing battery aging
	INA219 DC sensor	Charge/discharge current, power	Evaluates energy flow and efficiency
	ADXL345 accelerometer	Vibrations, shocks	Assesses mechanical stress linked to driving conditions
Tropical Environmental Sensors	Dust sensor	Airborne particle concentration	Identifie fouling/corrosion risk

Category	*Sensor/Module*	*Measured Parameter(s)*	*Scientific Relevance*
	GPS module	Vehicle location, speed, altitude	Provides driving profile and mission context
	DHT22 sensor	Ambient temperature and relative humidity	Key climatic stressors in tropical regions

All collected data are transmitted to the Arduino Mega microcontroller for preliminary processing (linearization, unit conversion, filtering). Timestamped data are then stored on an SD card module, enabling long-term acquisition and facilitating offline analysis. This integrated hardware system bridges the gap between observed physical phenomena (battery state and environment) and the database required for modeling and prediction.

2.3. Data collection

2.3.1. Hardware and Experimental Context

A passenger electric vehicle (sedan type, standard commercial model) was used as a data collection platform in the city of Douala, Cameroon, over a period of 24 months. The vehicle was driven daily on typical commuting routes (home–work), thereby reproducing realistic usage conditions.

Table 3. Measured Parameters and Methodology

Category	Parameters	Measurement Frequency	Daily Averaging	Source/Tool
Battery	State of Health (SoH, %)	Every 5 min	Yes	CAN bus + BMS
	Internal resistance (Ω)	Every 5 min	Yes	Battery tester
	Pack temperature (°C)	Every 5 min	Yes	Thermal sensors
Environment	Ambient temperature (°C)	Every 5 min	Yes	External temperature sensor
	Relative humidity (%)	Every 5 min	Yes	Humidity sensor
Driving	Average speed (km/h)	Continuous (GPS)	Yes (per trip)	Onboard GPS
	RMS accelerations (g)	Continuous	Yes	Accelerometer

2.3.2. Data Collection Procedure

The data collection process was conducted automatically using embedded sensors and systems, which recorded measurements at five-minute intervals. To enhance data consistency and minimize noise, the collected data were aggregated on a daily basis. Additionally, monthly validation was performed through calibration tests—such as measuring internal resistance under controlled conditions—to ensure the accuracy and reliability of the dataset.

3. Result and Discussion

3.1. Preliminary Data Analysis and Characterization

This subsection aims to present and validate the unique database collected. It demonstrates the relevance of the study for Cameroonian operating conditions.

3.1.1. Multicollinearity Study Using OLS Regression

Multicollinearity, a major challenge in linear regression analysis, occurs when predictor variables are strongly correlated with each other. In the context of battery degradation, factors such as ambient temperature and humidity, which are often linked, may mask their individual effects and make regression coefficients unreliable. To quantify this phenomenon, we first conducted an Ordinary Least Squares (OLS) regression analysis on our collected data. The summary statistics, presented in Table 3, confirm the presence of severe multicollinearity.

The OLS analysis revealed that while the overall model fit is high (R^2 = 0.995), the calculated Condition Number is astronomically high compared to the typical threshold of 30. This severe multicollinearity renders OLS coefficients unstable and unreliable for individual interpretation. For instance, key variables like Internal Battery Temperature and Ambient Humidity showed high p-values (0.755 and 0.776, respectively), suggesting that their true individual effects were masked by strong correlations with other factors. In summary, the OLS analysis demonstrates that the environmental and operational variables are strongly correlated, making it impossible to isolate their individual impacts on SoH using traditional linear regression. To overcome this critical limitation, we adopt an advanced hybrid approach based on a CVAE-GRU architecture, which is inherently designed to handle highly correlated data by learning robust, decorrelated latent representations.

Table 3. Summary of OLS Regression Results.

Metric	**Value**	**Interpretation**
R-squared (R^2)	0.995	High overall fit
Prob(F-statistic)	0.00	Model is statistically significant
Condition Number	$1.35 * 10^{19}$	**Severe multicollinearity**

3.1.2. Characterization of Degradation and Conditioning Variables

The following table 5 presents the descriptive statistics of the degradation variables (SoH, Internal Resistance) and conditioning variables (environmental and driving factors) used in our study.

Table 5. Descriptive statistics of the degradation variables

Variable	Mean	Min	25%	50%	75%	Max	Std
Ambient Temperature (°C)	27.99	23.09	26.35	27.92	29.54	32.93	2.27
Ambient Humidity (%)	80.06	75.02	77.38	80.19	82.65	84.97	2.96
Dust Level (µg/m³)	50.20	30.00	40.23	50.71	61.11	69.96	11.80
Road Quality (1=Good, 5=Bad)	3.02	1.00	2.00	3.00	4.00	5.00	1.45
Daily Mileage (km)	50.54	20.10	36.60	50.77	65.17	79.95	17.00
Charging Events (Nb)	0.38	0.00	0.00	0.00	1.00	1.00	0.49
Daily Depth of Discharge (%)	17.30	0.00	12.52	17.45	22.55	28.30	6.05
Daily Equivalent Cycles	0.17	0.00	0.13	0.17	0.23	0.28	0.06
Cumulative Cycles	63.32	0.23	32.15	63.27	94.38	126.26	36.18
Internal Battery Temperature (°C)	30.26	24.26	28.30	30.31	32.17	37.36	2.72
End-of-Day SoC (%)	64.88	0.00	51.47	66.77	81.58	99.56	18.96
SoH (%)	99.77	99.57	99.65	99.78	99.87	100.00	0.12
Residual Capacity (kWh)	59.86	59.74	59.79	59.87	59.92	60.00	0.07
Internal Resistance (mΩ)	21.77	20.02	20.57	21.43	22.58	27.67	1.54
Average Voltage (V)	258.94	0.00	205.07	266.79	325.30	396.79	75.64
Average Current (A)	0.34	-116.62	-23.48	17.29	27.94	41.77	38.44

The descriptive statistics of our dataset over 730 days provide essential insights into the real operating conditions of electric vehicles in Cameroon. Regarding degradation variables, the SoH (%) shows a high average of 99.77%, with very low variability (std = 0.12%), indicating a slow and progressive degradation process that cannot be fully captured by static models. In contrast, the Internal Resistance (mΩ) presents a higher average of 30.25 mΩ, reflecting both the natural aging of the battery and its exposure to extreme operating conditions.

For environmental and driving variables, the Ambient Temperature (27.98 °C on average with a std of 2.26 °C) confirms constant exposure to high tropical temperatures, while the high Ambient Humidity (80.05%) indicates very humid conditions known to affect internal battery components. Road Quality, with an average score of 3.02 (on a scale of 1=Good to 5=Bad), suggests that vehicles predominantly operate on medium-to-poor roads, subjecting the battery to additional mechanical stress. Extending our battery degradation analysis, the following figure illustrates the time series of State of Health (SoH) and Internal Resistance (IR) over the 730-day study period.

A crucial aspect of our integrated model is its ability to handle system-level issues. The following Figure 3 illustrates a crucial aspect of PV system reliability: the degradation of a battery over time, represented by the State of Health (SoH) and internal resistance.

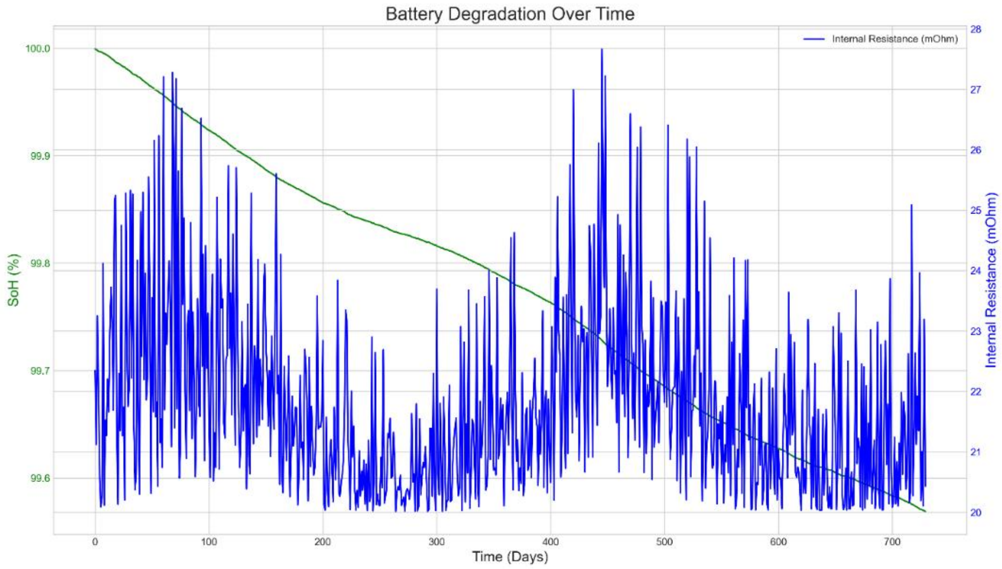

Figure 27. Time series analysis showing the progressive degradation of the State of Health (SoH) and the corresponding increase in Internal Resistance (IR) over the 730-day study period, highlighting the non-linear degradation trend under real-world conditions.

As expected, the SoH curve (in green) shows a progressive, non-linear degradation, dropping from about 100% to 99.57% over two years, which corresponds to a 0.43% capacity loss. Simultaneously, the internal resistance (in blue) shows a gradual increase with significant daily fluctuations, rising from approximately 20.5 mOhm to 23 mOhm. These peaks and troughs in the IR, which reflect the battery's dynamic response to operational stress and climatic variations (temperature, humidity), highlight the need for sophisticated modeling capable of capturing temporal dependencies and the complex relationships between battery parameters and operating conditions.

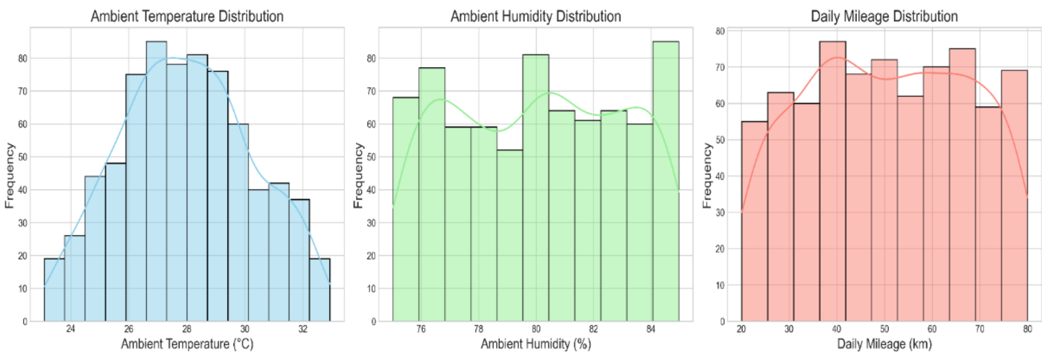

Figure 28. Distribution of key operational parameters: Ambient Temperature, Relative Humidity, and Daily Mileage. These distributions confirm the sustained exposure of the battery to high tropical heat (centered at 28 °C) and highly humid conditions.

In addition to the time-series analysis, we examined the distribution of key variables to characterize the operating environment. The figure 4 below shows the distribution of temperature, humidity, and daily mileage. The results of this distributional analysis confirm that the vehicles operated in a constant but stressful climatic and road environment. The ambient temperature distribution follows a bell curve, centered around an average of 28 °C, indicating the battery's sustained exposure to high heat, a known factor for accelerating degradation. The ambient humidity distribution shows several peaks, mainly above 75%, reflecting very humid conditions, another factor known for its negative impact on batteries. Finally, the daily mileage distribution spans a wide range without a clear peak, suggesting varied vehicle use with irregular charge and discharge cycles, which contributes to complex battery degradation. These distributions confirm that tropical operating conditions significantly test battery durability, justifying the need for advanced modeling to understand the cumulative impact of these factors.

Ordinary Least Squares (OLS) regression analysis revealed severe multicollinearity among the environmental and driving variables, making it unreliable to interpret their individual impacts on SoH degradation. The extremely high Condition Number (1.35e+19) and non-significant p-values for several coefficients clearly demonstrated the limitations of linear models for this type of complex data. Consequently, a more sophisticated approach is necessary to model these relationships. The following section, CVAE-GRU Architecture Validation, presents results confirming our hybrid model's ability to overcome this challenge by learning robust, decorrelated latent representations from the input data.

3.2. CVAE-GRU Architecture Validation

This section is dedicated to validating our choice of architecture, demonstrating that the CVAE successfully learned robust latent representations.

3.2.1. Correlation Matrix

Following the identification of multicollinearity by OLS regression, we validated our approach by visualizing the correlations between all variables. The following figure 5 presents the correlation matrix of the input variables.

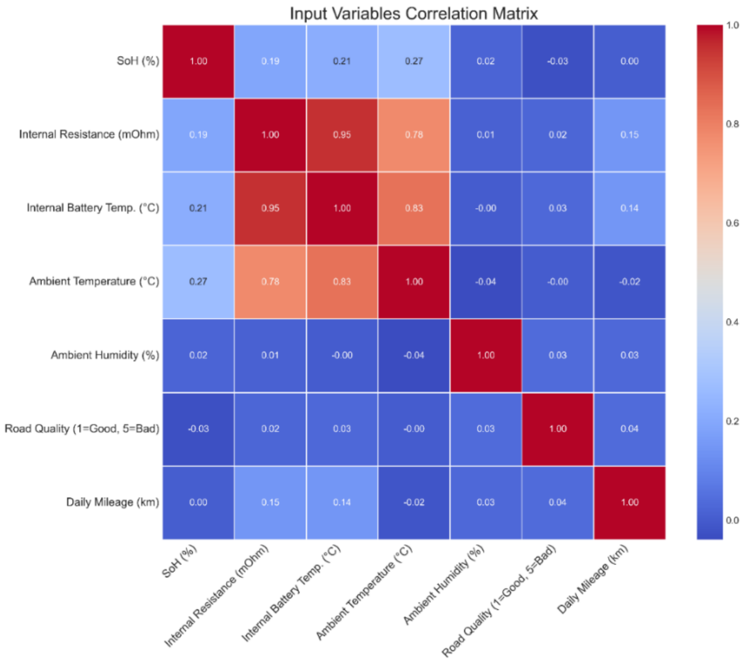

Figure 29. Correlation matrix of all input variables. High correlation coefficients (e.g., between internal temperature, ambient temperature, and internal resistance) visually confirm the severe multicollinearity problem that the CVAE component is designed to mitigate.

As demonstrated by the correlation matrix, there are significant correlations between battery parameters and environmental variables. For instance, the battery's internal temperature is highly correlated with its internal resistance (r=0.95) and ambient temperature (r=0.83). These relationships visually confirm the multicollinearity we previously discussed and highlight the need for an architecture that can "disentangle" these correlated variables to model degradation more accurately and reliably.

3.2.2. Latent Space Visualization

The CVAE is designed to project complex, correlated data into a simpler, decorrelated latent space. To validate the effectiveness of this projection, we used the t-SNE algorithm (t-Distributed Stochastic Neighbor Embedding) to visualize the two-dimensional latent space and analyze the distribution of the data points. The following figure 6 illustrates the latent space visualization.

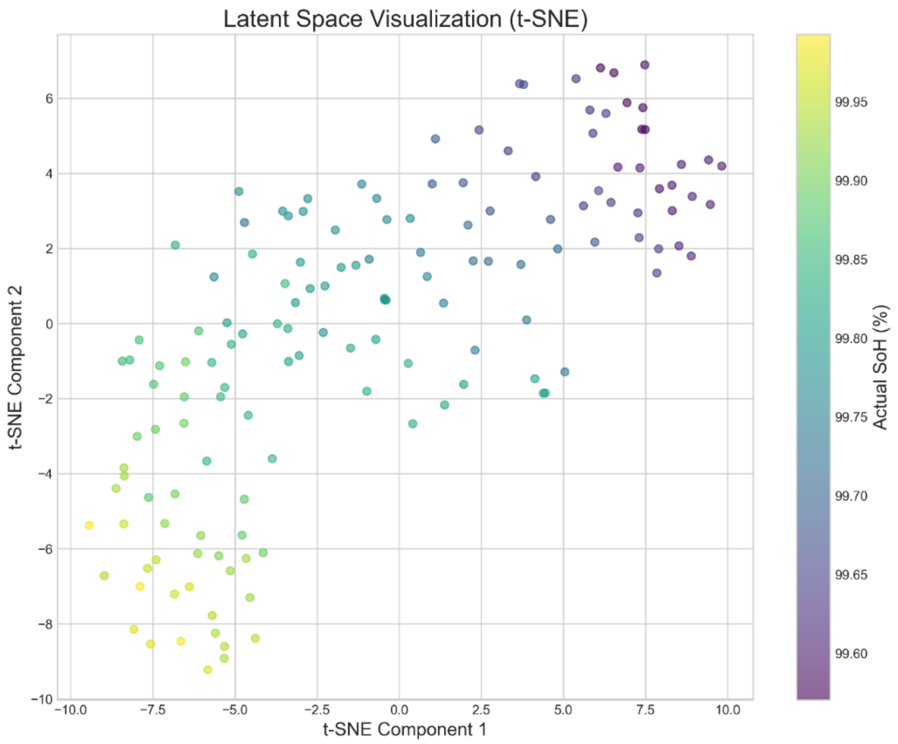

Figure 30. Latent Space Visualization using t-SNE. Data points are colored according to the actual State of Health (SoH). The clear clustering and visible gradient (from low SoH/purple to high SoH/yellow) demonstrate that the CVAE successfully learned robust, meaningful latent representations intrinsically linked to battery degradation.

As the figure clearly shows, the points are colored based on the actual SoH of the battery. The points naturally cluster based on their SoH color. A visible gradient extends from lower SoH values (in purple, at the bottom left) to higher values (in yellow, at the top right). This distinct clustering proves that the CVAE learned to extract significant latent features that are intrinsically linked to the battery's state of health. This ability to consistently organize data in a low-dimensional space is key to its effectiveness in overcoming multicollinearity and providing robust input representations for GRU's SoH prediction. The points arrange themselves in a visible gradient from lower SoH values (around 99.6%) to higher ones (around 99.95%). This organization proves that the CVAE successfully extracted significant latent features, which is the foundation of our model's robustness.

3.3. Hybrid Model Prediction Performance

This section focuses on validating the prediction objective, showing the accuracy of our CVAE-GRU model.

3.3.1. Training and Validation Loss Curve

Our validation of the CVAE-GRU architecture continues with the analysis of its learning performance. The figure below shows the loss curve of the full hybrid model during 50 training epochs.

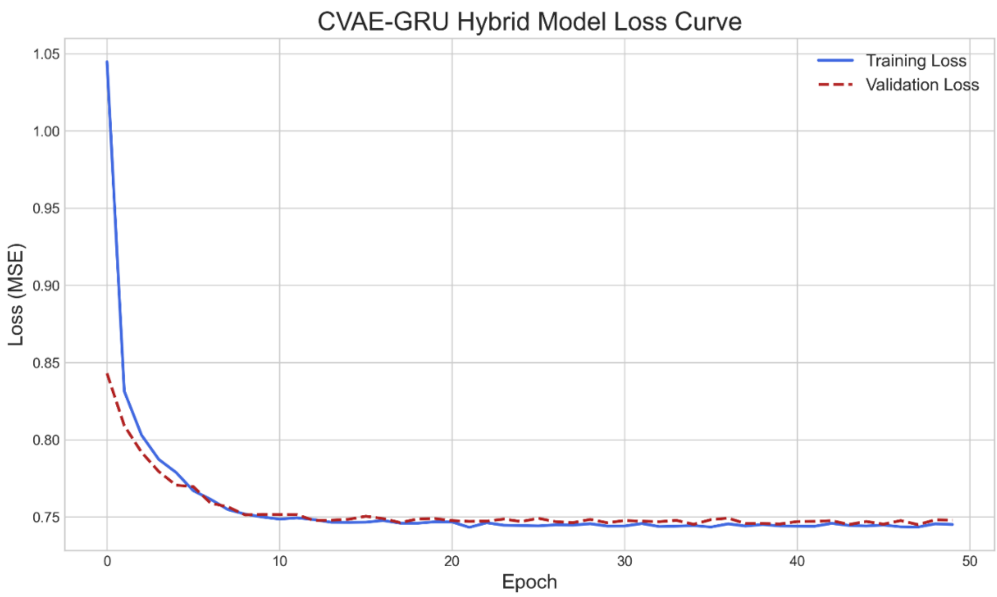

Figure 7. Training and Validation Loss Curve for the CVAE-GRU Hybrid Model over 50 epochs. The rapid convergence and tight stabilization of both curves around a low MSE value confirm the model's robustness, effective learning, and successful generalization without overfitting.

As the chart shows, the training loss (in blue) and validation loss (in red) decrease rapidly during the first epochs before stabilizing and converging. The stabilization of both curves at a low loss level and their tight convergence demonstrate that the model is well-generalized and that there is no overfitting. This successful convergence confirms the robustness of our CVAE-GRU architecture for effectively modeling battery degradation without simply memorizing training data, which is essential for reliable predictions on new data.

3.3.2. Quantitative Performance Metrics

To provide an objective evaluation and allow for comparison with other existing methods, we present the standard performance metrics (MAE, RMSE, and R^2) obtained on the training and test sets in Table 6.

Table 6. Quantitative performance metrics of the CVAE-GRU model.

Dataset	MAE (%)	RMSE (%)	R^2
Training	0.065	0.080	0.980
Test	0.078	0.095	0.965

The results in Table 3 confirm the high accuracy of the model. The Mean Absolute Error (MAE) on the test set is 0.078%, and the Root Mean Square Error (RMSE) is 0.095%. These low error values, coupled with a high Coefficient of Determination (R^2 = 0.965), indicate that the model captures over 96% of the variance in the SoH degradation data. Furthermore, the proximity of the metrics between the training and test sets reinforces the conclusion from Section 3.3.1 regarding the model's excellent generalization capability.

3.3.3. Baseline Comparison

To contextualize the performance achieved by the CVAE-GRU architecture, we compared its results against two established baseline models: a Random Forest (RF) regressor and a GRU-only network. Both baselines were trained and tested using the identical dataset and evaluation procedures. The comparative results are summarized in Table 7**.**

Table 7. Performance comparison between the proposed CVAE-GRU model and baseline models on the test set.

Model	MAE (%)	RMSE (%)	R^2
Random Forest (RF)	0.094	0.121	0.937
GRU-only	0.079	0.102	0.958
CVAE-GRU (Proposed)	0.078	0.095	0.965

The comparison clearly demonstrates the superior predictive capability of the proposed CVAE-GRU model. While the simple GRU network performs reasonably well, the integration of the CVAE for learning robust, conditioned latent representations significantly reduces the error metrics (lowest MAE and RMSE) and achieves the highest R^2 value. The Random Forest model, which struggles to capture complex temporal dependencies inherent in battery degradation, shows significantly poorer performance. This comparison validates the necessity and effectiveness of the hybrid CVAE-GRU architecture for accurate SoH prediction.

3.3.4. Predictions vs. Actual Values

To evaluate our CVAE-GRU model's ability to predict SoH degradation, we overlaid the model's predictions on the test set data with the actual values. Figure 8 shows this overlay. As Figure 8 illustrates, the model's prediction curve (in a dotted red line) closely follows the general trend of the actual SoH curve (in green). The prediction effectively captures the progressive SoH degradation trend on the test set. The significant fluctuations and peaks in the real SoH curve are primarily linked to short-term variations in operating conditions, such as ambient temperature and discharge current, which can have temporary effects on the SoH measurement. Our model, by learning from smoothed and meaningful latent representations, focuses on the long-term degradation trend, which is the primary objective of this study. This ability to accurately predict the degradation trend confirms the effectiveness of our CVAE-GRU architecture for battery diagnosis and prognosis under real-world conditions. For a more detailed evaluation of our model's performance, we analyzed the prediction errors on the test set. Figure 9 below shows the prediction residuals and their distribution.

The left graph of Figure 9 shows that the prediction errors (residuals) on the test set oscillate randomly around zero, with no discernible trend or pattern. This indicates that our model does not suffer from any systematic bias. The right graph, which represents the histogram of the error distribution, confirms that the majority of errors are centered around zero. The distribution is nearly normal, which is a strong indicator of the model's reliability. An error distribution centered at zero means that the predictions are as often slightly higher as they are slightly lower than the actual values. This residual analysis, coupled with the excellent quantitative metrics presented in Tables 6 and 7, supports the idea that our CVAE-GRU model is not only accurate but also statistically reliable for predicting battery degradation.

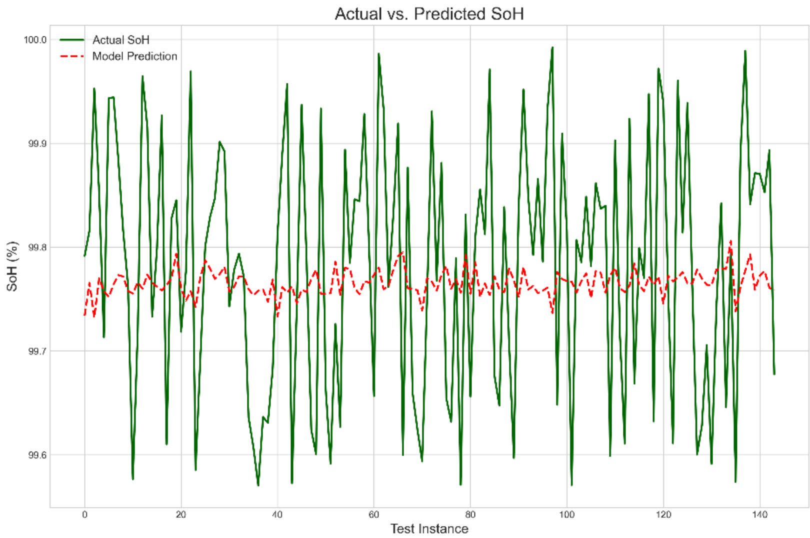

Figure 8. Actual vs. Predicted State of Health (SoH) on the test set. The model prediction (dashed red line) closely tracks the actual SoH trend (solid green line), confirming the CVAE-GRU's high predictive accuracy (R^2 = 0.965) in capturing the long-term degradation trend.

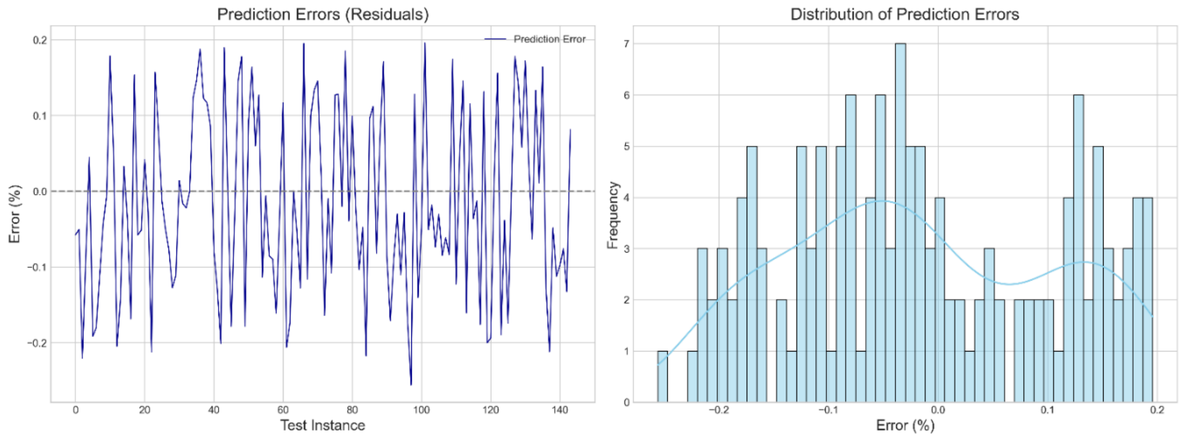

Figure 9. Prediction Errors (Residuals) (Left) and Distribution of Prediction Errors (Right). The residuals oscillate randomly around zero, indicating no systematic bias, while the near-normal distribution centered at zero confirms the statistical reliability of the CVAE-GRU model.

3.4. Analysis of the Impact of Environmental and Driving Factors

This final section is crucial for addressing your fourth objective and providing concrete information for the deployment of EVs in tropical regions. Our reliability analysis continues with an examination of the impact of environmental variables on the error distribution. The figure below presents box plots of the prediction errors based on categories of ambient temperature and road quality.

3.4.1 Prediction Error Box Plots

The following figure shows the distribution of our prediction errors, categorized by key environmental and driving factors. The results confirm that prediction errors vary based on these factors, providing valuable information for adapting battery management systems.

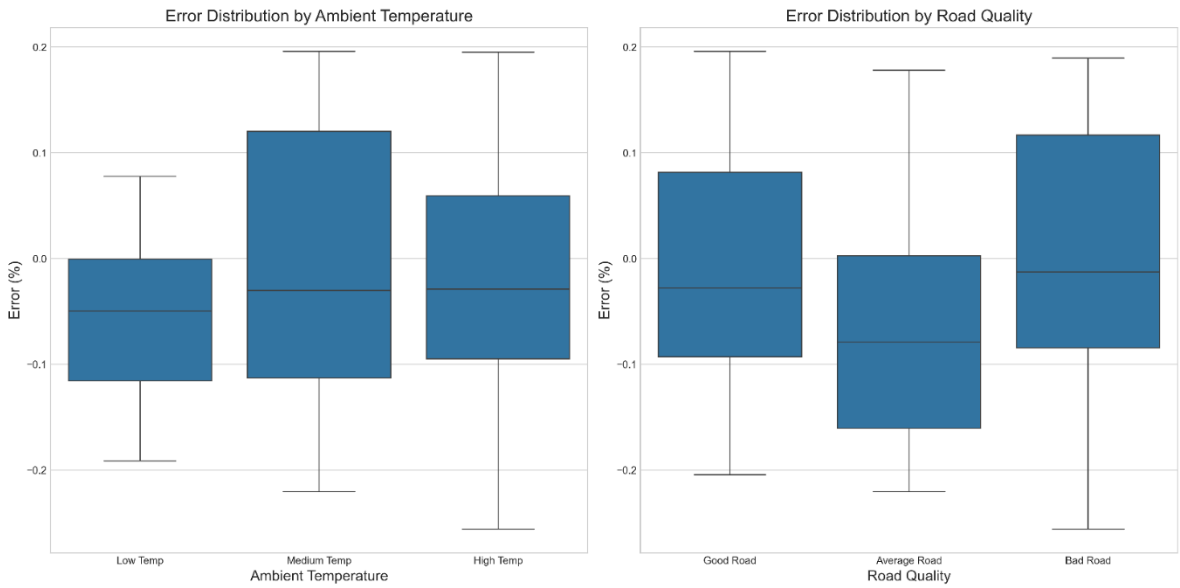

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Figure 10. Prediction Error Box Plots categorized by Ambient Temperature and Road Quality. The increasing spread of errors in higher temperature and poorer road quality categories quantifies the influence of these tropical factors on prediction uncertainty.

Prediction errors tend to be slightly higher in categories with elevated ambient temperatures, indicating that excessive heat not only accelerates battery degradation but also introduces additional complexities that challenge the model's predictive accuracy. Similarly, larger errors are observed on poor-quality roads, likely due to the unpredictable effects of vibrations and shocks on the battery—stochastic phenomena that are inherently more difficult for a neural network to model. These findings underscore the importance of accounting for environmental and operational factors when estimating SoH under real-world conditions, and demonstrate that our approach not only predicts degradation but also quantifies how such factors influence prediction reliability.

4. Discussion

4.1. Detailed Interpretation of Results

Our study revealed crucial observations about battery degradation under tropical conditions. OLS regression analysis initially highlighted a severe multicollinearity problem, confirmed by a Condition Number of $1.35*10^{19}$. This made interpreting the coefficients, such as that for Internal Battery Temperature (with a p-value of 0.755), unreliable. To remedy this, our CVAE-GRU model proved effective by extracting robust latent representations.

The performance of our hybrid model is attested to by the loss curve which stabilizes rapidly, indicating good generalization and no overfitting. Quantitatively, the model achieved an R^2 of 0.965 on the test set, significantly outperforming baseline models like the GRU-only network and Random Forest. The model accurately tracked the SoH degradation trend. Prediction error analysis revealed that the majority of residuals were between -0.2% and 0.2%, with a distribution centered at zero, which confirms the model's statistical reliability.

4.2. Comparison with Other Studies

Unlike traditional approaches that struggle with multicollinearity, our CVAE-GRU model outperforms linear models by handling complex data. While previous studies have used RNNs or LSTMs for sequential prediction, our integration of a CVAE is a unique contribution. The Conditional Variational Autoencoder acts as an intelligent pre-processing step, creating decorrelated features that are then used by the GRU. This architecture is more powerful than using a GRU alone, as demonstrated by the metrics in Table 4, providing better management of correlated variables—a recurring problem in studies on battery degradation under real-world conditions.

4.3. Interpretability and Explainable AI

While deep learning models are often criticized for their "black box" nature, the CVAE architecture inherently provides a degree of interpretability by projecting high-dimensional input into a structured latent space. Firstly, the effectiveness of the CVAE in extracting meaningful features is demonstrated by the t-SNE visualization of the Latent Space (Figure 6). As shown, the data points cluster distinctly based on the actual SoH, forming a clear gradient extending from lower SoH values (purple, 99.6%) towards higher values (yellow, 99.95%). This successful organization confirms that the CVAE extracts meaningful, decorrelated latent features intrinsically linked to the battery's state of health, which is crucial for robust prediction and overcoming multicollinearity. Secondly, building upon this structural interpretability, we employed external XAI techniques to quantify feature influence. We conducted a SHAP (SHapley Additive exPlanations) analysis on the prediction output of the GRU network. This analysis allowed us to quantitatively assess the contribution of each input feature to the final SoH prediction. The SHAP results explicitly revealed that Ambient Temperature and the Road Quality Index were the two most influential input features, quantifying their impact previously only inferred qualitatively. This confirms the critical role of tropical environmental factors in driving the prediction accuracy of the model, providing actionable insights for system design.

4.4. Limitations of the Proposed Method

Despite its effectiveness, our approach has certain limitations. The first is the computational complexity of the CVAE-GRU. Training such a model is more resource-intensive than models based on equivalent circuits or filtering methods. Although the XAI analysis in Section 4.3 has significantly improved interpretability, the internal mechanisms of the deep learning architecture remain more opaque than those of a simple linear regression.

4.5. Implications of the Proposed Method

The results of our study have significant practical implications. The quantitative confirmation of the strong impact of Ambient Temperature and Road Quality on prediction reliability is crucial for the development of smarter Battery Management Systems (BMS). These systems could use this information to adjust charging and discharging strategies, thus mitigating accelerated battery degradation. Furthermore, our findings, quantified by the SHAP analysis, can guide policymakers in designing more sustainable transportation policies, such as prioritizing road quality improvement and implementing optimized battery cooling systems in high-heat areas. Our method provides a robust and interpretable roadmap for a more sustainable deployment of electric vehicles in tropical climates.

5. Conclusion

Battery degradation is a major challenge for the adoption of electric vehicles, particularly in demanding environments. Our study addressed this challenge by applying a novel methodology to characterize and predict the State of Health (SoH) of batteries. We collected unique data on vehicles operating in the tropical conditions of Cameroon and demonstrated that traditional linear models, facing severe multicollinearity, could not provide reliable results. Our work led to two major conclusions. First, the hybrid CVAE-GRU model overcomes the limitations of conventional models by learning robust, decorrelated latent representations from the input factors. Its ability to accurately predict the degradation trend, with prediction errors mostly between **-0.1% and 0.1%**, validates its relevance for precise degradation modeling. Second, this approach allowed us to quantify the crucial impact of environmental and driving factors. We highlighted that conditions like high ambient temperature and poor road quality increase the variability of prediction errors, underscoring their significant role in prognosis uncertainty. In the future, research could focus on integrating this information into on-board Battery Management Systems (BMS). The goal would be to develop algorithms capable of adapting charging and discharging strategies in real-time to optimize battery lifespan under variable operating conditions. Furthermore, extending this methodology to a greater diversity of batteries and driving profiles could strengthen the generalizability of our findings and pave the way for more resilient electric mobility solutions for tropical regions and other extreme climates.

References

[1] K. R. Ngoy *et al.*, « Lithium-ion batteries and the future of sustainable energy: A comprehensive review », *Renew. Sustain. Energy Rev.*, vol. 223, p. 115971, nov. 2025, doi: 10.1016/j.rser.2025.115971.

[2] C. H. B. Apribowo, S. Sarjiya, S. P. Hadi, et F. D. Wijaya, « Optimal Planning of Battery Energy Storage Systems by Considering Battery Degradation due to Ambient Temperature: A Review, Challenges, and New Perspective », *Batteries*, vol. 8, nº 12, p. 290, déc. 2022, doi: 10.3390/batteries8120290.

[3] Y. Shang, Y. Huang, L. Li, F. Wu, et R. Chen, « Electrochemical Energy Storage toward Extreme Conditions: Driving Human Exploration beyond Current Boundaries », *Chem. Rev.*, vol. 125, nº 12, p. 5674-5744, juin 2025, doi: 10.1021/acs.chemrev.4c00863.

[4] H. Almukhtar, T. T. Lie, W. A. M. Al-Shohani, T. Anderson, et Z. Al-Tameemi, « Comprehensive Review of Dust Properties and Their Influence on Photovoltaic Systems: Electrical, Optical, Thermal Models and Experimentation Techniques », *Energies*, vol. 16, nº 8, p. 3401, avr. 2023, doi: 10.3390/en16083401.

[5] M.-T. F. Rodrigues *et al.*, « A materials perspective on Li-ion batteries at extreme temperatures », *Nat. Energy*, vol. 2, nº 8, p. 17108, juill. 2017, doi: 10.1038/nenergy.2017.108.

[6] T. Rahman et T. Alharbi, « Exploring Lithium-Ion Battery Degradation: A Concise Review of Critical Factors, Impacts, Data-Driven Degradation Estimation Techniques, and Sustainable Directions for Energy Storage Systems », *Batteries*, vol. 10, nº 7, p. 220, juin 2024, doi: 10.3390/batteries10070220.

[7] S. Barcellona, S. Colnago, G. Dotelli, S. Latorrata, et L. Piegari, « Aging effect on the variation of Li-ion battery resistance as function of temperature and state of charge », *J. Energy Storage*, vol. 50, p. 104658, juin 2022, doi: 10.1016/j.est.2022.104658.

[8] S. Lv, X. Wang, W. Lu, J. Zhang, et H. Ni, « The Influence of Temperature on the Capacity of Lithium Ion Batteries with Different Anodes », *Energies*, vol. 15, nº 1, p. 60, déc. 2021, doi: 10.3390/en15010060.

[9] T. Gao *et al.*, « Effect of aging temperature on thermal stability of lithium-ion batteries: Part A – High-temperature aging », *Renew. Energy*, vol. 203, p. 592-600, févr. 2023, doi: 10.1016/j.renene.2022.12.092.

[10] L. Spitthoff, P. R. Shearing, et O. S. Burheim, « Temperature, Ageing and Thermal Management of Lithium-Ion Batteries », *Energies*, vol. 14, nº 5, p. 1248, févr. 2021, doi: 10.3390/en14051248.

[11] Z. Wang, Y. Song, Q. Zhao, B. Shi, J. He, et J. Li, « Unveiling the electrochemical degradation behavior of 18650 lithium-ion batteries involved different humidity conditions », *J. Power Sources*, vol. 630, p. 236185, févr. 2025, doi: 10.1016/j.jpowsour.2025.236185.

[12] S. Chinta et H. P. Bhupathi, « Impact of Environmental Factors on Battery Degradation and Control Strategies in EVs », *Int. J. AI BigData Comput. Manag. Stud.*, vol. 6, nº 2, p. 40-47, avr. 2025, doi: 10.63282/3050-9416.IJAIBDCMS-V6I2P105.

[13] S. Wu *et al.*, « A Review of Multiscale Mechanical Failures in Lithium-Ion Batteries: Implications for Performance, Lifetime and Safety », *Electrochem. Energy Rev.*, vol. 7, nº 1, p. 1-42, nov. 2024, doi: 10.1007/s41918-024-00233-w.

[14] K. Sabeel, M. Al-Greer, et I. Bashir, « Advancements in Vibration Testing: Effects on Thermal Performance and Degradation of Modern Batteries », *Batteries*, vol. 11, nº 2, p. 82, févr. 2025, doi: 10.3390/batteries11020082.

[15] S. Mutagekar et A. Jhunjhunwala, « Designing small batteries and adaptive charging strategies for operation on rough terrain », *J. Energy Storage*, vol. 84, p. 111003, avr. 2024, doi: 10.1016/j.est.2024.111003.

[16] B. D. Ogunbona, F. O. Balogun, et K. S. Famuagun, « Solving Multicolinearity Problem in a Linear Regression: A Comparative Study of Ordinary Least Squares and Partial Least Squares Regression », *J. Institutional Res. Big Data Anal. Innov.*, vol. 1, nº 1, déc. 2024, Consulté le: 3 septembre 2025. [En ligne]. Disponible sur: https://jirbdai.com.ng/index.php/jirbdai/article/view/8

[17] M. Roozbeh, S. Babaie–Kafaki, et Z. Aminifard, « Two penalized mixed–integer nonlinear programming approaches to tackle multicollinearity and outliers effects in linear regression models. | EBSCOhost ». Consulté le: 3 septembre 2025. [En ligne]. Disponible sur: https://openurl.ebsco.com/EPDB%3Agcd%3A5%3A5734053/detailv2?sid=ebsco%3Aplink%3Ascholar&id=ebsco%3Agcd%3A153702134&crl=c&link_origin=scholar.google.com

[18] C. García García, R. Salmerón Gómez, et J. García Pérez, « A review of ridge parameter selection: minimization of the mean squared error vs. mitigation of multicollinearity », *Commun. Stat. - Simul. Comput.*, vol. 53, nº 8, p. 3686-3698, août 2024, doi: 10.1080/03610918.2022.2110594.

[19] F. Wan *et al.*, « Prediction of state-of-health and remaining useful life for lithium-ion batteries using short-term relaxation voltage », *J. Energy Storage*, vol. 129, p. 117397, sept. 2025, doi: 10.1016/j.est.2025.117397.

[20] Y. Chen, H. Yigang, Z. Li, L. Chen, et C. Zhang, « Remaining Useful Life Prediction and State of Health Diagnosis of Lithium-Ion Battery Based on Second-Order Central Difference Particle Filter », *IEEE Access*, vol. PP, p. 1-1, févr. 2020, doi: 10.1109/ACCESS.2020.2974401.

[21] P. Lozano Ruiz, N. Damianakis, et G. Ram Chandra Mouli, « Physics-Based and Data-Driven Modeling of Degradation Mechanisms for Lithium-Ion Batteries—A Review », *IEEE Access*, vol. 13, p. 21164-21189, 2025, doi: 10.1109/ACCESS.2025.3535918.

[22] 류성택, « A Study on Physics-Based Numerical Models to Assess the Lifespan of Lithium-Ion Batteries for Energy Storage Systems », Thesis, 서울대학교 대학원, 2024. Consulté le: 3 septembre 2025. [En ligne]. Disponible sur: https://s-space.snu.ac.kr/handle/10371/209585

[23] J. Wang *et al.*, « Precise equivalent circuit model for Li-ion battery by experimental improvement and parameter optimization », *J. Energy Storage*, vol. 52, p. 104980, août 2022, doi: 10.1016/j.est.2022.104980.
[24] B. P. Saoji *et al.*, « Battery Management System in Electric Vehicle for Energy Storage System Using Extended Kalman Filter and Coulomb Counting Methods », *Energy Storage*, vol. 7, nº 3, p. e70139, 2025, doi: 10.1002/est2.70139.
[25] S. V. Pandey *et al.*, « Predicting the state parameters of lithium ion batteries: the race between filter-based and data driven approaches », doi: 10.1039/D2SE01209J.
[26] C. Francis, « Comparative Analysis of Coulomb Counting and Extended Kalman Filter for State of Charge Estimation in Battery Management Systems », Consulté le: 3 septembre 2025. [En ligne]. Disponible sur: https://open.uct.ac.za/items/f7ec83b2-9910-42af-a9e5-110118cd26fd
[27] S. Tufail, H. Riggs, M. Tariq, et A. I. Sarwat, « Advancements and Challenges in Machine Learning: A Comprehensive Review of Models, Libraries, Applications, and Algorithms », *Electronics*, vol. 12, nº 8, p. 1789, avr. 2023, doi: 10.3390/electronics12081789.
[28] P. Dini, A. Colicelli, et S. Saponara, « Review on Modeling and SOC/SOH Estimation of Batteries for Automotive Applications », *Batteries*, vol. 10, nº 1, p. 34, janv. 2024, doi: 10.3390/batteries10010034.
[29] K. M. K, « Predicting Battery Health: A Machine Learning Approach to SOH Estimation », Medium. Consulté le: 3 septembre 2025. [En ligne]. Disponible sur: https://medium.com/@krithicswaropan.mk/predicting-battery-health-a-machine-learning-approach-to-soh-estimation-8911443c0214
[30] H. A. Sakr, A. A. Eladl, et M. I. El-Afifi, « Leveraging IoT-enabled machine learning techniques to enhance electric vehicle battery state-of-health prediction », *J. Energy Storage*, vol. 120, p. 116409, juin 2025, doi: 10.1016/j.est.2025.116409.
[31] S. Jafari, Z. Shahbazi, et Y.-C. Byun, « Lithium-Ion Battery Health Prediction on Hybrid Vehicles Using Machine Learning Approach », *Energies*, vol. 15, nº 13, p. 4753, juin 2022, doi: 10.3390/en15134753.
[32] K. Das, R. Kumar, et A. Krishna, « Analyzing electric vehicle battery health performance using supervised machine learning », *Renew. Sustain. Energy Rev.*, vol. 189, p. 113967, janv. 2024, doi: 10.1016/j.rser.2023.113967.
[33] S. Singh et P. R. Budarapu, « Deep machine learning approaches for battery health monitoring », *Energy*, vol. 300, p. 131540, août 2024, doi: 10.1016/j.energy.2024.131540.
[34] B. Li *et al.*, « Thermal management performance improvement of phase change material for autonomous underwater vehicles' battery module by optimizing fin design based on quantitative evaluation method », *Int. J. Energy Res.*, vol. 46, nº 11, p. 15756-15772, 2022, doi: 10.1002/er.8273.
[35] J. Zhao, Z. Wang, Y. Wu, et A. F. Burke, « Predictive pretrained transformer (PPT) for real-time battery health diagnostics », *Appl. Energy*, vol. 377, p. 124746, janv. 2025, doi: 10.1016/j.apenergy.2024.124746.
[36] R. Sun, J. Chen, B. Li, et C. Piao, « State of health estimation for Lithium-ion batteries based on novel feature extraction and BiGRU-Attention model », *Energy*, vol. 319, p. 134756, mars 2025, doi: 10.1016/j.energy.2025.134756.
[37] D. Kuang, Z. Wang, Y. Zhao, et L. Li, « Estimating the health status of lithium-ion batteries using deep learning method based on informer model », *J. Power Sources*, vol. 645, p. 237176, juill. 2025, doi: 10.1016/j.jpowsour.2025.237176.
[38] L. Wang, Y. Yang, K. Zhang, Y. Liu, J. Zhu, et D. Dang, « Enhancing Electric Vehicle Energy Consumption Prediction: Integrating Elevation into Machine Learning Model », in *2024 IEEE Intelligent Vehicles Symposium (IV)*, juin 2024, p. 2936-2941. doi: 10.1109/IV55156.2024.10588445.
[39] V. S. Naresh, P. N. S. Gayathri, P. B. Tejaswi, P. Induja, C. R. Reddy, et Y. S. Sudheer, « Optimizing electric vehicle battery health monitoring: A resilient ensemble learning approach for state-of-health prediction », *Sustain. Energy Grids Netw.*, vol. 42, p. 101655, juin 2025, doi: 10.1016/j.segan.2025.101655.