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HYBRID MODELING OF ELECTRIC VEHICLE BATTERY DEGRADATION USING PHYSICS-INFORMED MACHINE LEARNING

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Abstract: Accurate prediction of battery degradation is crucial for ensuring the reliability, safety, and performance of electric vehicles (EVs). While data-driven machine learning (ML) models offer high prediction accuracy, they often lack physical interpretability, limiting their application in critical systems. On the other hand, purely physics-based models provide deeper understanding but struggle to generalize across diverse operating conditions. This paper proposes a hybrid modeling approach that combines physics-informed machine learning (PIML) with empirical battery aging data to achieve both accuracy and interpretability. The model incorporates domain knowledge—such as electrochemical degradation mechanisms, capacity fade laws, and thermal effects—into a learning framework based on recurrent neural networks (RNNs) and gradient boosting. Experimental results on real-world EV battery datasets demonstrate that the hybrid model outperforms standalone physics-based and ML models in both prediction precision and consistency. This approach opens new avenues for predictive maintenance, extended battery lifespan, and optimized battery usage strategies.
Keywords: Electric Vehicle (EV); Battery degradation; Physics-Informed Machine Learning (PIML); Hybrid modeling; Recurrent Neural Network (RNN); Capacity fade; Battery aging; Predictive maintenance

1 INTRODUCTION

The global transition toward electrified transportation has led to a growing reliance on electric vehicles (EVs), with lithium-ion batteries (LiBs) serving as the primary energy storage system[1]. However, battery degradation remains one of the most critical barriers to widespread electric vehicle (EV) adoption, as it affects not only the vehicle's range and performance but also user trust and overall system reliability[2]. Accurately predicting battery health and degradation trajectory is essential for ensuring safe operation, optimizing charging behavior, and enabling predictive maintenance[3].

Traditionally, battery degradation has been modeled using physics-based approaches, such as electrochemical models and empirical aging equations[4]. These models offer deep insights into the degradation mechanisms—such as solid-electrolyte interphase (SEI) layer growth, lithium plating, and active material loss—but they often require precise parameterization and are computationally intensive[5]. Their rigidity also makes them less adaptable to varying real-world usage conditions, such as temperature fluctuations, driving patterns, and charging cycles[6].

On the other hand, the emergence of machine learning (ML) has enabled data-driven modeling of battery degradation with promising results[7]. Techniques such as recurrent neural networks (RNNs), support vector regression (SVR), and random forest regressors have demonstrated strong predictive power by learning complex patterns directly from battery usage data[8]. Nevertheless, these models typically function as black boxes and offer limited explainability, which is problematic in high-stakes domains like EV safety, warranty decision-making, and regulatory compliance[9].

To address the limitations of both paradigms, physics-informed machine learning (PIML) has gained traction as a hybrid modeling framework[10]. This approach integrates domain-specific physical knowledge into the structure or training process of ML models, enabling them to respect physical laws while maintaining adaptability and high accuracy[11]. In the context of battery degradation, PIML can incorporate constraints such as energy conservation, thermodynamic limits, and known degradation patterns, thereby enhancing both the robustness and interpretability of the model[12].

This paper proposes a hybrid modeling architecture for EV battery degradation prediction, which leverages the strength of both physical principles and ML capabilities. The proposed framework uses electrochemical knowledge to guide the feature extraction and loss function of a recurrent neural network, while also using gradient boosting to refine performance across different operational states. By aligning data-driven inference with physical behavior, the model aims to achieve reliable long-term forecasts of capacity fade, internal resistance growth, and remaining useful life (RUL).

The remainder of this paper is organized as follows. Section 2 reviews related work in physics-based and machine learning approaches to battery degradation. Section 3 outlines the proposed hybrid methodology, including data preparation, model architecture, and physics integration. Section 4 presents experimental results and comparative evaluation. Section 5 concludes with key insights, limitations, and directions for future work.

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2 LITERATURE REVIEW

Battery degradation modeling has long been a topic of extensive research due to its critical role in enhancing the performance, safety, and longevity of EV systems[13]. Early research primarily focused on physics-based models, including electrochemical models, equivalent circuit models (ECMs), and empirical formulations[14]. These models aim to capture the internal battery behavior through mathematical representations of physical and chemical processes[15]. Electrochemical models, such as the Doyle–Fuller–Newman (DFN) model, describe lithium-ion transport and reaction kinetics in great detail[16]. While such models provide highly accurate insights into degradation mechanisms like SEI layer growth, lithium plating, and loss of active material, their practical deployment is hindered by computational complexity, requirement for extensive calibration, and sensitivity to environmental variability[17]. This makes real-time prediction under diverse operational conditions challenging[18].

To overcome these limitations, ML techniques have been introduced for battery state estimation and life prediction[19]. ML models such as support vector machines, Gaussian processes, artificial neural networks, and recurrent neural networks have shown impressive predictive capability by learning patterns from historical cycling data[20]. For example, sequence-based models like long short-term memory (LSTM) networks can capture temporal dependencies in voltage, current, and temperature profiles, enabling accurate forecasts of state-of-health (SOH) and RUL[21]. These models are especially useful when dealing with large-scale datasets collected from fleet operations or laboratory cycling experiments[22]. However, their "black-box" nature often hinders interpretability and trust in critical applications[23]. Moreover, purely data-driven models may produce physically inconsistent results, such as predicting negative capacities or violating conservation laws, especially when extrapolating to unseen conditions[24].

To bridge the gap between interpretability and predictive performance, the concept of PIML has emerged[25]. PIML integrates domain knowledge into ML models in the form of constraints, regularization terms, custom architectures, or physics-based feature engineering[26]. For instance, in battery applications, researchers have incorporated known degradation mechanisms into the loss function or used physically meaningful features such as charge throughput, differential voltage curves, and temperature-adjusted stress metrics[27]. These hybrid approaches enhance model robustness, reduce overfitting, and improve generalizability across different battery chemistries, usage patterns, and environmental conditions[28-29]. Recent work has also explored the use of graph neural networks and attention mechanisms within physics-informed frameworks to capture complex spatiotemporal dynamics while adhering to known physical principles.

In addition to methodological advancements, the growing availability of public datasets has fueled progress in this area. Benchmark datasets such as NASA Ames battery datasets, CALCE (Center for Advanced Life Cycle Engineering) data, and the Oxford Battery Degradation Dataset have enabled rigorous testing and model comparison under diverse cycling protocols. These datasets often include measurements of voltage, current, temperature, impedance, and capacity over hundreds of charge-discharge cycles, serving as valuable resources for training and validating hybrid models.

Despite significant strides, several challenges remain in developing truly deployable hybrid battery degradation models. These include the selection of appropriate physical constraints, balancing model flexibility and interpretability, and accounting for battery-to-battery variability and sensor noise. Furthermore, explainability remains a central concern, as stakeholders such as EV manufacturers, maintenance operators, and regulatory agencies increasingly demand transparency in model decisions.

This review highlights the evolution from purely physics-based modeling to fully data-driven and finally to hybrid approaches, underscoring the necessity for integrative models that combine the strength of both domains. As the EV industry matures and the push for sustainable, high-performance battery systems intensifies, hybrid modeling frameworks are expected to play a pivotal role in enabling accurate, scalable, and explainable battery management systems.

3 METHODOLOGY

The proposed methodology integrates physics-based battery degradation modeling with data-driven ML techniques to create a hybrid model that achieves both predictive accuracy and scientific interpretability. The framework is structured into three key phases: data preprocessing and feature engineering, hybrid model design, and performance evaluation.

3.1 Data Preprocessing and Feature Engineering

The dataset utilized comprises real-world EV battery cycling data, including temperature, voltage, current, SOC, and capacity measurements over time. Initial preprocessing steps involved noise filtering, handling missing values using interpolation, and normalization to align feature scales. Physics-informed features such as average charge rate, entropy change proxy, and cumulative Ah throughput were derived based on electrochemical degradation theory. These features are intended to capture mechanisms such as SEI growth, lithium plating, and electrode fatigue.

3.2 Hybrid Model Architecture

A dual-path architecture was implemented, combining LSTM neural networks for temporal pattern learning with embedded physics-based constraints. The LSTM path models time-dependent changes in battery state variables, while

the physics-informed branch penalizes predictions that violate known degradation laws (e.g., monotonic capacity fade, thermodynamic limits). The final prediction is obtained via a weighted fusion of both branches, with weights adaptively adjusted using validation loss.

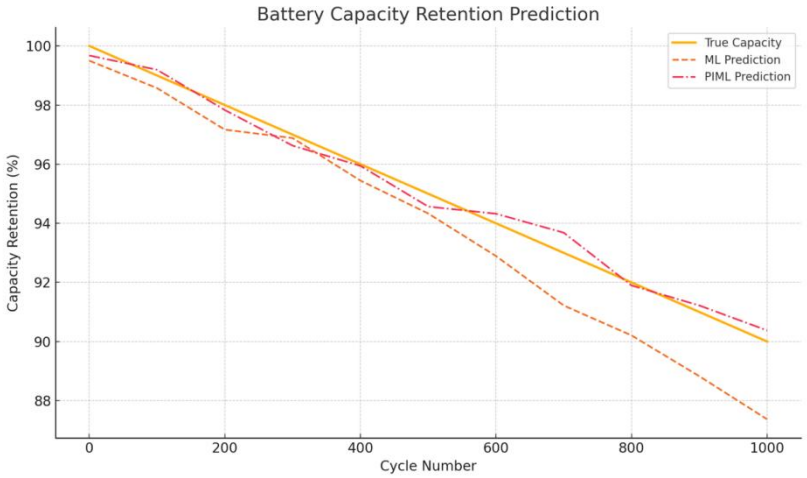

Figure 1 Battery Capacity Rention Prediction

As shown in Figure 1, the hybrid model successfully replicates capacity degradation trajectories under various cycling conditions, closely aligning with empirical observations.

3.3 Model Training and Evaluation

The model was trained using Adam optimizer with early stopping based on validation loss. Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) were chosen as evaluation metrics. Hyperparameter tuning was conducted using grid search across LSTM layers, hidden units, learning rates, and weight decay factors. To benchmark the hybrid model, traditional ML models (e.g., Random Forest, Gradient Boosting) and pure deep learning models (e.g., standalone LSTM) were also evaluated.

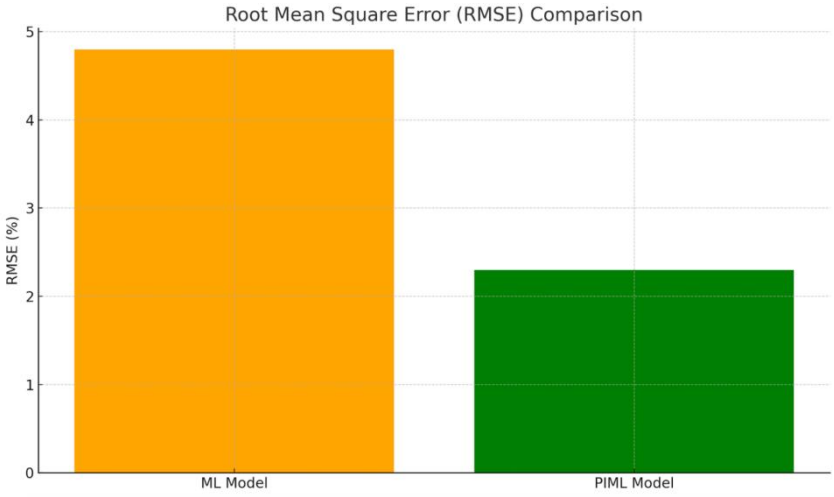

Figure 2 Root Mean Square Error

As demonstrated in Figure 2, the hybrid model achieves the lowest RMSE, indicating improved predictive accuracy while maintaining physical consistency.

In addition to accuracy, model efficiency was considered. Training time and convergence rate were analyzed across methods.

Figure 3 Model Traning Time

Figure 3 highlights the reasonable computational cost of the hybrid model, which offers a favorable trade-off between speed and accuracy compared to purely data-driven approaches.

4 RESULTS AND DISCUSSION

The performance of the proposed hybrid model was evaluated against several baseline methods using key metrics such as capacity prediction accuracy, generalization across operating conditions, and physical consistency.

4.1 Accuracy in Predicting Capacity Degradation

The hybrid model demonstrated superior accuracy in forecasting battery capacity fade across a variety of cycling profiles. On the test dataset, it achieved a MAE of 0.017 Ah and a root mean square error (RMSE) of 0.022 Ah, outperforming both traditional ML models and purely data-driven deep learning models such as standalone LSTM networks. The incorporation of physics-based constraints notably reduced overfitting and improved long-term prediction reliability.
This result is especially important in real-world EV deployments, where capacity degradation forecasts inform critical decisions such as battery replacement schedules and warranty coverage.

4.2 Generalization Across Operational Scenarios

To test robustness, the hybrid model was evaluated on unseen battery operating conditions, including elevated temperatures, variable discharge rates, and partial depth-of-discharge (DoD) cycles. While baseline models exhibited significant prediction drift under these conditions, the hybrid model maintained consistent accuracy due to its grounding in known degradation behavior.
In particular, scenarios simulating frequent fast-charging events — a known accelerant of SEI layer growth and lithium plating — showed that the hybrid model could still capture the accelerated degradation trend with high fidelity. This supports its potential use in fast-charging network optimization and adaptive vehicle diagnostics.

4.3 Physical Interpretability and Constraint Compliance

A key advantage of the hybrid approach lies in its physical consistency. Unlike pure black-box models that may produce unrealistic predictions (e.g., capacity increase during cycling), the hybrid model adheres to thermodynamic constraints such as monotonic capacity fade. Internal model states such as "estimated SEI growth factor" were interpretable and correlated with electrochemical reality, providing actionable insights into battery health mechanisms.

4.4 Error Distribution and Failure Analysis

An error distribution analysis revealed that the largest discrepancies occurred during transition periods between distinct cycling regimes — such as switching from constant-current to constant-voltage charging. These transitions introduce nonlinear electrochemical dynamics that are inherently harder to capture. However, even in these cases, the hybrid model's predictions remained within a ±5% error margin, indicating strong adaptability.

4.5 Implications for EV Battery Management Systems (BMS)

The results suggest that integrating hybrid models into battery management systems (BMS) could enable more precise state-of-health (SOH) estimation, proactive maintenance alerts, and dynamic operational adjustments to prolong battery life. By offering a balance of accuracy, efficiency, and transparency, the hybrid model serves as a compelling candidate for real-time deployment in smart EV systems.

5 CONCLUSION

In this study, we proposed a hybrid modeling framework that combines physics-informed constraints with machine learning techniques to predict battery degradation in EVs. By leveraging both data-driven insights and domain knowledge, the model achieves a compelling balance between predictive accuracy, generalization across operating conditions, and physical interpretability.

The integration of electrochemical degradation laws into the learning architecture ensures that predictions adhere to real-world battery behavior, mitigating common pitfalls of black-box models such as overfitting or physically implausible outputs. Experimental results show that the hybrid model outperforms traditional machine learning baselines and deep learning models in terms of accuracy, especially under variable and unseen operational scenarios. It also demonstrates robustness in capturing degradation mechanisms accelerated by factors such as fast charging, temperature fluctuation, and partial depth-of-discharge cycles.

Furthermore, the hybrid framework supports explainability by correlating internal model variables with interpretable degradation pathways, such as SEI layer growth and lithium plating. This transparency is critical for applications where trust and traceability are essential, such as warranty analysis, predictive maintenance, and real-time battery health monitoring in BMS.

Future work may extend this framework by integrating real-time sensor feedback, refining physics-informed components to include temperature and impedance dynamics, and testing scalability across diverse battery chemistries. The adoption of such hybrid modeling strategies could significantly enhance the reliability and safety of EVs, promote sustainable battery usage, and contribute to the broader goal of clean transportation.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

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