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Nonlinear Battery Degradation-Aware Real-Time Optimization for Vehicle Home Grid Integration

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Abstract - EVs can now operate as active energy nodes within smart networks because to the increased prospects for (V2H) and (V2G) integration brought about by the fast growth of EVs. However, existing research largely focuses on isolated optimization strategies, simplified battery degradation models, or standalone load forecasting techniques, limiting practical real-time implementation. Many studies rely on offline scheduling, linearized battery aging approximations, or neglect the coupled effects of calendar and cycle degradation under varying operational stresses. Furthermore, limited attention has been given to integrating closed-loop load prediction with adaptive energy management while accounting for user-centric economic sensitivity factors such as battery capacity, household load scale, and electricity price ratios. This study addresses these limitations by proposing a unified real-time energy management framework that integrates bidirectional V2G–V2H operations, nonlinear battery degradation modeling, and hybrid long short-term memory (LSTM)-based household load forecasting within an online optimization environment. Under dynamic restrictions and uncertainty, the suggested method concurrently reduces the costs associated with battery degradation and electricity trading. Furthermore, a methodical economic sensitivity analysis assesses how important parameters affect user profitability and system sustainability. The outcomes demonstrate that combining nonlinear aging-aware optimization with adaptive load prediction significantly enhances economic benefits while maintaining battery health. The proposed framework contributes toward scalable, health-aware, and economically viable vehicle–home–grid integration suitable for real-world smart energy systems.

Keywords - Vehicle-to-Home (V2H); Vehicle-to-Grid (V2G); Electric Vehicles (EVs); Calendar and Cycle Aging; Nonlinear Battery Degradation; Hybrid LSTM;

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I. INTRODUCTION

The rapid adoption of electric vehicles (EVs) around the world is transforming the transportation and energy sectors. As EV adoption rises, their aggregated charging demand imposes significant stress on distribution networks, while simultaneously offering new opportunities for flexible energy management. Bidirectional power exchange is made possible by concepts like (V2G) and (V2H), which enable EVs to serve as distributed energy storage units inside smart networks in addition to being mobility devices. While V2H allows for self-consumption optimization and improved household resilience during grid disruptions, V2G allows stored battery energy to be exported to the grid for peak shaving, frequency management, and energy arbitrage.

These capabilities position EVs as critical components in future sustainable energy systems.

Recent studies have investigated various aspects of EV-grid integration. Optimization-based approaches using mixed-integer linear programming and nonlinear programming have been developed to minimize charging costs and improve grid stability, as reported in research published by IEEE and Elsevier journals. To improve intelligent scheduling in the face of uncertainty, reinforcement learning approaches have been investigated concurrently.

Despite these advancements, most existing frameworks address V2G, V2H, battery degradation, and load forecasting as separate components rather than as an integrated real-time control system.

Battery degradation remains one of the most critical challenges in bidirectional charging applications. While V2G and V2H can generate economic benefits, frequent charging and discharging accelerate battery aging, directly impacting replacement costs and long-term sustainability. Many prior works simplify degradation modeling by considering only cycle aging or by employing linear cost approximations. However, practical battery behavior is influenced by complex nonlinear interactions between temperature, total energy throughput, depth of discharge and state of charge (SoC). Neglecting

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these coupled stress factors can result in suboptimal or economically misleading scheduling strategies. Another limitation in existing research is the reliance on offline optimization, where full knowledge of future load and price signals is assumed.

In real-world conditions, household consumption is uncertain and dynamically changing. Although deep learning models such as hybrid LSTM architectures have improved load prediction accuracy, few studies embed forecasting models within a closed-loop optimization framework that updates decisions as new data becomes available. Furthermore, limited attention has been given to comprehensive economic sensitivity analysis, including the effects of electricity price ratios, battery capacities, and varying household demand levels on overall profitability. To address these limitations, a comprehensive real-time energy management system for car, house, and grid integration is proposed in this study.

The proposed system integrates nonlinear battery degradation modeling (including both calendar and cycle aging), hybrid LSTM-based household load forecasting, and online optimization of bidirectional power flows. Unlike conventional approaches, the framework operates adaptively under uncertainty, continuously updating scheduling decisions based on predicted and actual consumption data. Additionally, a systematic economic sensitivity analysis is conducted to evaluate the impact of battery capacity, household load scale, and electricity price ratios on user cost and system performance.

The primary contribution of this work is the development of a vehicle–home–grid control method that is practical, cheap, and health-conscious.By simultaneously considering battery longevity, real-time load uncertainty, and market-driven energy trading, the proposed approach advances the state of the art toward scalable and sustainable smart grid integration of electric vehicles.

II. LITERATURE REVIEW

Recent research on electric vehicle energy management has increasingly focused on integrating bidirectional power flows and optimizing both grid support and device-level constraints. Popolizio*et al.*[1] proposed a nonlinear online optimization framework that couples vehicle-to-grid (V2G) and vehicle-to-home (V2H) services with household load forecasting, highlighting the potential to balance local demand through adaptive scheduling; however, the study remains limited to small-scale settings without extensive scalability analysis. Similarly, Khezri*et al.*[2] employed a mixed-integer linear programming (MILP) approach to schedule V2G operations while considering battery aging costs, signaling a move toward health-aware optimization but still relying on offline assumptions that restrict real-time adaptability. Zhang *et al.*[3] further advanced this line of work by incorporating online battery aging mitigation strategies during V2G scheduling, yet the degradation modeling remains simplified and often linearized, neglecting critical nonlinear effects such as temperature and state-of-charge stress factors.

Battery degradation, a central challenge in long-term EV energy management, has been addressed from various angles. Li *et al.*[4] introduced fuzzy logic for protecting battery life during V2G operations; nonetheless, their model considered only cycle aging, omitting calendar effects that significantly influence battery health over time. Gao *et al.*[5] adopted stochastic optimization to handle uncertainties in EV availability and grid conditions, but failed to include any real-time correction mechanism to adapt decisions dynamically as new information arrives. Lee *et al.*[6] and Wang *et al.*[7] contributed linear programming models that balance technical and economic objectives, but these approaches oversimplify degradation costs and lack detailed sensitivity analysis, leaving unresolved questions about how price ratios, battery capacities, and household load scales interact in real scenarios.

Simultaneously, advancements in load forecasting and AI integration have offered tools to improve scheduling performance. Lu *et al.*[8] and Huang *et al.*[9] used hybrid long short-term memory (LSTM) networks for electric load and solar irradiance prediction, showing promising accuracy improvements; however, these forecasting models were not tightly coupled with energy trading or V2G control loops, creating a disconnect between prediction outputs and optimization inputs. Reinforcement learning approaches, such as the one explored by Dong *et al.*[10], suggest the potential for intelligent decision-making under uncertainty, yet these methods often overlook explicit battery degradation costs and fail to co-optimize economic and health objectives.

Beyond technical modeling, broader system considerations have also been explored. Kern *et*

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al. [11] examined revenue opportunities from combined V2H and V2G applications, illustrating economic benefitsin intelligent residences but without rigorous modeling of battery stress factors. Qazi*et al.*[12] introduced blockchain-inspired energy trading frameworks that enhance fairness and transparency in EV-grid interactions, though these approaches currently lack mechanisms to ensure battery health is preserved during transactions. Comprehensive reviews of V2X modes by Islam *et al.*[13] highlighted future research directions but remain conceptual without practical implementation guidance.Collectively, the literature demonstrates persistent progress toward integrating forecasting, optimization, and energy trading for EV-enabled smart grids. Nonetheless, a significant gap remains in developing unified frameworks that combine nonlinear aging models, real-time adaptive scheduling, closed-loop forecasting, and economic sensitivity analysis at scale**.** Most existing studies isolate specific components and rely on simplified assumptions, underscoring the need for more holistic solutions that reflect real operational constraints and uncertainties in vehicle availability, load demand, and market dynamics.

Table 1: Comparative analysis of review work

Ref.	**Study (Year)**	**Focus Area**	**Method Used**	**Limitations Identified**	**Research Gap**
1	Popolizio et al. (2025) – arXiv	Vehicle–Home–Grid integration	Nonlinear online optimization + LSTM	Single-user case; limited scalability analysis	Need multi-user/aggregator-level real-time framework
2	Khezri et al. (2024) – IEEE	V2G scheduling with aging	MILP optimization	Offline scheduling assumption	Real-time adaptive scheduling under uncertainty
3	Zhang et al. (2024) – MDPI Energies	V2G battery aging mitigation	Online optimization	Simplified degradation modeling	Nonlinear coupled cycle + calendar aging integration
4	Li et al. (2022) – Elsevier Energy	Battery-protective V2G	Fuzzy logic control	Only cycle aging considered	Comprehensive electrochemical aging model inclusion
5	Gao et al. (2022) – Elsevier	Stochastic EV scheduling	Probabilistic optimization	No real-time correction mechanism	Online correction-based adaptive control
6	Lee et al. (2023) – IFAC	V2G with battery aging	Linear programming	Linear degradation approximation	Nonlinear aging under temperature &SoC stress
7	Wang et al. (2023) – IEEE	Battery degradation-aware charging	Optimization model	Limited sensitivity analysis	Multi-parameter economic sensitivity study
8	Lu et al. (2024) – arXiv	Load forecasting	Hybrid LSTM	Not integrated with energy trading optimization	Closed-loop prediction–optimization framework
9	Huang et al. (2022) – Elsevier	Hybrid deep learning forecasting	Deep learning	Forecasting only; no grid interaction	Forecast-driven energy trading control
10	Dong et al. (2023) – IEEE	Multi-agent V2G	Reinforcement learning	No detailed battery degradation cost modeling	Economic + degradation co-optimization
11	Kern	V2H +	Econom	No	Real

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	et al. (2022) – Elsevier Applied Energy	V2G revenue analysis	ic modeling	nonlinear battery stress modeling	battery stress-based optimization
12	Qazi et al. (2024) – MDPI	Blockchain-based energy trading	Smart grid + EV trading	Focus on fairness; ignores battery health	Battery degradation-aware blockchain trading
13	Islam et al. (2022) – Elsevier	V2X review	Review study	Conceptual, no practical implementation	Real-world real-time implementation models
14	Chung et al. (2022) – IEEE	Charging optimization	Maintenance-focused scheduling	No V2H integration	Unified V2G + V2H + aging optimization

This table gives an overview on research gap in the field of research area, experimental method Used and their limitations.

III. METHODOLOGY

A. System Architecture

The proposed methodology considers a vehicle–home–grid (VHG) integrated system consisting of three main entities:

1. Electric Vehicle (EV)
2. Residential Household
3. Utility Grid

The EV battery functions as a two-way energy storage device that can:

- G2V (grid-to-vehicle) charging
- Vehicles that discharge to the grid (V2G)
- The provision of vehicles to homes (V2H)
- Grid-to-home (G2H) distribution

Under real-time operational restrictions, the system's goal is to minimize overall user costs, which includes both electricity trading and battery degrading costs.

B. Problem Formulation

The overall objective function is defined as:

$$min \sum_{t=1}^{T} (ECC_t + BC_t + S_t)$$

where:

- ECt = Energy cost at time ttt
- BCt = Battery degradation cost
- stt = Slack variable for state-of-charge (SoC) constraint
- TTT = Optimization horizon

Energy Cost Model

Energy cost is calculated as:

$$EC_t = (E_{G2V,t} + E_{G2H,t})P_t - \gamma E_{V2G,t\ Pt}$$

where:

- ptp_tpt = Electricity price
- γ\gammaγ = Price ratio (selling/buying price)

IV. CONCLUSION

This study presented a unified real-time energy management framework for vehicle–home–grid (VHG) integration that simultaneously considers bidirectional energy exchange, nonlinear battery degradation, and adaptive household load forecasting. In contrast to traditional methods that depend on offline scheduling assumptions or simplified aging models, the proposed framework integrates calendar and cycle aging mechanisms within an online optimization environment supported by hybrid LSTM-based load prediction.

The results demonstrate that incorporating nonlinear battery health modeling into V2G and V2H scheduling provides a more realistic estimation of long-term operational costs. While bidirectional charging increases battery utilization, the proposed degradation-aware optimization ensures that economic benefits outweigh additional aging costs under favorable electricity price conditions. Furthermore, the closed-loop adaptive structure effectively manages uncertainty in household consumption by continuously updating predictions and re-optimizing control actions in real time.

Sensitivity analysis confirms that system profitability strongly depends on electricity price ratios, battery capacity, and household load scale. Larger battery capacities offer greater flexibility for grid interaction, particularly under high price differentials, whereas high household demand prioritizes self-consumption benefits through V2H operations. Importantly, even under conservative pricing scenarios, the integrated framework maintains economic advantages compared to unidirectional smart charging.

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Overall, by providing a health-conscious, financially viable, and practically implementable VHG control method, this work enhances the state of the art.

By allowing EVs to operate as active energy nodes while maintaining battery longevity, the suggested method advances the scalable and sustainable incorporation of electric vehicles into the smart grid.

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