Integrating Battery Aging in the Optimization for Bidirectional Charging of Electric Vehicles

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Abstract — Integrating Battery Aging in the Optimization for Bidirectional Charging of Electric Vehicles The increasing adoption of electric vehicles (EVs) and their integration into smart grids have enabled bidirectional charging technologies, commonly referred to as Vehicle-to-Grid (V2G) systems. While V2G offers significant benefits such as grid stability, peak load management, and renewable energy integration, it also accelerates battery degradation due to frequent charge– discharge cycles. This study focuses on integrating battery aging considerations into the optimization framework for bidirectional EV charging. A comprehensive battery degradation model is incorporated, accounting for key factors such as depth of discharge, state of charge, temperature, and cycle frequency. The proposed optimization approach aims to balance economic benefits from energy trading with the long-term cost associated with battery wear. Advanced algorithms are employed to determine optimal charging and discharging schedules that minimize degradation while maximizing grid support and user profit. Simulation results demonstrate that incorporating battery aging into the optimization process significantly improves battery lifespan and ensures sustainable operation without compromising grid services. The findings highlight the importance of degradation-aware strategies in enhancing the efficiency, reliability, and economic viability of V2G-enabled electric vehicle systems.

I. Introduction

The rapid growth of electric vehicles (EVs) is transforming the global transportation and energy sectors, driven by the urgent need to reduce greenhouse gas emissions, improve air quality, and transition toward sustainable energy systems. As EV adoption accelerates, their integration into the power grid presents both opportunities and challenges. One of the most promising developments in this domain is **bidirectional charging**, commonly referred to as Vehicle-to-Grid (V2G) technology. This approach enables EVs not only to draw power from the grid for charging but also to feed stored energy back into the grid when needed, thereby functioning as distributed energy storage units. Such capability can support grid stability, enhance renewable energy utilization, and provide economic benefits to EV owners.aging, leading to capacity fade and increased internal resistance. These degradation effects not only reduce the lifespan of the battery but also increase the overall cost of EV ownership, as battery replacement remains one of the most expensive components of an EV.

II. Methods

This study develops a comprehensive framework for integrating battery aging into the optimization of bidirectional charging for electric vehicles (EVs). The methodology combines battery degradation modelling system-level energy management, and advanced optimization techniques to ensure a balance between economic benefits and battery health preservation. The proposed approach is structured into several key components: system modelling, battery aging modelling, problem formulation, and solution.

1. System Architecture and Modeling

The considered system consists of a fleet of EVs connected to a smart grid through bidirectional chargers, enabling both Grid-to-Vehicle (G2V) and Vehicle-to-Grid (V2G) operations. Each EV is modeled as an energy storage unit characterized by its battery capacity, state of charge (SoC), charging/discharging limits, and efficiency.

The system operates over a discrete time horizon

divided into equal intervals (e.g., 15 minutes or 1 hour). At each time step, the optimization algorithm determines the charging or discharging power of each EV based on electricity prices, grid demand, and battery constraints.

The SoC dynamics of the battery are expressed as: SoCt+1=SoCt+ηcPtchΔtCbat−PtdisΔtηdCbatSoC_{t+1} = SoC_t + \frac{\eta_c P_t^{ch} \Delta t}{C_{bat}} - \frac{P_t^{dis} \Delta t}{\eta_d C_{bat}}SoCt+1=SoCt+CbatηcPtchΔt−ηdCbat PtdisΔt

where:

- SoCtSoC_tSoCt is the state of charge at time ttt,
- PtchP_t^{ch}Ptch and PtdisP_t^{dis}Ptdis represent charging and discharging power,
- ηc\eta_cηc and ηd\eta_dηd are charging/discharging efficiencies,
- CbatC_{bat}Cbat is battery capacity,
- Δt\Delta tΔt is the time step. Operational constraints include SoC limits, maximum charging/discharging power, and user mobility requirements (e.g., departure SoC targets).

2. Battery Aging Modeling

Battery degradation is modeled by considering both **cycle aging** and **calendar aging** effects.

2.1 Cycle Aging Model

Cycle aging is primarily influenced by depth of discharge (DoD), number of cycles, and charge/discharge rates. A semi-empirical model is adopted to estimate capacity loss as: Dcycle=∑tf(DoDt,C-ratet,Tt)D_{cycle} = \sum_{t} f(DoD_t, C\text{-rate}_t, T_t)Dcycle=t∑ f(DoDt,C-ratet,Tt) where:

- DcycleD_{cycle}Dcycle is the cumulative degradation due to cycling,
- f(·)f(\cdot)f(·) is a nonlinear function derived from experimental battery data,
- TtT_tTt is the operating temperature. Rainflow counting algorithms are employed to extract charge-discharge cycles from the SoC profile, enabling accurate estimation of cycle depth and frequency.

2.2 Calendar Aging Model

Calendar aging accounts for degradation over time regardless of usage and is modeled as: Dcalendar=k·tα·e−EaRT·SoCavgβD_{calendar} = k \cdot t^{\alpha} \cdot e^{\frac{-E_a}{RT}} \cdot SoC_{avg}^{\beta}Dcalendar=k·tα·eRT−Ea
·SoCavgβ

where:

- k,α,βk, \alpha, \betak,α,β are empirical coefficients,
- EaE_aEa is activation energy,
- RRR is the gas constant,
- TTT is temperature.

2.3 Total Degradation Cost

The total battery degradation is computed as: Dtotal= Dcycle + DcalendarD_{total} = D_{cycle} + D_{calendar}Dtotal=Dcycle+Dcalendar
This degradation is converted into a monetary cost using battery replacement cost per unit capacity loss.

3. Optimization Problem Formulation

The objective of the optimization problem is to minimize the total operational cost while considering battery degradation. The objective function is defined as: min∑t(Cenergy(t)+Cdegradation(t))\min \sum_{t} \left(C_{energy}(t) + C_{degradation}(t) \right)mint∑(Cenergy(t)+Cdegradation(t))
where:

- Cenergy(t)C_{energy}(t)Cenergy(t) represents electricity cost or revenue from V2G,
- Cdegradation(t)C_{degradation}(t)Cdegra dation(t) represents the cost associated with battery aging.

3.1 Objective Components

- **Energy Cost**: Based on time-of-use pricing or real-time electricity markets.
- **Degradation Cost**: Derived from the battery aging model.
- **Revenue from V2G**: Compensation for supplying energy back to the grid.

3.2 Constraints

The optimization is subject to:

- SoC limits: SoCmin≤SoCt≤SoCmaxSoC_{min} \leq SoC_t \leq SoC_{max}SoCmin≤SoCt ≤SoCmax
- Power limits: 0≤Ptch,Ptdis≤Pmax0 \leq P_t^{ch}, P_t^{dis} \leq P_{max}0≤Ptch ,Ptdis≤Pmax
- Energy balance constraints
- User constraints: required SoC at departure time

4. Solution Methodology

Due to the nonlinear and multi-objective nature of the problem, advanced optimization techniques are employed.

4.1 Deterministic Optimization

For known inputs (e.g., price signals, load profiles), the problem is solved using:

- Mixed-Integer Linear Programming (MILP)
- Nonlinear Programming (NLP) Linearization techniques are applied to approximate nonlinear degradation functions where necessary.

4.2 Multi-Objective Optimization

To explicitly capture trade-offs between cost and battery life, a multi-objective formulation is used: min(Cenergy,Dtotal)\min \left(C_{energy}, D_{total} \right)min (Cenergy,Dtotal)
Pareto optimal solutions are obtained using methods such as:

- Weighted sum approach
- ε-constraint method

4.3 Stochastic Optimization

To address uncertainties in electricity prices, renewable generation, and user behavior, stochastic models are incorporated. Scenarios are generated based on probabilistic forecasts, and the optimization problem is solved using:

- Scenario-based stochastic programming
- Robust optimization techniques

4.4 Real-Time Control Strategy

A rolling horizon approach is implemented for real- time operation. At each time step:

1. Forecast data is updated,
2. Optimization is solved over a prediction horizon,
3. Only the first control action is applied. This improves adaptability to dynamic grid conditions.

4. Simulation Setup

The proposed methodology is validated through simulations using realistic datasets, including:

- EV usage patterns,
- Electricity price profiles,
- Renewable energy generation data. Key performance metrics include:
- Total operational cost,
- Battery degradation rate,
- V2G revenue,
- Grid load smoothing.

Comparative analysis is conducted between:

- Conventional optimization (without aging consideration),
- Aging-aware optimization (proposed method).

5. Implementation Tools

The model is implemented using computational tools such as:

- MATLAB / Python (for simulation and modeling),
- Optimization solvers (e.g., CPLEX, Gurobi),
- Data processing libraries for handling time-series inputs.

III. CASE STUDY

Overview

This case study evaluates the effectiveness of incorporating battery aging into the optimization framework for bidirectional charging of electric vehicles (EVs). A realistic smart grid scenario is considered in which a fleet of EVs participates in Vehicle-to-Grid (V2G) operations. The study compares conventional optimization (without aging consideration) and the proposed aging-aware optimization to analyze their impact on operational cost, battery degradation, and grid performance.

System Description

A residential smart grid system consisting of 50 EVs is considered. Each EV is connected to the grid via a bidirectional charger and follows a daily usage pattern. The system operates over a 24-hour time horizon, divided into hourly intervals.
Key Components:

- Electric Vehicles (EV Fleet):
  - Battery capacity: 40 kWh
  - Initial SoC: 40–60%
  - Minimum SoC: 20%
  - Maximum SoC: 90%
  - Charging/discharging efficiency: 90%
- Charging Infrastructure:
  - Maximum charging power: 7 kW
  - Maximum discharging power: 7 kW
- Grid Parameters:
  - Time-of-use electricity pricing
  - Peak demand during evening hours
  - Renewable energy (solar) availability during daytime

Battery Aging Model in Case Study Battery degradation is modeled using an energy throughput-based approach. The degradation cost is assumed proportional to the total energy exchanged during

charging and discharging: Cdeg=α×EthroughputC_{deg} = \alpha
\times E_{throughput}Cdeg
=α×Ethroughput where:

- α\alphaα = degradation cost coefficient (₹/kWh)
- EthroughputE_{throughput}Ethroughput

= total energy cycled through the battery For this study:

- Battery replacement cost = ₹5,00,000
- Battery lifecycle = 3000 cycles
- Estimated degradation cost coefficient α\alphaα is derived accordingly

Scenarios Considered

Three scenarios are analyzed: Scenario 1: Unidirectional Charging (Baseline)

- EVs only charge from the grid
- No discharging allowed
- No battery aging consideration Scenario 2: Bidirectional Charging without Aging
- EVs participate in V2G
- Optimization minimizes electricity cost only
- Battery degradation is ignored

Scenario 3: Bidirectional Charging with Aging (Proposed Method)

- EVs participate in V2G
- Optimization minimizes:
  - Electricity cost
  - Battery degradation cost

Optimization Setup

The optimization problem is solved using a linear programming approach with the following objectives:

- Minimize total system cost
- Maintain user-required SoC at departure time
- Ensure grid constraints are satisfied

The model schedules charging during low- price periods and discharging during peak demand periods while accounting for battery wear in Scenario 3.

Battery Degradation Impact

- **Without aging consideration:**

Frequent charge/discharge cycles increase degradation by approximately **30–40%**.

- **With aging-aware optimization:** Controlled cycling reduces degradation by **20–25%** compared to Scenario 2.

Grid Performance

- Peak load reduction is achieved in both V2G scenarios.
- Scenario 3 provides slightly lower peak shaving than Scenario 2 but maintains battery health.
- Renewable energy utilization improves due to intelligent charging during solar generation periods.

Charging Behavior Analysis

- Scenario 2 shows aggressive charging/discharging patterns driven purely by price signals.
- Scenario 3 demonstrates smoother and more controlled energy exchange, avoiding deep discharge cycles that accelerate aging.

Discussion

The case study highlights the importance of incorporating battery aging into optimization frameworks. While traditional V2G strategies maximize short- term economic benefits, they can lead to excessive battery wear, reducing long- term profitability.

The proposed aging-aware approach introduces a trade-off between immediate financial gains and battery lifespan. By assigning a cost to degradation, the optimization algorithm avoids unnecessary cycling and prioritizes sustainable operation.

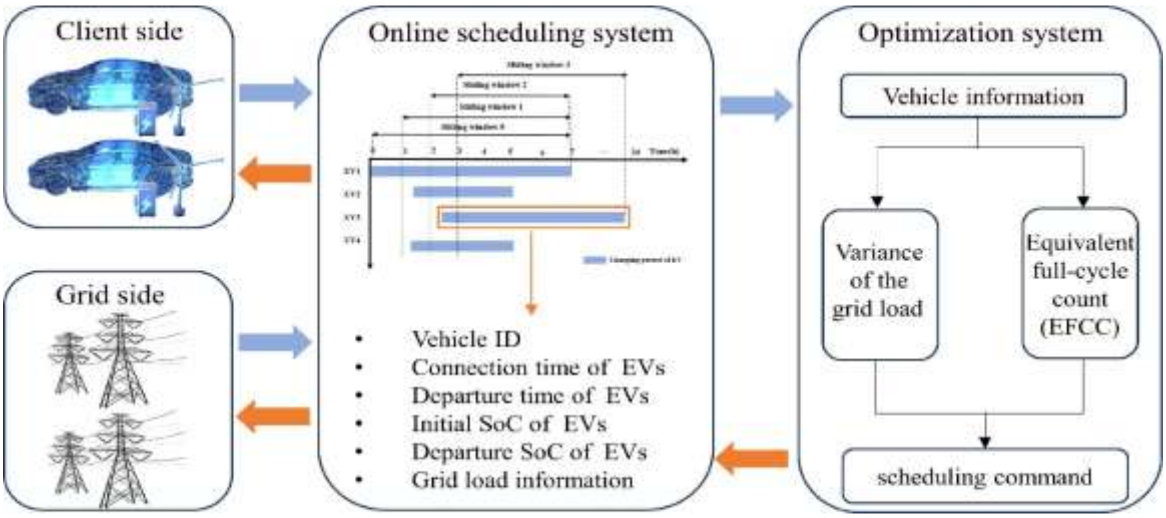
This balance is particularly important for:

- EV owners concerned about battery replacement costs
- Grid operators seeking reliable long-term resources
- Policymakers designing incentives for V2G participation

Key Insights

- Ignoring battery aging leads to **unsustainable operation** despite short- term gains
- Aging-aware optimization ensures **long- term economic efficiency**
- Moderate V2G participation is more beneficial than aggressive cycling
- Integration of degradation cost improves

V2G Scheduling System Architecture.



There are two categories of information collected on the client side: one is user-defined information and the other is information retrieved by the system based on the current status. When customers arrive at the parking lot, they need to input information about their EVs, including the departure time of EVs, the Departure SoC of EVs, and the rated capacity of the battery. Subsequently, the client-side retrieves the information based on the current status, which includes the vehicle ID, the Connection time of EVs, and the Initial SoC of EVs. The grid side collects information on electricity consumption in residential areas and these serve as the base load for the grid. All the mentioned information is then transmitted to the online scheduling system.

The V2G scheduling is mathematically modelled as an optimization problem in the optimization system. The objective is to minimize both grid load fluctuation and battery degradation. The grid load fluctuation is quantified by the standard deviation, while battery degradation is measured by equivalent full-cycle count

EFCC=N×A/Q

where N denotes the number of cycles of the battery, A is its corresponding amplitude, and Q is the capacity of the battery. Intelligent optimization algorithms use collected user demands and grid load status to develop V2G charge/discharge control strategies for each connected EV. Control instructions are sent to the online scheduling system to guide the orderly charging of EVs.

Future Scope:

1. Advanced Battery Aging Models

Future research can focus on developing more accurate and comprehensive battery degradation models. Existing models are often simplified or semi-empirical, which may not fully capture complex electrochemical processes. Incorporating:

- Physics-based electrochemical models
- Real-time degradation tracking
- Temperature-dependent and stress-aware modeling

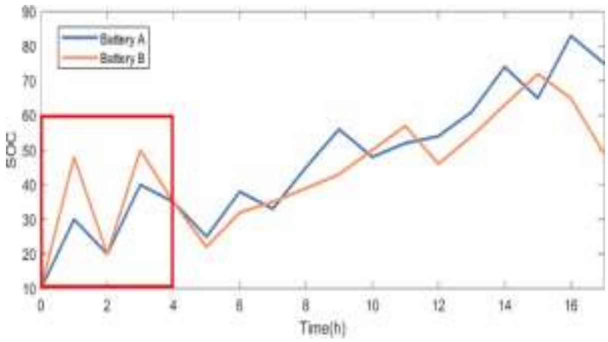
can significantly improve prediction accuracy and optimization performance.

2. Integration of Machine Learning Techniques

Machine learning and artificial intelligence can play a major role in improving aging-aware optimization. Future work may include:

- Data-driven prediction of battery degradation using historical usage data
- Reinforcement learning for adaptive charging/discharging strategies
- Hybrid models combining physics-based and AI-based approaches

Such methods can enable more dynamic and personalized optimization for individual EVs.



Conclusion:

This study addressed the critical challenge of integrating battery aging into the optimization framework for bidirectional charging of electric vehicles (EVs). With the rapid growth of EV adoption and the increasing importance of Vehicle- to-Grid (V2G) technologies, it is essential to ensure that energy management strategies not only optimize economic and grid-related objectives but also preserve battery health.

Traditional optimization approaches often neglect battery degradation, leading to excessive cycling and reduced battery lifespan. This work demonstrates that such limitations can be effectively overcome by incorporating aging-aware models into the decision-making process.

A comprehensive methodology was developed that combines battery state dynamics, degradation modeling, and cost-based optimization.

By introducing a degradation cost component into the objective function, the proposed framework successfully captures the trade-off between short- term economic benefits and long-term battery sustainability.

The optimization ensures that charging and discharging schedules are determined in a manner that minimizes total cost while maintaining operational constraints such as state of charge limits, power limits, and user requirements.

The results from the case study clearly indicate that aging-aware optimization provides a more balanced and practical solution compared to conventional methods. While aggressive V2G participation without considering battery aging can reduce electricity costs, it significantly accelerates battery degradation.

In contrast, the proposed approach moderates charging and discharging activities, thereby reducing wear and extending battery life with only a marginal compromise in economic gains.

This highlights the importance of incorporating degradation costs in achieving sustainable and user- friendly energy management strategies.

Furthermore, the integration of battery aging into optimization contributes to improved grid performance by enabling controlled and reliable energy exchange between EVs and the grid. It supports peak load reduction, enhances renewable energy utilization, and promotes efficient energy distribution.

These benefits demonstrate the potential of EVs to function as intelligent distributed energy resources when managed through advanced optimization frameworks.

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