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A Sustainable V2G Optimization Strategy Balancing User Profit, Battery Life, and Grid Support

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ABSTRACT
With the development of V2G (Vehicle-to-Grid) technology, electric vehicles have shown great potential in enhancing grid resilience and energy utilization efficiency. Addressing the coordination challenges between user benefits, battery lifespan, and grid support objectives in existing strategies, this paper proposes a sustainable V2G optimization strategy and constructs a multi-objective optimization model encompassing four dimensions: economic viability, battery health, grid regulation, and operational stability. To address the inherent conflicts among objectives, an enhanced NSGA-II algorithm is designed to improve the diversity and feasibility of solutions. Simulation results based on a typical load scenario from the PJM-AECO grid demonstrate that the proposed strategy significantly increases user net benefits, reduces battery degradation, and effectively reduces grid peak-to-valley differences, validating its adaptability and engineering application potential across multiple scenarios.

KEYWORDS
Vehicle-to-grid; Multi-objective optimization; NSGA-II algorithm; Battery health; Peak-valley difference; Sustainability

1 Introduction

With the rapid development of electric vehicles (EVs) in the context of the energy transition, their large-scale grid integration has posed new challenges and requirements for the operation and control mechanisms of power systems. Systematic research on V2G (Vehicle-to-Grid) scheduling strategies is gradually becoming an important topic in the field of energy and transportation integration [1]. V2G technology, by endowing electric vehicles with dual "source-load" attributes, can achieve peak shaving, frequency regulation assistance, and facilitate the integration of renewable energy, creating a win-win situation for the grid and users. However, the promotion of this technology still faces numerous challenges, particularly in terms of significant battery life degradation and difficulties in coordinating charging and discharging behavior [2].

Regarding V2G optimization scheduling issues, previous studies have developed various optimization models centered on objectives such as user costs, grid load balancing, and revenue enhancement, and have continuously improved in terms of prediction accuracy and infrastructure layout [3-5]. Additionally, some studies have adopted a two-layer structure, integrating user response behavior with grid scheduling plans to enhance the coordination and effectiveness of strategies [6]. However, overall, most studies have not incorporated battery life degradation as a quantifiable long-term cost into the optimization framework, making it difficult to accurately assess the impact of V2G interactions on battery health, thereby affecting the sustainability and engineering applicability of the strategy.

Previous studies have attempted to address this issue by introducing metrics such as average discharge rate and dynamic discharge loss costs to reduce user costs while suppressing battery life loss and improving the overall performance of scheduling strategies [7]. However, such methods mostly adopt sequential optimization frameworks, which only reflect scheduling results under specific objective preferences and are unable to systematically demonstrate the complex trade-off relationship between users, the power grid, and batteries. The flexibility and adaptability of these strategies still need to be improved.

To address this research gap, this paper proposes a multi-objective optimization-based V2G collaborative scheduling strategy to systematically reveal and balance the complex trade-off relationships among users, the grid, and batteries.

2 Problem description and mathematical modeling

2.1 System framework and problem description

This paper aims to address the optimization scheduling problem for electric vehicle (EV) fleets, seeking a balance among three conflicting objectives: user economics, battery health, and grid support. The problem is formulated as a multi-objective optimization model, with the core objective being to determine an optimal charging and discharging power sequence over a 24-hour dimension (decision variables) $x = [x_1, x_2, \cdots, x_{24}]$ to minimize the comprehensive objective function vector F(x). The decision variable x_t in the sequence represents the charging/discharging power (in kW) for time slot t, where x_t > 0 indicates charging and x_t < 0 indicates discharging.

To construct the simulation environment, this study uses real-world grid load data from the AECO region of the U.S. PJM power market, scaled by a factor of 400 to simulate a community-level grid. This scaling factor was chosen to ensure that the simulated community's load volume is on the same order of magnitude as the V2G regulation potential of an 80-vehicle EV fleet, thereby ensuring the validity of the study.

2.2 Multi-objective optimization functions

To construct a comprehensive evaluation system, this study quantified four optimization objectives that are inherently conflicting.

(1) Economic benefit objective (f1). This objective aims to minimize the total daily operating cost for users, i. e., maximize net revenue. Its mathematical expression is:

$$minf_1 = \sum_{t=1}^{24} x_t \cdot price_t$$

(2) Battery health degradation objective (f2). To accurately assess the impact of V2G on battery life, this study employs a nonlinear battery cycle life degradation model that considers both the depth of discharge (DOD) and the starting state of charge (SOC) [8]. To accommodate the high-frequency evaluation required by the optimization algorithm, the model is simplified into a discrete time-step incremental degradation model. This model first calculates the equivalent degradation of a "micro-cycle" at a single time step t:

$$n_{eq,t} = \left(\frac{DOD_t}{DOD_{ref}}\right)^{\lambda_1} \cdot e^{\lambda_2\left(SOC_t - SOC_{ref}\right)}$$

where DOD_t is the net change in SOC at time step t, and SOC_t is the initial state of charge. The model parameters λ_1=1.98,λ_2 =2.79,DOD_{ref}=0.8 and SOC_{ref}=0.8 are adopted from the reference literature [8].

Subsequently, the total degradation cost is obtained by summing all micro-cycle losses and monetizing them:

$$minf_2 = C_{loss} = \frac{\sum_i n_{eq,i}}{N_0} \cdot C_{bat}$$

Here, N_0 is the battery's rated cycle life (1500 cycles), and C_{bat} is the battery replacement cost.

(3) Grid support objective (f3). This objective aims to maximize the reduction in the grid's peak-to-valley difference (PVD) resulting from EV participation. It is formulated as a minimization problem:

$$minf_3 = -\left(PVD_{\text{original}} - PVD_{\text{optimized}}\right)$$

(4) Operational stability objective (f4). This objective ensures the vehicle's end-of-day state of charge (SOC) returns to a target value while also penalizing large fluctuations in the SOC trajectory. It improves the strategy's practicality and is formulated using a composite function:

$$minf_4 = \alpha \cdot \left(SOC_{24} - SOC_{target}\right)^2 + \beta \cdot var\left(SOC_{1..24}\right)$$

where the weighting coefficients are set to α=10 and β=1 to strongly penalize deviations from the final target SOC while moderately suppressing trajectory fluctuations.

2.3 Key constraints

To ensure the physical feasibility of all scheduling strategies, the model must adhere to a series of strict constraints, primarily including SOC health range constraints (10%–90%)[7] and vehicle power constraints (-11.5 kW to +11.5 kW)[9]. To address the complex SOC dynamic constraints, this study employs an efficient penalty function method, whereby a large penalty value is applied to the objective function of the solution once the SOC trajectory exceeds the bounds, causing it to be naturally eliminated during evolution.

3 Solution algorithm and enhancement strategies

To solve this multi-objective optimization problem, this study uses the NSGA-II algorithm implemented in the MATLAB gamultiobj toolbox as the basic framework and designs and integrates the following enhancement strategies to improve the solution performance.

(1) Heuristic population initialization. To accelerate algorithm convergence, a high-quality solution generated based on a “low-valley charging, high-peak discharging” greedy logic is injected into the initial population (population size N=400) as a “seed” to guide the algorithm toward rapidly exploring the region of high-quality solutions.

(2) Preference-guided search. To incorporate strategy preferences into the search, the algorithm dynamically scales the normalized objective functions based on a predefined weight vector W during optimization. This guides the evolutionary process toward specific regions of the Pareto front.

(3) Hybrid constraint-objective guidance. For the “battery-first” strategy, a hybrid guidance method combining

objective functions with constraint boundaries is employed. By assigning the highest weight to the battery degradation objective (f2) while imposing stricter charge/discharge power constraints, dual guidance is achieved.

4 Simulation and results

4.1 Simulation setup

To validate the effectiveness and adaptability of the proposed collaborative optimization strategy, the simulation scenarios and parameter settings are as follows:

(1) Simulation scenarios: Two types of experiments were designed: "Typical Day Deep Analysis" and "Multi-Scenario Adaptability Validation." The typical day selected was April 1, 2025; Adaptability validation covered different seasons and weekend/weekday modes. [10]

(2) Baseline strategies: To compare performance, two non-V2G baseline charging modes were defined:

a) Immediate unordered charging: This strategy simulates the most common "charge upon arrival" habit, the vehicle returns home at 19:00 [11] and charges at a power of 7 kW [12] from an initial SOC of 50% (a typical setting representing significant charging demand) to the daily charging limit of 80% [13]

b) Simple timed charging: Simulates users setting the vehicle to charge only during the lowest-cost off-peak hours at midnight to save costs, with the same charging task and power as above.

(3) Basis for key parameters: To ensure the model's realism, all key parameters are based on industry standards and authoritative literature. The battery replacement cost is set to $130/kWh, which is used as a reasonable approximation of the 2023 average price ($139/kWh) reported by BNEF [14]. The typical battery capacity is selected as 60 kWh, a value representative of the specifications of current mainstream mid-size electric vehicles [15, 16].

(4) Parameter and strategy summary: Detailed simulation parameters are shown in Table 1. The objective weights for the V2G comparison strategies (economy-priority, grid-priority, battery-priority) used in the Pareto analysis are defined in Table 2.

Table 1 Main simulation parameters

Parameter	Parameter Name	Value / Unit
EV Parameters	Battery Capacity	60 kWh [15-16]
	Maximum SOC	0.9[7,17]
	Charging/Discharging Power Limit	11.5 kW [9]
	Fleet Size	80
Battery Degradation Model	Replacement Cost	130 $/kWh [14]
	Rated Cycle Life	1500[8]
Optimization Algorithm	Population Size	400
	Maximum Iterations	500

Table 2 Objective weights for v2g comparison strategies

Strategy Name	W_{f1} (Economic)	W_{f2}(Battery)	W_{f3} (Grid)	W_{f4}(Stability)
Balanced Strategy	1.5	2.5	1	1
Economic-first	5	0.5	1	0.8
Grid-first	1	0.5	5	0.8
Battery-first	1.5	5	1.5	1

4.2 Simulation results and analysis

4.2.1 Performance quantification and trade-off analysis

The comprehensive performance evaluation results of the proposed "balanced strategy" are shown in Table 3. Compared with the "Immediate Unordered Charging" baseline, this strategy transforms the user's daily cost from $1.05 to a net profit of $1.43, representing a relative benefit improvement of 235.75%. Additionally, the grid peak-to-valley difference decreases from 1, 438.14 kW to 900.01 kW, a reduction of 37.42%. Furthermore, compared to the purely economically oriented "aggressive strategy," daily battery degradation is reduced by 25.34%.

To reveal the trade-off relationships among the objectives, Figure 1 shows the distribution of different preference

Table 3 Performance comparison of the 'balanced strategy' vs. baseline strategies

Assessment Dimension	Comparison Baseline	Baseline Performance	Proposed Strategy's Performance	Optimization Effect
User Economic Benefit	Immediate Unordered Charging	Net Benefit:-$1.05	Net Benefit: $1.43	235.75% Improvement
	Simple Timed Charging	Net Benefit:-$0.45	(Same as above)	415.36% Improvement
Grid Load Balancing	Original Grid Load	Peak-to-Valley Difference: 1438.14 kW	PVD (post-optimization): 900.01 kW	37.42% Reduction
Battery Health Protection	Aggressive Strategy (Economics-driven)	Daily Degradation Cost: $0.7227	Daily Degradation Cost: $0.5396	25.34% Reduction

strategies in the objective space. The strategy points form a Pareto optimal frontier, indicating that there is no single optimal solution and highlighting the necessity of multi-objective optimization. Among these, the 'Economic-first' strategy achieves high profitability at the cost of high battery degradation, while the 'Grid-first' strategy sacrifices profitability to maximize its grid contribution. In contrast, the 'Balanced Strategy' achieves an effective balance among the objectives, avoiding the performance shortcomings of extreme strategies.

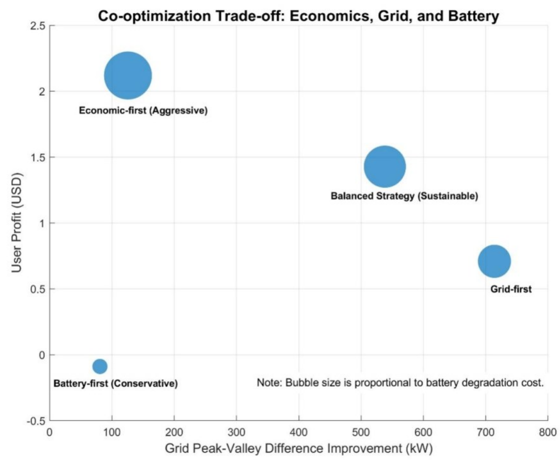

Figure 1 Co-optimization trade-off among economics, grid support, and battery health

4.2.2 Comparison of behavioral patterns for key strategies

Figure 2 compares the dynamic behavior of different strategies to explain their performance differences. The results show that the 'Economic-first' and 'Grid-first' strategies exhibit high-frequency, large-amplitude charging and discharging behavior, leading to significant fluctuations in SOC. In contrast, the 'Battery-first' strategy maintains SOC stability by minimizing V2G interaction, but its optimization effect on the grid is limited. The 'Balanced Strategy' keeps charging/discharging power and SOC fluctuations within moderate ranges. Its performance does not stem from the optimization of a single objective but rather from an effective balance of conflicting multi-objective goals.

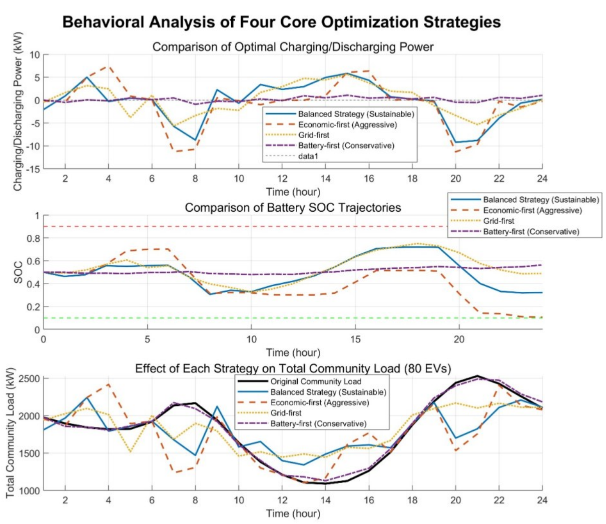

Figure 2 Behavioral analysis of four core optimization strategies

4.2.3 Analysis of strategy adaptability and generality

To validate the adaptability of the “balanced strategy,” Figure 3 shows its charging and discharging behavior in relation to electricity prices. The strategy follows the economic principle of “buy low, sell high” and integrates a quantitative assessment of battery degradation costs into the algorithm. Therefore, when the potential gains from price differentials are insufficient to offset battery degradation costs, the strategy selectively abandons arbitrage opportunities, demonstrating the model's intelligent decision-making capabilities.

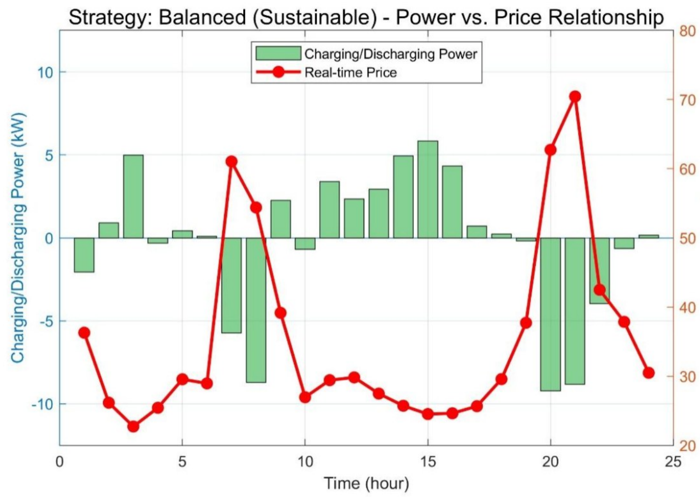

Figure 3 Strategy: balanced (sustainable) - power vs. price relationship

To verify the generality of the strategy, Figure 4 shows its performance in multiple different scenarios. The results indicate that the strategy can consistently achieve the optimization objectives in all test scenarios. This proves that the strategy does not adopt a fixed behavior pattern, but rather dynamically adjusts its scheduling behavior based on external conditions (such as electricity prices and load patterns), thereby maintaining its effectiveness in different environments.

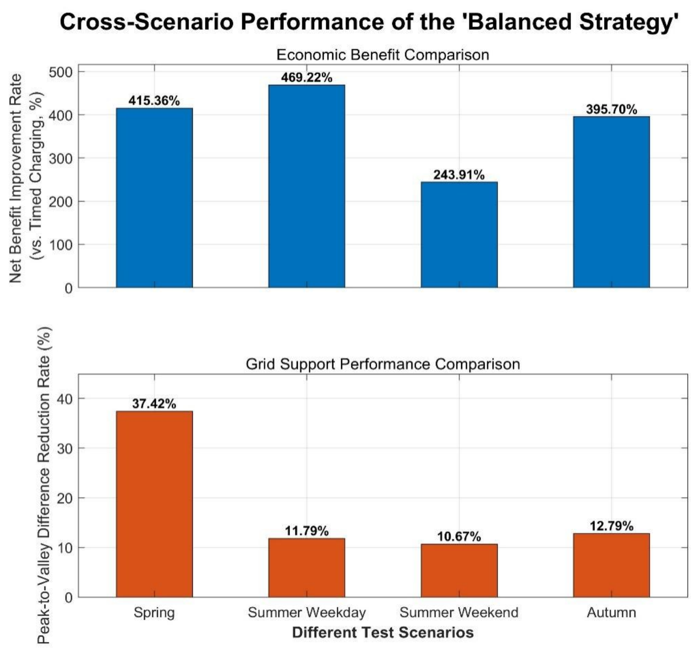

Figure 4 Cross-scenario performance of the 'balanced strategy'

5 Conclusion

This paper addresses the coordination challenges between user benefits, battery lifespan, and grid support in electric vehicle V2G (Vehicle-to-Grid) applications, proposing a sustainable collaborative scheduling strategy based on multi-objective optimization. The strategy constructs a multi-objective optimization model encompassing four dimensions: user economics, battery health, grid regulation capacity, and operational stability. An enhanced NSGA-II algorithm, incorporating heuristic initialization and preference-guided mechanisms, is designed to solve the model. Simulation experiments based on the PJM-AECO typical load scenario validate the effectiveness and adaptability of the proposed strategy. The main conclusions are as follows:

(1) Simulation results indicate that the proposed "balanced strategy" demonstrates excellent performance across users, the grid, and batteries. While ensuring users achieve stable economic benefits, the strategy significantly reduces the peak-to-valley difference in system load and effectively suppresses excessive battery life degradation, showcasing the

potential of multi-objective optimization methods for achieving collaborative control in V2G scheduling.

(2) Compared to traditional single-objective-oriented strategies, this strategy achieves an effective balance among multiple conflicting objectives, avoiding performance losses caused by trade-offs between objectives. Additionally, it maintains stable performance across various typical daily load scenarios, demonstrating strong generalization capabilities and engineering adaptability, and holds potential for being generalized as a universal V2G scheduling scheme.

(3) This study employs deterministic modeling based on historical data and does not account for external environmental uncertainties. Future research could incorporate stochastic modeling methods to integrate dynamic changes in load, electricity prices, and user travel behavior into the scheduling framework, thereby enhancing the strategy's robustness and adaptability in real-world operations.

(4) The current battery life model employed in this study remains simplified in terms of modeling dimensions and does not yet account for critical factors such as temperature and charge/discharge rate (C-rate). Future research could further develop more refined battery degradation models and explore collaborative optimization strategies for additional ancillary service scenarios, such as EV clusters participating in frequency regulation.

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