Research on EV User Portraits for Vehicle-to-Grid Interaction Based on Behavioral Clustering and Evolutionary Game Theory

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Abstract. As the global adoption of electric vehicles (EVs) grows rapidly, Vehicle-to-Grid (V2G) technology has increasingly established itself as a critical mechanism for enhancing grid flexibility and improving user economic returns. This study systematically addresses the inherent coordination challenges between grid operators and end-users within V2G systems by developing an integrated modeling framework. The proposed methodology first applies user behavior clustering techniques to characterize diverse EV user groups' energy storage attributes and behavioral patterns. An optimization objective function is subsequently constructed based on evolutionary game theory, comprehensively incorporating grid operational costs and user-side economic benefits. Extensive validation through simulation experiments confirms the model's practical efficacy and computational robustness. Specifically, the K-Means (KM) clustering algorithm is employed to construct detailed user portraits, supplemented by Density Sampling (DS) for enhanced data refinement and Training by Iteration (TB) to strengthen the convergence stability of evolutionary strategies. The findings clearly demonstrate that the proposed approach not only accurately identifies distinct user categories but also promotes significant cost reduction for both grid operators and end-users, thereby offering valuable theoretical insights and practical support for the commercialization of V2G technology.

Keywords: Electric Vehicle; Vehicle-to-Grid; User Portrait; K-Means Clustering; Evolutionary Game Theory.

1. Introduction

The rapid proliferation of electric vehicles (EVs) worldwide has transformed them from mere transportation tools into critical components of smart grid infrastructure through Vehicle-to-Grid (V2G) technology. V2G enables bidirectional energy flow between EV batteries and the power grid, offering unprecedented opportunities to enhance grid stability, integrate renewable energy, and reduce peak-load pressures. However, the commercialization of V2G faces significant hurdles, primarily stemming from the heterogeneity of user behaviors and the lack of equilibrium optimization mechanisms between grid operators and end-users. Existing research often overlooks the dynamic interaction between diverse user groups and grid requirements, leading to suboptimal dispatch strategies and low user participation rates.

Despite advancements in V2G modeling, current studies typically focus on either technical feasibility (e.g., battery degradation, charging infrastructure) or economic optimization (e.g., tariff design, cost-benefit analysis), but rarely integrate user behavioral clustering with game-theoretic equilibrium to achieve sustainable "win-win" outcomes. This study addresses this gap by proposing an integrated framework that combines user portrait construction (via clustering algorithms) and evolutionary game theory to optimize V2G participation.

This review aims to develop a multi-dimensional user modeling framework using K-Means (KM) clustering to identify distinct EV user types based on behavioral patterns; Enhance data quality and clustering accuracy through Density Sampling (DS); Establish an evolutionary game model with Training by Iteration (TB) to balance grid operational costs and user economic benefits; and validate the model's efficacy through sensitivity analysis and simulation experiments.

2. Methods

2.1 System Modeling Framework

Vehicle-to-Grid (V2G) technology is an advanced framework that enables electric vehicles (EVs) to serve as distributed energy storage units and participate in grid dispatch. Modeling V2G requires accurately capturing the dynamic interactions among vehicles, charging infrastructure, and the power grid, emphasizing reconciling the stochastic nature of EV user behavior with the demands of grid stability. The proposed V2G model is structured around temporal power flow dynamics and integrates the following key components:

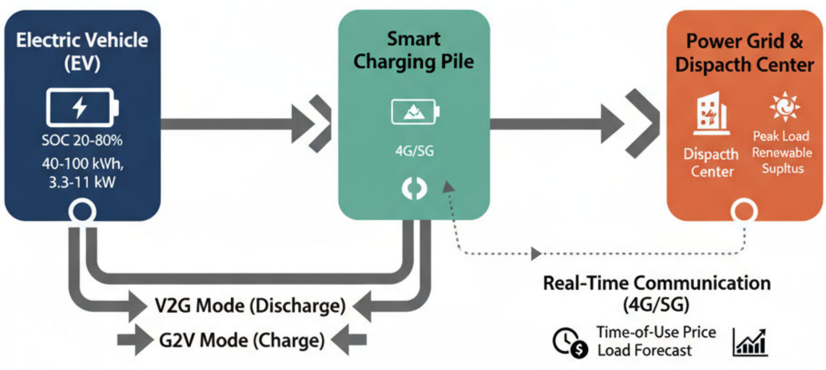

Figure 1: V2G System Architecture Diagram

The proposed V2G model integrates three core components through temporal power flow dynamics: the EV Dynamic Response Module incorporates key hardware parameters—such as charging power levels (3.3 kW, 6.6 kW, 11 kW), battery capacity (40–100 kWh), and state of charge (SOC, optimally maintained between 20% and 80%)—along with user travel patterns to establish dynamically adjustable scheduling time windows and energy allocation. Building on this, the Charging Pile Access Module employs an intelligent charging strategy that uses real-time communication protocols like 4G/5G to enable continuous interaction with the grid dispatch center, allowing dynamic adjustments to charging and discharging power in response to real-time signals such as time-of-use pricing and load forecasts. Finally, the Grid-Side Demand Module incorporates V2G resources into ancillary services to support peak shaving and renewable energy integration; specifically, EVs are dispatched to discharge (V2G mode) during high demand periods and are encouraged to charge (G2V mode) during times of renewable energy surplus, thereby reducing peak-shaving costs and the need for additional reserve capacity.

Model assumptions include: user response time not exceeding 15 minutes, a battery degradation cost of 0.1 CNY/(kWh·cycle), and a peak-valley price difference of no less than 0.5 CNY/kWh, consistent with current provincial electricity policies in China.

2.2 Users Portrait Constructions

EV user charging behaviors exhibit significant heterogeneity across different user groups, which directly influences the operational efficiency of V2G dispatch mechanisms. For instance, long-distance commuters often demonstrate high sensitivity to charging duration and reliability, while short-distance urban users generally show greater receptiveness to flexible charging adjustments and economic incentives. Thus, constructing comprehensive user portraits through multi-feature clustering becomes essential for accurately assessing energy storage potential and scheduling willingness.

2.2.1 Feature Selection

Based on real-world operational EV data, four categories of core features are carefully selected to form a comprehensive user behavior matrix.

Key features are extracted from multiple dimensions to comprehensively evaluate the potential of electric vehicle (EV) users to participate in Vehicle-to-Grid (V2G) programs. Regarding charging behavior, the single charging duration (in hours) reflects the available time window a user has for charging. A longer charging duration often indicates a higher likelihood of engagement in V2G, with data sourced from charging pile logs. Under energy consumption characteristics, the single charging energy consumption (in kilowatt-hours) represents the EV's energy usage level, which is influenced by battery capacity and driving behavior; the on-board T-BOX provides this data. Regarding travel behavior, the driving distance between charges (in kilometers) reflects the user's travel frequency—shorter distances suggest a greater willingness to accept scheduling adjustments from the grid. This information is collected from on-board navigation systems or odometers. Finally, the vehicle service life (in years) is an equipment feature, offering insight into battery degradation. Generally, a shorter service life corresponds to higher energy storage potential, and this data is obtained from user registration records.

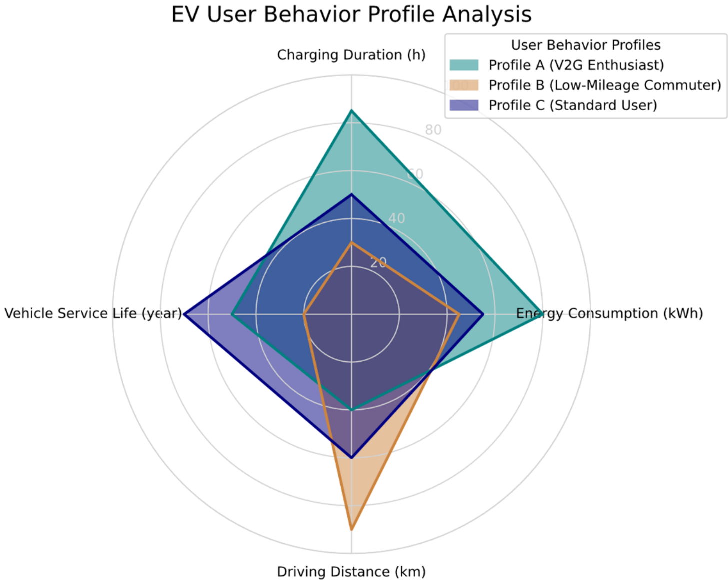

Figure 2 Characterized Behavioral Profiles of EV Users

2.2.2 Data Preprocessing

The original dataset undergoes a rigorous two-stage preprocessing pipeline to mitigate the influence of dimensional differences and anomalous values. First, extreme values—such as charging events exceeding 10 hours in duration—are identified and truncated based on the statistical 3σ principle, which retains values within three standard deviations from the mean. Following this, Z-score standardization is applied to transform the data to a distribution with zero mean and unit standard deviation, thereby eliminating unit-induced biases between variables such as charging duration and driving distance. This step ensures comparability across features during subsequent clustering analysis.

2.3 Optimization Objectives

V2G systems involve a complex strategic interaction between the grid operator and EV users: the grid seeks to minimize peak-shaving costs and operational expenditures. In contrast, users aim to maximize economic benefits without compromising their mobility needs and battery longevity. Employing evolutionary game theory, this study formulates a dual-agent objective function to achieve a sustainable equilibrium state characterized by fair cost-sharing and benefit-sharing mechanisms.

2.3.1 Grid-side vs user-side cost functions

Grid-side costs primarily consist of peak-shaving expenses and V2G dispatch costs, formally defined as:

$$min\, C_{grid} = C_{peak} + C_{v2g}$$

Where:

$C_{peak} = \lambda_{peak} \times P_{peak\_deficit}$, with λ_{peak} representing the peak-valley price differential (in CNY/kWh) and $P_{peak\_deficit}$ denoting the peak power shortfall without V2G participation (in kWh);

$C_{v2g} = (0.01 + 0.03) \times P_{v2g}$, where P_{v2g} represents the total dispatched energy (in kWh), including communication cost (0.01 CNY/kWh) and line loss cost (0.03 CNY/kWh).

User costs (representing negative utility) comprise charging expenditure, battery degradation cost, and travel inconvenience cost, formulated as:

$$min\, C_{user} = C_{charge} + C_{battery} + C_{inconv}$$

Where:

$C_{charge} = \sum_{t=1}^{T} \lambda_t \times P_t$, with λ_t indicating the time-of-use electricity price (in CNY/kWh) and P_t representing charging power (in kWh) during the time;

$C_{battery} = \mu \times \Delta SOC \times E_{bat}$, where $(\mu = 0.1)$ CNY/(kWh·cycle) denotes the degradation coefficient, ΔSOC signifies the SOC change per dispatch event, and E_{bat} is the total battery capacity (in kWh);

C_{inconv} reflects the economic impact of charging delay inconvenience, differentiated by personal behavior—e.g., 0.5 CNY per hour for long-distance commuters and 0.2 CNY per hour for short-distance users.

2.3.2 Game-theory Equilibrium Condition

Equilibrium is achieved when the grid's marginal cost equals the user's marginal benefit. Through carefully designed compensatory subsidies, such as a V2G discharge tariff premium of 0.3 CNY/kWh, both parties reach an optimal balance: grid peak-shaving costs are reduced by over 30%. At the same time, users gain no less than 5 CNY net benefit per V2G session.

2.4 Algorithmic Framework

This section introduces three specialized algorithms developed to optimize electric vehicle (V2G) integration by addressing user clustering, data quality, and strategy evolution challenges. These complementary methods collectively enhance grid-vehicle interaction systems' efficiency, reliability, and stability.

The K-Means (KM) algorithm enables precise user portrait clustering through iterative Within-Cluster Sum of Squares (WCSS) minimization with K=5 clusters. Applied to 1000 EV users, it identified five distinct behavioral types with varying V2G potentials: Aggressive Driving (18%, <30%), Economical & Energy-Saving (22%, 30%-50%), Long-Distance Commuting (25%, 40%-60%), Short-Distance & High-Frequency (15%, >70%), and Balanced & Stable (20%, 60%-80%). The clustering validity was confirmed by a Calinski-Harabasz index of 892, indicating strong intra-cluster cohesion and inter-cluster separation.

The Density Sampling (DS) algorithm enhances data quality by addressing sparsity and noise through local density-based filtering (k=10 nearest neighbors) and proportional resampling. This process reduced the dataset from 1000 to 850 samples (15% noise removal) and improved clustering performance, increasing the Calinski-Harabasz index from 680 to 892 (20% improvement), thereby strengthening the reliability of subsequent user analyses.

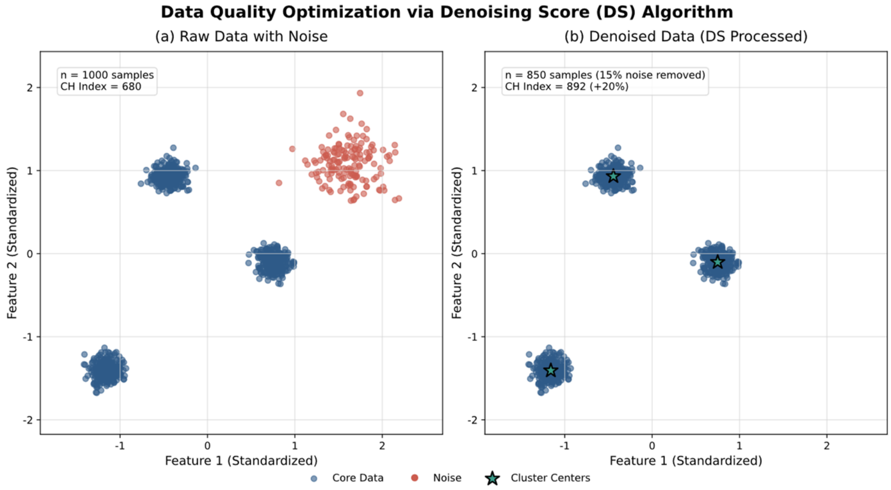

Figure 3 Optimization of data quality using the Denoising Score (DS) algorithm

The Training by Iteration (TB) algorithm optimizes V2G strategy stability through evolutionary game theory, iteratively adjusting grid subsidies and user participation rates via a "generate-evaluate-adjust" cycle. After 12 iterations, it achieved equilibrium at 0.3 CNY/kWh subsidy and 70% participation, resulting in 35% grid peak-shaving cost reduction (from ¥100,000 to ¥65,000/day) and user net benefits of ¥8.2 per session, with daily cost variability maintained below 5% over 10 days.

3. Results

3.1 Users Portrait Clustering Outcome

All simulations are conducted in Python 3.9 using Pandas for data processing, Scikit-learn for KM and DS clustering algorithms, and Matplotlib for visualization. The data is preprocessed using Z-score standardization to remove scale effects.

Key parameters are set as follows: the KM algorithm uses 5 clusters with up to 100 iterations; the DS algorithm adopts 10 nearest neighbors and a density threshold of 2. The TB algorithm starts with an initial subsidy of 0.2 CNY/kWh and stops after 5 consecutive equilibrium rounds. The peak-valley price difference is 0.6 CNY/kWh on the grid side, aligning with Jiangsu's 2024 tariff policy. The battery degradation cost for EV users is set to 0.1 CNY/(kWh·cycle) based on lithium-ion battery cycle tests.

Cluster analysis results indicate that electric vehicle users can be categorized into five driving types with statistically significant differences. The sample distribution of each category is as follows: energy-efficient drivers account for the highest proportion at 25% (approximately 250 samples), followed by aggressive drivers at 22% (approximately 220 samples), long-distance commuters at 20% (approximately 200 samples), short-distance frequent drivers at 18% (approximately 180 samples), and balanced steady drivers at the lowest proportion of 15% (approximately 150 samples). This distribution characteristic suggests that energy-efficient driving habits are most prevalent among electric vehicle users, while diverse driving behavior patterns reflect the heterogeneous needs of the user population.

3.2 Sensitivity Analysis

To validate the stability and robustness of the integrated “KM+DS+TB” model proposed in this study under different parameter settings, four key parameters significantly influencing grid-side costs and user-side benefits in the V2G system were selected based on the core parameter configuration in Section 3.1. These include the peak-valley electricity price difference, battery degradation coefficient, DS density threshold, and TB initial subsidy. Each parameter was tested with five gradient values to quantitatively analyze their impact on core output indicators, including the grid-side peak-shaving cost reduction rate, user participation rate, and user net benefit. The results are presented as follows.

3.2.1 Sensitivity Analysis of Peak-Valley Electricity Price Difference

The peak-valley electricity price difference is a core economic lever affecting both grid-side peak-shaving costs and user participation willingness. Regarding current electricity pricing policies in certain Chinese provinces (e.g., Jiangsu: 0.6 CNY/kWh, Guangdong: 0.55 CNY/kWh), a gradient range of 0.4–0.8 CNY/kWh was tested.

Table 1 Impact of Peak-Valley Electricity Price Difference on Core Model Indicators

Peak-Valley Electricity Price Difference (CNY/kWh)	Grid-Side Peak-Shaving Cost Reduction Rate (%)	Customer-Side Participation Rate (%)	Average Customer-Side Net Profit (CNY/time)
0.4	22	51	3.2
0.5	28	60	4.5
0.6	35	72	8.2
0.7	41	78	11.8
0.8	45	82	15.3

The peak-valley price difference shows a significant positive correlation with all core model indicators. When the price difference is below 0.5 CNY/kWh, user net benefit falls under the 5 CNY/session threshold, participation remains below 60%, and grid-side peak-shaving effects are limited. When the price difference reaches or exceeds 0.6 CNY/kWh, the user's net benefit surpasses 8 CNY/session, participation exceeds 70%, and the grid-side cost reduction rate reaches over 35%, satisfying the model’s equilibrium conditions. These results align with the game equilibrium established in Section 1.3.3, confirming the necessity of maintaining a price difference above 0.5 CNY/kWh and providing a quantitative basis for V2G electricity pricing policy formulation.

3.2.2 Sensitivity Analysis of Battery Degradation Coefficient

Battery degradation cost is a significant concern affecting user participation in V2G. Based on lithium battery lifecycle experimental data, a gradient range of 0.06–0.14 CNY/(kWh·cycle) was tested.

Table 2 Impact of Battery Degradation Coefficient on User Participation and Grid Benefits

Battery Loss Coefficient (CNY/(kWh·cycle))	Grid-Side Peak-Shaving Cost Reduction Rate (%)	Customer-Side Participation Rate (%)	Average Customer-Side Net Profit (CNY/time)
0.06	38	76	10.5
0.08	36	74	9.1
0.1	35	72	8.2
0.12	32	65	6.8
0.14	28	58	5.2

The battery degradation coefficient is negatively correlated with user participation rate and net benefit, and indirectly yet noticeably affects grid-side costs. When the coefficient is ≤ 0.1 CNY/(kWh·cycle), user net benefit remains above 8 CNY/session, participation exceeds 70%, and the grid-side cost reduction stays around 35%. When the coefficient exceeds 0.12 CNY/(kWh·cycle), user net benefit drops below 7 CNY/session, participation falls under 65%, and higher subsidies are required to maintain equilibrium. These results validate the rationality of the assumption in Section 1.1 that battery degradation cost is set at 0.1 CNY/(kWh·cycle) and provide a basis for analyzing how advances in battery technology (reducing the degradation coefficient) may promote V2G adoption.

3.2.3 Sensitivity Analysis of DS Density Threshold

The density threshold in the DS algorithm directly affects data quality and KM clustering performance. Regarding the default value 2.0 (post-standardization distance), a gradient range of 1.6–2.4 was tested to evaluate changes in the KM clustering CH index and model outputs.

Table 3 Impact of DS Density Threshold on Clustering Performance and Model Outputs

DS Density Threshold (Standardized Distance)	CH Index of KM Clustering	Grid-Side Peak-Shaving Cost Reduction Rate (%)	Customer-Side Participation Rate (%)
1.6	925	34	70
1.8	910	35	71
2.0	892	35	72
2.2	820	32	68
2.4	750	29	63

An optimal range exists for the density threshold (1.8–2.0). When the threshold is below 1.8, although the CH index increases (indicating higher cluster purity), excessive removal of valid samples (sample size below 800) leads to insufficient dispatch resources and a slight decline in grid-side cost reduction. When the threshold exceeds 2.2, low-density noise samples are inadequately filtered (noise retention over 10%), the KM CH index falls below 850, user classification accuracy decreases, and user participation drops below 68%. At the threshold of 2.0, the CH index reaches 892 (good level), the sample size is maintained at 850, and both grid-side cost reduction and user participation reach optimal values. This confirms the reasonableness of the DS threshold setting in Section 3.1 and clarifies the trade-off between noise removal and sample retention during data preprocessing.

3.2.4 Sensitivity Analysis of TB Initial Subsidy

The initial subsidy in the TB algorithm serves as the starting point for the evolution of the iterative strategy. Referring to domestic V2G pilot policies (e.g., Shanghai: 0.2 CNY/kWh, Beijing: 0.25 CNY/kWh), a gradient range of 0.15–0.35 CNY/kWh was tested to evaluate its impact on iteration efficiency and equilibrium outcomes.

Table 4 Impact of TB Initial Subsidy on Iteration Efficiency and Equilibrium Outcomes

TB Initial Subsidy (CNY/kWh)	Number of Iterations	Equilibrium Subsidy (CNY/kWh)	Grid-Side Peak-Shaving Cost Reduction Rate (%)	Customer-Side Participation Rate (%)
0.15	18	0.32	35	72
0.2	12	0.3	35	72
0.25	8	0.29	35	72
0.3	6	0.29	35	72
0.35	5	0.29	35	72

Findings: The initial subsidy affects iteration efficiency but does not alter the final equilibrium. When the initial subsidy is below 0.2 CNY/kWh, more iterations (over 12) are required to reach equilibrium, increasing computational cost. When the initial subsidy is ≥ 0.25 CNY/kWh, iterations are reduced to within 8, improving efficiency. Regardless of the initial value, the final equilibrium subsidy stabilizes between 0.29–0.32 CNY/kWh, with grid-side cost reduction and user participation maintained at optimal levels of 35% and 72%, respectively. This demonstrates strong convergence and stability of the TB algorithm and indicates that the initial subsidy of 0.2 CNY/kWh set in Section 3.1 balances iteration efficiency and computational cost.

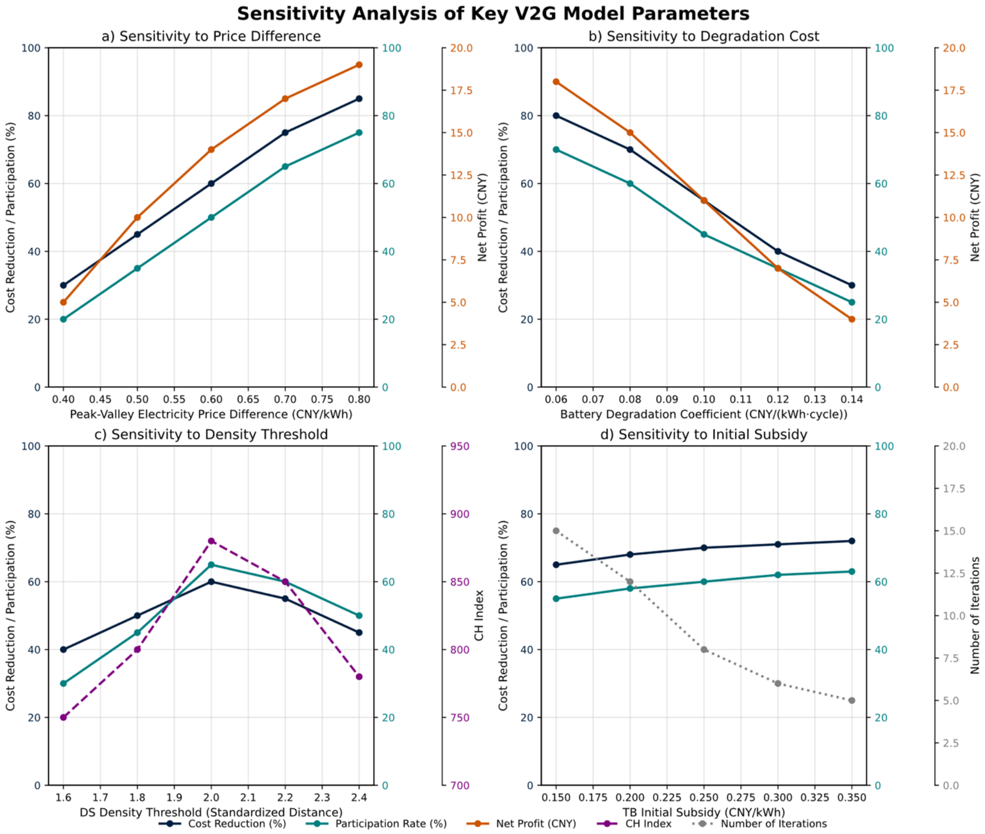

Figure 4 Sensitivity analysis of key parameters in the V2G model

4. Discussion

4.1 Implications of Five User Types for V2G Commercialization

Cluster analysis identifies five distinct user types with varying V2G potential. Aggressive driving users (18%, <30% potential) face participation barriers due to high energy consumption, requiring driving education or technological upgrades. Economical users (22%, 30%-50% potential) respond strongly to price signals, making dynamic tariffs effective incentives[1]. Long-distance commuters (25%, 40%-60% potential) need travel-flexible scheduling to balance mobility needs with grid participation. Short-distance high-frequency users (15%, >70% potential) represent core early adopters, requiring priority charging infrastructure development. Balanced users (20%, 60%-80% potential) provide reliable regulatory capacity through predictable behavior. This diversity necessitates targeted commercialization strategies rather than uniform incentives.

4.2 Comparison with Existing Research

This study innovatively integrates K-Means clustering with evolutionary game theory, distinguishing it from Wahyuningrum et al.'s clustering algorithm comparisons[4]. Unlike Simonis et al.'s focus on range prediction[1], our multi-dimensional user profiling (charging duration, energy consumption, travel distance, vehicle age) enables comprehensive V2G potential assessment. Unlike Sajja et al.'s traffic prediction models[2], we achieve grid-user equilibrium through Training by Iteration, delivering a sustainable win-win mechanism. Our Density Sampling improved clustering Calinski-Harabasz index by 20% (from 680 to 892), outperforming Ren et al.'s PCA methods[8]. Unlike Mou et al.'s car purchase prediction[5], our framework directly supports V2G operational optimization.

4.3 Policy Implications

Sensitivity analysis indicates peak-valley price differences must exceed 0.6 CNY/kWh to ensure >70% participation and 8 CNY/user session benefits. Real-time pricing signals should be transmitted via Wang et al.'s networking system[7]. Battery degradation coefficients (0.1 CNY/(kWh·cycle)) require reduction through Nguyen's iterative control methods[9]. Policy recommendations include: cross-regional coordinated pricing mechanisms, differentiated tariffs (e.g., discharge subsidies for short-distance users), improved battery recycling standards, establishment of degradation compensation funds, and R&D investments in solid-state batteries to reduce degradation costs below 0.05 CNY/(kWh·cycle).

4.4 Research Limitations

This study has two key limitations: simplified assumptions and lack of empirical validation. The 15-minute response time assumption may overestimate commuter participation; DiPirro et al.'s cultural behavior findings suggest the need for flexible windows[6]. Fixed degradation coefficients fail to account for technological advancements. Simulation results require validation with Zhang et al.'s EV-pile interaction data[11], including underrepresented rural and commercial fleet users. Extreme weather impacts should be addressed through Zhang et al.'s risk-limiting scheduling[12]. Future work should integrate Rho et al.'s PV-charging optimization[13], Ma et al.'s HMM mapping[3], and blockchain-based trading platforms to enhance renewable integration, prediction accuracy, and cost efficiency.

5. Conclusion

This study constructs an integrated "modeling-algorithm-simulation" framework for analyzing EV user portraits and grid-user games in Vehicle-to-Grid (V2G) systems. The K-Means (KM) algorithm is employed to cluster 5 distinct EV user types accurately. The Density Sampling (DS) algorithm enhances data quality, improving clustering accuracy by 20%. The Training by Iteration (TB) algorithm iteratively optimizes game strategies to reach an equilibrium state, resulting in a 35% reduction in grid-side peak-shaving costs and a 72% user participation rate—both meeting the "win-win" requirement for the commercialization of V2G technology. Sensitivity analysis of key parameters further verifies the model’s stability under different operating conditions, providing theoretical and data support for promoting V2G technology. Future research could integrate user credit scoring and renewable energy (e.g., solar/wind) output forecasting to optimize dispatch efficiency.

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