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Estimation of Vehicle-to-Grid Potential and Its Impact on Grid Flexibility Using Real-time Electric Vehicle Data: A Korean Case

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Executive Summary

This study analyzed real-time driving and charging data from 464 Electric Vehicle (EV) users to evaluate Vehicle-to-Grid (V2G) potential as a grid resource. Key findings reveal EV users drive significantly more annually (24,156 km) than conventional drivers. Using a Linear Programming model optimized for user profit based on price fluctuations in wholesale electricity market at Jeju islands in Korea, while guaranteeing sufficient charge for next trips, significant V2G potential was identified. This potential is concentrated during long evening and nighttime parking periods, enabling profitable charging and discharging aligned with grid needs. Parking duration and frequency emerged as the dominant factors influencing V2G capacity. The study concludes that V2G, dependent on future EV adoption, infrastructure rollout, and user participation, offers substantial promise for enhancing grid flexibility, integrating renewables, and mitigating grid ramping challenges.

Keywords: Electric Vehicles, Consumer behavior, V2H & V2G, Smart grid integration and grid management, Climate change

1 Introduction

The increasing penetration of renewable energy sources, particularly in regions like Jeju islands in Korea, has led to challenges such as output curtailment due to excess generation. Concurrently, the rising adoption rate of Electric Vehicles (EVs) presents both a challenge, due to increased electricity consumption and peak load impacts, and an opportunity through Vehicle-to-Grid (V2G) technology. V2G allows EVs to not only draw power from the grid (charging) but also inject stored energy back into it (discharging), acting as distributed energy resources.

Effective V2G implementation promises several benefits: reduced operating costs and potential revenue streams for EV users, absorption of surplus renewable energy thereby minimizing curtailment, mitigation of steep net load increases during ramp-up periods, stabilization of daily load curves, reduced investment in generation and grid infrastructure, and lower carbon emissions from power generation.[1][2]

Accurate estimation of V2G potential is crucial for designing efficient V2G systems, formulating effective policies, and planning future grid infrastructure. While previous studies often relied on processed data or simulations, this research utilizes real-time EV driving and charging data collected from a user panel to provide a more realistic assessment. [3][4]

This study has two primary objectives:

1. To analyze the detailed driving and charging characteristics of EV users based on real-time panel data.
2. To estimate the V2G potential based on this real-world data, employing a user-profit maximization perspective using a Linear Programming (LP) model.

The analysis of driving and charging patterns provides foundational insights into EV usage, informing energy and transportation policies. The subsequent V2G potential estimation, grounded in actual usage data and specific pricing of Jeju wholesale electricity market, offers practical information for V2G policy decisions and future planning in Korea.

2 Literature Review

2.1 Vehicle-to-Grid Integration in Electric Vehicles

The concept of V2G has emerged as an innovative paradigm that positions EVs as active participants in the energy environment, enabling bidirectional energy transfer between EVs and the power grid. This allows EVs to draw power from the grid when needed and return surplus energy when their batteries have available capacity, acting as mobile energy storage devices.[5]

Current V2G research focuses on several key areas. Grid Management and Services (45%) aims for efficient bidirectional energy transfer and grid support. Renewable Energy Integration (25%) explores using V2G for distributed energy storage to integrate renewables. The EV Market and Economics (15%) studies charging infrastructure and business models. Technology and Infrastructure (10%) focuses on bidirectional chargers and communication protocols. Policy and Regulations (5%) examines supportive policies and standards, such as California's LCFS and EU initiatives like ISO 15118.[3]

Despite progress, challenges remain. A key issue is the lack of standardized communication protocols and interoperability. The regulatory framework is often inadequate. Limited availability of V2G-enabled charging stations is an infrastructure hurdle. Battery degradation due to frequent cycling is a concern, with research exploring advanced BMS using AI to optimize charging. Cybersecurity is an increasing concern. Consumer understanding and acceptance are limited, requiring education. The economic viability of V2G needs further investigation.[2]

Furthermore, consumer understanding and acceptance of V2G benefits remain limited, necessitating education initiatives and incentives. The economic viability of V2G and establishing sustainable business models require further investigation to incentivize both EV owners and grid operators. Accordingly, accurately estimating V2G potential is crucial for effectively utilizing V2G as a resource.[4]

2.2 V2G Potential Estimation

2.2.1 Studies on V2G Potential Estimation

Estimating the potential of V2G is essential for effective planning and implementation. The estimation of V2G potential is a multifaceted endeavor employing various methods, including modeling and simulation, data-driven analysis, techno-economic evaluations, and the critical consideration of user behavior. These studies reveal that V2G potential is significantly influenced by factors such as EV penetration, regional characteristics, technological advancements, economic incentives, and user acceptance.

- **Modeling and Simulation Approaches**: Agent-Based Modeling (ABM) assesses potential considering factors like EV ownership, user behavior, and regional characteristics (e.g., Zhang et al.'s study in Japan).[6] Optimization models (like MILP) estimate achievable capacity under technical constraints.[7] Machine learning (e.g., LSTM) is used for predicting schedulable capacity.[8]
- **Data-Driven Analysis**: Analyzing real-world EV usage data (charging location, duration, timing) provides empirical insights. Floating Car Data (FCD) helps identify suitable V2G locations based on parking patterns. [9]

- **Techno-Economic Evaluations**: Assess economic benefits and costs, considering infrastructure investment and battery degradation alongside grid service revenues (e.g., Huda et al. in Indonesia, Almehizia & Snodgrass on profit maximization, Han & Han on frequency regulation feasibility).
- **Consideration of User Behavior**: Understanding user concerns (inconvenience, range anxiety) and actual behavior (plug-in habits, response to incentives) is crucial for realistic potential estimates.

2.2.2 Optimization of V2G Scheduling based on MILP

Mixed-Integer Linear Programming (MILP) models have been frequently employed to optimize V2G operations and assess their potential under diverse objectives and constraints. These models typically aim to maximize profits for EV owners or aggregators, minimize grid operational costs, reduce congestion, or optimize energy management. Constraints often include EV battery characteristics (capacity, state-of-charge), user preferences, grid limits, and battery degradation. [10]

Several studies highlight the efficacy of MILP in quantifying V2G potential. For instance, one study developed a MILP model that optimized V2G scheduling while considering battery degradation. The results demonstrated significant cost reductions for EV owners (between 48% and 88% compared to immediate charging) even when accounting for battery wear. This underscores the substantial economic advantages of V2G when optimized using MILP. [11]

Furthermore, MILP has been utilized to develop evaluation frameworks for V2G service providers. These frameworks characterize V2G output capability by providing metrics for power capacity, service cost, and profit, aiding in the strategic planning of V2G services. The application of MILP in transactive energy management for V2G-capable EVs in residential buildings has also been explored, aiming to balance user preferences with grid support. [7][11]

In addition to economic benefits at the individual or aggregator level, MILP has been used to assess the potential of V2G for addressing grid-level challenges. For example, techno-economic analyses using MILP have indicated that widespread EV adoption with V2G could lead to peak load reduction, as seen in the Indonesian grid where a 2.8% to 8.8% reduction was projected depending on EV availability scenarios. [12]

Despite the variety of approaches, MILP remains a valuable tool for its ability to model complex systems with multiple constraints and objectives, providing quantitative insights into the technical and economic potential of V2G technology. The accuracy of these estimations, however, is contingent on the quality of input data and the comprehensiveness of the modeled system, including considerations for user behavior and grid dynamics. Future research continues to refine these models to better capture real-world complexities and uncertainties associated with V2G implementation.

3 Data and Methodology

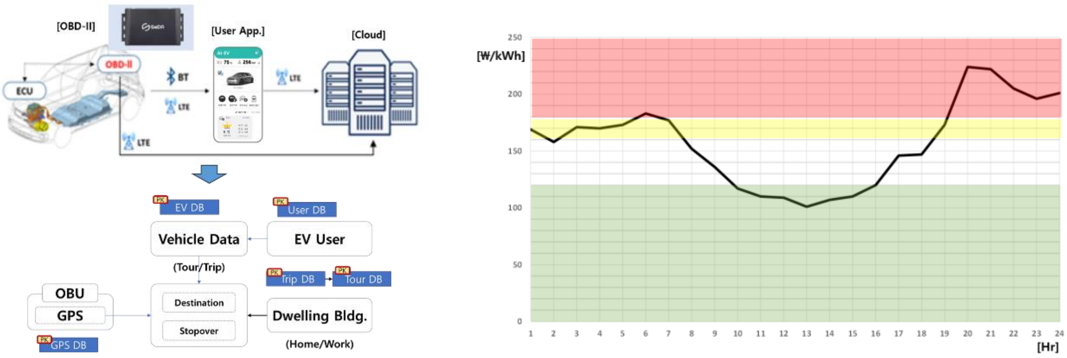
3.1 Data Description

The analysis presented in this study is fundamentally based on real-time operational data collected directly from EV users, hereinafter referred to as panels, through installed On-Board Diagnostics (OBD) devices. The data comprises three main categories: panel information, driving and charging events, and electricity market pricing data.

- **Panel Information Data**: Data was initially gathered from 802 validated participants across passenger cars, freight vehicles, and taxis. This analysis focuses specifically on the 727 passenger car panels (90% of total). Recorded information for each includes a unique OBD device number (linking data across datasets), EV make and model, manufacturer-specified maximum battery capacity (kWh), primary vehicle usage purpose (categorized as 1: commuting, 2: personal errands including leisure/school runs, 3: business excluding commercial freight/taxi), primary driver's age group and gender, residential administrative district code (125 categories), and panel class (passenger/freight/taxi).
- **Driving and Charging Event Data**: This dataset contains timestamped records for individual driving ('trip') and charging events. Each record typically includes: device number, event start/end date and time (Y-M-D h:m:s), start/end battery State of Charge (SOC, reported as %), start/end vehicle

odometer reading (km), start/end cumulative energy charged (kWh), start/end cumulative energy discharged (kWh), charger connection status at start/end (e.g., SLOW, FAST, CONNECT, NONE), and start/end location represented by administrative district codes (OD zones). The initial raw collection yielded 757,746 event records from 806 panels.

- **Jeju Electricity Pricing Data**: Hourly System Marginal Price (SMP) data from the Jeju island electricity market, operated by the Korea Power Exchange (KPX), was used for the V2G economic modeling. To capture representative price volatility relevant to V2G arbitrage opportunities, the study utilized average hourly SMP values derived from days exhibiting the largest price differentials within the month of April for the years 2019 to 2023. This average SMP profile serves as the input for calculating charging costs (p_t^+) and discharging revenues (p_t^-) in the optimization model. The Jeju SMP typically shows a distinct "duck curve" pattern, particularly in spring/autumn, with lowest prices around midday due to high solar generation and highest prices during the evening peak load hours (approx. 19:00-23:00). This pattern is considered a plausible representation of future grid pricing dynamics under high renewable penetration scenarios.



(a) (b)

Figure 1: (a) Driving and charging event data collection system using OBD-II (b) Average hourly SMP profile of Jeju island electricity market

3.2 Data Preprocessing for Analysis and Estimation

To ensure data integrity for analyzing driving and charging patterns, rigorous preprocessing was applied to the raw OBD data, addressing inconsistencies and removing outliers that could skew results. Key steps included calculating trip distance and duration from odometer readings and timestamps. Events with zero distance were categorized: those with increasing State of Charge (SOC) were separated as charging events, while others (likely idling or errors) were removed. Outlier trips, defined as those exceeding 500 km or lasting 48 hours or more, were removed as probable data loss; exceptionally long-distance trips within plausible durations had their distance flagged as potentially inaccurate (NaN). Very long-duration trips over 24 hours were kept, but their duration was flagged (NaN) for time-based analysis.

Continuity between consecutive events was checked by calculating inter-event distance and time intervals. Significant gaps (e.g., $\geq$ 100 km and $\geq$ 3 days) were marked as missing data periods. Net energy consumed per trip was calculated by subtracting estimated regenerated energy from the total discharged energy, derived from cumulative energy logs.

Specific preprocessing was applied to the 127,534 identified charging events. Charged energy was calculated from cumulative logs, with corrections based on SOC change for negative results. Inter-charge interval time, distance, and energy consumption were calculated. To avoid distorting averages, charging events lasting over 14 hours were excluded from average charging time calculations. After these steps, 512,509 valid driving events from 727 passenger car panels remained for analysis.

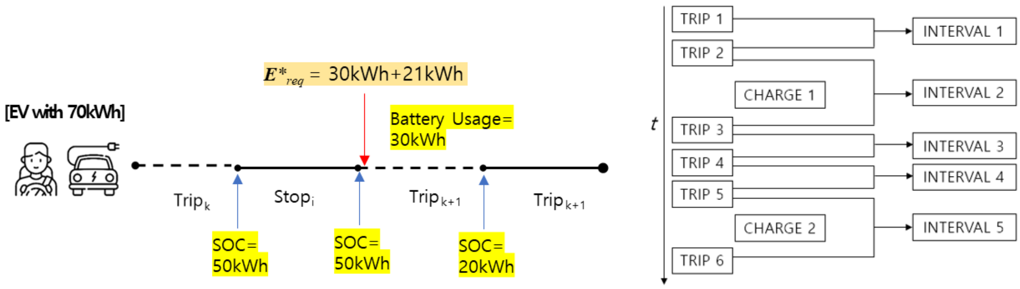
Further specific preprocessing was required to prepare data for the V2G schedule optimization model. Firstly, the analysis cohort was restricted to 464 panels primarily used for 'commuting', representing a user group with predictable parking patterns suitable for V2G participation. Secondly, SOC values were converted from percentages to kWh using each vehicle's specific battery capacity. Thirdly, the event-based data was transformed into 'parking interval' data, where each interval represents the time between the end of one trip and the start of the next. Each interval record included duration and a flag indicating if charging occurred.

A crucial parameter, the 'Required Charge Amount' (E_{req}), was calculated for each parking interval. This represents the minimum energy needed at the end of parking to complete all subsequent driving until the next long parking event (duration ≥ 6hours). It was calculated based on the energy consumed during that future driving period. To account for range anxiety and battery health, a safety margin equivalent to 30% of battery capacity was added to E_{req}. This final 'Realistic Required Charge Amount' was then capped between 30% and 95% of the battery's capacity for use in the model. Finally, rigorous filtering was applied to the parking interval dataset. Intervals were removed if E_{req} was missing, if significant odometer changes (>2km) or SOC decreases (>3%) occurred during parking, if start/end SOC was zero, or if calculated E_{req} was excessively negative (< -5% capacity). Importantly, parking intervals where actual charging occurred were excluded from the V2G scheduling simulation dataset. Panels with fewer than 50 valid, long-duration (≥6hours), non-charging parking events remaining after filtering were also excluded to ensure robustness. This resulted in a final dataset for V2G analysis comprising 127,856 valid parking events from 464 commuting panels.

3.3 MILP-based V2G Participation Profit Maximization Model

To estimate the V2G potential, a LP model was formulated. The model aims to determine the optimal hourly charging and discharging schedule for each individual valid parking event (defined as parking durations of 6 hours or more with no actual charging recorded in the preprocessed data). The optimization seeks to maximize the economic benefit for the EV user, based on the fluctuating hourly Jeju island’s SMP, while adhering to operational and battery-related constraints.

In this context, V2G potential refers to the available energy capacity (measured in kWh) that an electric vehicle user can potentially offer to the power grid through optimally controlled charging and discharging actions during stationary parking periods. This study focuses on estimating the average hourly V2G capacity achievable, considering the constraints imposed by typical, observed driving patterns and charging needs. The optimization is performed from the perspective of the EV user, aiming for User Profit Maximization. This objective implies scheduling charging activities during low-price hours and discharging activities during high-price hours, thereby minimizing electricity purchase costs and maximizing revenue from selling energy back to the grid, based on the dynamic SMP signals.



(a) (b)

Figure 2: (a) Illustration of the required final energy level (E_{req}) for an individual trip event (b) Valid V2G participation intervals between trips

The LP model is structured with an objective function and a set of constraints governing the EV's charging/discharging behavior over the parking duration. The objective is to maximize the net profit accrued from V2G participation over the parking duration and its function can be described as follows;

$$Maximize \sum_{t=1}^{T} (-p_t^+ a_t^+ - p_t^- a_t^-) \tag{1}$$

Here, p_t^+ and a_t^+ denote, respectively, the charging price (W/kWh) and the charged energy amount (kWh) at time t, while p_t^- and a_t^- and represent the discharging price and the discharged energy amount.

In addition to these, the model incorporates several variables, including: the time horizon representing the parking duration in hourly slots (t=1..., T); the maximum allowable hourly charging (A_T^+) and discharging

(A_T^-) rates; the initial battery energy level (E_0); the required final energy level (E_{req}); the minimum (E_{min}) and maximum (E_{max}) permissible energy levels in the battery; the time(t_s) at which the battery's SOC first enters the 30 %–95 % range; coefficients(μ^+, μ^-) limiting the charge/discharge amount by accounting for the actual charger-connection duration at the initial and final charge/discharge events; and coefficient (C^+, C^-) restricting operations to only charging or discharging until the battery's state of charge first enters the 30 %–95 % allowable range.

The optimization model is governed by the following key constraints:

- **Start/End SOC** (Constraints 1, 2): The SOC at the parking start time (E_0) must equal the recorded SOC in the dataset, and the SOC at parking end must equal the required charge (E_{req}) for the next trip.
- **Energy Balance** (Constraint 3): Battery energy level (E_t) evolves hourly based on charging (a_t^+) and discharging (a_t^-).
- **Operational SOC Limits** (Constraints 4, 5, 11-14): To preserve battery health, the SOC is maintained conservatively within a 30% to 95% range ([E_{min}, E_{max}]) during the V2G operation period. If the initial SOC (E_{init}) is outside this range, mandatory charging (if <EE_{min}) or discharging (if >E_{max}) is prioritized until the SOC enters the range at time t_s. Standard profit optimization proceeds only from t_s onwards, and the SOC is strictly kept within [E_{min}, E_{max}] for t≥t_s.
- **Charge/Discharge Rate Limits** (Constraint 6): Hourly charging and discharging amounts are capped by maximum power rates (A_t^+ = 11 kW, A_t^- = 10 kW used in experiments) since this study focuses on AC-V2G and incorporates the performance characteristics of the AC/DC onboard charger installed in EVs.
- **Partial Hour Adjustment** (Constraints 7-10): To account for the difference between the 1-hour of metering interval and scheduling resolution, and potentially shorter actual connection times in the first and last hour of parking, the allowable charge/discharge amounts in these specific hours are scaled by an adjustment coefficient (μ, 0 to 1) reflecting the true connection duration within that hour.

The V2G optimization model was implemented using Python version 3.8, leveraging the PuLP library (version 2.7) for formulating the linear programming problem. The optimization problems were solved using the CBC (COIN-OR Branch and Cut) solver, suitable for Mixed-Integer Linear Programming (though this formulation appears primarily LP). Computational experiments were conducted on a system running Ubuntu 20.04, equipped with an AMD EPYC 7742 CPU and 64GB of RAM.

Table 1: Constraints of V2G participation optimization model

No.	Constraint	No.	Constraint
1	$E_0 = E_{init}$	8	$a_0^- \geq -A_t^- \cdot \mu^-$
2	$E_{\tau+1} = E_{rea}$	9	$a_T^+ \leq A_t^+ \cdot \mu^+$
3	$E_{\tau+1} = E_\tau + a_t^+ + a_t^-$	10	$a_T^- \geq -A_t^- \cdot \mu^-$
4	$t_s = \begin{cases} ceil\left(\frac{E_{min} - E_{init} - A_t \cdot \mu^+}{A_t}\right) + 1 & if\ E_{init} < E_{min} \\ ceil\left(\frac{E_{init} - E_{max} - A_t \cdot \mu^-}{A_t}\right) + 1 & if\ E_{init} > E_{max} \\ 0 & otherwise \end{cases}$	11	$C_t^+ = 1_{(E_{init} \leq E_{min})}, \forall t \in [0, t_s]$
5	$E_{min} \leq E_t \leq E_{max}, \forall\ t \in [t_s, T]$	12	$C_t^- = 1_{(E_{init} \geq E_{maz})}, \forall t \in [0, t_s]$
6	$-A_t^- \leq a_t \leq -A_t^+$	13	$a_t^+ \leq A_t^+ \cdot C_t^+, \forall t \in [0, t_s]$
7	$a_0^+ \leq A_t^+ \cdot \mu^+$	14	$a_t^- \geq -A_t^- \cdot C_t^-, \forall t \in [0, t_s]$

4 Results

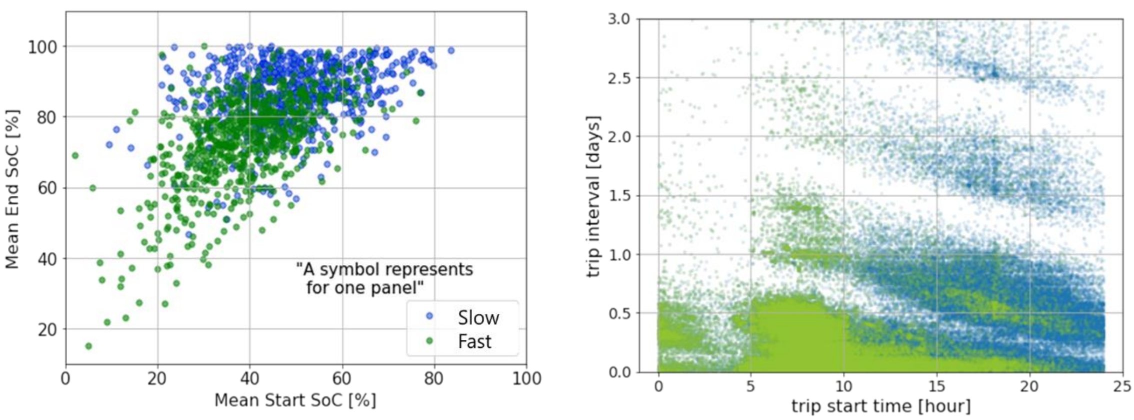
4.1 EV Driving and Charging Patterns

The analysis primarily focused on 727 passenger car users (panels). Driving patterns were initially analyzed based on averages calculated for each of the 727 panels, yielding results with a margin of error of ±3.63% at 95% confidence. For panels with nearly complete annual data (n=321), the average annual mileage was found to be 24,156.2 km (Std Dev: 12,098.9 km), with a median of 22,095 km, indicating a left-skewed distribution. On average, panels used their vehicles on 80.6% of the days within their valid data collection period. The mean distance driven per day, averaged over all days, was 67.0 km, substantially higher than the 2022 national average for non-commercial cars (31.1 km/day). Considering only days with driving activity, the average distance increased to 85.2 km/trip day. Panels undertook an average of 2.7 trips per day overall, or 3.1 trips per driving day, resulting in an average distance per single trip of approximately 28.2 km.

Analysis by primary driving purpose revealed that business users exhibited significantly higher annual mileage (avg. 30,740 km) compared to commuting (23,511 km) and leisure users (17,272 km). However, differences in other daily driving metrics across purpose groups were less pronounced. Comparing groups by battery capacity (approx. <60 kWh, 64-66 kWh, 77.4 kWh) showed a slight trend towards higher daily distance and distance per trip with larger batteries, though often within the margin of error. Notably, the largest battery group (77.4 kWh) displayed a more strongly skewed daily distance distribution, suggesting a higher proportion of long-distance driving days compared to the 64/66 kWh group. No significant differences in driving patterns were confirmed based on driver age groups, partly due to smaller sample sizes in older demographics.

Panel-level average charging characteristics showed a mean energy input of 28.1 kWh per charging session, with a near-normal distribution. On average, panels drove 161.3 km between charges, with charging events occurring roughly every 2.9 days, equating to about 12.5 charges per month. Typical charging started at an average SOC of 46.7% and ended at 84.8%.

Distinguishing between charging methods, Slow (AC) and Fast (DC) charging delivered similar average energy per session (27.6 kWh vs. 25.4 kWh). However, charging times differed dramatically: Slow AC charging averaged 6.75 hours connection time (suggesting vehicles remained connected long after charging finished), while Fast DC charging averaged 40 minutes. Slow charging was significantly more frequent (avg. 9.8 times/month) than Fast charging (avg. 5.3 times/month), likely reflecting cost considerations. Fast charging typically initiated at lower SOC levels (avg. start 39.1%) compared to Slow charging (avg. start 48.8%).



(a) (b)

Figure 3: (a) Distribution of charging start and end pairs of 727 passenger EVs (b) Distribution of trip start time and interval between trips

Analysis of the entire population of valid driving events (158,821 driving days) showed that the distribution of total distance driven per day was highly left-skewed, peaking at 10-20 km (mode 14 km), with a median of 50 km. Seventy-five percent of driving days covered less than 100 km, suggesting typical daily activities, while outliers (>214.5 km) constituted 6.7% of days. Daily energy consumption distribution was similarly skewed with a mean of 10.2 kWh/day. Weekly trends indicated increased driving activity on weekends (Fri-Sun), particularly for leisure users. Trip start/end time distributions showed distinct commuting peaks (7-9 AM starts, 5-7 PM ends). Analysis of first daily trips revealed patterns consistent with potential daytime V2G availability (trip before 10 AM, duration < 60 min, followed by > 6 hours parking), observed in 98.5% of panels at least once.

Analysis of filtered charging events (77,086 events) showed less clear SOC range distinctions between Slow and Fast charging compared to panel averages. The mean distance driven between charges was 150.6 km, and the mean time interval was 1.9 days (median 1.0 day). Distance between charges correlated positively with battery capacity. The charging energy distribution revealed a high frequency of low-energy charges (<8 kWh), influenced partly by one outlier panel exhibiting frequent top-up behavior, potentially indicative of future trends with ubiquitous charging access. Excluding this panel, mode charging amounts were 16 kWh (Slow) and 14 kWh (Fast). Weekly average charge amounts showed less variation than driving distance, with commuting users exhibiting relatively consistent charging across weekdays. Charging start times peaked around morning/evening commutes, with the overall highest frequency occurring around 6 PM, suggesting charging often commences after the day's final trip.

4.2 V2G Potential Estimation

The V2G potential was estimated by applying the formulated MILP optimization model to the preprocessed parking event data from 464 commuting users, covering 127,856 valid instances. This model generates an optimized hourly charging and discharging schedule for each analyzed parking event, aiming to maximize the user's potential profit based on the hourly Jeju SMP. These schedules adhere strictly to operational constraints, including maintaining the SOC within a 30-95% range and ensuring the final charge meets the calculated required energy level (E_{req}). Specific examples illustrate this process; for instance, a vehicle parked for around 10 hours demonstrated scheduled discharging during high-price evening SMP periods and charging during lower-price afternoon periods, effectively optimizing profit while satisfying all SOC constraints. The model consistently adapted schedules based on varying initial conditions across numerous analyzed events.

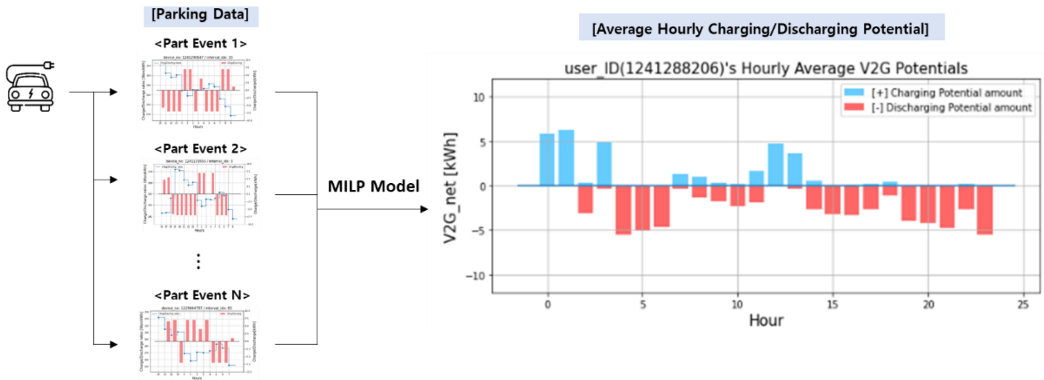


Figure 4: Illustration of construction of charging/discharging potential estimation using an individual EV panel data

Aggregating these individually optimized schedules across all events and users allowed for the derivation of an average hourly V2G potential profile. While individual users exhibited distinct potential patterns reflecting their unique driving and parking behaviors, the overall average pattern across the 464 commuting users revealed significant trends. Peak average charging potential was identified during hours with the lowest SMP, specifically in the early morning (0-1 AM, 3 AM) and notably during midday (12 PM - 4 PM). Conversely, peak average discharging potential aligned with the highest SMP hours in the morning (4-6 AM) and evening (7 PM - 11 PM). This aggregate hourly pattern strongly reflects the superposition of typical commuter parking behaviors: overnight parking after work and daytime parking at the workplace. During overnight stops, the optimization strategy favors charging in the cheapest early morning hours and discharging during expensive evening/pre-morning periods, while still meeting the next day's energy requirements. During daytime parking, charging potential aligns with the lower midday electricity prices. A slight dip observed in charging potential around 2 AM is attributed to optimization logic navigating relative price differences within the generally cheap overnight period. Parking start/end time distributions further corroborated this interpretation. Crucially, these hourly figures represent averages across many days and vehicles, indicating the potential capacity likely available at that specific hour, rather than depicting a continuous 24-hour potential profile for a single vehicle.

To understand the key determinants of this estimated potential, correlation and multiple regression analyses were performed, examining factors influencing daily V2G potential expressed both in energy (kWh) and potential revenue (KRW). Regarding energy potential, the analyses revealed strong positive correlations with the daily frequency and duration of long parking periods (≥6 hours) and a negative correlation with the required charge amount (E_{req}), while the starting SOC showed weak correlation. The regression model (R^2=0.970) confirmed these relationships, emphasizing that parking duration was the most influential factor, followed by parking frequency. Battery capacity also played a role, whereas starting SOC and required charge had less impact. This underscores that vehicle availability—primarily the length and frequency of parking—is the most critical factor governing the sheer amount of energy that can be cycled through V2G.

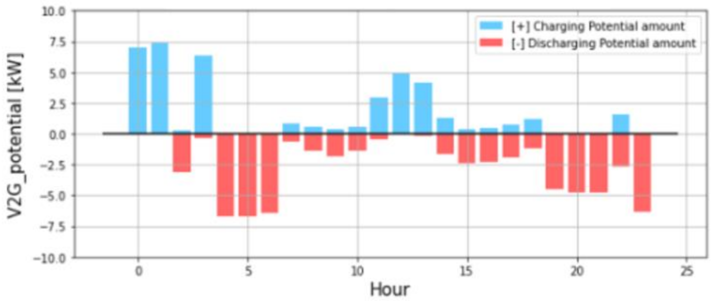


Figure 5: Average hourly charging/discharging potential of EV

When considering potential revenue, the relationships were more nuanced. While similar correlation trends were observed, they were less pronounced. The regression model (R^2=0.939) showed that all considered variables significantly influenced revenue potential. However, the relative importance was more distributed compared to energy potential, with starting SOC exhibiting the slightly highest influence, followed by parking duration, frequency, battery capacity, and required charge amount, all contributing significantly. These findings suggest that maximizing potential revenue is a more complex interplay of factors, heavily dependent on having sufficient charge available at the right times (influenced by starting SOC and battery capacity) and sufficient parking duration during periods with favorable SMP fluctuations for profitable discharging.

4.3 Mid-to-Long Term V2G Potential

Building upon the analysis of current driving patterns and simulated V2G capabilities, an estimation of the mid-to-long-term V2G potential in Korea was conducted. This projection leverages official Korean government targets for EV adoption, aiming for 4.2 million EVs by 2030, and the associated expansion of charging infrastructure, targeting 1.23 million Slow AC chargers by the same year, including approximately 660,000 residential and workplace locations. The estimation incorporates several key assumptions regarding the market penetration of V2G technology and user behavior.

Specifically, it was assumed that V2G-capable EVs would become commercially available starting in 2026, gradually increasing to represent 100% of new EV sales by 2027. The potential estimation focuses primarily on the commuting passenger EV segment, which was projected based on current ratios of private car ownership (approx. 77%) and the proportion of those vehicles primarily used for commuting (approx. 75%). Recognizing that not all users with V2G-capable vehicles parked at suitable times would participate, varying V2G participation rates (10%, 30%, 50%, 70%, 90%) were simulated for eligible parking events. Furthermore, the availability of V2G-enabled charging infrastructure was assumed to align with the rollout targets specified in government policy for residential and workplace chargers.

Two primary scenarios were considered to evaluate the impact of infrastructure availability. The first scenario assumes that the deployment of V2G-specific charging infrastructure perfectly matches the growing fleet of V2G-capable vehicles. Under this optimistic infrastructure scenario, by 2030, with an estimated 1.23 million commuting V2G EVs on the road, the potential grid contribution could be substantial. At a 10% participation rate, the aggregated potential is estimated at approximately 210 MW for charging and 316 MW for discharging. This scales significantly with higher participation: a 30% rate yields roughly 631 MW (charge) / 947 MW (discharge), and a 50% rate reaches approximately 1,052 MW (charge) / 1,579 MW (discharge). When compared to national energy storage targets, such as those outlined in the national electricity plan of Korean government in 2022, the V2G potential under 30% participation could fulfill around 30% of the planned energy storage needs by 2030. This contribution could be even more valuable considering V2G's inherent alignment with grid operational needs, such as absorbing excess renewable energy during midday (mitigating curtailment) and providing power during evening ramp-up periods.

The second scenario explores a more constrained future where V2G-enabled charger installation strictly adheres to the national policy targets for residential and workplace chargers (projected around 463,000 by 2030), without specific allocation for the V2G fleet. In this case, the number of V2G-capable EVs is projected to outpace the available compatible chargers from approximately 2027 onwards, creating an infrastructure bottleneck. Consequently, the estimated V2G potential by 2030 is significantly reduced. At 10% participation, the potential drops to approximately 79 MW (charge) / 119 MW (discharge). At 30% participation, it reaches only about 238 MW (charge) / 358 MW (discharge), and at 50%, it is limited to roughly 397 MW (charge) / 596 MW (discharge). Under this infrastructure-constrained scenario, the contribution of V2G to meeting national storage targets diminishes considerably, estimated at only around 10% at a 30% participation rate.

Table 2: Charging/discharging potential (MW) of V2G EVs under national policy of Korea with different participation rate assumptions

Year		2026		2027		2028		2029		2030	
		Ch.	Disch.	Ch.	Disch.	Ch.	Disch.	Ch.	Disch.	Ch.	Disch.
V2G EV		120,000		329,000		628,000		927,000		1,227,000	
Residential/Workplace AC V2G Infrastructure		147,000		204,000		275,000		362,000		463.300	
V2G Participation Rate	10%	20.5	30.8	35.0	52.5	47.2	70.8	62.1	93.2	79.4	119.2
	30%	61.6	92.4	105.0	157.5	141.5	212.4	186.3	279.5	238.2	357.5
	50%	102.7	154.1	175.0	262.6	235.8	353.9	310.5	465.9	397.1	595.9
	70%	143.7	215.7	244.9	367.6	330.2	434.6	1113.5	652.3	555.9	834.3
	90%	184.8	277.3	314.9	472.6	424.5	558.8	1431.6	838.6	714.7	1072.6

Comparing these scenarios underscores a critical dependency: realizing the full potential of V2G as a significant grid resource hinges on the implementation of coordinated and synchronized policies. Effective strategies must not only encourage the adoption of V2G-capable vehicles but also ensure the timely and targeted deployment of the necessary V2G-enabled charging infrastructure, particularly at residential and workplace locations where vehicles spend considerable time parked [490]. Without such alignment, infrastructure limitations risk significantly curtailing the valuable grid flexibility V2G technology promises to offer.

5 Discussion and Implications

This study, grounded in the analysis of extensive real-world EV operational data from Korea, provides significant insights into the potential value of V2G and carries substantial implications for the future power system. The findings generally align with international perspectives which forecast that EVs, through intelligent charging strategies including V1G and V2G, could emerge as one of the most significant sources of grid flexibility globally. The potential capacities estimated in this research, even under more conservative assumptions regarding user participation and infrastructure, indicate that the EV fleet represents a considerable future resource pool for enhancing grid stability and efficiency.

The analysis particularly highlights V2G's potential to address key challenges associated with the increasing penetration of variable renewable energy sources. Significant EV charging potential was identified during midday hours (approximately 12 PM to 3 PM), aligning closely with periods of peak solar generation and potential curtailment events, a notable issue particularly in regions like Jeju. Commuters parking at workplaces during these hours present a prime opportunity to absorb surplus renewable energy, potentially creating value for both the grid and the user under appropriate tariff structures. Furthermore, demonstrable discharging potential exists during evening ramp-up periods (e.g., 6 PM to 8 PM), offering a means to mitigate steep increases in net load. While the number of available vehicles might be somewhat limited during the immediate post-work commute, targeted V2G programs and financial incentives could encourage participation during these critical hours.

A key strength of this work lies in its reliance on actual driving, charging, and parking data, which yields more grounded estimates of V2G potential compared to purely theoretical simulations. By incorporating realistic SOC levels upon parking, observed parking durations, and the energy required for subsequent trips, the model provides a more accurate reflection of operational constraints. Among the most critical findings is the confirmation that vehicle availability—specifically the duration and frequency of parking periods—is the dominant factor determining V2G energy potential, significantly outweighing the influence of battery capacity alone. This emphasizes the strategic importance of focusing V2G initiatives on user segments with predictable and sufficiently long parking durations, such as commuters parking at workplaces during the day or residents parking overnight at home.

The mid-to-long-term potential estimations starkly illustrate a critical dependency: realizing the substantial benefits offered by V2G requires more than just the availability of V2G-enabled vehicles. It necessitates a parallel and potentially accelerated rollout of compatible V2G charging infrastructure, particularly concentrated at residential and workplace locations. The analysis indicates that relying solely on current general charging infrastructure expansion targets may lead to significant bottlenecks, hindering the scaling of V2G services as the V2G-capable fleet grows. Therefore, synchronized policy frameworks that actively promote both V2G vehicle adoption and the deployment of dedicated V2G infrastructure are imperative.

Finally, while this study modeled user behavior based on rational profit maximization responding to SMP signals, real-world V2G adoption will inevitably involve complex user behavior and economic factors. Actual participation rates will depend heavily on user acceptance, the design of effective and understandable tariff schemes (which may need to extend beyond simple SMP arbitrage), adequate compensation or mitigation strategies for perceived or actual battery degradation (partially addressed by SOC limits in the model), and the overall ease of participation, potentially facilitated by aggregators or Virtual Power Plant (VPP) operators. The observation of diverse charging behaviors, such as the frequent, low-energy "smartphone charging" pattern seen in one panel, suggests that user approaches to EV charging and potential V2G participation may vary, requiring flexible program designs. Effectively harnessing the V2G potential identified requires an integrated approach addressing these technical, economic, policy, and behavioral dimensions.

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