Received 31 July 2025, accepted 24 September 2025, date of publication 29 September 2025, date of current version 7 October 2025.
Digital Object Identifier 10.1109/ACCESS.2025.3615595

TOPICAL REVIEW

A Review on Vehicle-Grid-Integration Development in South Korea

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This work was supported by Korea Institute of Energy Technology Evaluation and Planning (KETEP) and the Ministry of Trade, Industry and Energy (MOTIE) of Republic of Korea under Grant 20226210100020 and Grant RS-2024-00509239.

ABSTRACT The uncertainty in demand and supply in the power grid due to the widespread adoption of renewable energy resources is a significant concern. Electric vehicles (EVs) can be utilized as resources to mitigate the concern. However, to apply these resources, it is necessary to verify their suitability, resource potential, and economic impact. Therefore, this study analyzes how EVs can be utilized as resources and proposes a pilot project for operating smart charging (V1G) of EVs in South Korea. This pilot project includes experiments performing V1G in response to Demand Response (DR) signals and surveys to determine EV users' preferences for V1G participation. Additionally, an analysis of charging characteristics was conducted because resource potential depends on EV users' charging behaviors. The experimental results confirmed the technical value of EVs as resources. However, the economic analysis revealed that there is no economic benefit for V1G operators, making V1G implementation difficult under the current system. Finally, meaningful suggestions are provided for the application and activation of EVs as resources.

INDEX TERMS Electric vehicle, smart charging, pilot project, charging characteristics analysis, participation preference survey.

I. INTRODUCTION

As part of the global initiative toward carbon neutrality, electrification policies in the transportation sector are being actively implemented worldwide, accelerating the transition to electric vehicles (EVs). Furthermore, several countries are adopting phased measures to discontinue the production and use of internal combustion engines (ICEs), while major automobile manufacturers have announced plans to phase out ICEs and introduce EVs [1], [2], [3], [4]. Driven by these policy measures, the global adoption of EVs reached approximately 40 million units by 2023. By 2035, EV electricity demand is projected to account for roughly 10% of global electricity consumption [5]. Given that EVs represent a substantial portion of the overall energy landscape, their efficient utilization is critically important. The current power system requires greater flexibility due to the volatility introduced by the increasing penetration of renewable energy. Traditionally, grid flexibility has been achieved through the use of generators with high ramp rates. Recently, however, the focus has shifted to incorporating demand-side resources, including buildings, heat pumps, and EVs. Among these, EVs stand out as effective resources due to their natural proliferation and significant capacity potential [6]. The technologies that enable EVs to contribute to the power grid are collectively referred to as vehicle-grid integration (VGI). Depending on the control strategy for charging and discharging, VGI can be categorized into V1G and V2G. V1G involves controlling EV charging through charger management, while V2G, which integrates control and communication technologies between vehicles, chargers, and the power system, enables not only controlled charging but also reverse power flow of surplus energy based on grid conditions. Since VGI technologies rely on the available battery capacity of EVs, it is essential

The associate editor coordinating the review of this manuscript and approving it for publication was Qiwei Zhang.

TABLE 1. Overview of literature review.

Type	Purposes	Reference
V0G	Increase the availability and accessibility of EV charging	[15], [16], [17]
V1G	Reduce peak demand	[18], [19], [20], [21], [22], [23], [24]
	Load balancing	[25], [26], [27]
	Grid stabilization	[28], [29], [30], [31], [32], [33]
	Provide revenue streams for EV owners & aggregator	[19], [28], [34], [35], [36], [37], [38]
	Reduce carbon emissions	[39]
	Decrease the system operating cost	[40], [41], [42], [43]
V2G	Grid stabilization	[44], [45], [46], [47], [48], [49], [50], [51], [52], [53], [54], [55], [56], [57], [58]
	Renewable energy integration	[47], [59], [60], [61], [62], [63], [64], [65], [66]
	Cost savings and revenue generation	[49], [59], [62], [67], [68], [69], [70], [71], [72], [73], [74], [75], [76], [77], [78], [79], [80], [81], [82], [83], [84]
	Reduce carbon emissions	[68], [71]

to consider EV charging characteristics, including charging cycles, locations, and capacities, to optimize their integration into the power system.

The analysis of EV characteristics for flexible resource utilization consists of generating representative charging patterns, predicting charging schedules, and creating probabilistic models of charging characteristics [7], [8], [9]. Based on this analysis, there are generally two methods for

estimating resource availability: calculation based on real data and estimation through charging scheduling based on probability distributions [10], [11]. Most studies estimate using optimal simulations based on probability distributions. However, this method has limitations in considering various variables related to EV users. Therefore, pilot projects are effective in determining more realistic resource availability. However, resource availability is significantly influenced not only by the usage characteristics of EVs but also by the participation rate of EV users. Hence, customer preferences should also be considered.

Concerns about not guaranteeing the minimum State of Charge (SoC) lead to low participation preferences among EV users regarding the monetization of EVs as resources. To measure this preference, surveys are conducted based on the choice experiment methodology, including discrete choice experiments and context-dependent stated choice experiments [12], [13], [14]. Additionally, methods to increase preference include rapid charging technology, adequate compensation, and infrastructure convenience, as derived from the surveys. To obtain realistic results regarding the introduction of Vehicle-to-Grid Integration (VGI), quantitative analysis of EV charging characteristics and quantification of EV user participation preferences through surveys must be based on the acquisition of real data through technology-based experiments.

This study conducted large-scale V1G experiments in South Korea, comprising both physical experiments and user surveys. Charging data including DR events were collected under real-world conditions, and survey responses captured EV user preferences and charging characteristics.

Focusing on the deployment of V1G technology, the analysis examines the technical feasibility of V1G in responding to DR signals, explores user charging behaviors and participation preferences, and evaluates the economic impacts on stakeholders. These findings offer valuable insights into the operational characteristics and policy implications of VGI in the Korean energy context.

Drawing on the empirical results, this study makes three contributions to the literature:

First, it provides realistic and generalizable insights into VGI through a nationwide V1G pilot implementation, utilizing a robust dataset of over 10,000 recorded charging sessions under actual operating conditions.

Second, it offers an in-depth assessment of user uncertainty's impact on DR effectiveness and capacity estimation, simulating penalty scenarios and highlighting the importance of resilient, user-aligned participation frameworks.

Third, it proposes strategic considerations for VGI expansion in South Korea, tailored to its policy and market environment, including actionable recommendations for incentive policies, tariff structures, and targeted customer segmentation to overcome economic barriers and low participation rates.

The rest of the paper is organized as follows: literature review is contained in section II. Section III covers the V1G pilot project in South Korea. Section IV presents result of pilot project in perspective of V1G technology and Survey. Discussion is covered in Section V. Finally, Section VI presents the conclusions of this study.

II. LITERATURE REVIEW

A comprehensive overview of different EV charging types and their primary purposes based on the literature review is shown in Table 1.

A. V0G

V0G is referred to as dumb charging method at constant full power from when the electric vehicles are plugged in until they are unplugged of full, whichever occurs earlier. In the V0G scenario, the objective is to increase the availability and accessibility of EV charging stations, aiming to plan their installation. The installation of public charging stations is orchestrated by evaluating the impact of electric vehicle driver behavior on charging infrastructure [15]. Additionally, factors such as renewable energy generation, general loads, and electric vehicle charging station loads are considered to minimize operational costs [16]. Geographic Information Systems are utilized to estimate the likelihood of charging at EV stations, thereby mitigating the impact of urban EV charging and facilitating the planning of EV charging infrastructure [17].

B. V1G

V1G is referred to as unidirectional smart charging method, characterized by the ability to adjust charging capacity, implement charging time shifting, and devise strategies based on charging fees after the electric vehicle is plugged into the charger. So, it can provide the following services: reducing peak demand, balancing loads, stabilizing the power grid, generating revenue streams for both EV owners and aggregators, minimizing carbon emissions, and lowering overall system operating costs.

1) REDUCING PEAK DEMAND

Diverse methods have been researched to reduce peak loads on the power grid. To indirectly shift charging loads for EV drivers, peak charging loads are moved to cheaper charging rate periods or optimized based on EV drivers' preferred charging time slots and energy market prices [18], [19]. Controlling EV charging to utilize surplus power from the grid as much as possible or aligning charging with renewable energy output maximizes self-consumption of renewable energy while reducing peak loads [20], [21]. The potential for shifting EV charging loads is evaluated, and EV charging is controlled based on this assessment to regulate the voltage of the power grid [22]. Uncertain arrival and departure times of EVs are predicted based on past charging data or surveying EV driver behavior to participate in DR services, mitigating power fluctuations [23], [24]. Ultimately, controlling EV charger usage reduces peak loads.

2) BALANCING LOADS

Price fluctuation systems are implemented to indirectly regulate the charging behavior of EVs [25]. To shift charging loads, a charging price mechanism that can provide incentives is created [26]. Charging schedules for EVs are adjusted through reinforcement learning to generate coordinated charging schedules for electric vehicle fleets of any size, considering the baseload present in the power grid [27].

3) STABILIZING THE POWER GRID

A structure is built where EV owners bid for charging capacity, allowing the grid operator to leverage the bidding results to control EV charging capacity [28]. The EV charging algorithm is implemented by sampling the current state of the grid, keeping track of all charging activities, storing and sorting EV information (including priorities, locations, plug-in, and plug-out times), and deciding whether to activate or delay EV charging [29]. Location-based incentives are utilized to manage EV charging [30]. Participation in the real-time power market is undertaken from the perspectives of both EV owners and utilities [31]. A model is utilized to stochastically match wind power generation and EV charging load [32]. Electric buses participate in DR to mitigate network congestion and reduce power distribution loss [33].

4) GENERATING REVENUE STREAMS FOR BOTH EV OWNERS AND AGGREGATORS

EV charging prediction control is employed to reduce charging fees [34]. The charging fees forecast is utilized to prevent early EV withdrawal and shift EV charging load, thereby reducing charging costs [19]. Optimal EV charging times are determined to minimize charging station operating costs while limiting the grid capacity [35]. EV charging demand is managed by setting hourly charging limits at each charging point [36]. Energy Storage System (ESS) integration is used to minimize charging station operating costs by charging during periods of low demand [37]. Photovoltaics (PV) power revenue is maximized by shifting charging load to reduce PV power curtailment [28]. A variation of latent semantic analysis categorizes EV users into four behavioral models, from which a predictive user mixture model is derived to establish day-ahead EV availability and energy demand boundaries, guiding optimization to minimize charging costs within user model constraints using forecast baseload profiles and day-ahead wholesale energy rates [38].

5) REDUCING CARBON EMISSIONS

Carbon emissions are mitigated through a charging method that maximizes the consumption of renewable energy sources [39].

6) LOWERING OVERALL SYSTEM OPERATING COSTS

Considering charging fees, charging demand, constraints of charging stations, and the probabilistic nature of EV driving, the optimal start time for EV charging is determined according to their charging urgency levels [40]. Based on charging time and price bidding information provided by EV drivers, the aggregator generates a charging schedule that minimizes overall costs for the power grid [41]. By creating schedules for starting and stopping EV charging, the building's power demand is regulated, thereby reducing system operating costs [42]. A managed EV charging strategy based on a unit commitment simulation model for Istanbul's urban network effectively reduces peak demand and system operating costs by reflecting hourly load and renewable energy generation profiles [43].

C. V2G

Vehicle-to-Grid (V2G) is described as a bidirectional smart charging method. EVs can be considered distributed battery ESS with behavioral constraints imposed by EV drivers. Once

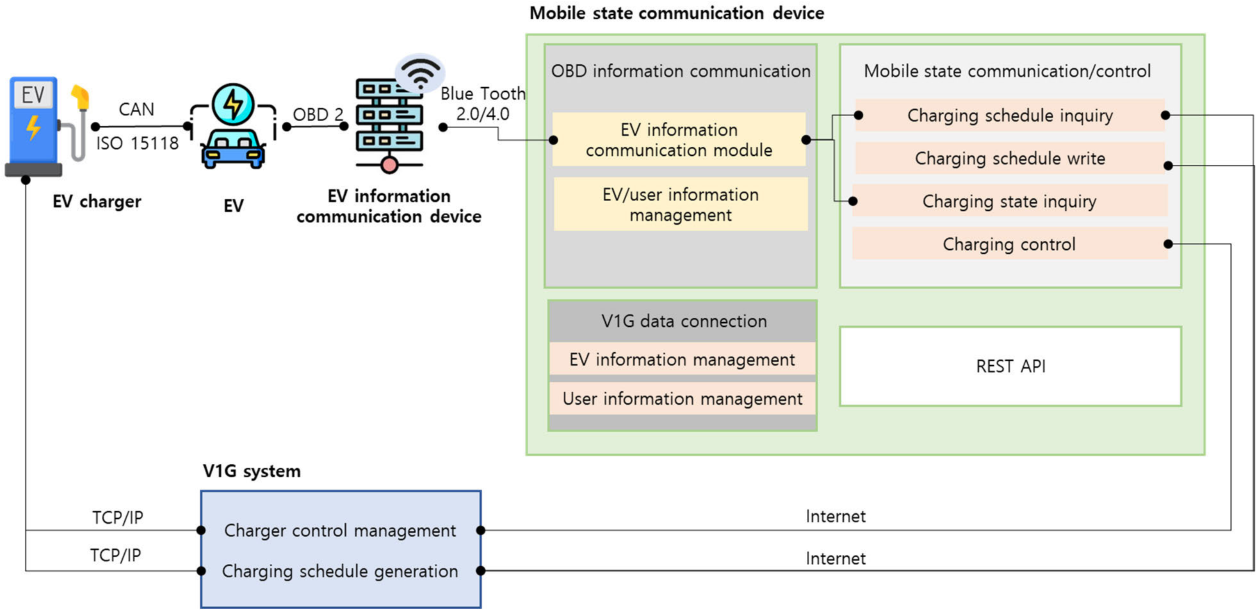

FIGURE 1. Overview of V1G system.

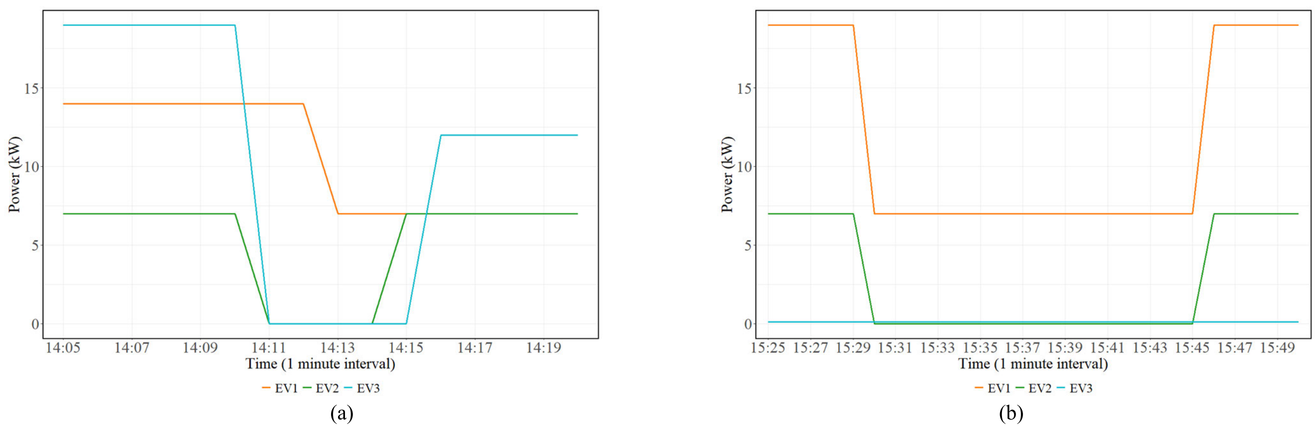

FIGURE 2. EV charging profile according to DR signal: (a) 2021.11.11, (b) 2021.11.16.

connected to a charging station, both the charging and discharging capacities, as well as the charging and discharging time schedules, can be adjusted.

1) STABILIZING THE POWER GRID

EV charging control manages the grid voltage while maintaining SOC close to the desired level of the driver at the EV departure time [44]. The remaining capacity of the charger is utilized to generate reactive power for voltage control [45]. The voltage phase difference is adjusted by modifying EV charging and discharging according to the phase voltage [46]. Integrated scheduling of renewable energy generation and EV charging and discharging mitigates the negative impact of renewable energy uncertainty. EV charging and discharging are controlled to mitigate irregular fluctuations in wind power generation and regulate system frequency [47]. Ramp up and down reserves are provided through EV charging and discharging control by the EV aggregator [48]. Reserve power is provided from an EV group to ensure stability of the Virtual Power Plant (VPP) output [49]. A distributed frequency control scheme is constructed for EVs to restore power grid frequency after supply-demand imbalances, wherein EVs independently monitor grid frequency and adjust operational modes, accordingly, utilizing designed inter-response times to prevent frequency overshoot or undershoot [50]. The event-triggered scheduling scheme can address the uncertainty due to their mobility as transportation tools by updating the optimization model and performing rescheduling whenever triggering events, such as EVs connecting to or unexpectedly disconnecting from the grid, occur [51]. To minimize overall load variance, optimal

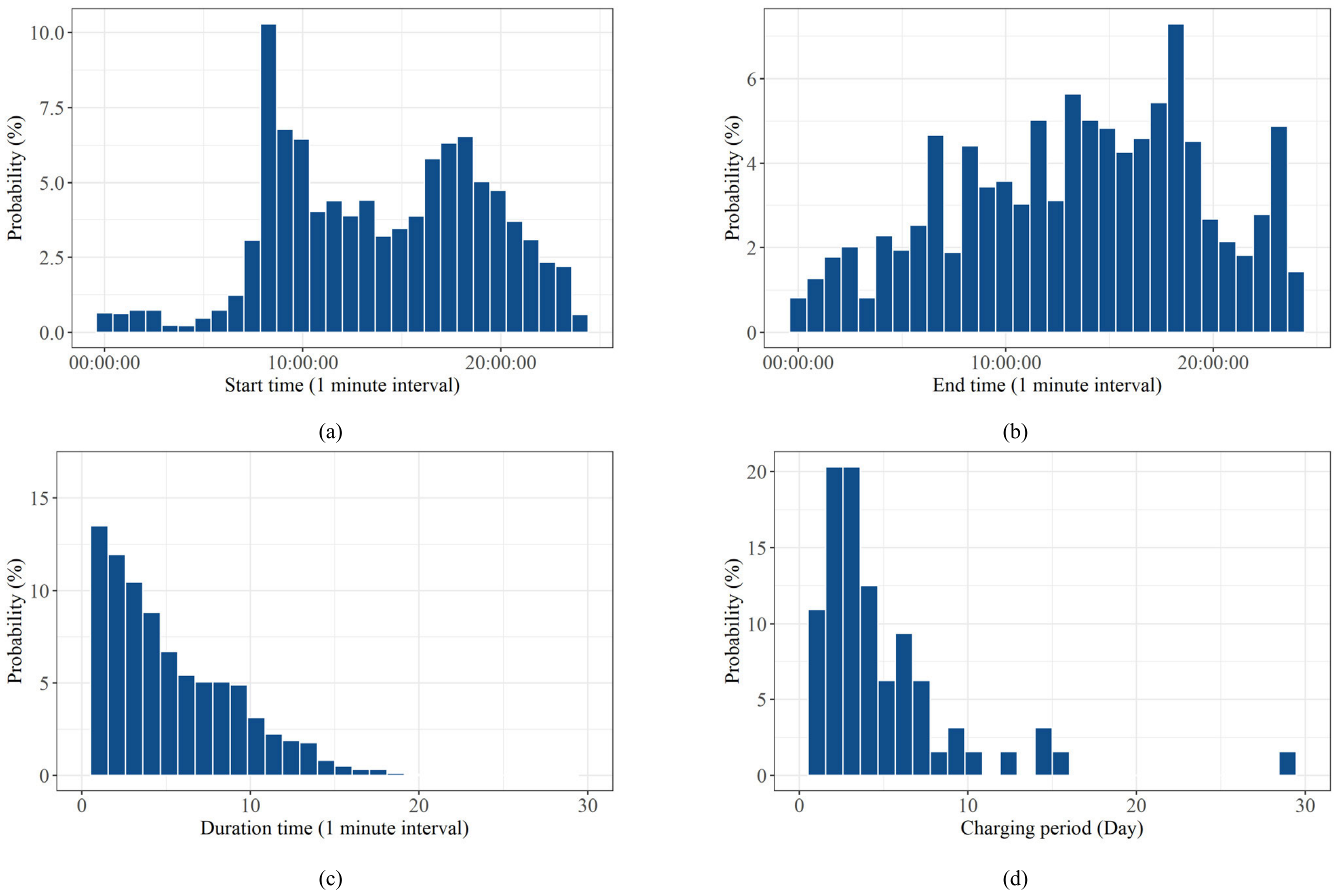

FIGURE 3. EV charging characteristics histogram: (a) EV coupling, (b) EV decoupling, (c) charging duration, (d) charging period.

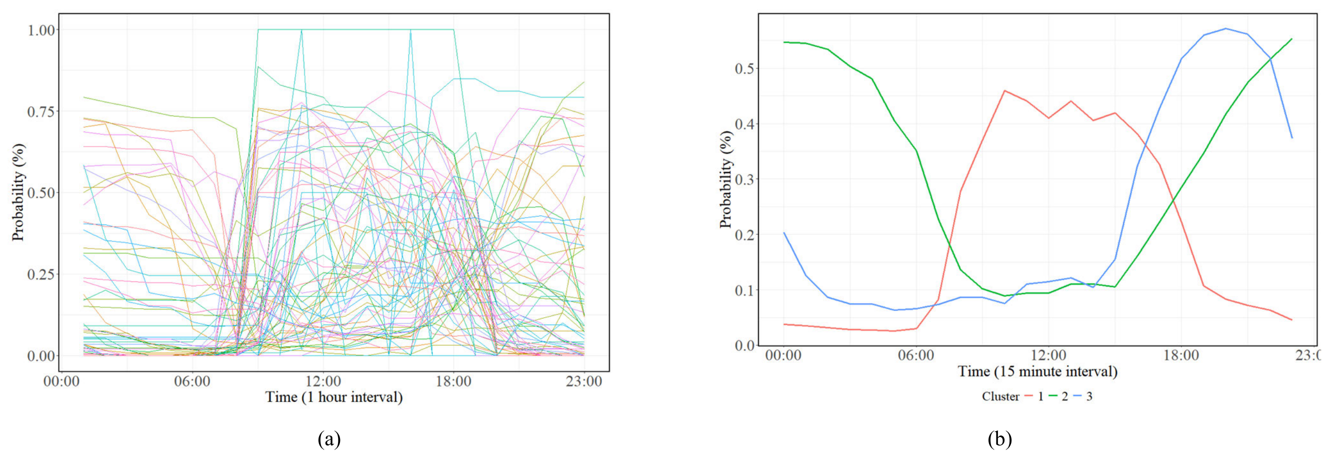

FIGURE 4. EV coupling patterns: (a) patterns of all EV users, (b) representative patterns.

power schedules for each charging station are collectively designed by the Central Control Center. Subsequently, individual charging station power is adjusted accordingly [52]. By participating in three trading floors of a short-term electricity market, including day-ahead, adjustment, and balancing markets, to trade the EVs' flexibility, from 24 h before the energy delivery time until near real-time, in the electricity market, the parking lot aggregators guarantee power system flexibility [53].

Batteries in EVs are modeled to manage capacity loss at various charging/discharging rates (Crate), controlling the Crate to achieve desired power flow rates between the grid and the EV battery, thus enabling coordination of EVs at the substation level to support the grid through

TABLE 2. Overview of VGI pilot project.

Name	Country	Timespan	Chargers	Fleet	Services	Charger type	Charging location	Ref
Smart Mobility V2X	CH	2019-2022	2	2	Freq. Response, Dist. Services, Time shifting	AC	Home	[85]
Domestic Energy Balancing EV Charging Trial	GB	2020-2022	4(v2g), 8(v1g)	4(v2g), 8(v1g)	Time shifting	DC	Home	[86]
Solarcamp	FR	2018-2020	1	1	Freq. Response, Arbitrage, Dist. Services, Time shifting, Emergency back up	AC, DC	Public	[87]
V2G @ home	NL	2021-2022	1	1	Time shifting, Emergency back up	DC	Home	[88]
FlexGrid	NL	2018-2022	1	1-3	Freq. Response, Time shifting, Emergency back up	DC	Home, Work	[89]
Share the Sun / Deeldezon Project	NL	2019-2021	63	150	Freq. Response, Dist. Services, Time shifting	DC	Home	[90]
INCIT-EV	ES	2020-2024	3	3	Freq. Response, Reserve, Dist. Services, Time shifting, Emergency back up	AC, DC	Home, Public	[91]
BloRin	IT	2019-2022	1	1	Freq. Response, Time shifting	DC	Work	[92]
V2X By Marubeni	GB	2021-2022	2	2	Freq. Response, Arbitrage, Dist. Services, Time shifting	AC, DC	Work	[93]
VGI	KR	2018-2022	100(v1g), 113(v2g)	136(v1g), 190(v2g)	Freq. Response, Reserve, Time shifting	AC, DC	Home, Public, Work	[94]

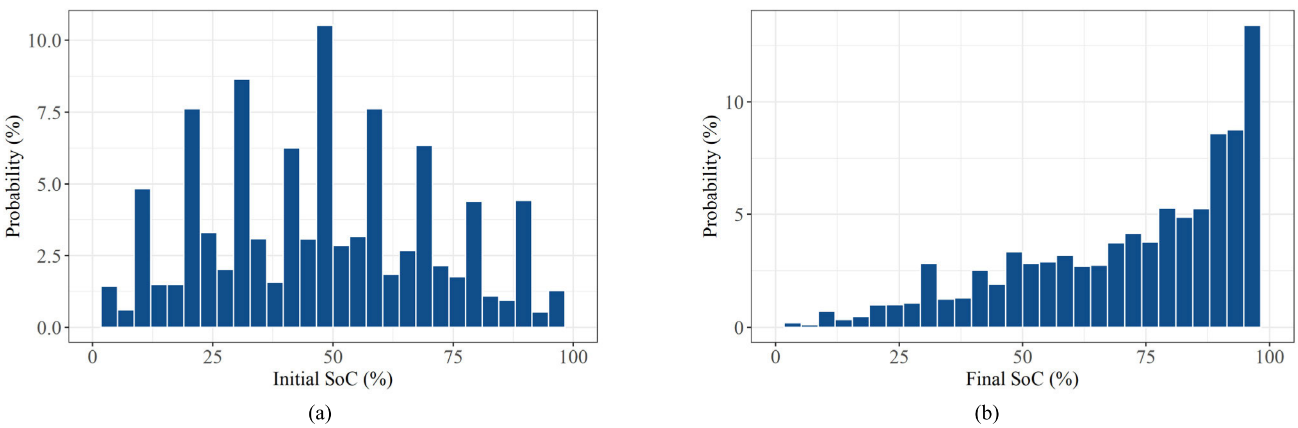

FIGURE 5. SoC histogram: (a) initial SoC, (b) final SoC.

peak shaving and valley filling [54]. If congestion occurs, transmission system operator adjusts EV charging ahead of congested points to utilize excess electricity and coordinates discharging behind congested points to maintain grid balance. Transmission grid stabilization involves contracting battery corridors from electric vehicle owners to alleviate congestion, with the provision of EV flexibility differentiated geographically through bidding areas [55]. V1G control decides which vehicles are temporarily disconnected from the grid, while V2G control determines which vehicles feed energy back to the grid, allowing for the management of power balance between generation and load, thereby facilitating reduction of charging load (G2V) and expansion of generation capacity (V2G). However, V2G control extends

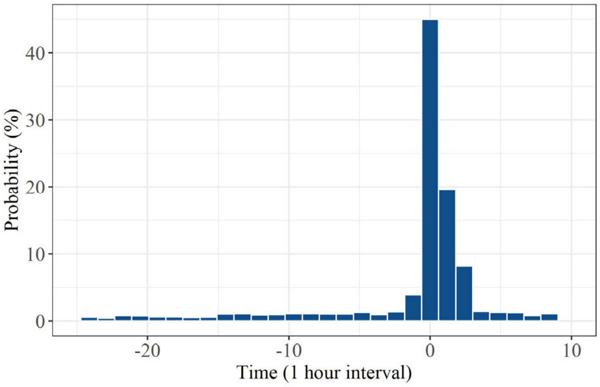

FIGURE 6. Difference time between decoupling schedule and actual decoupling time.

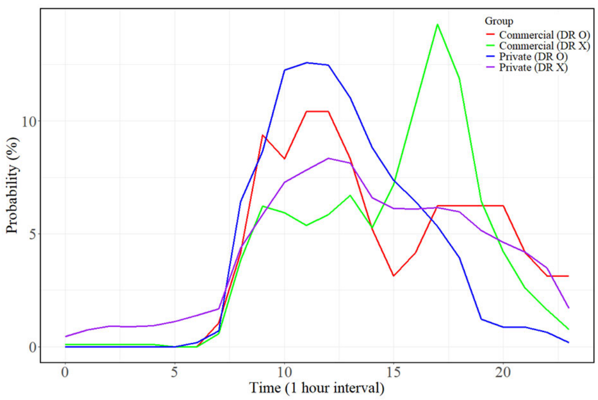

FIGURE 7. Plug-in probability by EV type and DR participation status.

TABLE 3. Summary of experiment and survey.

Category	Value
The number of chargers	100
The number of EVs	136
Records	10399
The number of surveyors	54

charging time, posing a potential impact on customer trips due to uncertain future driving behaviors [56]. Integrated the intrinsic randomness of EV availability and charging demand to manage EV commuter behavior unchanged, demonstrating the ability to reduce peak values induced by household appliances by more than 20% [57]. If the frequency falls below a given threshold, load shedding parameters including frequency thresholds and time delay in each round, are configured by estimating power imbalance. Subsequently, the available capacity of EVs is calculated, and load shedding is allocated accordingly, followed by charging/discharging control, with the load shedding process halted upon the frequency returning to the allowable range [58].

2) INTEGRATING RENEWABLE ENERGY RESOURCES

In distributed networks, EV charging and discharging mitigate irregular fluctuations in wind power generation and

TABLE 4. The benefits and costs for stakeholder.

Stakeholders		Factors
Program operator	Benefit	Settlement for reliability DR
		Settlement for economic DR
		Government subsidy
	Cost	Payment for EV owners
		VGI operating system
		Chargers installation
		Operation/management
Utility	Benefit	DSM cost reduction
		Blackout compensation
		Government subsidy
	Cost	Transmission and distribution investment
		Disbursement costs for service providers
		VGI operating systems
Participants	Benefit	Reward for VGI participation
		Government subsidy
	Cost	Battery degradation
		Vehicle charging management system
		Bidirectional on-board charger
Government	Benefit	Grid investment deferral
		Blackout compensation
		Demand side management cost reduction
		CO_2 emission reduction
		Value-added creation
		Production inducement
	Cost	Subsidy

regulate system frequency [47]. Power demand within building clusters is adjusted based on 24-hour power demand and renewable energy generation data, leveraging charging and discharging of buildings and EVs [59]. EV aggregators purchase energy from the day-ahead market and provide balancing services for wind power producers through self-scheduling [60]. Temporal interdependence of renewable energy generation prediction data and available capacity from charging stations is captured. Then, by using a stochastic distributed sub-gradient method, power and voltage control of V2G capacity within the network is realized [45]. Various distributed energy sources, including wind and solar power generation and EV parking lots, are optimally located and sized, and energy scheduling is conducted according to the determined system [61]. Overload and power mismatches are prevented by integrating renewable energy and EVs within microgrids and controlling EV charging and discharging [62]. V2G scheduling supports the self-consumption of PV output through Plug-in Electric Vehicle (PEV) charging, reducing the peak-valley difference of net load, while also applying voltage regulation and real-time control to ensure distribution grid security and mitigate uncertain conditions [63].

The investigation of V2G regulation capabilities in the West Denmark power system is carried out by utilizing an aggregated battery storage model in load frequency control to alleviate large amounts of fluctuating wind power [64]. To achieve load flattening and voltage regulation simultaneously, the strategy involves maximizing the usage of PEV storage to flatten the load while minimizing charging costs and determining the maximum PEV power usage from the Pareto-front obtained by MOGA to minimize deviation in slack bus power without violating voltage limits [65]. The first stage involves creating rolling schedules for EV charging and online load tap changing positions, while the second stage focuses on EV control to mitigate solar generation fluctuations and maintain voltage profiles, thus reducing both over and undervoltage risks [66].

3) LOWERING OVERALL SYSTEM OPERATING COSTS AND COSTS SAVING

Establishing a competitive bidding structure among EV aggregators enables EV drivers to select an electricity provider for buying or selling purposes [67]. V2G capability as well as the actual patterns of drivers are considered to generate the Pareto-optimal solutions for the purpose of minimizing system operating costs and carbon emissions [68]. Leveraging the energy sharing and storage capabilities of electric batteries in both buildings and EVs, coordinated control of building prosumer which improve cluster-level performance increases renewable energy self-consumption while reducing daily electricity bills [59]. The thermal units operation is used considering with smart houses including EVs which can compensate the power for the forecast error of renewable energy sources and reduce the incremental expected total cost of thermal units [69]. The unitized regenerative fuel cell and EV are intelligently scheduled to minimize line losses as well as cost of operation and maximize residual energy of storage elements, for the given load and generation available [70]. Local dispatchable generators and intelligent parking lots provide spinning reserve to eliminate generation and consumption mismatch, while controlling EV charging and discharging considering the impact of electricity prices on the sale of stored energy and on provision of spinning reserve [62]. The spinning reserve provided by the electric vehicle group guarantees the stability of the VPP's output, while DR improves customers' power consumption patterns and strengthens the VPP's grid connection capabilities [49]. Renewable Base Control(RBC) mechanism controls EV charging and discharging to reshape the net load curve in response to total renewable power availability, utilizing time-of-use prices and discharging EVs when renewable power exceeds load, and utilizing the electric grid when EV power is insufficient. Load Base Control(LBC) mechanism adjusts EV charging and discharging throughout the day to balance load around the average load level, considering peak and off-peak prices in charging and discharging decisions [71]. The applications include self-consumption increase, peak shaving, frequency regulation, and spot market trading, with various combinations of these applications resulting in additional annual cash flows of up to 2224 EUR per electric vehicle [72]. Due to reliance on PV generation, Vehicle-to-home (V2H) is employed as cost reduction options during the summer season, while V2G arbitrage trading, providing consistent profits, is more extensively utilized during the winter season, resulting in an increased utilization of the vehicle [73]. A scheduling mechanism for a load aggregator facilitates participation in the wholesale market amid uncertain energy and reserve prices, enabling the scheduling of flexible loads to provide ancillary services in the form of interruptible loads [74]. A centrally coordinated EV charge-discharge scheduling method addresses EV customer economics and distribution grid constraints by maintaining quasi-steady-state feeder voltages within power quality limits while minimizing operational costs and battery degradation through a quadratic programming formulation and receding horizon implementation to handle non-deterministic EV arrivals and departures [75]. At the global level, the EV charging station aggregator's global agent gathers the local models from individual EV charging stations' local agents to construct a global model. At the local level, each local agent iteratively refines its model using the global model to ascertain the lucrative selling price and oversee the scheduling of ESS charging and discharging. To achieve optimal performance, the process of refining the model is repeated at both the global and local levels [76]. Identifying and investigating the dynamics between EV customer and system objectives led to the implementation of a three-way multi-objective optimization on battery degradation costs, customer charging costs, and valley filling objectives, supporting EV charging and discharging scheduling schemes [77]. An operational cost minimization model is developed for residential energy system comprising of EV, ESS, PV and other residential loads [78]. Based on the availability of EVs at each time slot and location, clustering of EVs is performed, and the dispatchable region of the EV cluster is derived, followed by the submission of bids to the Distribution System Operator (DSO) by the EV cluster, aiming for the optimal dispatch of the DSO and minimizing the total cost in the day-ahead market [79]. PEVs optimize charging and discharging in the spot market to minimize energy costs while simultaneously providing regulation power on days with varying wind speeds, yielding a daily revenue of 30.0 kEUR per PEV on studied Denmark winter weekdays and an estimated annual revenue of 204 EUR per PEV when optimizing both market participation and regulation power provision [80]. EVs participate in balancing power and energy markets through aggregators, which strategically compose their pools with EVs that actually contribute to the pool's performance to increase revenue per vehicle instead of a random composition [81]. An efficient EV charging and discharging scheduling strategy is designed for V2G aggregators to improve the reliability and profitability of V2G operations, addressing operational uncertainties such as users' travel demands without requiring full information regarding the distribution data [82]. Electric buses report real-time information, including locations, velocities, and bus loads, to electric bus charging stations for energy management, which then transmit PV, ESS, and electric buses data to DSOs for charging impact mitigation, while functioning as aggregators to interact with the main grid directly and behaving as energy prosumers [83]. An optimal V2G aggregator planning strategy was developed through a stochastic optimization simulation implanted in Matlab, incorporating real-world Turkish power system data, EV availability, and battery constraints, with the aim of maximizing aggregator profits and minimizing electricity costs [84].

TABLE 5. For each Scenario, the charging amount, dr reduction amount, and settlement amount.

Seasons	Scenarios	DR issuance	Charging amount(kWh)	DR reduction amount(kWh)	Settlement amount(Won)
Summer	1	-	40127.84	-	-
		9:00	40127.84	3701.10	581717.40
		11:00	40127.84	2784.90	452263.02
	2	-	41541.42	-	-
		9:00	41541.42	4588.98	721269.30
		11:00	41542.20	5570.91	904706.85
	3	-	37891.85	-	-
		9:00	36901.15	4588.98	584911.63
		11:00	37315.36	5570.90	814231.40
winter	1	-	40127.84	-	-
		9:00	40127.84	2059.68	319590.86
		11:00	40127.84	0	0
	2	-	41541.42	-	-
		9:00	39139.36	2684.93	416608.48
		11:00	39146.36	730.66	103446.25
	3	-	38842.19	-	-
		9:00	35708.69	2684.93	345844.93
		11:00	35715.69	730.66	72082.78

4) MINIMIZING CARBON EMISSIONS

To minimize carbon emissions, EVs are charged during periods of maximum renewable energy generation, when emissions are low, and discharged during periods of high emissions when diesel generators are active, with the aim of minimizing overall carbon emissions [68]. The RBC mechanism mentioned in chapter 3.3 reduces carbon emissions by maximizing the utilization of renewable energy sources [71].

D. V1G AND V2G CONCEPT TRIAL

A comprehensive analysis of various VGI pilot projects is shown in Table 2. The project "Smart mobility with sustainable e-car sharing and bidirectional Vehicle-to-everything (V2X)" introduces an intelligent regulation and tariff system at a site with sector coupling and e-car sharing to optimize residents' mobility behavior and the site's energy consumption. Two bidirectional EVs were used to implement sector coupling with e-car sharing and reduce load peaks [85]. From 2020 to 2022, the Milton Keynes Domestic Energy Balancing EV Charging trial involved 12 participants, comprising four equipped with V2G chargers and eight with V1G chargers, resulting in more than 3,500 charge cycles and an excess of 35 MWh of energy charged [86]. The project "Solarcamp" utilizes V2G technology to enable parked EV to store electricity for local power grid usage, with testing conducted at the Aix TGV train station, which incorporates various distributed energy resources. Travelers use a mobile app to inform the station of their return date and required battery charge, receiving digital tokens in return for providing energy storage services [87]. In early 2021, the living lab "V2G @ home" was established to facilitate homeowners and small businesses in contributing to the energy transition, leading to the development of the V2G Liberty app. This app automates the optimization of charging and discharging schedules, ensuring both economic and ecological benefits by maintaining the battery within its optimal charge range (20-80%), continuous drivability with a minimum charge, and enabling a full charge when necessary through calendar integration, while also offering user control via a "Charge Now" button for rapid maximum power charging [88]. The project "FlexGrid" implements a smart building energy management system integrating solar energy, EV, stationary storage charging, and a heat pump, optimizing operation by using forecasts of solar energy/load and real-time electricity prices to reduce costs and increase local solar energy utilization [89]. The project "Deeldezon" aims to create energy-neutral living environments by combining solar roofs with electric shared cars equipped with smart bi-directional charging stations, enabling the storage and utilization of generated energy in a sustainable and flexible manner to meet high electricity demand [90]. A community bidirectional charging program offers residents a three-year subscription to a shared electric car scheme, providing access to electric vehicles and bidirectional charging stations, while studying socio-economic aspects of the ecosystem [91]. The project "BloRin" primarily emphasizes incorporating the V2G charger into the BLORIN blockchain platform for managing energy resources, rather than establishing a fleet of vehicles [92]. The project "Marubeni V2X" collaborates with energy and automotive technology partners to explore V2G optimizations and dynamic energy tariffs, integrating two V2G chargers, a customized solar carport, and rooftop solar installations, while optimizing on-site solar generation forecasts, EV utilization plans, site power demand, and air conditioning systems, all while considering associated energy costs and physical constraints [93]. Most of the projects have been carried out by small areas, buildings, or charging stations. It is possible to confirm the effectiveness of V1G and V2G, but it is not an empirical experiment at the large scale. The project "VGI" focuses on developing VGI core components and demonstrating V2G technology using the Combined Charging System (CCS) type 1 standard, with the goal of advancing V2G technology integration and evaluating its feasibility and performance in real-world applications [94].

E. SUMMARY AND LIMITATIONS

Due to the small-scale experiments, the limited sample size restricts the impact and generalizability of the results [85],

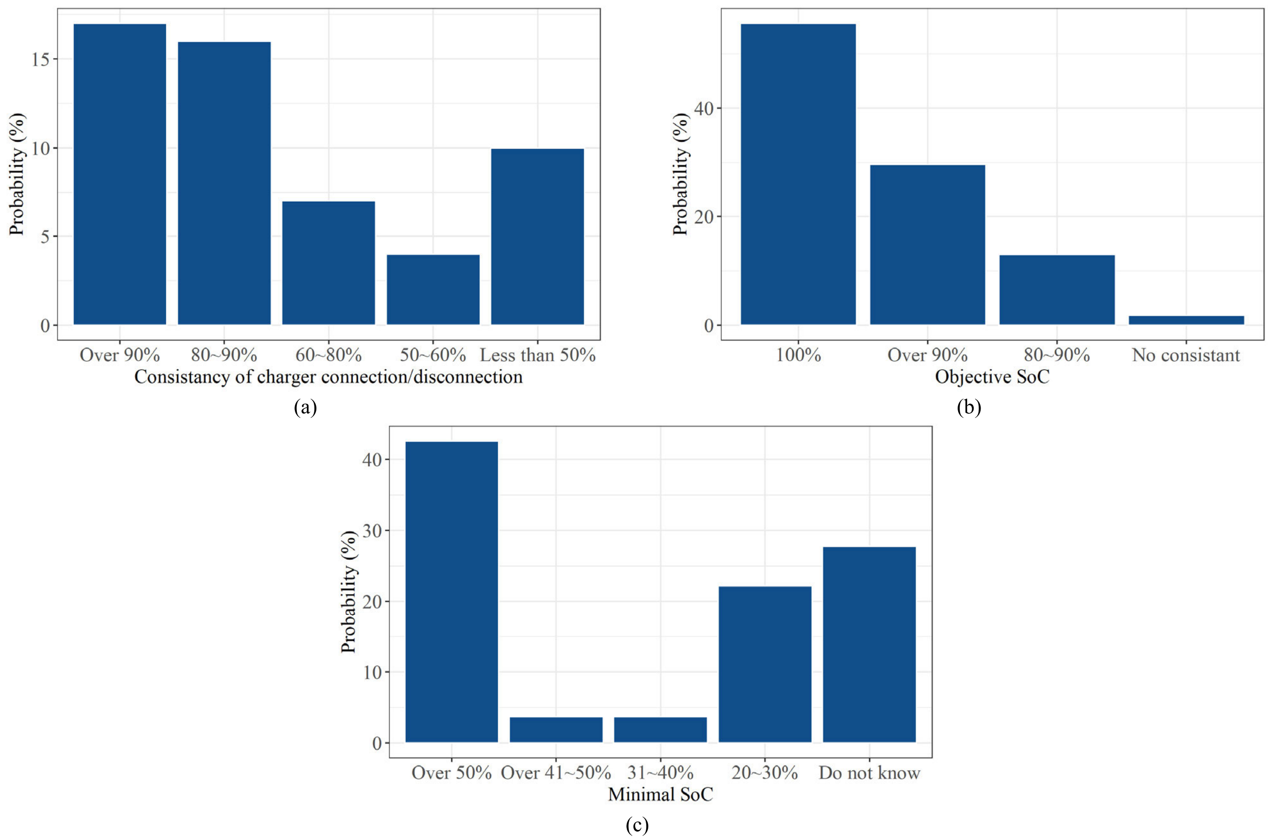

FIGURE 8. Survey results: (a) consistency of charger connection and disconnection, (b) objective SoC, (c) minimal SoC.

[86], [87], [88], [89], [91], [92], [93]. The charging stations were installed in specific locations, limiting the diversity of user participation. Specifically, the experiments in projects [85], [86], [88], and [90] were conducted with chargers installed exclusively in home environments. Project [87] implemented the charger at a train station, while projects [92] and [93] focused on installations in work areas. These constrained settings resulted in a lack of engagement from a broader range of users. The use of blockchain adds complexity to the system, making it difficult to scale in other settings [87]. Ensuring interoperability between different stakeholders and technologies is challenging [89]. The focus is on charging the electric shared vehicles using renewable energy from their own PV installations, rather than relying solely on EV drivers' participation in the service [90]. Encouraging consistent user behavior and participation is difficult. Specifically, the use of shared electric cars may lead to highly variable usage patterns, making it difficult to generalize the effectiveness of the experiments based on the collected data, as patterns of energy use, driving habits, and charging behaviors can differ widely among users [90], [91].

Unlike other projects, which do not specify a particular standard, the VGI project demonstrates the use of the CCS type 1 standard. This adherence to an international standard is crucial for the commercialization of the technology, differentiating it in terms of compliance with global standards. Additionally, it stands out in its approach to research and development, focusing on the technical feasibility and commercialization of the technology.

The VGI project conducted large-scale V1G demonstration experiment in phases to validate the performance and reliability of the technology. Regular individuals who owned electric vehicles for daily use were recruited for the study. To ensure that participation in the demonstration did not inconvenience the drivers in their daily vehicle use, participants were asked to provide their target SoC and expected decoupling time. Additionally, surveys were conducted before and after the experiments, and data on charger usage was collected to provide comprehensive insights into the project's impact and effectiveness.

III. LARGE-SCALE V1G PILOT PROJECT IN SOUTH KOREA

A. V1G SYSTEM

The system for V1G control is structured as shown in Figure 1. This system can be classified into the EV information communication device, the mobile state communication device module and control device, and V1G system modules. Communication between the EV and the EV charger follows the ISO 15118 standard, which supports the Plug-and-Charge (PnC) functionality. The PnC function enables secure communication during user verification and

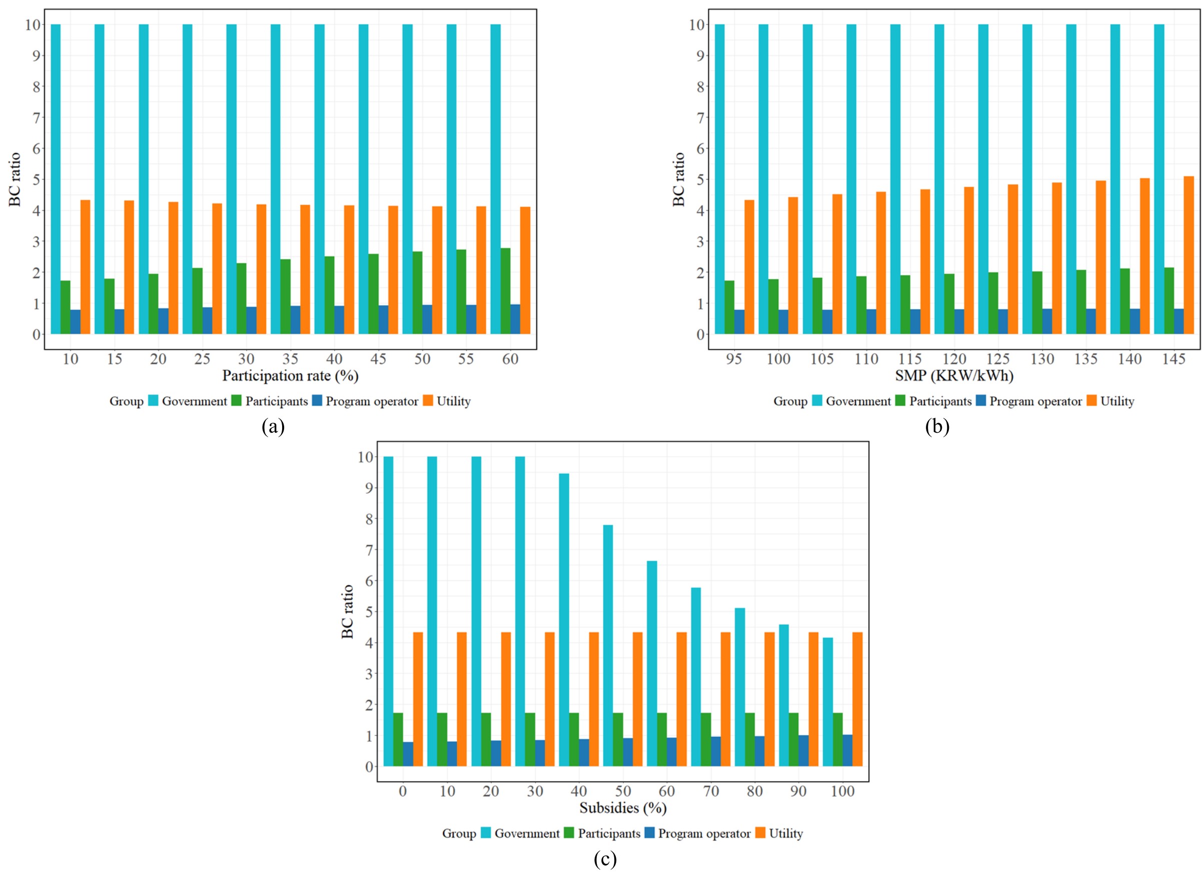

FIGURE 9. Sensitivity analysis: (a) Participation rate, (b) Unit price, (c) Government subsidy.

authorization by employing public key infrastructure technology when the EV is connected to the charger. The EV information communication device provides the function of collecting OBD II standard information and transmitting it to the connected mobile communication device using Bluetooth 2.0/4.0 protocol. It also sends real-time extracted information about the EV, including connected EV status, battery status, and device state, to the mobile state communication device module.

The mobile state communication device module is segmented into OBD information communication, V1G data connection, mobile status transmission, and control. OBD information communication collects and interprets information of the respective vehicle, including driving distance and SoC, by integrating with the EV vehicle information communication device and maintains the data in its latest state. V1G data connection performs updates for maintaining the latest information about the vehicle and the user.

Lastly, mobile state communication and control link the V1G system according to the schedule created by the user, allowing the charger to be operated as the schedule. It compares the real-time vehicle information through the EV vehicle information transmission device and outputs the schedule results. The communication protocol between the charger and the V1G system has been custom developed to comply with ISO 15118, supporting key functions such as user authentication, control, reservation, billing, and charger management. In accordance with this framework, the V1G system is responsible for charger control and device management, charging schedule generation, and data storage within the system's internal database.

B. V1G EXPERIMENT AND SURVEY

Experiment and survey were conducted to estimate the value and verify the effects of utilizing V1G's demand resources and to analyze customer acceptance. The experiment was based on data acquisition through infrastructure construction, installed 100 V1G chargers, and secured 136 EVs capable of using these chargers as shown in Table 3. The chargers were deployed across the capital region, metropolitan cities, and provincial cities according to a 4:3:3 distribution ratio. Each charger was designated either for business use or for general customer use. Similarly, EVs were categorized based on their intended purpose, distinguishing between private use and commercial use.

When an EV connects to the charger, the charging schedule is generated based on the information provided by the driver and the charging session data collected from the charger. This includes the charging start time, the scheduled end time, the

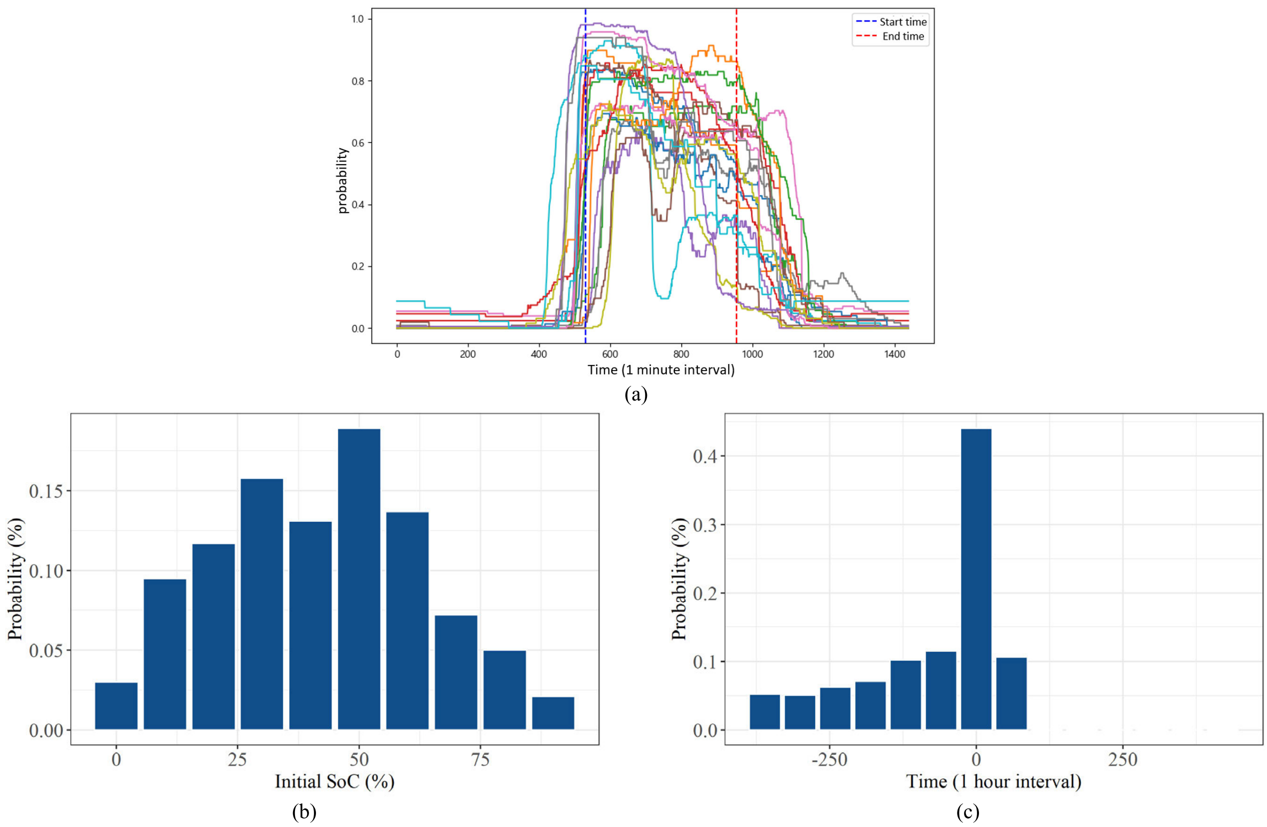

FIGURE 10. Histogram: (a) EV coupling patterns of cluster 1, (b) Initial SoC, (c) Difference time between decoupling schedule and actual decoupling time.

EV's current SoC, the target SoC, and the charging speed. V1G charging methods are categorized into standard charging, tariff-based charging. If the time required to reach the target SoC is shorter than the available charging time, a cost-minimizing schedule is applied using tariff-based charging based on Time of Use (ToU). Conversely, if the available time is insufficient to fully charge the EV, a schedule that maximizes charging during all available time is applied using standard charging. In this demonstration, DR signal is not predicted in advance. Instead, DR signal is sent to the charger in real time to control ongoing charging sessions. When DR event ends, the end time of the event is treated as the new charging start time, with EV's status continuously monitored and updated every 5 minutes to reflect real-time conditions. A new charging schedule is then generated based on the remaining time and the remaining energy required to reach the target SoC.

Through the experiment, data including charging information such as time, amount of charge, charging history, driving distance, and SoC, as well as EV type and EV user information, were acquired. The data was collected from April 1st, 2021 to April 1st, 2022, including 10,399 records from 69 EV users.

In addition to data acquisition, a satisfaction-related survey regarding V1G was conducted with representative EV users. The conditions for survey participants were personal use of level 2 chargers, charging during morning, afternoon, and evening hours accounting for more than 60% of total charging, monthly average charging amount of over 300 kWh, and being an electric vehicle customer for more than 2 years. The survey was conducted with 54 EV users meeting these conditions.

C. V1G RESOURCE EVALUATION

Assessing the suitability of EVs as demand resources is essential. The resource evaluation criteria are based on the history of DR participation. The evaluation criteria consider the matching ratio with DR hours and the duration ratio, with the evaluation score calculated as a multiplication of these criteria. The matching ratio with DR hours is calculated as the average ratio of actual participation in DR($T^{DR}_{i,d}$) to total charging($T^{charging}_{i,d}$) over the total number of days(N_d), as shown in (1). The duration ratio is defined as the average ratio of actual charging interruption time($ST_{i,d}$) to mandatory reduction duration($T^{man.}_{i,d}$) over the total number of days(N_d), as shown in (2). The results of the resource evaluation range from 0 to 1, with values closer to 1 indicating superior performance as a resource. The score for resource evaluation is calculated as the product of each criterion, as shown in (3).

$$MT_i = \frac{1}{N_d}\sum_{d=1}^{D}\frac{T^{DR}_{i,d}}{T^{charging}_{i,d}} \tag{1}$$

$$DT_i = \frac{1}{N_d} \sum_{d=1}^{D} \frac{ST_{i,d}}{T_{i,d}^{man.}} \quad (2)$$

$$Score_i = MT_i \times DT_i \quad (3)$$

IV. RESULT

A. V1G OPERATION RESULT

An experiment was conducted on V1G in response to demand reduction requests. The demand reduction experiment was conducted a total of 188 times, confirming accurate operation for connected EVs excluding non-charging EVs. The changes in specific EV charging according to the demand reduction signal are illustrated in Figure 2. It was observed that charging control or interruption occurred simultaneously with the demand reduction signal. As depicted in Figure 2 (a), departure time and final preferred SoC are considered for charging interruption time and charging control. The error in preferred SoC was at the level of -1.9%, resulting in slightly lower charging amounts; however, this error is very small, confirming that V1G control operates according to customer requests.

B. V1G CHARGING CHARACTERISTICS RESULT

The histograms for V1G's connected/disconnected time, charging duration, and charging cycles are depicted as shown in the following Figure 3. The connected time shows a high frequency in the morning and evening. Additionally, the time of connection termination shows a sporadic distribution, but there is a tendency for it to be higher during the evening and late night hours. From these histograms, it can be inferred that charging typically occurs at the workplace (connected from morning to evening) and at home (connected from evening to late night). The charging duration is typically 2-3 hours since V1G chargers are slow chargers. Users mostly utilize personal chargers at home or at the workplace, showing a tendency to connect the charger every 2-3 days.

C. REPRESENTATIVE CHARGING PATTERN RESULT

The charging patterns for each customer are depicted in Figure 4. A tendency to charge primarily during daytime hours is observed for the majority, with some patterns showing charging during certain nighttime hours as well. Based on these patterns, clustering was performed to derive representative charging patterns for charging customers, as shown in Figure 4. The clustering was conducted using the k-means methodology [95]. As a result, the data was segmented into three patterns, with 47, 16, and 6 customers included in each cluster, respectively. Each charging characteristic was classified into daytime, evening, and late-night charging. Among these, the significantly high number of customers charging during daytime hours suggests that the majority of chargers are located at workplaces.

D. SOC RESULT

The histogram for the customers' State of Charge (SoC) upon arrival and departure is depicted in Figure 5. A tendency towards charging at around 50% SoC is observed. Additionally, it was found that the majority of users prefer to end charging when the SoC reaches 90%.

E. UNCERTAINTY IN DEPARTURE SCHEDULES

Most participating customers were observed to disconnect the charger at the scheduled departure time. In some cases, departure occurred earlier than the specified time due to unexpected circumstances, but this deviation did not exceed 10 hours as shown in Figure 6. However, situations where departure occurred later were less common, but instances of departures extending beyond a day did occur. A portion of 22.45% of EV users disconnected their EVs prior to the completion of the scheduled charging session. Within this group, 28.56% departed within 1 hour before the scheduled end time, 20.49% left between 1 and 2 hours early, 13.88% between 2 and 3 hours, and the remaining 37.07% unplugged more than 3 hours in advance. In contrast, for the 77.55% of sessions where charging was completed as planned, 72.7% of EVs were unplugged within 1 hour following completion, 7.7% between 1 and 2 hours afterward, 5.6% between 2 and 3 hours, and 14% remained connected for over 3 hours after charging had finished.

F. DR PARTICIPATION

An experiment on DR participation through V1G was conducted. The DR participation experiment was conducted for a total of 188 times. Figure 7 presents the plug-in probability across the day, comparing EVs that responded to DR signals with those that did not, segmented by commercial and private users. For commercial EVs participating in DR, charger connection probability was markedly higher between 9:00 and 14:00, while private EVs exhibited peak connection between 8:00 and 16:00. In particular, the largest difference in plug-in probability occurred at 11:00 for commercial EVs and 10:00 for private EVs. In addition to connection timing, user behavior also differed. On average, EVs that responded to DR signals remained connected to chargers 17-18% longer and spent 15-18% more time actively charging compared to non-responding users. Although 52.27% of all EVs were connected during DR event hours, only 11.75% met the operational conditions required for an active response. This gap indicates that many EVs, while physically connected, were not charging at the time of DR events due to pre-established schedules optimized for minimizing charging costs. The average contribution per electric vehicle to the DR event was 1.61 kWh. DR requests primarily occurred during daytime hours, and accordingly, it was confirmed that customers charging during daytime hours participated. After the DR event, the charging schedule is rescheduled using V1G charging methods, with the EV's status updated every 5 minutes. Among the vehicles that responded to the DR signal, 70.58% completed their charging sessions, while 29.42% were disconnected by the user before charging was completed. Consequently, it can be inferred that there are challenges in utilizing V1G resources for electric vehicles charging during nighttime hours.

G. DR RESOURCE PARTICIPATION

Assessing the suitability of EVs as demand resources is essential. EV resource evaluation was conducted based on DR participation history data. The average resource evaluation score for each EV was 0.11, with the maximum score being 0.16. The results showed a high matching ratio with DR hours but were affected by low duration times. Since the evaluation score was calculated as the product of these two factors, it resulted in very low values. This indicates that if either factor has a low value, the resource is considered to have no value as a demand resource.

H. SURVEY RESULT

61.0% of customers responded that they connect the charger for at least 80% of a consistent time period presented as Figure 8. Among them, 18.5% always connect at a consistent time, and the majority, accounting for 42.6%, connect at a consistent time most of the time. The consistency in disconnection follows a similar pattern to that of connection as mentioned earlier. The rate of disconnecting the charger for at least 80% of a consistent time period is 61.1%. Among them, 31.5% always disconnect at a consistent time, and the majority, comprising 29.6%, disconnect at a consistent time most of the time. It is presumed that the consistency in charger connection/disconnection is maintained due to regular schedules such as commuting.

V. DISCUSSION

A. ECONOMIC EFFECTS

The results of utilizing V1G show a peak contribution effect similar to 6.06MW, securing a reduction of 1,139.94MWh annually. Additionally, the economic effects of V1G were analyzed from the perspectives of program operators, participants, utility company and government. Table 4 shows a comprehensive breakdown of benefits and costs analyzed by stakeholders in V1G. Each stakeholder category's potential benefits and associated costs are identified, providing insights into the economic implications of V1G. For a comprehensive economic evaluation, the analysis considered a multi-year horizon. The evaluation period was set from 2020 to 2030, spanning a total of 10 years. To reflect the time value of money, a social discount rate of 5.5% was applied, and the Benefit-Cost Ratios were calculated based on net present value. From a stakeholder perspective, the cost structure of V1G implementation can be categorized as follows. For the program operator, the primary cost components include capital expenditures (CAPEX) associated with chargers installation and operating expenditures (OPEX) such as payments to EV owners, expenses related to the operation and management of V1G system, and general administrative and maintenance costs. For the utility, CAPEX encompasses investments in transmission and distribution enhancements as well as the initial deployment of V1G operating infrastructure. Their OPEX mainly consists of disbursement costs paid to the program operator. For the participant, CAPEX may involve the purchase of bidirectional on-board charger and associated charging management systems, while their OPEX primarily reflects battery degradation costs. The Benefit-Cost Ratios for program operators, participants, utility company and government were 0.778, 4.328, 1.727 and 63.857. In the domestic power market, EV resources are currently available for participation in DR programs. Furthermore, sensitivity analysis demonstrated that neither increasing the participation rate nor raising the unit price alone was sufficient to elevate the program operator's BCR above 1, as illustrated in Figure 9(a) and 9(b). However, when government subsidies were applied to offset charger installation costs, the program operator's BCR surpassed the breakeven point, as shown in Figure 9(c). These findings underscore the importance of targeted public support, not only for infrastructure deployment but also for other elements of V1G programs, to achieve economic viability. To support broader EV participation and promote scalability, enhancements in market mechanisms and the introduction of effective policy incentives will be considered.

B. V1G PARTICIPATION

Since V1G is a resource not yet applied domestically, the surveys were conducted when customers had not experienced the related service. Customers cannot assess the value of participation preference for a completely new service they haven't experienced. Therefore, rather than directly asking about the service, it's necessary to present consumers with various choice options to understand preferences. This includes methods like conjoint analysis and discrete choice models [12], [13], [14]. The survey questions were designed based on the discrete choice model.

According to the survey conducted among EV users, the preference for participating in V1G was relatively high, with a ratio of 75.5%, among which 16.9% preferred active participation. Furthermore, among the participating customers, the response regarding the frequency of participation indicated that weekly participation (43.8%) was the highest, and it was observed that as the number of weekly participations increased, the willingness to participate gradually decreased. Therefore, the majority of EV users prefer V1G participation and tend to participate to reduce charging costs.

C. ENHANCING EV PARTICIPATION IN DR PROGRAM

In Figure 4(b), Cluster 1, which has the highest probability of charging control during the DR program period, is extracted. Figure 10(a) depicts the median values of the charging start and end times for 20 patterns belonging to Cluster 1, which are 8:50 AM and 3:56 PM, respectively. Next, Figure 10(b) presents a histogram of the initial SoC of EVs in Cluster 1 distributed as a probability over the 24-hour day. Finally, Figure 10(c) illustrates a histogram showing the difference between the scheduled and actual departure times of EVs in

Cluster 1, with approximately 44% of the EVs departing as scheduled.

The aim is to enhance the effectiveness of EV participation in DR program by eliminating uncertainties arising from the gap between the scheduled decoupling time and the actual decoupling time, which creates difficulties in calculating the controllable capacity. So, three scenarios are discussed to effectively enhance EV participation in DR program through comparative analysis. In all scenarios, the battery capacity of EVs is assumed to be 77.4kWh. The initial SoC value when connected to the charger follows the distribution shown in Figure 10(b), with the charging start time uniformly set at 8:50 AM. Furthermore, ToU charging rate system of Electric Power Corporation is applied, and the system marginal price is applied as a settlement amount according to the DR participating time. If the actual decoupling time is earlier than the scheduled decoupling time, a differential settlement penalty of 10% per hour is applied. This penalty is arbitrarily set as an assumption for simulation purposes and is intended to simplify the expression of potential disadvantages. These include reduced resource reliability, where user behavior variability undermines the predictability of aggregate load reductions, and operational inefficiency, in which inaccurate departure assumptions lead to suboptimal charging schedules that increase rebound effects and limit DR flexibility.

- Scenario 1: The scheduled decoupling time (3:56 PM) is the same as the actual decoupling time (3:56 PM)

- Scenario 2: The scheduled decoupling times are randomly distributed based on the histogram in Fig. 8(b), and the actual decoupling time follow these scheduled times.

- Scenario 3: The scheduled decoupling times are randomly distributed, but all actual decoupling times are at 3:56 PM regardless of the scheduled decoupling times.

Table 5 shows three metrics: charging amount, DR reduction amount and settlement amount across different scenarios for summer and winter. This detailed breakdown enables the evaluation of seasonal variations in charging behavior, DR effectiveness, and associated financial implications.

Scenario 1 and 3, despite having different scheduled decoupling times, both decoupled at 3:56 PM. Scenario 3 consistently exhibited lower charging levels compared to Scenario 1 due to Scenario 3's EVs participating in DR despite being ineligible. Moreover, the load reduction amounts at 9:00 and 11:00 during the summer season are higher in Scenario 3. While Scenario 3 achieved the highest settlement amount at 11:00, penalties for early decoupling led to a decrease in the settlement payment. Therefore, EVs that should not participate in DR ended up participating, resulting in a participation of 2786 kWh at 11:00 during the summer season. Also, these EVs fail to meet the charging target SoC while incurring penalties for DR participation settlement.

Scenario 2 and 3 are assigned identical scheduled decoupling times at random, but discrepancies arose in their actual decoupling times. Scenario 3 consistently displayed lower charging levels compared to Scenario 2 due to its failure to adhere to the scheduled decoupling time and decoupled early. Despite having the same scheduled decoupling times, resulting in identical DR participation charging schedules, the reduction amount remained consistent between Scenario 2 and 3. However, Scenario 2 received a higher settlement payment, attributed to Scenario 3 incurring penalties for early decoupled. Consequently, during the summer reduction order at 9:00, Scenario 3 fell short by 4640.27 kWh compared to Scenario 2, potentially influencing subsequent charging. Despite having an equivalent reduction amount, Scenario 3 incurred a loss of 136,357.67 won at 9:00 during the summer season due to the penalties.

Providing clear information on initial SoC, target SoC, charging start time, and scheduled decoupling time for EVs, along with ensuring drivers adhere to scheduled decoupling times, can maximize the effectiveness of DR programs. Predicting the potential reduction capacity of EVs participating in DR program by time slots can be done accurately. Through this, EV drivers can achieve their charging target SoC, pay lower charging fees, and seamlessly participate in DR for additional income. Implementing penalties for non-compliance with decoupling times can minimize prediction errors in potential reduction capacity and effectively manage power supply imbalances.

D. CONSIDERATION FOR V1G EXPANSION

EVs utilized as resources for V1G are limited in terms of availability. Therefore, considerations including time slot settings, rebound effect mitigation, and customer targeting are necessary to apply and activate V1G. Firstly, V1G cannot secure resources all the time, throughout the day. Hence, it's necessary to set the required time and duration for V1G. Particularly, the uncertainty caused by the increase in renewable energy generation and the sharp decrease in renewable energy generation due to sunset should be considered as resource utilization periods. The effect of time designation results in a capacity of 2.14 kW per unit EV, which is 0.54 kW higher compared to the previous available capacity. The second consideration is rebound effect mitigation, where the load increases sharply after resource utilization. Since the charging capacity of EVs is quite high, if multiple EVs charge simultaneously after V1G, a considerable demand peak is inevitable. To mitigate the rebound effect, a method of gradually reducing incentives as the resource utilization end time approaches can be applied. Lastly, incentive-based V1G, where the resource availability capacity is determined by customer participation, requires consideration of customer targeting. Especially, participation based on V1G technology requires considerable infrastructure costs. Therefore, operating targeting customers with high potential is efficient from the operator's perspective.

Although considerations for incentive-based V1G technology application have been discussed, ultimately, if ToU tariffs are designed reasonably, the aforementioned issues can be resolved. The mentioned issues arise because the system situation and EV charging characteristics are not integrated. The correlation between system load and EV ToU tariff is relatively low at 58%. Therefore, it is expected that if tariff plans that can respond to system situations, such as real-time pricing, are designed, VGI including V2G will naturally expand for the rational operation of EVs.

E. LIMITATION AND FUTURE STUDIES

The V1G pilot project conducted in South Korea was designed to verify the operational feasibility of V1G systems, demonstrate their potential at a national level, and evaluate their economic viability. However, the technological readiness of V1G systems remains limited, suggesting that additional research is required to enhance system maturity and operational reliability.

From an infrastructure standpoint, the stable operation of V1G facilities is essential. Future studies should address uncertainties related to infrastructure failures, including charger malfunctions and communication disruptions, which may affect system stability and reliability. From a system-level perspective, future research directions include enhancing the robustness of DR participation, evaluating the impact of V1G deployment on power system operations, and developing standardized communication protocols and data formats to ensure interoperability among diverse systems. Additionally, the development of V2G systems that allow bidirectional energy exchange should be considered as a long-term strategy beyond V1G. To support reliable DR participation using V1G systems, further efforts are needed to design control algorithms that mitigate DR rebound effects and incorporate real-time estimation of the SoC and driving range prediction to determine DR participation feasibility. Moreover, to ensure that V1G systems contribute meaningfully to grid operation, their effectiveness must be validated through detailed impact assessments. Based on these insights, continuous improvement of V1G systems and progressive transition toward V2G integration will be essential. In anticipation of large-scale deployment, it is also critical to establish common standards for communication and data structures to enable seamless interoperability across various V1G platforms.

The pilot experiment, though limited in sample size, was conducted with general users. While the number of participants was relatively small, the selected sample reflects the behavioural characteristics of early adopters participating in DR events. In future study, DR control strategies should be designed to incorporate behavioural differences between early adopters and the general user population, particularly regarding temporal preferences, price sensitivity, and SoC flexibility.

VI. CONCLUSION

This study proposed a large-scale pilot project for the application and dissemination of V1G technology to utilize electric vehicles (EVs) for mitigating uncertainty caused by the expansion of renewable energy. It conducted experiments on the technical suitability of V1G operation and considered policy design for technological application. Analysis of EV charging characteristics and a survey on V1G participation preferences were also performed.

The national pilot project, designed through the development of V1G systems and the deployment of 100 V1G chargers and 136 EVs, represents the first large-scale empirical study in South Korea. Unlike previous smaller-scale pilots or simulation-based analyses, this robust dataset comprising over 10,000 recorded charging sessions allowed for the derivation of realistic and generalizable insights into the technical suitability of V1G operation, showing and average potential capacity of 1.61 kW per individual EV and an estimated nationwide potential of 6.06 MW.

Crucially, this study offered a detailed assessment of uncertainties influenced by users, specifically how discrepancies between scheduled and actual EV decoupling times impact DR program effectiveness and capacity estimation. Our analysis based on scenarios highlighted potential issues like penalty risks for early decoupling and unmet charging targets, underscoring the need for robust policy measures to mitigate these effects and enhance program predictability.

The economic analysis revealed a BCR of 0.778 for program operators, indicating non-profitability under the current system. This necessitates a strategic roadmap tailored for VGI activation within Korea's policy and market environment. We proposed actionable recommendations including targeted subsidy policies, improvements in ToU tariffs to align with grid signals, and strategic customer targeting based on user behavior analysis to overcome economic barriers and low participation rates. Ultimately, for widespread VGI deployment, continuous efforts are critical for enhancing V1G system maturity, ensuring operational robustness against infrastructure failures, and developing standardized communication protocols. This also lays the groundwork for a progressive and reliable transition from V1G to V2G integration in the future.

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