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A New Simulation Framework for Vehicle-to-grid Adoption in Heterogeneous Trade Mechanism Scenarios

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ABSTRACT

The current vehicle-to-grid (V2G) project pilots generally face the problem of low user participation willingness, mainly due to the lack of detailed consideration of trade mechanisms and incentive policies. To address the potential threat posed by the large-scale application of electric vehicles (EVs) to the power grid system, an analysis of the promotion strategies of V2G technology among EV owners is deemed necessary. In this study, a new simulation framework for V2G adoption and heterogeneous trade mechanism evaluation based on social network theory is constructed. The diffusion process of V2G adoption and charging/discharging behavior is simulated under three trading mechanism scenarios: Time-of-Use (ToU) pricing + fixed service fee (ToU-F), regulated pricing + fixed service fee (Reg-F), and dynamic pricing + fixed service fee (Dyn-F). The research results indicate that (1) In terms of V2G adoption scale, both the Reg-F and Dyn-F scenarios have reached the maximum number of adopters, increasing by 41.8% compared to the ToU-F scenario. The main reason is that the former two trading mechanisms achieve a larger price difference, creating more opportunities for charge and discharge arbitrage. (2) Regarding EV load regulation, the discharge amount of EVs under the Reg-F and Dyn-F scenarios is much higher than that under the ToU-F scenario. The Dyn-F scenario further avoids drastic fluctuations in load. (3) In terms of benefit distribution, only under the Reg-F scenario have both the aggregator and V2G adopters gained higher profits.

Keywords: Electric vehicle, Vehicle-to-grid (V2G), Social network, Trade mechanism

NONMENCLATURE

Abbreviations	
EV	Electric vehicle
V2G	Vehicle-to-grid
SoC	State of Charge
Symbols	
i	EV owner
t	Time slice (half an hour)
$\Delta soc_{i,t}$	SoC variation
$soc_{i,t}^{gua}$	The guaranteed SoC for normal operation
soc_{i}^{min}	The minimum SoC required to protect the battery
$soc_{i,t}^{next}$	The SoC required for the next trip
p_{i}^{exp}	Expected price of EV owner *i*
θ	Coefficient of mileage anxiety and expected bias
μ	The intensity of noise effects
cp	Charge price

1. INTRODUCTION

Promoting the substitution of electric vehicles (EVs) for internal combustion engine vehicles (ICEVs) is a key method to achieve carbon neutrality in the transportation sector. However, the EV charging demand often exhibits a disorderly distribution, resulting in adverse impacts on the grid [1]. To solve this challenge, vehicle-to-grid (V2G) technology is proposed and discussed widely. As of August 2023, there have been 125 V2G pilot demonstration projects worldwide, distributed in 27 countries and regions [2]. However,

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most pilot projects are still in the stage of technical verification, lacking sound incentive mechanisms for users and mature business models. At the same time, EV owners are also beginning to pay attention to the potential benefits brought by V2G technology. However, due to the lack of widespread V2G technology, EV owners have limited access to information in real social life, so they choose to communicate on social media. Existing studies have proved that communication among consumers is a key factor influencing their green purchasing behavior [3,4]. How social network communication affects the diffusion of V2G technology still needs to be explored.

This study aims to simulate the travel behavior and V2G adoption decisions of EV owners, while exploring the promotional effects of V2G in heterogeneous trade mechanism scenarios. The marginal contributions include: (1) constructing a social network-based diffusion model of V2G technology to explore the impact of EV owner's communication; (2) comparing the number of V2G adopters, load regulation effects, and costs and benefit under different trading mechanisms to optimize the promotion strategy.

2. METHODOLOGY

2.1 Model framework

The model simulation framework is shown in Fig. 1. The first step is to initialize the characteristics of EV owners, and then the travel profile based on travel chain theory and statistical data is generated, considering the difference between weekdays and weekends. The next step is to simulate the charging and discharging behavior of EV owners. For EV owners who adopt and do not adopt V2G, different decision rules are developed. The main influencing factors include the availability and attributes of bi-directional charging piles in different locations, EV owners' expected price and the SoC required to meet the next trip. At the end of the week, EV owners will be informed of their charging fee, the calculation method of which is related to the pricing and benefit allocation strategy adopted, i.e., the trading mechanism. At this point, EV owners will exchange EV charging cost information through the social network, further updating the V2G adoption decision for the next week until the end of the cycle.

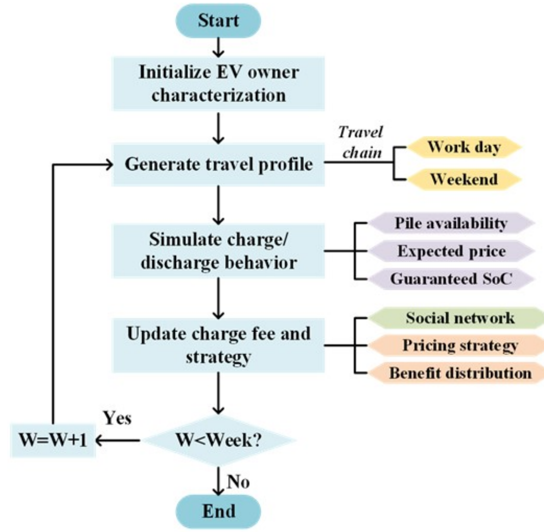

Fig. 1. Model simulation framework

2.2 Assumption

In order to analyze the theoretic result, several assumptions are made as follows:

(1) The model sets 4 am as the end time of each day, as over 99% of daily trips begin after this time [5].

(2) EV owners are allowed to change their charging strategy, whether to participate in V2G, at the beginning of each week. The charging fee will be calculated at the end of each week.

(3) EV owners determine their charging strategies by comparing the charging costs of others with their own. But all participants are bounded rational, and the information they receive is incomplete.

(4) It is assumed that the EV owners' daily travel behavior is not affected by charging strategy. The possibility of switching to other modes of transportation, such as cycling and public transportation, is not considered, nor does it consider long-distance travel behavior.

2.3 Simulation process

2.3.1 EV owner characterization

The characterization of EV owners includes two aspects: EV attributes and social network structure. EV attributes include battery capacity, charging and discharging power, charging efficiency, and travel profile. The travel profile of each EV owner is generated based on the travel chain theory and distinguishes between weekdays and weekends.

The social network is a social structure composed of many nodes, usually referring to individuals or organizations, and representing various social relationships [6]. EV owners' information sharing interaction process and behavior decisions will be affected by their social network topology. Based on our previous study, the Barabási-Albert model is used to generate a scale-free network among EV owners[4].

2.3.2 Travel profile generation

The travel chain refers to the entire travel process of individuals, based on their travel purpose, starting from the starting point, passing through several destinations in a certain time sequence, and finally reaching the end point. This study describes the EV travel chain as a spatiotemporal chain that links the travel and parking processes of electric vehicles in chronological order, starting from home and ending at home. Based on the 2009 US National Household Travel Survey data (NHTS2017), considering different travel characteristics on weekdays and weekends, Monte Carlo simulation was used to randomly generate user travel sequences within a day. Different dimensional time variables, first trip departure time, driving time, parking time, are used to quantify the time characteristics of user daily travel [7].

The start time of the first travel follows the Burr Type XII distribution, and the probability density function is as follows.

$$f(x|\alpha,c,k)=\frac{\frac{kc}{\alpha}\left(\frac{x}{\alpha}\right)^{c-1}}{\left(1+\left(\frac{x}{\alpha}\right)^{c}\right)^{k+1}} \tag{1}$$

The driving duration of a single trip follows a lognormal distribution, and its probability density function is as follows.

$$f(x|\mu,\sigma)=\frac{1}{x\sigma\sqrt{2\pi}}e^{\frac{-(logx-\mu)^2}{2\sigma^2}} \tag{2}$$

Parking time limits the charging time and battery level. According to the type of parking location and date, parking time is divided into six categories (Table 2), and parking time data is generated based on different distribution types.

Table 1 Probability density function of parking time

Days Type	Location Type		
	W	H	O
Weekday	Stable distribution	Burr distribution	Generalized extreme value distribution
Weekend	Normal distribution	Weibull distribution	Burr distribution

2.3.3 Charging/discharging behavior simulation

EV owners who adopt V2G follow the charging/discharging rules shown in Fig. 2. According to the change in SoC, $\Delta soc_{i,t}$, there are five charging/discharging strategies for V2G adopters at each time slice.

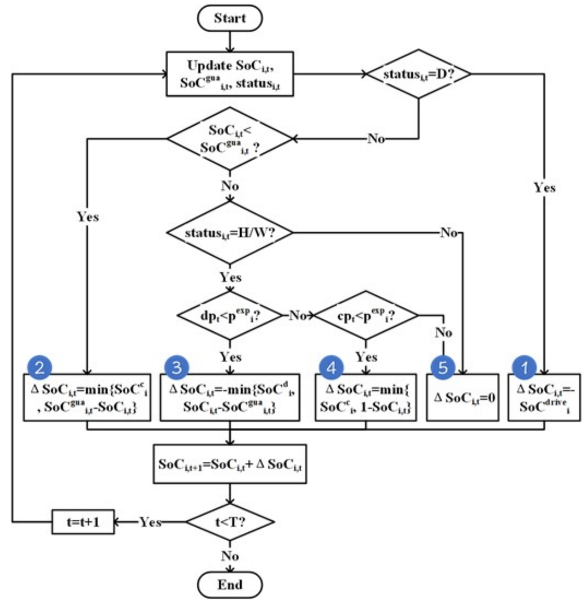

Fig. 2. The flow chart of V2G adopters

When the user is in driving state, $\Delta soc_{i,t}$ is equal to the SoC consumed per unit of driving time (Strategy 1). When the EV is in a stationary state, if the SoC is less than the guaranteed SoC, the EV owner will immediately take measures to charge until SoC is sufficient (Strategy 2). Guaranteed SoC, $soc_{i,t}^{gua}$, is defined as the sum of the minimum SoC required to protect the battery and the SoC required for the next trip. Considering that EV owners have varying degrees of mileage anxiety and expected bias, a coefficient, θ, is introduced (Formula 3). If SoC is greater than $soc_{i,t}^{gua}$, to avoid sudden driving situations when going to other place, it is ruled that the EV owner will only consider whether to charge/ discharge when the EV is located at home or in the workplace. When the discharge price is higher than the EV owner's expected price, p_i^{exp}, the EV owner will choose to discharge (Strategy 3); otherwise, if the charging price is lower than p_i^{exp}, the EV owner will choose to charge (Strategy 4). p_i^{exp} of each EV owner will be adjusted based on the previous week's income and cost, which will be explained in section 2.3.4. If none of the above conditions are met, the EV owner will not be connected to the power grid and $\Delta soc_{i,t}$ is equal to 0 (Strategy 5).

$$soc_{i,t}^{gua}=\left(soc_i^{min}+soc_{i,t}^{next}\right)\times e^{\theta} \tag{3}$$

EV owners who don't adopt V2G follow the charging rules shown in Fig. 3. The main difference from the rules followed by V2G adopters is that these users do not need to determine whether to discharge, so there are only four strategies available.

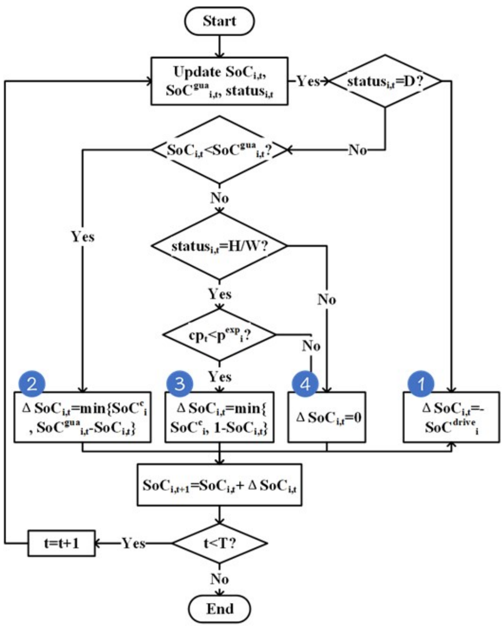

Fig. 3. The flow chart of non-V2G adopters

2.3.4 Update electricity bill and strategy

At the end of each week, the EV owners will receive their own electricity bill, which is equal to the charging fee plus service fee minus discharge income. Next, EV owners will compare the amount of fees they pay with neighbors: Define their own charging strategy and fees as (s1, bill1). Firstly, neighbors are divided into two categories based on whether V2G is adopted or not, and their average payment costs are calculated. The smaller one is selected, and its charging strategy and average cost are represented by (s2, bill2). The update process is shown in the Fig. 4.

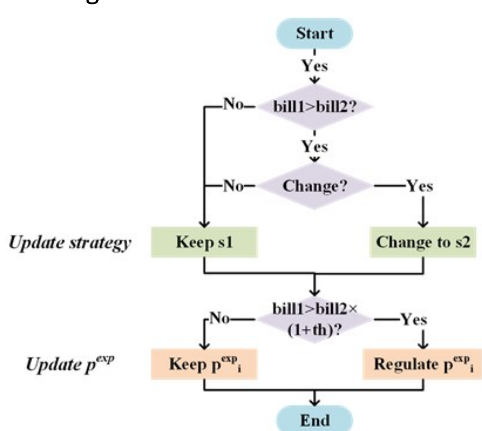

Fig. 4. The flow chart of updating charging strategy and expected price

When bill1 is greater than bill2, EV owners have a certain probability, $P(s1 \rightarrow s2)$, of changing their strategy into s2 (Formula 4). This rule is also called Fermi rule [8]. μ is the intensity of noise effects, which describes uncertainties such as fluctuations and errors in the decision-making process.

$$P(s1 \rightarrow s2) = \frac{1}{1 + exp[(bill1 - bill2) \times \mu]} \tag{4}$$

After updating the charging strategy s1, EV owners will continue to consider whether to adjust the expected price to reduce electricity bill. As there is decision-making inertia for EV owners towards the current situation, this study sets a threshold, *th*, for decision change[9]. The EV owners will only change the expected price according to Formula 5 when bill1 is greater than (1+*th*)×bill2.

$$p_i^{exp} = \begin{cases} max\{cp^{min}, p_i^{exp} \times (1-r)\}, s1 = V2G \\ min\{cp^{max}, p_i^{exp} \times (1+r)\}, s1 = no\ V2G \end{cases} \tag{5}$$

3. DATA COLLECTION AND SCENARIO SETTING

A case study with 200 EV owners is conducted. And the simulation duration is 52 weeks. At the beginning, the proportion of V2G adopter is 15%. The initial SoC of the EVs follows uniform distribution. This study adopts a time of use electricity price mechanism, with pricing reference from literature [10]. It is assumed that the charging or discharging behaviors are implemented in the charging station, and the charging station power is 13 kW. EV is driven on urban roads at a speed of 40km/h. The energy consumption is 0.21 kWh/km and the battery capacity is 70 kWh.

Through a review of literature, this study introduces three pricing strategies (Time-of-Use Pricing, Regulated Pricing, and Dynamic Pricing) and one profit distribution method (Aggregator charging a fixed service fee) to form three trading mechanism scenarios, which are denoted as ToU-F, Reg-F, and Dyn-F, respectively. Regulated Pricing refers to adjusting prices based on the distribution of residential electricity loads on top of the charging price, where the discharge price is higher during periods of high residential electricity load and lower during periods of low load. Dynamic Pricing is decided based on relative size of the expected discharge from V2G adopters and the power dispatch demand issued by the grid.

4. RESULTS

4.1 Number of V2G adopters

The V2G adoption number under three trading mechanisms is shown in Fig. 5. Compared to the BAU-F scenario, the final V2G adopters in the Reg-F and Dyn-F scenarios increase 41.8% to 200. Moreover, The Reg-F scenario requires the shortest time to reach the final number of V2G adopters (20 weeks). ToU-F and Dyn-F scenarios reach their final adoption numbers in weeks 26 and 34, respectively. From the perspective of the trend, the Reg-F scenario remains stable after a rapid growth phase. In contrast, both the BAU-F and Dyn-F scenarios experienced a significant decline in adoption during the early stages of development, followed by a gradual recovery in growth.

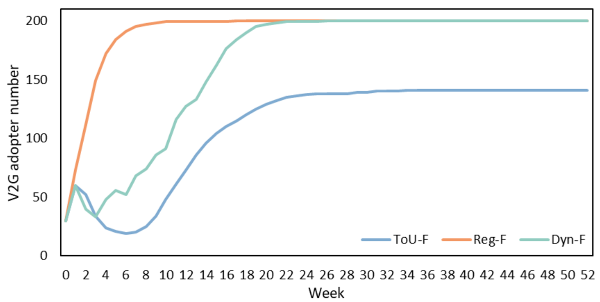

Fig. 5. Number of V2G adopter under different scenarios

4.2 *EV load regulated effect*

This study mainly evaluates the EV load regulated effect under different trading mechanisms from three aspects: total EV discharge, average discharge, and load fluctuations. The result is shown in Fig. 6. Overall, each scenario exhibits higher discharge levels and per-vehicle averages on weekends, indicating that EV owners have more free time during weekends, and the dispatchable storage potential of EVs is greater (Fig. 6.(a) and (b)). Under the Reg-F scenario, both the total discharge and per-vehicle averages are significantly higher than those in the ToU-F scenario, with the fluctuation amplitude of the load increasing substantially (Fig. 6(c)). In the Dyn-F scenario, the discharge level is slightly higher than that in the Reg-F scenario, but the fluctuation amplitude of the load noticeably decreases. This suggests that the use of a dynamic pricing model with a fixed service fee allows for an increase in discharge levels while avoiding excessive fluctuations in load amplitude.

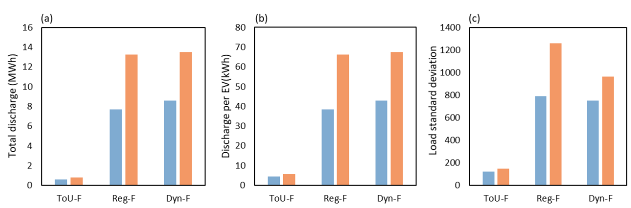

Fig. 6. EV load regulation effect: (a) Daily total discharge volume; (b) Daily discharge volume per EV; (c) EV load distribution std

4.3 *Cost-benefit analysis*

It is defined that the revenue of the aggregator consists of service fees and income from selling electricity to the grid minus the cost of purchasing electricity from the grid. Since this study primarily explores the user-side V2G trading mechanism, the complex electricity trading process has not been considered. The weekly profit of the aggregator under different trading mechanisms is illustrated in Fig. 7.(a), where transaction revenue equals income from selling electricity to the grid minus the cost of purchasing electricity. The total net revenue of the aggregator is indicated on the y-axis.

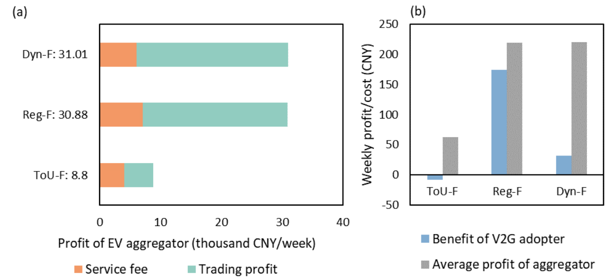

Fig. 7. Cost- benefit analysis of the aggregator and EV owners: (a) Cost and income structure of the aggregator; (b) Weekly cost/benefit of EV owners and average promotion cost of the aggregator

Under the Dyn-F scenario, the total revenue of the aggregator is 31.01 thousand CNY/week, which is the highest one among the three trading mechanisms. The return under the Reg-F scenario is 30.88 thousand CNY/week, slightly lower than that of Dyn-F scenario. In the ToU-F scenario, the low profit (8.8 thousand CNY/week) are primarily due to insufficient income (both the service fee and trading profit), indicating that under the ToU-F scenario, the fixed electricity price leads to a small arbitrage space and limited revenue.

Fig. 7.(b) illustrates the weekly total revenue from charging and discharging for V2G adopters, as well as the average profit by aggregators per V2G adopter. In the Reg-F scenario, users have the highest revenue, followed by the Dyn-F scenario, while V2G adopters incur negative revenue in the ToU-F scenario. Similar to the conclusion in Fig. 7(a), in both the Reg-F and Dyn-F scenarios, the average profit by aggregators is significantly higher than that in the ToU-F scenario.

Fig. 7.(b) indicates that in the ToU-F scenario, although the aggregator gain positive profits, V2G adopters' discharge revenue cannot cover the electricity costs. In the Dyn-F scenario, the profit of the aggregator has significantly increased, but the revenue of V2G adopters remains at a relatively low level. Only in the Reg-F scenario does both the aggregator and the V2G adopters receive high returns.

5. CONCLUSIONS AND DISCUSSION

This study constructed a new framework to simulate V2G diffusion process and effect under heterogeneous trade mechanisms. The obtained results show that: (1)

Compared to the ToU-F scenario, the final V2G adopters in the Reg-F and Dyn-F scenarios increase 41.8% and the rate of adopter growth in the Reg-F scenario is the fastest. (2) From the aspect of EV load regulation, the Dyn-F scenario not only performs well in increasing discharge capacity, but also avoids drastic fluctuations in EV load. (3) In the Dyn-F scenario, the aggregator achieve the highest profits, but V2G adopters' earnings are relatively low. In the Reg-F scenario, both the aggregator's and V2G adopters' profits reach higher levels.

This research can be further extended in exploring more benefit distribution strategies with a detailed V2G pilot cases.

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DECLARATION OF INTEREST STATEMENT

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. All authors read and approved the final manuscript.

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