A Spatial Agent-based Joint Model of Electric Vehicle and Vehicle-to-Grid Adoption: A Case of Beijing

Junbei Liu[1], Chengxiang Zhuge[1, *], Justin Hayse Chiwing G. Tang[1], Meng Meng[2], Jie Zhang[3]

[1] Department of Land Surveying and Geo-Informatics, The Hong Kong Polytechnic University, Hung Hom, Kowloon, Hong Kong, China

[2] School of Management, University of Bath, Bath, BA2 7AY, United Kingdom

[3] Department of Engineering, University of Cambridge, Cambridge, CB3 0FS, United Kingdom

Email addresses: Junbei Liu (junbei.liu@connect.polyu.hk); Chengxiang Zhuge* (Corresponding Author, chengxiang.zhuge@polyu.edu.hk); Justin Hayse Chiwing G. Tang (justin-chiwingg.tang@connect.polyu.hk); Meng Meng (mm3042@bath.ac.uk); Jie Zhang (jz519@cam.ac.uk)

Abstract

The potential widespread adoption of Electric Vehicles (EVs) has received considerable attention across the globe. However, as a promising technology for both EVs and smart grid, Vehicle-to-Grid (V2G) tended to receive much less attention. This paper developed an agent-based joint EV and V2G model to simultaneously simulate how EVs and V2G might diffuse across space and over time, with empirical findings from a questionnaire survey in Beijing. In particular, random forest models were developed with the survey data to generate each agent's preferences and attitudes towards EVs and V2G. The joint model also considered three typical levels of social influence, i.e., global influence, neighbor effect, and friendship effect, in the diffusion of EVs and V2G. Finally, the joint model was tested through several "what-if" scenarios, considering different V2G prices, EV/V2G advertisement intensities, and vehicle purchase restrictions. The survey results suggested that 67.7% of the respondents were familiar with EVs, but only 3.3% of them were familiar with V2G. However, over 70% of them would/might try V2G given that they had an EV. The model results suggested that the number of CV applicants was 6.19 times that of BEV applicants in 2030 in the baseline scenario, and only 27.8% of BEV users adopted V2G. Furthermore, V2G selling price, EV/V2G advertisement, and dedicated PHEV purchase permits were not very influential to the diffusion of V2G. The outcomes would be helpful for EV- and V2G-related stakeholders in policy making and technology investment.

Keywords: Electric Vehicle; Vehicle-to-Grid; Agent-based Modelling; Diffusion Model; Spatial Modelling

1 Introduction

The past decade has witnessed a burgeoning interest from the worldwide automotive industry in both energy-saving and low-carbon vehicle technologies (Raines, 2009). Electric vehicles (EVs) have received considerable attention from various automotive companies and startups (e.g., Tesla, Nio, Rivian, WM Motor, and Nikola Motors). As these environmentally-friendly vehicles are expected to reduce carbon emissions, decarbonize the transport sector, and fight climate change, governments support the adoption of EVs through various policies and regulations (Chen et al., 2018; Markewitz et al., 2012; van der Steen et al., 2015). For example, the Chinese government strongly supports EVs by releasing dozens of policies, such as subsidies for purchasers and EV manufacturers, zero-emissions vehicle mandate (a mandatory requirement for vehicle manufacturers to produce a certain number of electric vehicles), tax exemptions, and developing charging infrastructures. New Zealand sets a target of 64,000 EVs by 2021 and implements several policies, such as supporting the development of charging posts, exempting road use charges, and providing funds for innovation. With the efforts of various countries, the global sales volume of EVs achieved a new record in 2019 of 2.1 million units, and totaling approximately 7.2 million (International Energy Agency, 2020).

With the accelerated development and surging adoption of EVs, Vehicle-to-Grid (V2G), an important technology for both EV users and the grid, was invented in 1997 (Kempton and Letendre, 1997). V2G offers a reciprocal flow of power between EVs and the power grid system (Kempton et al., 2001). In the context of V2G, an EV thus becomes a mobile energy-storage device and could potentially benefit the power grid system through spinning reserve, load peak shifting and voltage and frequency regulation (Amamra and Marco, 2019), so as to make the grid system efficient, stable, and reliable (Yilmaz and Krein, 2013). Furthermore, V2G would also help to integrate renewable energy (e.g., wind and solar energy) into the power grid system and thus would bring environmental benefits as well (Kempton and Tomić, 2005). As an ancillary service to EV users, V2G could also potentially promote the uptake of EVs, as EV users could receive rewards by participating in a V2G scheme, which would help to save the EV cost. For example, a recent study by Chen et al. (2020) found that adding V2G capability to EV attributes could facilitate the EV adoption in the five Nordic countries, i.e., Denmark, Finland, Iceland, Norway, and Sweden. One of the first projects of V2G was conducted in North America from 2009 to 2014, where 140 PHEVs were used to test the capability of V2G (V2G Hub, 2020). Then, the Tokyo Institute of Technology conducted a small-scale experiment using 5 EVs from 2010 to 2013, which reduced peaks by 12.7%. Meanwhile, Nissan started a large-scale vehicle-to-building (electricity is sent to buildings from vehicles) project, aiming to provide power back for households. Up to now, there are dozens of pilot projects worldwide.

However, V2G still stays at an experimental stage. Moreover, existing studies tended to focus on the technical perspective of V2G, but neglect its social dimensions (Sovacool et al., 2018). It remains unclear whether people are willing to adopt V2G, and how V2G might diffuse over time and across space. In response, this paper will investigate the diffusion of V2G from both empirical and theoretical perspectives, considering the diffusion of EVs as a precondition. Specifically, it will provide insights into people's willingness to adopt EVs and V2G with survey data collected in Beijing in 2020. Based on the empirical findings, an agent-based EV-V2G joint model is developed to simulate the adoption of EVs and V2G simultaneously over time and across time. Although a large variety of agent-based EV diffusion models have been developed (see Section 2.1 below for a review), this paper will be focused on the modelling of V2G diffusion and consider the EV adoption as a precondition of the V2G diffusion in the EV-V2G joint model. With the joint model, we can further explore how EVs and V2G might diffuse at the individual level within various "what-if" scenarios. The results are expected to be helpful for power companies and policymakers to promote the development of both EVs and V2G, for example, through policymaking, infrastructure planning, and technology investment. Therefore, the proposed EV-V2G model is exploratory in nature, and is not for prediction purpose.

2 Literature Review

2.1 Adoption of Electric Vehicles (EVs)

People's willingness to adopt EVs could be influenced by various factors, including sociodemographic characteristics, vehicle price, environmental awareness, EV subsidies, and vehicle characteristics (e.g., limited driving range) (Zhuge and Shao, 2019). To understand and predict people's willingness and preferences, various models and methods have been used, including discrete choice models and agent-based models (Zhuge et al., 2019). In general, discrete choice models (e.g., multinominal logit model and mixed logit model) can relate influential factors (e.g., vehicle price) to people's EV adoption behaviors; while agent-based modeling, which is a typical approach to exploring dynamic complex systems, can simulate the EV adoption behavior at the individual level over time (Al-Alawi and Bradley, 2013). Attempts have also been made to couple discrete choice models with agent-based models (Brown, 2013), so as to use discrete choice models to simulate agent's heterogeneous behaviors (e.g., vehicle purchase behavior).

In an agent-based EV market model, consumer agent generally plays a dominant role. Based on specific rules, each consumer agent can make decisions autonomously, considering the potential interactions with other connected agents, such as the government and automakers agents. Previous agent-based EV market models mainly differ from each other in the behavioral rules of agents involved. For example, in the model developed by Silvia and Krause (2016), the behavioral rules of consumer agents were developed with eight survey questions associated with consumers' attributes and driving habits, vehicles' characteristics, and the market environment. With the model, Silvia and Krause further tested four EV-related policies, namely city fleet, charger, incentives, and policy hybrid. In the model by Eppstein et al. (2011), consumer agents would choose a vehicle with the highest relatively desirability that was quantified with the consideration of the relative cost, the social and media influences, and relative benefits of the vehicle. With this model, penetration rates of PHEVs were predicted in scenarios with various incentives. Furthermore, some agent-based EV market models also tried to simulate consumer agents' behavior using utility functions (considering both agents' and vehicles' attributes), with the assumption that agents will always adopt the vehicle with the highest utility. For instance, Shafiei et al. (2012) modeled consumer agents' behavior using a multinominal logit (MNL) model. More specifically, given a set of candidate vehicles, each consumer agent's probability to buy them was associated with the consumer's preference towards attributes of vehicles, social influences, and market conditions. The model provided insights into the effects of fuel prices, vehicle taxes, and charging concerns on the market penetrations of internal combustion engines (ICE) and EVs. Adepetu et al. (2016) developed an agent-based ecosystem model that used a utility function to calculate agents' relative desirability for each pair of vehicles. The model could be used to investigate how policies and EV-related technology change would influence the adoption of EVs, and further explored the effects of the EV adoption, for example, on the electricity load. Likewise, in the model by Wolf et al. (2015), agents' decision on vehicle purchase was made based on the rule of maximizing their benefits and emotions. The model was applied to assess the impact of three policies associated with consumers' transport mode choices.

2.2 Adoption of Vehicle-to-Grid (V2G)

Previous studies tended to focus on technical aspects of V2G with much less attention paid to social dimensions of V2G (Sovacool et al., 2018). However, understanding and modeling people's willingness and preferences towards V2G are of great importance to the development of V2G.

As V2G still stays at its experimental stage, previous studies generally investigated influential factors of V2G adoption and the potential market of V2G with questionnaire survey data, for example, using discrete choice models. In 2009, the University of Delaware carried out three choice experiments in a survey in the US, aiming at estimating the potential market of EVs, consumers' preference towards V2G contracts, and the potential need for V2G-EVs, respectively. In total, 3029 respondents participated in the experiments. Based on the first two choice experiments, Parsons et al. (2014) used a latent class random utility model to assess how designs of EVs and V2G contracts would influence consumers' choices. Based on the third experiment, Hidrue and Parsons (2015) developed a standard binary logit model and a latent class model to assess the potential market of V2G by comparing consumers' willingness to pay and costs of V2G projects. The results of the analysis held a negative attitude towards the potential market of V2G, and suggested to design more flexible contracts for promoting the adoption of V2G. More recently, Noel et al. (2018) launched another choice experiment across five Nordic countries, and used mixed logit models to compare preferences towards EVs and V2G among the five countries. They found that people's preferences towards V2G might vary across countries. Lee et al. (2020) conducted a contingent valuation survey in South Korea and found that the mean willingness to accept V2G was USD 106.01. Furthermore, for those respondents who were unwilling to accept V2G, they were mainly concerned about the restrictions specified in a V2G contract and battery degradation.

Some attempts have also been made to explore the potential market of V2G and the impacts that V2G diffusion might bring (e.g., to the electricity price) by using agent-based models. For example, Freeman et al. (2017) developed an hourly economic model to simulate intelligent individuals' participation in V2G in five years. With this model, Freeman et al. designed three scenarios (i.e., work-hour price-taker V2G, Arbitrage-guided V2G with perfect information, and user-defined selling price V2G) to test the economic benefits that V2G could bring to adopters, and further test the influence of carbon tax on V2G adoption. Wolinetz et al. (2018) simulated whether plug-in electric vehicle (PEV) owners would adopt a utility-controlled charging (UCC) program using a latent-class choice model. In particular, market shares were explicitly considered for each consumer agent. By integrating a PEV market model and an electricity system model, they further developed four scenarios to assess the impacts of UCC on the electricity price, the integration of renewable energy, and the adoption of PEVs. Likewise, Wehinger et al. (2010) presented a model that asked agents to optimize their actions about transportation based on a reinforcement learning approach. This model was further used to assess the impacts of V2G on the electricity price.

2.3 Research Gaps and Aims

As a precondition of the diffusion of V2G, the uptake of EVs has received considerable attention in previous studies: lots of efforts have been made to understand the influential factors to the adoption of EVs, and further to explore the diffusion of EVs at the individual level, for example, using discrete choice models and agent-based models. On the other hand, as V2G is still at the initial stage of its development, previous studies were mostly focused on technical aspects of V2G, but paid significantly less attention to its social aspects. It remains unclear how people's willingness to adopt V2G, and further how V2G might diffuse over time. In response, this paper will provide insights into people's willingness to adopt EVs and V2G with survey data in Beijing. Based on the empirical findings, we will develop a spatial joint EV-V2G model to simultaneously simulate the diffusion of EVs and V2G at the micro-scale. Such joint modeling of the EV and V2G diffusion has received scant attention in previous studies. Furthermore, we will explore the future of EVs and V2G with the joint model through a set of "what-if" scenarios, so as to understand how different policies and strategies would promote the development of EVs and V2G. The outcomes would be helpful for both EV- and V2G- related stakeholders, such as vehicle manufacturers, policymakers, and power companies.

3 Study Area, Data Sources, and Empirical Findings

3.1 Study Area: Beijing, China

3.1.1 The Development of EVs and V2G in Beijing

As the capital of China, Beijing has put intense efforts into the development of new energy vehicles, especially BEVs, as evident from its monetary and non-monetary policies. EV subsidy is a typical monetary policy. Before 26 June 2019, BEV purchasers in Beijing could receive subsidies from both central and local governments (The People's Government of Beijing Municipality, 2019). In terms of non-monetary policies, BEV purchasers do not need to go through the license plate lottery policy (Zhuge et al., 2020), and BEV users are exempted from the end-number license plate policy (Zhuge and Shao, 2019), which are typical types of traffic restriction in some of China's cities. With these supportive policies, the EV penetration rate is on the rise. The number of alternative fuel vehicles (nearly all of them were BEVs) in Beijing reached 324,000 in 2019, accounting for about 7% of the total number of alternative fuel vehicles in China (Beijing Transport

Institute, 2020). Unlike EVs, V2G is still in the experimental stage in Beijing, with few attempts made. For example, the Beijing Electric Power Corporation conducted a project with 288 intelligent charging stations in Beijing's urban areas (Wang, 2020). The project was comprised of two phases: the first phase tested the system stability and the second focused on achieving Vehicle-to-Home (V2H).

3.1.2 The License Plate Lottery Policy in Beijing

The license plate lottery policy is one typical traffic restriction policy in many cities of China, and it has been implemented in Beijing in 2011 (see Table 1 for specific rules). For residences who meet the requirements, they can apply for either a New Energy Vehicle (NEV) license plate or a Conventional Vehicle (CV) one. It should be noted that nearly all private NEVs in Beijing are BEVs, and PHEVs are treated as one CV type. As a result, the potential PHEV and CV purchasers need to compete for a limited number of so-called CV license plates.

Table 1. The License Plate Lottery Policy in Beijing

Type of License Plate	***Applicable Vehicles***	***Number of License Plates Available each Year***	***Application Requirements***	***Rule***
NEV License Plate	NEV (Note: nearly all of them are BEVs in Beijing)	54,000	1) Having a driving license 2) Having no vehicle	First-come-first-served basis; applicants are put on a waiting list when no plate is available
CV License Plate	Including CVs (e.g., petrol ar) and PHEVs	38,000		Randomly allocate a fixed number of purchase permits to applicants

3.2 Survey Data on EV and V2G Adoption

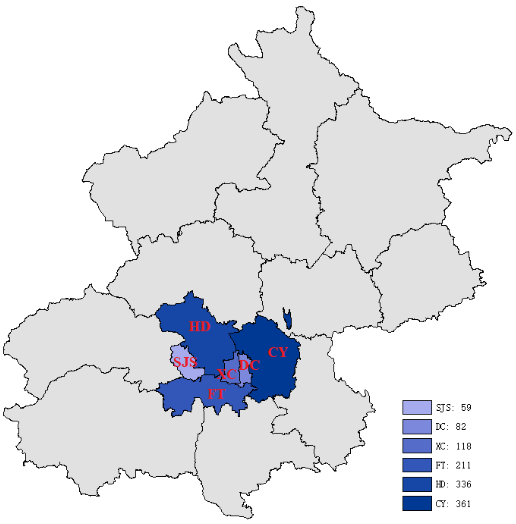
We conducted a questionnaire survey in Beijing to collect essential information on the adoption behavior of EVs and V2G. The empirical findings from the survey were further used to define behavioral rules of agents in the EV-V2G joint model (see Section 4).

3.2.1 Questionnaire Design

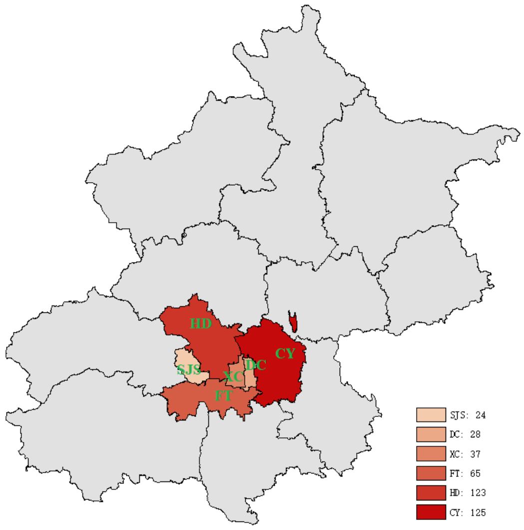
A questionnaire was designed to collect respondents' information. The questionnaire includes four parts: Part 1 was to collect socio-demographic attributes; Part 2 was to collect information on the familiarity with and willingness to buy EVs; Part 3 was to collect information on the familiarity with V2G and willingness to adopt V2G; and Part 4 was to collect information on the attitudes towards V2G price and social influences. More details about the questionnaire design can be found in Appendix 1.1 of the Supplementary Materials.

3.2.2 Survey Design

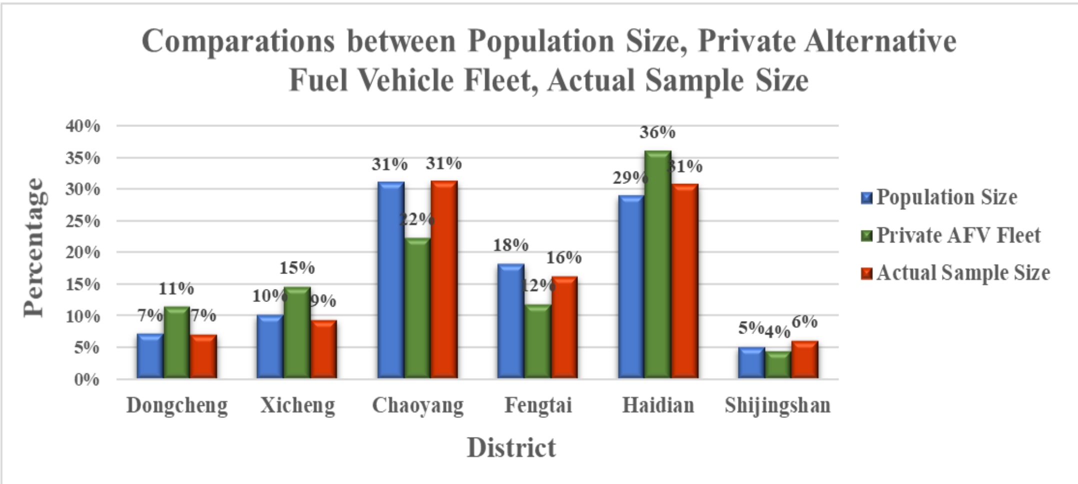
As shown by Fig. 1, the survey was conducted in Beijing, covering 6 central administrative regions (out of 16), namely Dongcheng (DC), Xicheng (XC), Chaoyang (CY), Fengtai (FT), Haidian (HD), and Shijingshan (SJS), which had a population of 11.7 million in 2018, accounting for 54.2% of the total population (Beijing Municipal Bureau of Statistics, 2019). In total, these 6 central districts had around 118,000 private alternative fuel vehicles (note: nearly all of them were BEVs) in 2018, accounting for 74%. Paper-based questionnaires were distributed by 10 survey assistants at shopping malls across these central districts from 10th to 12th January 2020. This design of survey allowed us to easily approach respondents from different backgrounds and to provide them with additional explanations about the definition, benefits, and drawbacks of V2G, because most of the respondents were not familiar with this emerging technology. The number of questionnaires distributed in each district was directly proportional to its population size. Eventually, we obtained 402 samples in total, which was over the target sample size of 385 (determined by the formula by Krejcie and Morgan (1970)). The distribution of the respondents can be found in Appendix 1.2 of the Supplementary Materials.



(a) Population (Unit: Ten Thousand)



(b) Actual Sample Size of each District



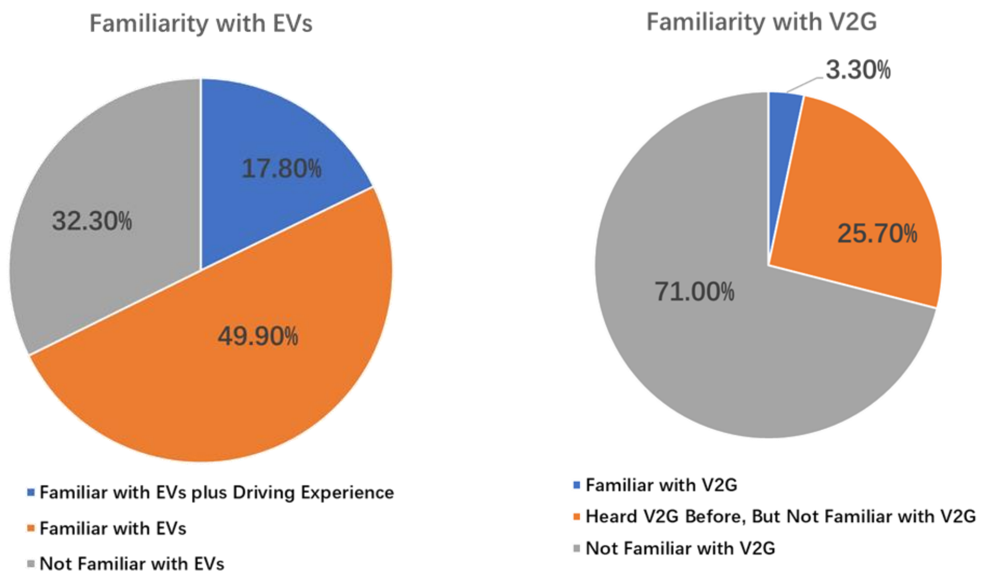
(c) Comparisons between Population Size, Private AFV Fleet, Actual Sample Size

Fig. 1. Population size, Private Alternative Fuel Vehicle (AFV) Fleet and Actual Sample Size of each District

3.3 Empirical Findings of the Adoption of Electric Vehicles (EVs) and Vehicle-to-Grid (V2G)

3.3.1 Familiarity with EVs and V2G

In general, people should first become familiar with new technology (e.g., EVs and V2G) and then become willing to buy or use it. Fig. 2-(a) and Fig. 2-(b) present respondents' familiarity with EVs and V2G respectively. 67.7% (49.9% + 7.8%) of the respondents were familiar with EVs, and 17.8% of them had a driving experience with EVs. However, only a small fraction of them (3.3%) were familiar with V2G, and 25.7% of them had heard about V2G, but knew little about it. In addition, we used a cross-table to explore the relationship between familiarity with EVs and V2G, and the result indicated that they were statistically associated with each other (see Appendix 1.3 in Supplementary Materials).

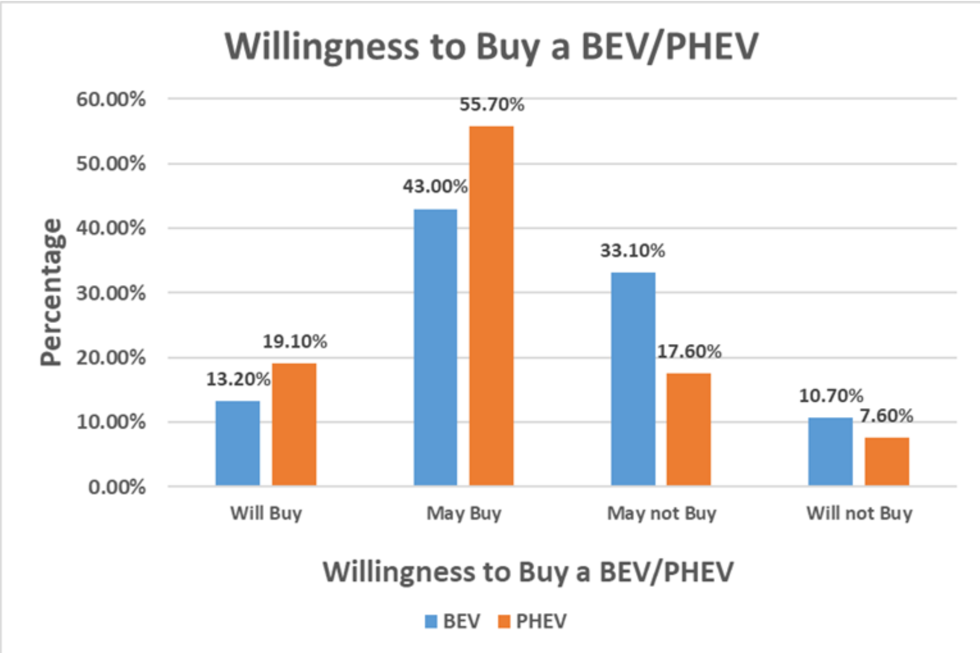


(a)Familiarity with EVs *(b) Familiarity with V2G*

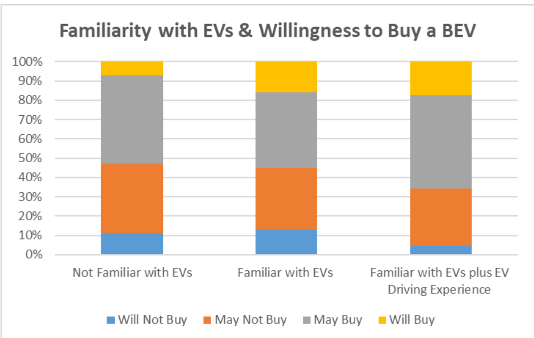
Fig. 2. Familiarity with EVs and V2G

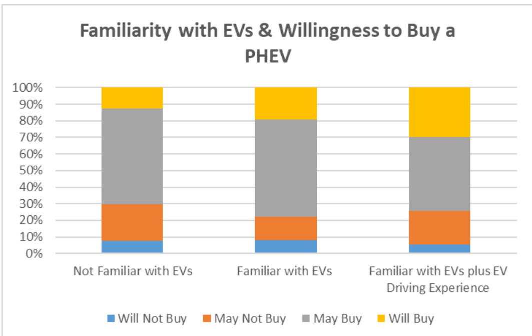
3.3.2 Willingness to Buy EVs

Fig. 3 shows the willingness to buy EVs and its relationship with the familiarity with EVs. As shown by Fig. 3-(a), overall, only 13.2% of the respondents would purchase a BEV, while 19.1% of them would purchase a PHEV. Moreover, 43.0% and 55.7% of them might purchase a BEV and PHEV, respectively. These indicated that people tended to be more willing to purchase a PHEV than BEV. One reason might be that PHEVs run on both electricity and petrol, and users can get PHEVs either recharged through charging facilities (e.g., charging posts) or refueled at refueling stations (e.g., petrol stations). We further used a cross-tabulation to investigate the respondents' familiarity with EVs and their willingness to buy a BEV/PHEV (see Fig. 3-(b) and -(c)). Overall, with the increase in familiarity with EVs, people tended to be more willing to buy a BEV or PHEV. For example, among those people who were not familiar with EVs, only 7.1% of them would buy a BEV and 12.6% of them would buy a PHEV; while among those people who were familiar with EVs and also had driving experience with EVs, 17.1% and 30% of them would purchase a BEV and PHEV respectively. Furthermore, we quantified the relationship between familiarity and willingness for both BEVs and PHEVs with Pearson's chi-square test. The results suggested that people's willingness to buy a PHEV tended to be more significantly associated with their familiarity with EVs, according to Pearson's chi-square values (specifically, 10.9 and 12.9 for BEVs and PHEVs respectively).



(a) Respondents' Willingness to Buy an EV





(b) Familiarity with EVs & Willingness to Buy a BEV

(c) Familiarity with EVs & Willingness to Buy a PHEV

Fig. 3. Respondents' Willingness to Buy an EV and the Relationship between Willingness to Buy an EV and Familiarity with EVs

3.3.3 Willingness to Adopt V2G

Fig. 4 shows respondents' willingness to adopt V2G in two different scenarios given that respondents had a BEV and PHEV respectively. Essentially, most respondents might/would try V2G if they had an EV (either BEV or PHEV), but there was no significant difference between PHEV and BEV users in their willingness to adopt V2G. Specifically, around 74.5% (9.1% + 65.4%) of the respondents were interested in V2G given that they had a BEV; while 72.8% (6.6% + 66.2%) of them would or might use V2G given that they had a PHEV.

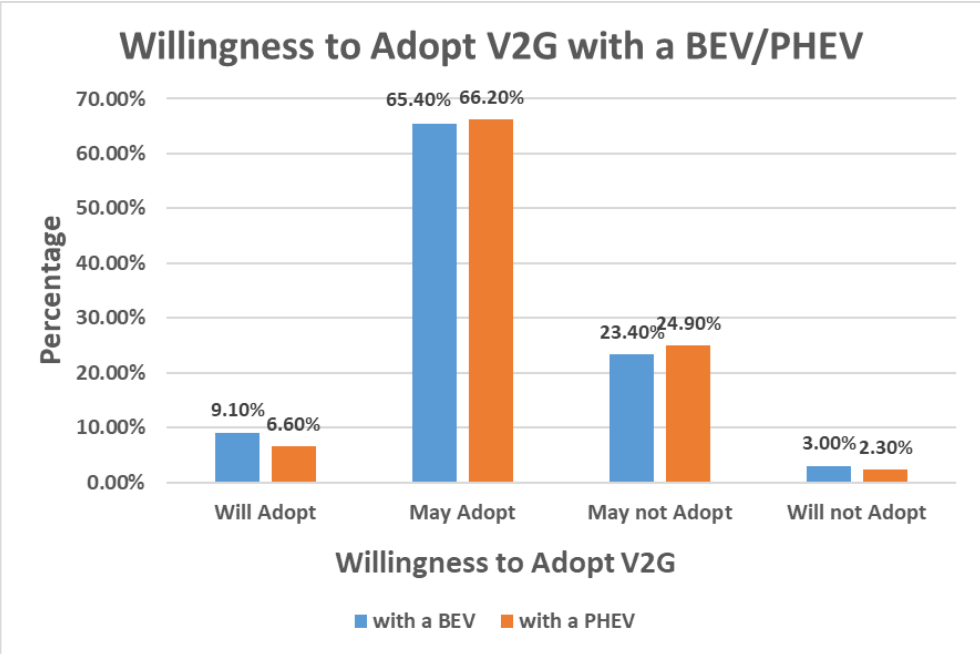


Fig. 4. Willingness to Adopt V2G with a BEV/PHEV

4 An Agent-based Joint Model of Electric Vehicles (EVs) and Vehicle-to-Grid (V2G) Diffusion

4.1 The Framework of the EV-V2G Joint Model

With the empirical findings from the survey data in Beijing, we developed a spatial agent-based joint model of EV and V2G adoption to simultaneously simulate how EVs and V2G would diffuse over time and across space at the individual level. Specifically, the EV-V2G joint model is composed of several sub-models, which can be grouped into two modules (see Fig. 5): population synthesis and simulation. Through population synthesis, we generated a synthetic population containing agents, as well as their socio-demographic attributes, residential locations, social networks, and preferences and attitudes towards EVs and V2G. An introduction to the population synthesis is given in Section 4.2. The simulation module is composed of two models, namely an EV market model and a V2G market model. In the EV market model, the government will issue a specific number ($N_{License}$) of driving licenses to those eligible agents at random. Then, EV-related stakeholders (e.g., government and vehicle manufacturers) will promote the development of EVs through advertisement. The potential influence of advertisement on adoption was also known as global influence, which was a type of social influence. Due to the global influence, the potential adopters will become more familiar with EVs and thus more likely to purchase an EV. The proportion of agents exposed to EV advertisement is used to measure the intensity of EV advertisement (I_{GlobEV}). Further, the model can simulate how potential vehicle purchasers apply for license plates through the lottery policy. Here, the model considers potential purchasers' willingness to buy EVs as well as the three types of social influence (i.e., global influence by EV advertisement, neighbor effect based on residential locations, and friendship effect based on social networks). As a result, the potential purchasers will be grouped into CV and BEV applicants who would apply for the limited numbers of CV and BEV license plates, respectively. It is worth noting that the potential PHEV purchasers will become CV applicants, as PHEVs are treated as CVs in the Beijing lottery policy. Finally, a specific number of CV and BEV license plates will be allocated to those applicants each year. Since owning an EV is a precondition of adopting V2G, only EV owners can enter the V2G market. Similarly, the V2G model also simulates the V2G advertisement provided by V2G-related stakeholders (e.g., government and power grid companies), so as to quantify the so-called global influence on the V2G adoption; and the intensity of V2G advertising ($I_{GlobV2G}$) is measured by the proportion of agents exposed to V2G advertisement. Then the model simulates the adoption of V2G, considering potential adopters' willingness to use V2G (with empirical findings from Section 3.3.3), as well as the three types of social influence (i.e., friendship effect, neighbor effect, and global influence).

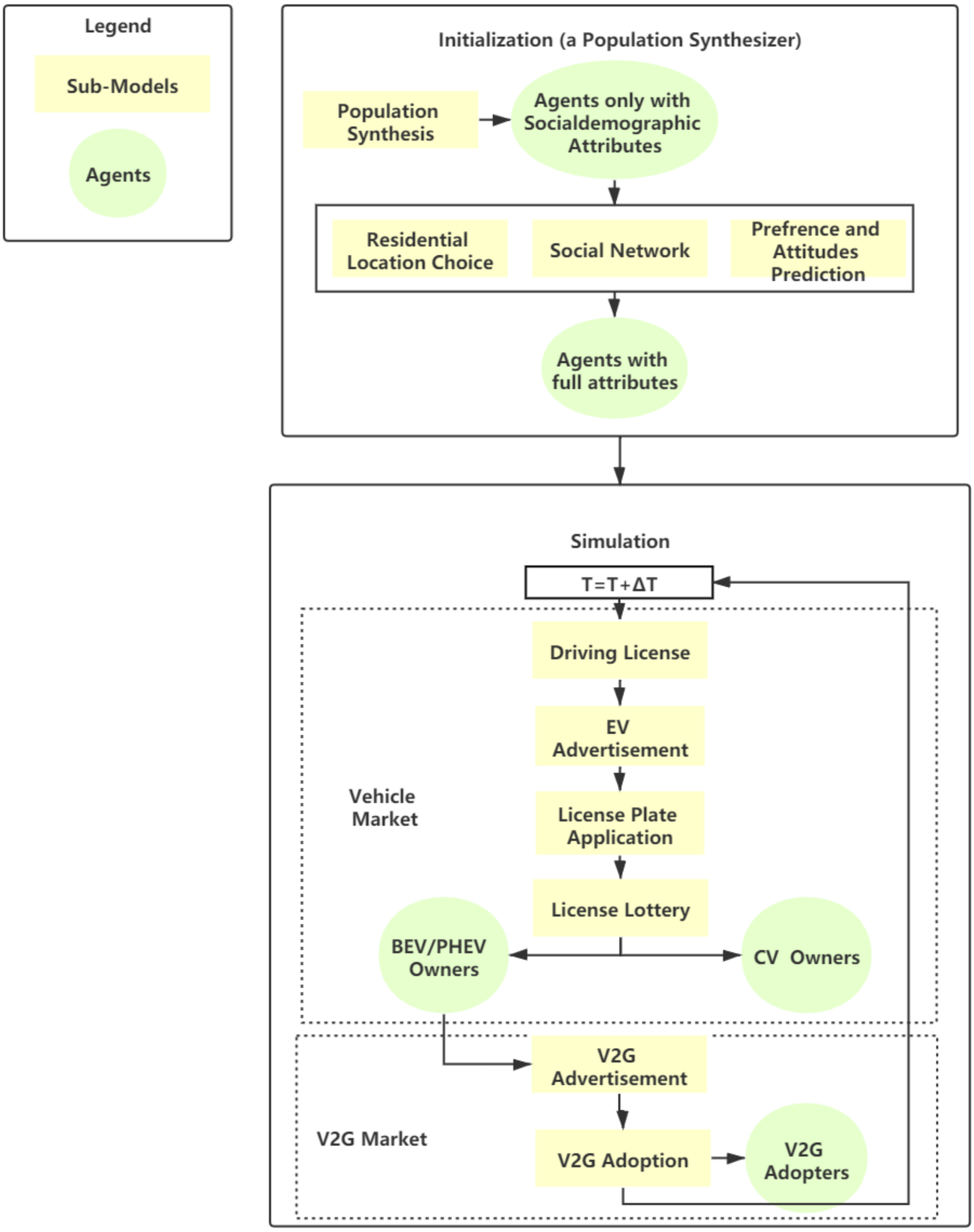


Fig. 5. The Framework of Agent-Based EV-V2G Joint Model

4.2 Population Synthesis

As aforementioned, a population synthesizer is used here to first generate a synthetic population, as well as their socio-demographic characteristics (e.g., age and income), using a classical algorithm, Iterative Proportion Fitting (IPF) (see Section 4.2.1). Then, each agent will be allocated with a residential location (see Section 4.2.2), to quantify the so-called neighbor effect in the adoption of EVs and V2G. Further, agents will be linked with a social network (see Section 4.2.3), to quantify the so-called friendship influence in the diffusion of EVs and V2G. Finally, random forest models will be developed with the survey data to generate each agent's preferences and attitudes towards EVs and V2G (see Section 4.2.4), based on which this model can further quantify their willingness to adopt EVs and V2G.

4.2.1 Iterative Proportion Fitting (IPF)

Population synthesis is a critical step in urban micro-simulation. There are various population synthesizers: see the study of Müller and Axhausen (2010) for a review. Here, we use a classical population synthesizer, Iterative Proportion Fitting (IPF) to generate a synthetic population, with macro-level distributions of control variables (from statistical yearbook) and micro-level sample data (from the questionnaire survey). The central idea of IPF is to fit individual-level distributes of control variables, such as age and gender, aimed to minimize the gap between the generated and observed distributions: see Müller and Axhausen (2010) for a detailed model specification.

4.2.2 Residential Location Choice Model

Residential location choice of agents might be influenced by various factors, such as accessibility and housing price (Zhuge et al., 2016). In this model, a simple residential location choice model is applied to find a house for each agent in the synthetic population based on the evidence that there is a strong correlation between housing price and household income. For example, Wu et al. (2013) found that high-income households tended to live closer to the city center where housing prices were generally high, based on a survey in Beijing. Therefore, we simply assigned those housing properties with a higher selling price to those households with a high income. After allocating residential locations to each agent, we would be able to further quantify the so-called neighbor effec: we here defined that a pair of agents are neighbors to each other if the distance between their residential locations is shorter than a specific range $D_{neighbor}$.

4.2.3 Social Network Model for Linking Agents in the Population

Each agent in the synthetic population had a social network, based on which we could quantify the friendship effect in the diffusion of EVs and V2G. Given a population, we used a social network model to link agents as friends, aimed to represent the real network degree (i.e., the number of friends that an agent has, denoted as N_{friend}). Specifically, we generated each link between a pair of agents based on a random graph *G (N, L)* (Bollobás, 1985), fitting the total number of links *L*. *L* was calculated by equation (2).

$$L = N * D/2 \tag{2}$$

Where, *N* denotes the total number of agents; D denotes the network degree. In the Beijing scenario, we set D to 12 according to the empirical finding about the social network in Beijing from the work by Zhuge and Shao (2019). Specifically, a questionnaire survey was conducted in Beijing from September, 2015 to March, 2016 to collect data on individual social networks, with 651 samples obtained. In the survey, participants were asked to tell the number of friends that they had, based on which we estimated the degree of social network in Beijing (Zhuge and Shao, 2019).

4.2.4 Generating Agents' Preferences and Attitudes towards EVs and V2G

According to the empirical findings in Section 3.3, each agent had its preferences and attitudes towards EVs and V2G. We developed ordered logit models and random forest models to link the survey participants' socio-demographic attributes with their preferences and attitudes towards EVs and V2G, so as to predict (or generate) preferences and attitudes for each agent in the synthetic population. Random forest is a classical type of Artificial Intelligence (AI) algorithm for classification and regression (Ho, 1995), which is comprised of a collection of classification and regression trees (CARTs) (Steinberg and Colla, 2009). The model first trains each tree by a randomly selected subset and then takes the most voted result as the final output: see the work by Criminisi et al. (2011), Pal (2005), and Shi and Horvath (2006) for model specification. We evaluated the performances of ordered logit models and random forest models with a set of agents' attitudes and preferences, including the familiarity with EVs/V2G, willingness to adopt a BEV/PHEV, willingness to adopt V2G with a BEV/PHEV, and attitudes towards influential factors about V2G.

The results suggested that random forest models outperformed ordered logit models according to the prediction accuracies. Specifically, the average accuracies for ordered logit models and random forest models were 64.1% and 87.0%, respectively (see Appendix 2.2 in Supplementary Materials for more details). Therefore, random forest models were used to generate each agent's attitudes and preferences towards EVs and V2G in the Beijing scenarios.

4.3 Simulating the Adoption of Electric Vehicles (EVs)

We developed an algorithm to simulate how an agent applies for a license plate under the so-called license plate lottery policy (see Section 3.1.2). The algorithm is composed of six steps below (see Fig. 6):

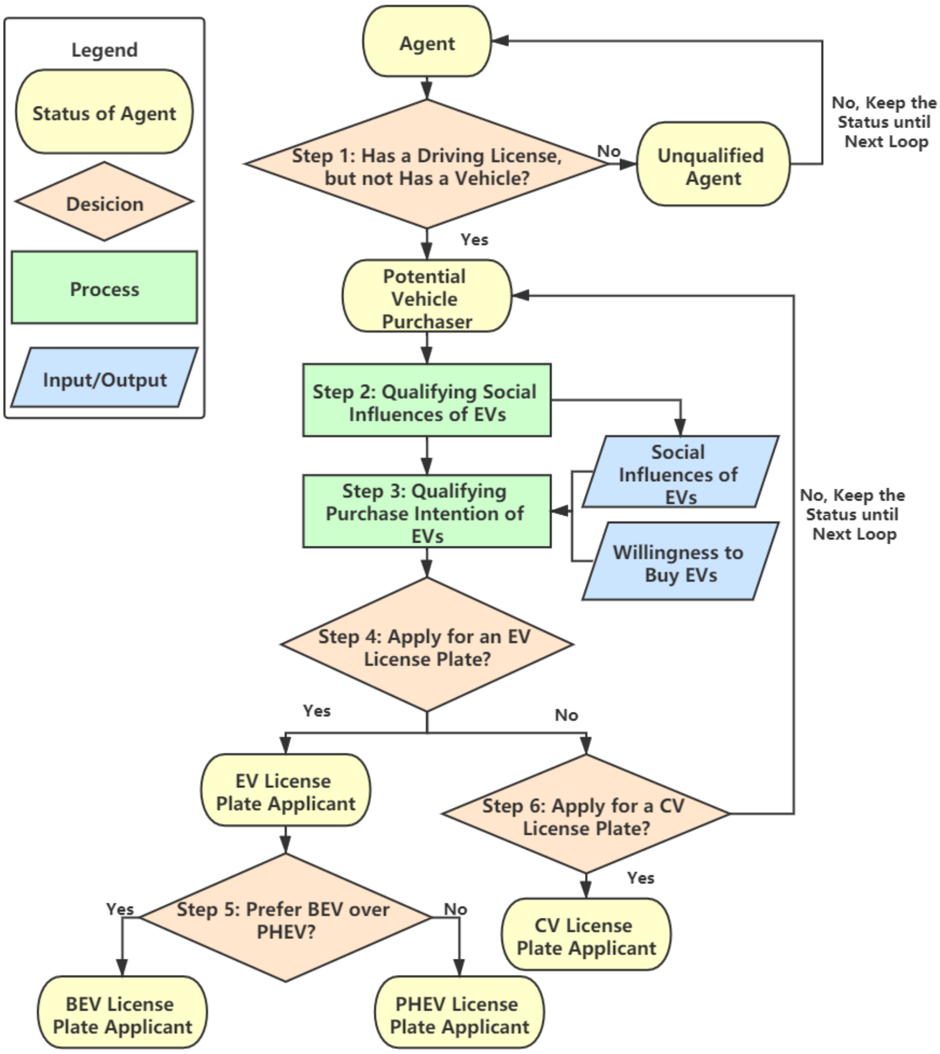


Fig. 6. An Algorithm for Simulating How Agents Apply for a License Plate in the Lottery Policy

Step 1: checks whether an agent is qualified for applying for a driving license with two conditions: 1) having a driving license; 2) not having a vehicle. If the agent passes the two conditions, it will become a potential vehicle purchaser, and will enter the vehicle market; otherwise, it will not enter the market in the current loop (i.e., in this simulation year).

Step 2: quantifies social influences by Equation (3). Social influences are commonly considered as an influential factor to the diffusion of new technologies, such as EVs (Axsen et al., 2013; Liao et al., 2017; Pettifor et al., 2017). For example, an empirical study by Zhuge and Shao (2019) found that social influences accounted for 9.7% of the total importance among the typical influential factors to the adoption of EVs in Beijing, including vehicle price (32.3%), vehicle usage (28.1%), environmental awareness (9.6%), purchase-related policies (12.4%) and usage-related policies (7.8%). Here, the three types of social influence, namely friendship effect, neighbor effect, and global influence, accounted for 5.0%, 2.0% and 2.8%, respectively. Therefore, a few attempts have been made to incorporate social influences into the EV diffusion models as a variable (Eppstein et al., 2011; Shafiei et al., 2012). For example, an EV market model by Zhuge et al. (2019) included social influences into its utility function for simulating vehicle choices of consumers in the EV market. Therefore, our model also considers three types of social influence I = (1, 2, 3), namely friendship effect (i = 1), neighbor effect (i = 2), and global influence (i = 3). It is defined that an agent will be influenced by its friends (if at least one of its friends has an EV and also is sensitive to the friendship effect), its neighbors (if at least one of its neighbors has an EV and also it is sensitive to the neighbor effect), and the EV advertisements (if it is exposed to any advertisement and also it is sensitive to the global influence).

$$SI = \Sigma_{i=1}^{3} W_i * C1_i * C2_i \tag{3}$$

Where, W_i denotes the weight of social influence i, which indicates the extent to which the social influence i will influence the adoption of BEVs. According to an empirical finding in Beijing from the work by Zhuge and Shao (2019), the weight of the friendship effect in the adoption of EVs in Beijing was two times those of the neighbor effect and the global influence. Therefore, W_1, W_2, and W_3 are set to 2, 1, and 1 in our Beijing scearnio, respectively. $C1_i$ and $C2_i$ are two binary variables. If the agent is influenced by social influence I, then $C1_i$=1; otherwise, $C1_i$=0. If the agent was sensitive to social influence I, then $C2_i$=1; otherwise, $C2_i$=0. Whether an agent is sensitive to a specific type of social influence is determined by a random forest model, which was developed with empical findings in Beijing (see Appendix 2.2 in the Supplemenatry Materials).

Step 3: quantifies the EVs purchase intentions of an agent according to its willingness to buy a BEV/PHEV (which is the primary determinant in vehicle purchase) and the three types of social influence (which is the secondary determinant). Specifically, this model will first check an agent's willingness and then will further check whether the agent will be influenced by EV advertisement, its friends, and its neighbors. As set in the Beijing questionnaire, the willingness to buy a BEV/PHEV is grouped into four categories, namely "will buy", "may buy", "may not buy", and "will not buy" (see Appendix 1.1 in Supplementary Materials). The social influences of BEV/PHEV can be quantified by Equation (9) with five different scores, ranging from 0 to 4 (note: 4 means that the agent is influenced by all the three types of social influence, and 0 means that it is not influenced by any type of social influence). Given the four categories for the willingness to buy a BEV/PHEV and the five categories for the three types of social influence, we developed a classification method (see Fig. 7) to group an agent into one of the twenty classes. Those agents with a higher class (i.e., a higher willingness and a higher value of social influence) will be more likely to purchase an EV.

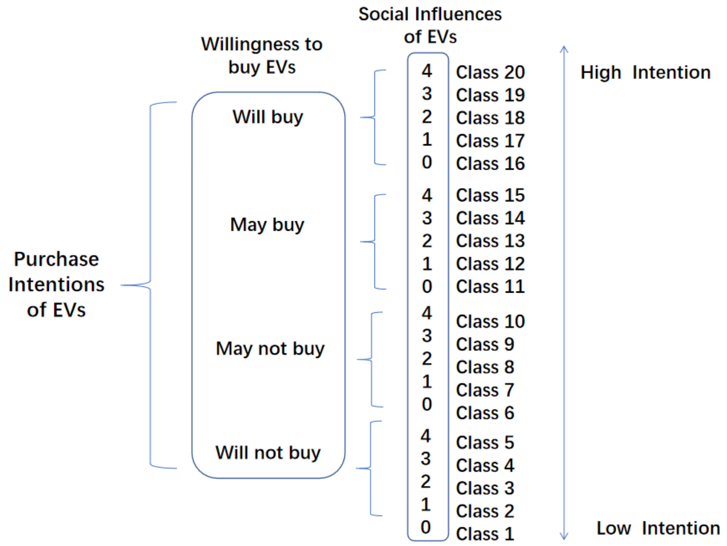


Fig. 7. Quantifying EVs Purchase Intentions with Twenty Classes

Step 4: determines whether the agent will apply for an EV license plate through the lottery policy according to the agent's intentions to purchase EVs, following a specific rule: if the agent's purchase intention is greater than a specific threshold (T_{BEV} and T_{PHEV} for BEV and PHEV, respectively), it will apply for an EV license plate; if the intention is equal to T_{EV}, it has a specific probability of applying for an EV license plate (P_{BEV} and P_{PHEV} for BEV and PHEV, respectively). Note that T_{BEV} and P_{BEV} are key model parameters and will be calibrated by comparing the simulated and observed numbers of EV applicants in the Beijing scenario (see Section 5.1.2). If the agent decides to apply for an EV license plate, the algorithm will go to Step 5; otherwise, it will go to Step 6.

Step 5: further compares the agent's intentions to purchase a BEV and PHEV. It is assumed that the agent will always choose the EV type with the higher intention value. Furthermore, the agent will become a BEV applicant in the case where the purchase intentions of BEV and PHEV were the same, because in Beijing, BEV owners can receive additional benefits, such as exemption from the so-called end-number license plate policy (Lu et al., 2020). This algorithm will check the applicant's preference towards EVs in each simulation step until it finally gets a license plate, or the simulation is finished.

Step 6: determines whether the agent will apply for a CV license plate. It is defined that if the agent's BEV purchase intention is lower than a specific threshold (T_{CV}), then it will apply for a CV license plate; if it is equal to T_{CV}, it has a specific probability of applying for a CV license plate (P_{CV}); otherwise, it will not apply for a license plate in the current simulation step. T_{CV} and P_{CV} are another two key model parameters to be calibrated (see Section 5.1.2).

4.4 Simulating the Adoption of V2G

We developed another algorithm to simulate the process of V2G adoption (see Fig. 8), based on the simulation of EV adoption, as an agent should have an EV before adopting V2G. The algorithm is composed of five steps:

- **Step 1:** checks whether the agent is an EV owner: if yes, the algorithm will move to Step 2; otherwise, it will stop, and the agent will not adopt V2G in this simulation year.
- **Step 2:** checks whether the price of selling electricity back to the grid (P_{V2G}) (which is determined by the power company) is higher than what the agent expects; if yes, the algorithm will move to Step 3; Otherwise, it will stop, and the agent will not adopt V2G in this simulation year.
- **Step 3:** quantifies the agent's V2G adoption intention based on their willingness to adopt V2G with a BEV/PHEV and social influences of V2G, which is similar to the approach to quantifying the EV adoption intention (see Section 4.3). It is worth noting that we distinguish between BEV and PHEV owners when quantifying their willingness to adopt V2G, according to the empirical findings from the Beijing survey data (see Section 3.3.3).

- **Step 4:** checks whether the agent will adopt V2G. Specifically, if the agent's V2G adoption intention is greater than a specific threshold (T_{BEVV2G} and $T_{PHEVV2G}$ for BEV and PHEV owners respectively), it would adopt V2G. Otherwise, it will not adopt V2G in this simulation year.

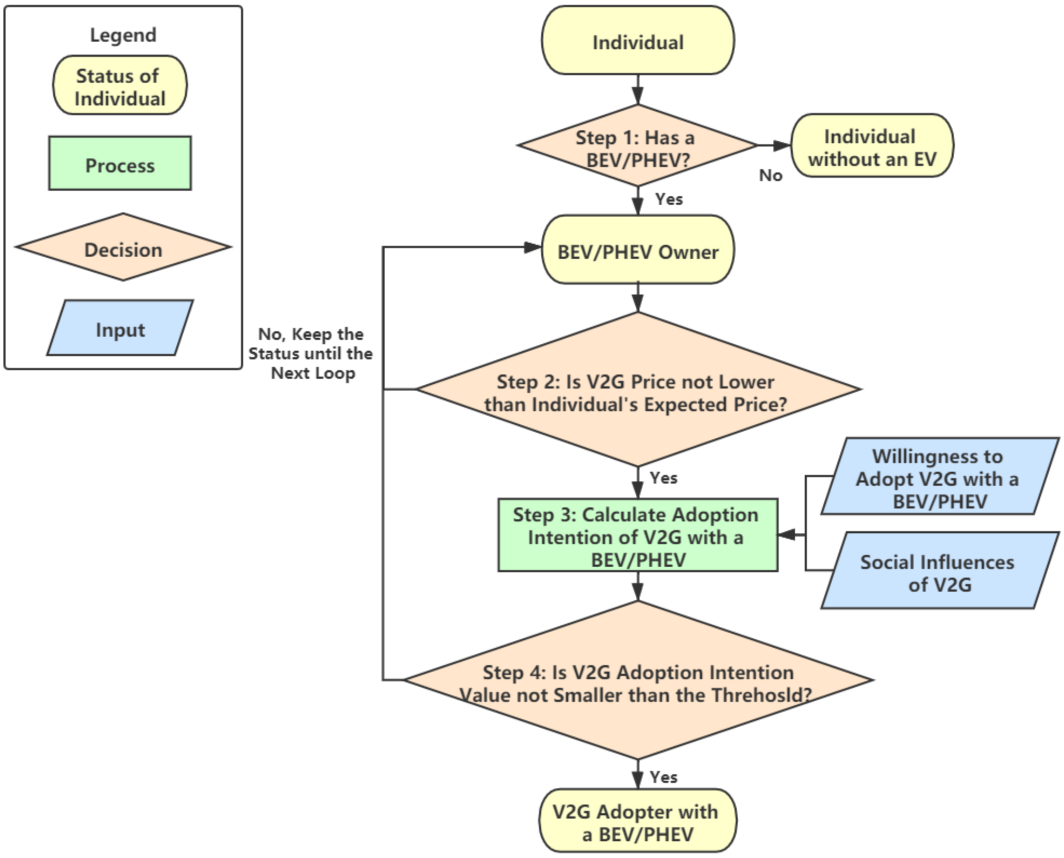


Fig. 8. An Algorithm for Simulating the Process of Adopting V2G with a BEV/PHEV

5 Exploring the Joint Adoption of EV and V2G in Beijing

5.1 Scenario Description

5.1.1 A Synthetic Population in Beijing

Beijing was used as a case study to examine the performance of the proposed EV-V2G joint model. We initialized the joint model by generating a virtual Beijing population using the population synthesis method in Section 4.2. We compared the generated and observed distributions of control variables, including age, gender, education level, number of family members, driving license, BEV ownership, and CV ownership. The results suggested that the distributions were well-matched with a mean absolute percentage error of 0.35% (see Appendix 2.1 in supplementary materials for more details). In total, the synthetic population comprised 215,36 agents, which meant each agent represented 1,000 citizens in reality. This would help to save computing time. Furthermore, each agent would be treated as a representative of a household, and would be responsible for making household-level decisions, such as vehicle purchase. Fig. 9 shows the spatial distribution of agents based on their residential locations, suggesting that most agents live in the central districts of Beijing. The joint EV-V2G model was implemented in NetLogo (Tisue and Wilensky, 2004), which is one of the most-used platforms for agent-based modeling.

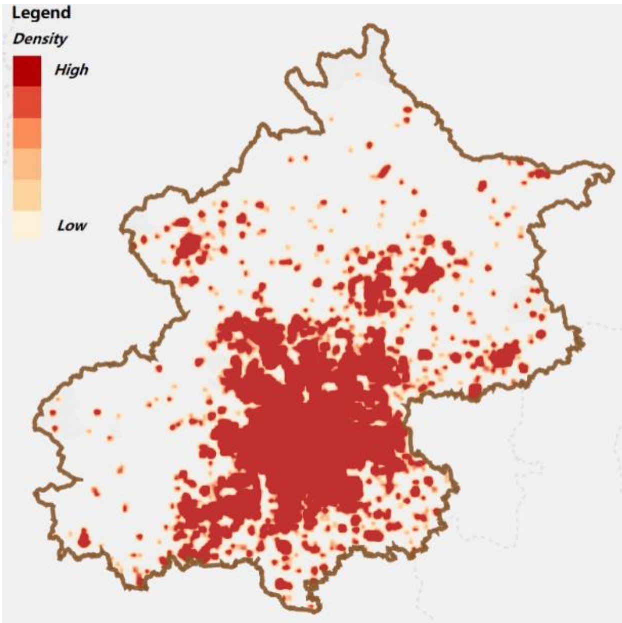
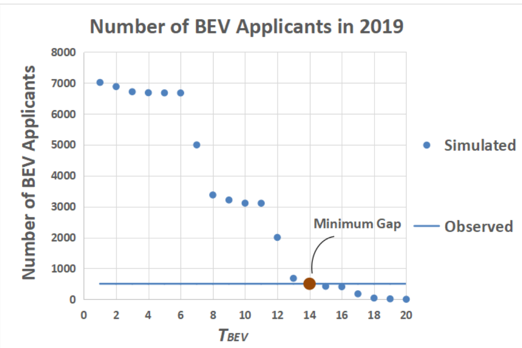


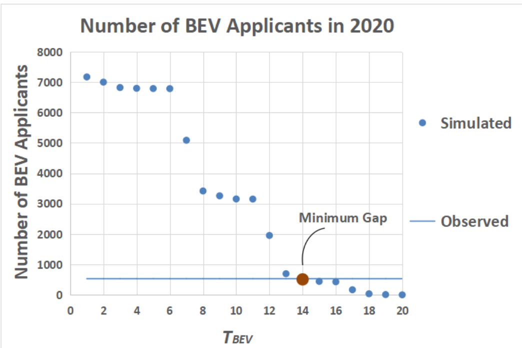
Fig. 9. Residential Location of Agents in the Synthetic Population

5.1.2 Model Calibration

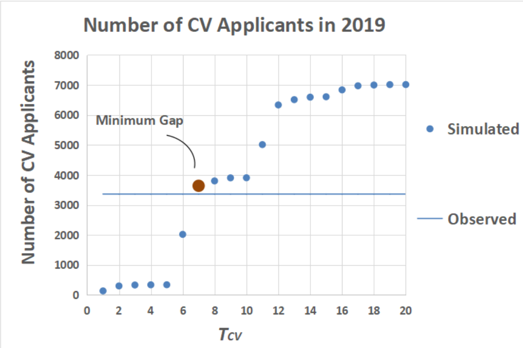
The joint EV-V2G model was calibrated in three ways: first, we calibrated the model with empirical findings from the Beijing survey data as far as possible. For example, we set the weights of global influence, neighbor effect, and friendship effect to 1, 1, and 2, respectively, according to the empirical findings of social influences from Beijing (Zhuge and Shao, 2019). Specifically, the study suggested that global influence, neighbor effect, and friendship effect accounted for 2.8%, 2.0% and 2.8%, respectively, using the survey data collected from September 2015 to March 2016. Second, we set some of the parameters according to our experience. For example, we used a radius of 400 meters to search for neighbors for each agent, to quantify the so-called neighbor effect. For these parameters, we conducted a sensitivity analysis to examine how different parameter ranges would influence the outputs of interest. Third, we calibrated the remaining key parameters by minimizing the gap between the observed and simulated outputs of interest, including the numbers of BEV and CV license plate applicants in 2019 and 2020. These parameters included the threshold of applying for a BEV license plate (T_{BEV}), the probability of applying for a BEV license plate (P_{BEV}), the threshold of applying for a CV license plate (T_{CV}), and the probability of applying for a CV license plate (P_{CV}). For example, when calibrating the vehicle market sub-model in the joint model, we first tested the sub-model with the 20 classes of BEV purchase intention, and compared the outcomes against the observed data (in both 2019 and 2020) to find the optimal class which can minimize the gap between the simulated and observed numbers of BEV applicants (see Fig. 10-(a) and -(b)); then, we further tested P_{BEV} from 0% to 100% to minimize the total absolute error for the two years: we found a minimum total absolute error of 3.88% (specifically, -2.19% and 1.69% in 2019 and 2020, respectively), with P_{BEV} of 84%, as shown in Fig. 10-(c). Likewise, P_{CV} and P_{CV} could be calibrated: they were finally set to class 7 (see Fig. 10-(d) and -(e)) and 84% (see Fig. 10-(f)) respectively, with a total absolute percentage error of 3.61% (specifically, 0.21% and 3.34% in 2019 and 2020, respectively). More details on the model parameterization can be found in Appendix 2.3 in supplementary materials.



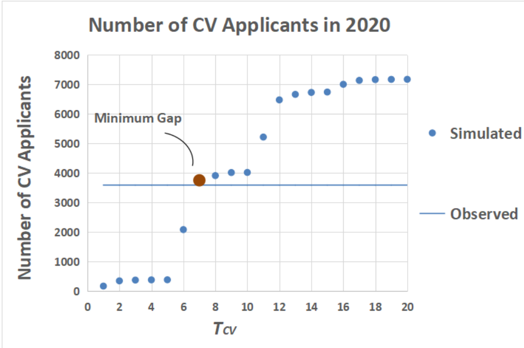
(a) Comparing the Observed and Simulated Numbers of BEV Applicants in 2019 with T_{BEV} from Class 1 to 20



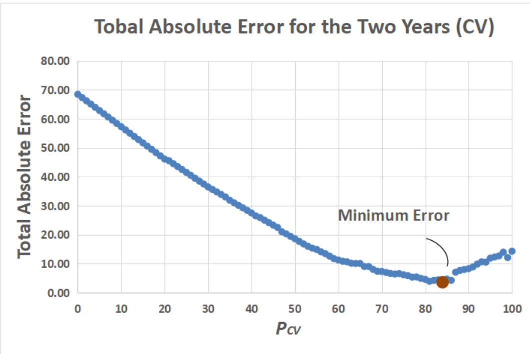
(b) Comparing the Observed and Simulated Numbers of BEV Applicants in 2020 with T_{BEV} from Class 1 to 20



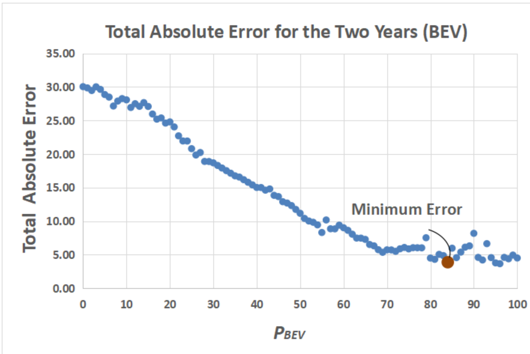
(c) Comparing the Observed and Simulated Numbers of CV Applicants in 2019 with T_{CV} from Class 1 to 20



(d) Comparing the Observed and Simulated Numbers of CV Applicants in 2020 with T_{CV} from Class 1 to 20



(e) The Total Absolute Error for the Number of BEV Applicants in 2019 and 2020 with P_{BEV} from 0% to 100%



(f) The Total Absolute Error for the Number of BEV Applicants in 2019 and 2020 with P_{CV} from 0% to 100%

Fig. 10. EV Market Model Calibration Results

5.1.3 Reference and "What-if" Scenarios

We first set up a reference scenario and ran the calibrated model from 2021 to 2030, with an assumption that the vehicle market would evolve as before. To test the sensitivity of some important model parameters (i.e., $D_{neighbor}$ and T_{BEVV2G}) and how EV- and V2G-related policies (i.e., V2G price, V2G advertisements, EVs advertisements, and PHEV permit) would influence the diffusion of EVs and V2G, we set up another six "what-if" scenarios that would be compared against the reference scenario. A summary of some key settings of both reference scenario and "what-if" scenarios can be found in Table 5. Please note that the results from the scenarios V2GBEV and Neighb are discussed in Appendix 3.6 and Appendix 3.7 of the Supplementary Materials.

Table 5. Comparing the Differences between the "What-If" and Reference Scenarios

	V2G Price	*Proportion of Agents Exposed to V2G Advertisements*	*Proportion of Agents Exposed to EVs Advertisements*	*PHEV Permit*	*Threshold of Adopting V2G*	*Definition of Neighbor*
Reference Scenario (See Section 5.2)	**30% greater than the charging fee**	**30%**	**70%**	**No PHEV permit**	**Class 14**	**400 Meters**
V2GPrice (See Section 5.3.1)	**0%, 10%, 50% and 100% greater**	30%	70%	No PHEV permit	Class 14	400 Meters
V2GGlobal (See Section 5.3.2)	30% greater	**10%, 50%, 70% and 90%**	70%	No PHEV permit	Class 14	400 Meters
EVGlobal (See Section 5.3.3)	30% greater	30%	**10%, 30%, 50% and 90%**	No PHEV permit	Class 14	400 Meters
PHEVPermit (See Section 5.3.4)	30% greater	30%	70%	**Treating PHEV as an EV type in the license plate lottery policy**	Class 14	400 Meters
V2GBEV (See Appendix 3.6)	30% greater	30%	70%	No PHEV permit	**Class 11, 12, 13, 15, 16 and 17**	400 Meters
Neighb (See Appendix 3.7)	30% greater	30%	70%	No PHEV permit	Class 14	**200, 600, 800 and 1000 Meters**

5.2 Reference Scenario (RefSc)

Fig. 11 shows the expansion of BEV, CV, and V2G markets from 2021 to 2030. Due to the limited number of CV permits in the license plate lottery policy, the number of CV owners increased slightly from 4.40 million in 2021 to 4.74 million in 2030, with an average yearly growth rate of 0.8%. However, the actual CV demand increased faster, as evident from the number of CV applicants. Specifically, the number of CV applicants increased from around 3.96 million in 2021 to 5.16 million in 2030, with an average yearly growth rate of 3.22%. Furthermore, the number of CV applicants was much higher than that of BEV applicants: for example, in 2030, the number of CV applicants was 6.19 times that of BEV applicants. This indicated that BEVs were still much less attractive than CVs, though BEV owners received several benefits, such as EV subsidies and exemption from the end-number license plate policy. In terms of V2G diffusion, the number of V2G adopters was relatively low during the whole period. Specifically, the number of V2G-BEV adopters (i.e., BEV owners adopting V2G) was 232,000 in 2030, accounting for 27.8% of the whole BEV population. It is worth noting that PHEVs and CVs shared the so-called CV purchase permits. However, almost no people are interested in PHEV, due to its much higher sale price and no EV subsides for PHEV buyers. Therefore, in this Reference Scenario (RefSc), we did not simulate the PHEV diffusion. However, we set up a scenario to explore how a different vehicle purchase permit allocation method (i.e., PHEV and BEV purchasers share the so-called EV purchase permits) would influence the diffusion of EVs and V2G (see Section 5.3.4).

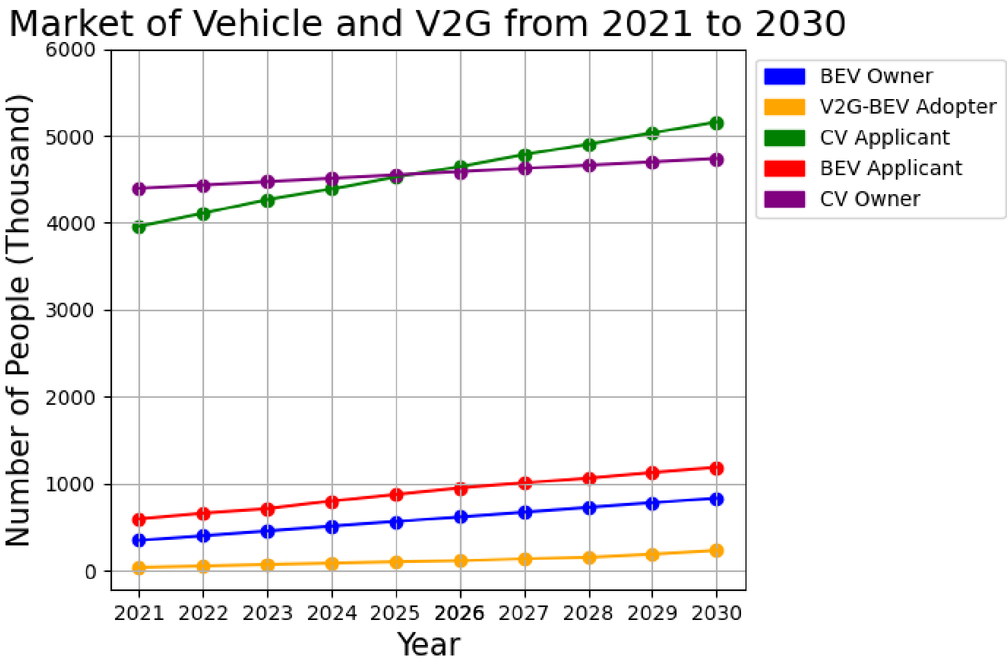
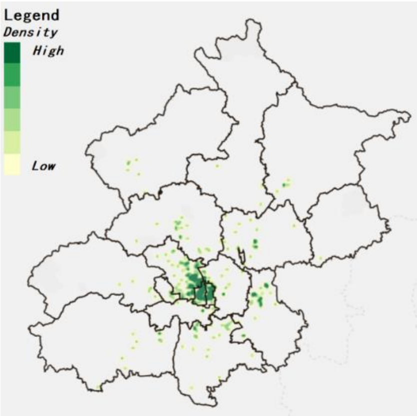


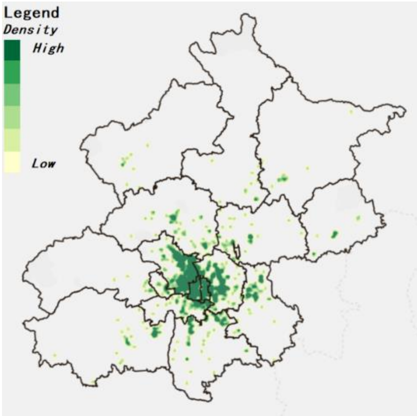
Fig. 11. Diffusion of EV and V2G from 2021 to 2030 in Reference Scenario (RefSc)

Fig. 12 shows the spatial distributions of BEV owners (Fig. 12-(a) and -(b)), BEV applicants (Fig. 12-(d) and -(e)), and V2G-BEV adopters (Fig. 12-(g) and -(h)) based on their residential locations. It could be found that BEV owners were mostly located in the two core districts of Beijing (i.e., Dongcheng and Xicheng districts) in 2021, with a few of them located in other districts (see Fig. 12-(a)). In 2030, the clusters of BEV owners in central districts (including Dongcheng, Xicheng, and Haidian, Chaoyang, Fengzhou, and Shijingshan districts) became much larger, indicating the BEVs diffused across space, while the numbers of BEV owners in the suburbs and outer suburbs were still small (see Fig. 12-(b)). In terms of BEV applicants, most of them were located in the central districts in 2021, with a few of them located in the other districts (see Fig. 16-(d)). In 2030, the cluster of BEV applicants became much larger, indicating that more people in the central districts were interested to buy BEVs (see Fig. 12-(e)). For V2G-BEV adopters, there were no significant large clusters, indicating that V2G appeared not to diffuse across space.

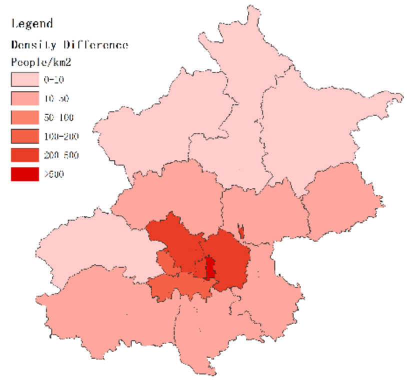
We further compared the difference between 2021 and 2030 in the densities of license plate applicants, BEV owners, and V2G-BEV adopters at the district level. According to the spatial difference, the central districts tended to get much more BEV owners and license plate applicants, relative to their district areas (see Fig. 16-(c) and -(f)). In particular, the new sub-center of Beijing, Tongzhou district, also got more license plate applicants than other districts in suburban areas. Furthermore, the spatial patterns of BEV owners and V2G-BEV adopters were almost the same, suggesting that those districts with more BEV owners were more likely to had more V2G adopters.



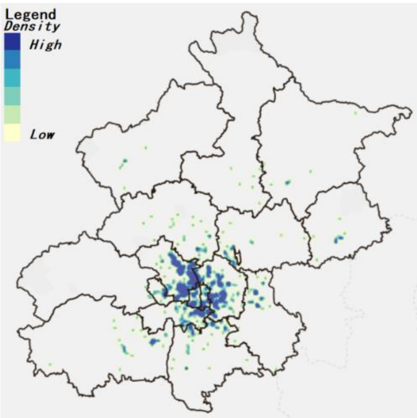
(a) BEV Owners in 2021



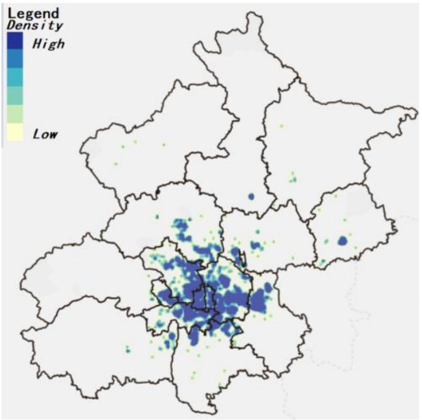
(b) BEV Owners in 2030



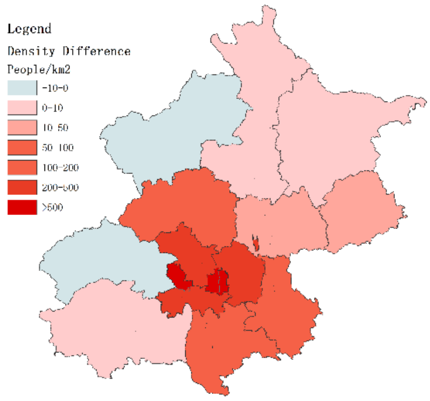
(c) Spatial difference in BEV Owners between 2021 and 2030



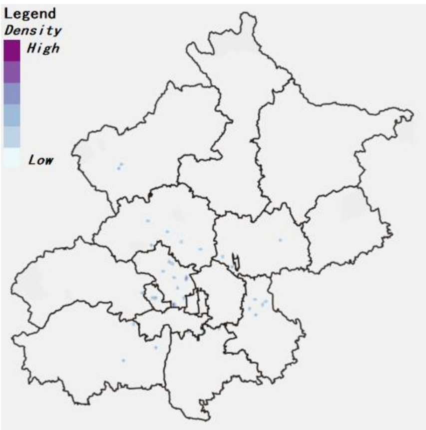
(d) BEV Applicants in 2021



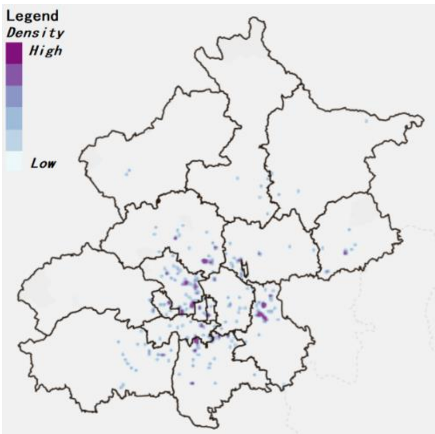
(e) BEV Applicants in 2022



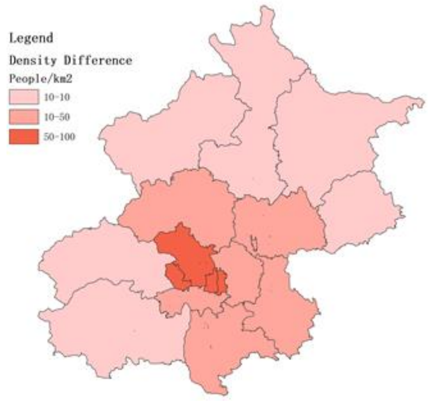
(f) Spatial difference in BEV Applicants between 2021 and 2030



(g) V2G-BEV Adopters in 2021



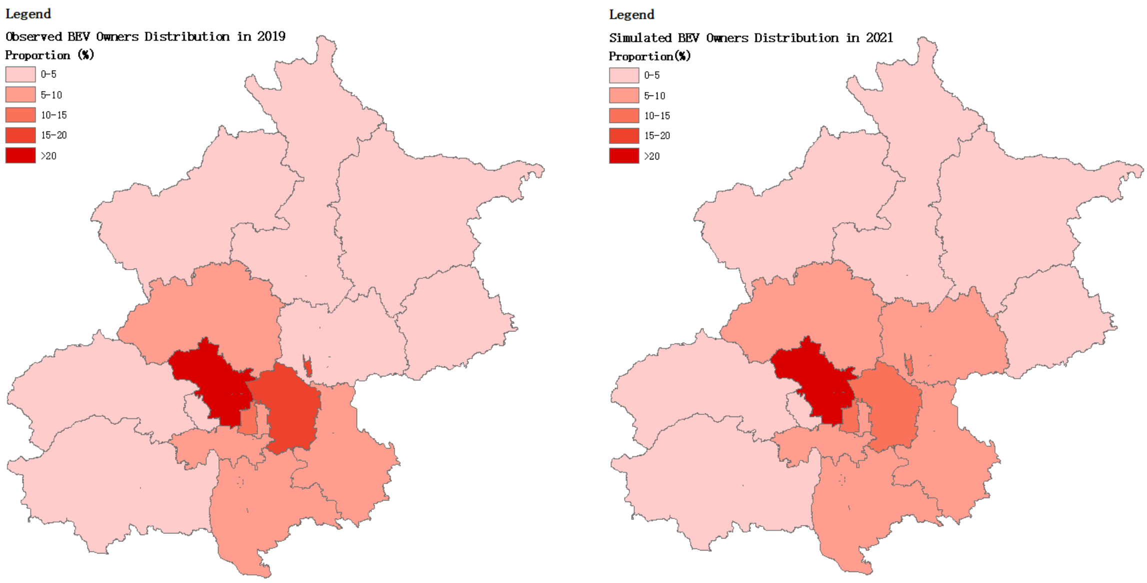
(h) V2G-BEV Adopters in 2030



(i) Spatial difference in BEV-V2G Adopters between 2021 and 2030

Fig. 12. Spatial Distributions of BEV Owners, BEV Applicants, and V2G-BEV Adopters in RefSc

To validate the model, we further compared the simulated spatial patterns of BEV owners in 2021 against the observed spatial patterns of BEV owners in 2019, as shown in Fig.13. It can be found that the agent-based model could well represent the spatial patterns of BEV owners at the district level. In other words, the model could represent the real-world diffusion of EVs in Beijing to some extent, and thus could be further used to explore how different policies might influence the adoption through "what-if" scenarios.



(a) Observed Spatial Patterns of BEV Owners in 2019

(b) Simulated Spatial Patterns of BEV Owners in 2021

Fig. 13. Comparing Observed and Simulated Spatial Patterns of BEV Owners

5.3 "What-If" Scenarios

5.3.1 Scenario V2GPrice: Exploring the Influence of V2G Selling Price

As discussed in Section 4.1, BEV owners would adopt V2G only if the price of selling electricity back to the grid (P_{V2G}) was higher than the price they expect (compared to the charging fee). Hence, the selling price might be an influential factor in the V2G diffusion. Here, we developed four scenarios (i.e., V2GPrice1.0, V2GPrice1.1, V2GPrice1.5, and V2GPrice2.0) to explore how different selling prices P_{V2G} (i.e., 0%, 10%, 50%, and 100% greater than the charging fee) would influence the adoption of V2G.

Fig. 14 compares the V2G diffusion from 2021 to 2030 in Scenarios V2GPrice and RefSc. Overall, the difference between the scenarios in the number of V2G adopters was small, suggesting that the price of selling electricity back to the grid (P_{V2G}) could only influence the V2G diffusion to a limited extent. In 2030, the scenarios with a lower selling price tended to get more V2G adopters. For those scenarios with a selling price of 30% greater than the charging fee or above (i.e., RefSc, V2GPrice1.5, and V2GPrice2.0), there was almost no difference in the number of V2G adopters, indicating that the selling price could only be influential within a specific range. Therefore, power companies were suggested not to apply a too high selling price, because once the selling price exceeded a specific threshold (i.e., 30% greater than the charging fee in this case), a further increase in selling price would not promote the adoption of V2G.

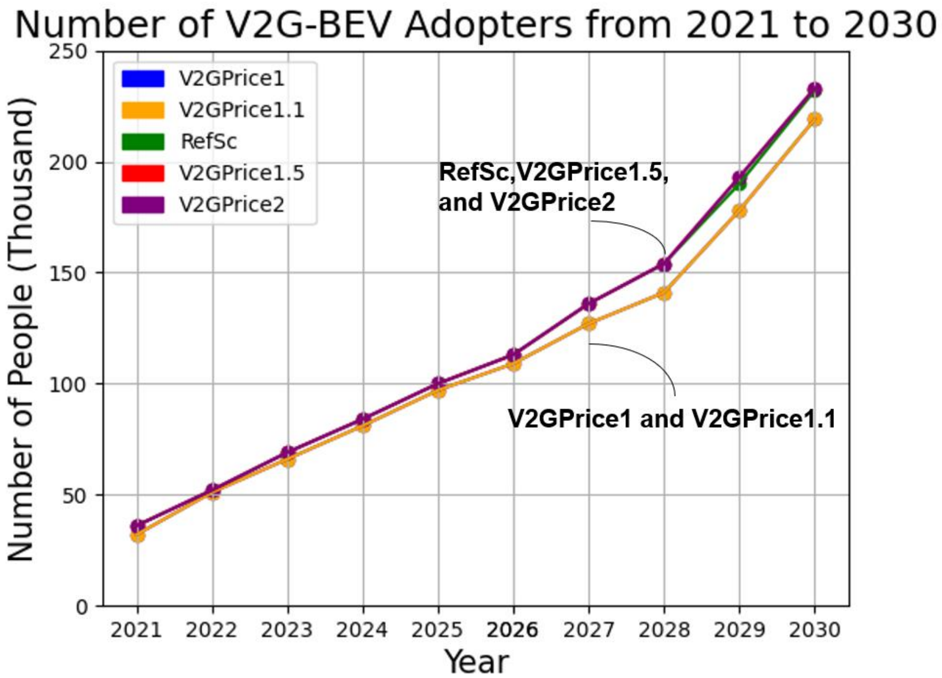


Fig. 14. Influences of Parameter P_{V2G} on the Number of V2G-BEV Adopters

5.3.2 Scenario V2GGlobal: Exploring the Influence of V2G Advertisement

V2G advertisement might influence the adoption of V2G through the so-called global influence of V2G, which was one kind of social influence. At the early stage, V2G-related stakeholders, such as government and power companies, would increase the exposure of agents to V2G advertisement ($I_{GlobV2G}$), so as to increase the global influence. To examine how the number of agents exposed to V2G advertisements would influence the V2G diffusion, we set up another four scenarios (i.e., V2GGlobal0.1, V2GGlobal0.5, V2GGlobal0.7, and V2GGlobal0.9), in which the percentages of agents exposed were set to 10%, 50%, 70%, and 90%, respectively.

Table 6 shows the differences between Scenario V2GGlobal and RefSc. The total numbers of V2G adopters in V2GGlobal and RefSc were almost the same at the end of the simulation (i.e., in 2030), but there were small differences before 2028. For those scenarios with a higher percentage of agents exposed to V2G advertisement, they tended to have more V2G adopters at the beginning: for example, increasing the percentage from 10% to 90% could increase the number of V2G adopters by 28.5% in 2022. However, the global influence became gradually ineffective as the market evolved. Therefore, V2G-related stakeholders (e.g., government and power companies) were suggested to promote the adoption of V2G through V2G advertisement only at the early stage of V2G development, but not to invest too much after the number of V2G adopters exceeded a specific threshold (about 150,000 in this case). Furthermore, there were slight spatial differences between Scenarios V2GGlobal and RefSc in the number of V2G adopters (see Fig. A6 in supplementary materials), likely because of the slight difference between the scenarios in the total number of V2G adopters.

Table 6. Influences of Parameter $I_{GlobV2G}$ on the Number of V2G-BEV Adopters

Scenario	2021	2022	2023	2024	2025	2026	2027	2028	2029	2030
V2GGlobal0.1	0%	-19%	-5%	-5%	-4%	-4%	-4%	1%	1%	0%
RefSc	**36000**	**52000**	**64000**	**81000**	**98000**	**120000**	**139000**	**150000**	**190000**	**232000**
V2GGlobal0.5	0%	2%	5%	2%	3%	-1%	1%	0%	0%	-1%
V2GGlobal0.7	0%	2%	5%	2%	4%	1%	-1%	2%	1%	0%
V2GGlobal0.9	0%	4%	5%	6%	8%	4%	2%	3%	2%	0%

Note: We used the number of V2G-BEV adopters for RefSc in this table, and used the relative percentage difference for the other "what-if" scenarios.

5.3.3 Scenario EVGloalal: Exploring the Influence of EV Advertisement

The so-called global influence might also influence the adoption of EVs through, for example, EV advertisement. Therefore, we set up four scenarios (i.e., EVGlobal0.1, EVGlobal0.3, EVGlobal0.5, and EVGlobal0.9) to explore how different percentages of agents exposed to EV advertisement (i.e., 10%, 30%, 50%, and 90%) would influence the adoption of BEV, and further V2G.

As shown in Fig. 15, increasing the percentage of agents exposed to EV advertisement would influence the adoption of EVs to some extent. For example, when the percentage of agents exposed increased from 10% to 30%, the number of BEV applicants increased by 9.5% in 2030 (from 1,059k to 1,160k applicants), according to Scenarios EVGloal0.1 and EVGloal0.3. However, after the percentage of agents exposed exceeds 30%, a further increase could not heavily influence the number of BEV adopters, as evident from the comparison among Scenarios EVGloal0.3, EVGloal0.5, RefSc, and EVGloal0.9. Therefore, EV-related stakeholders (e.g., local authorities and vehicle manufacturers) were suggested not to put too much effort into the promotion of EVs through advertisement. Although EV advertisement could influence the BEV purchase intention to some extent, it had little influence on numbers of BEV adopters and V2G adopters, due to the license plate lottery policy (specifically, the fixed number of BEV purchase permits).

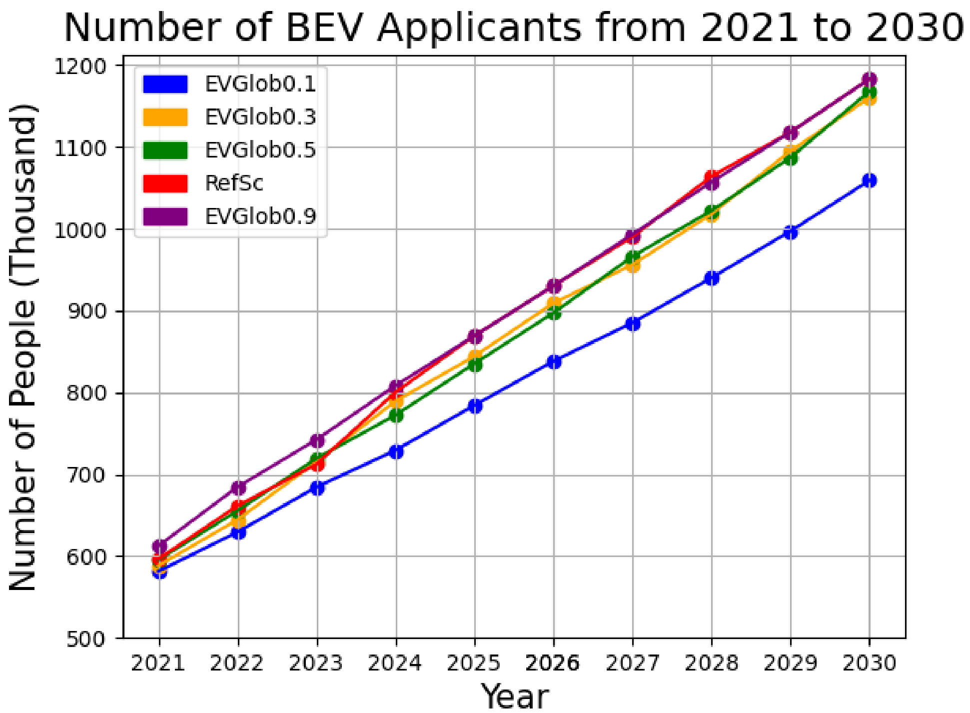
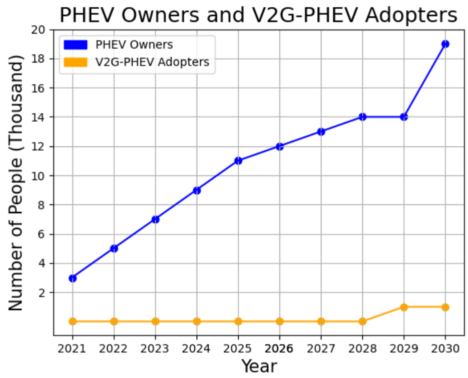


Fig. 15. Influences of EV Advertisements on the Numbers of BEV Applicants

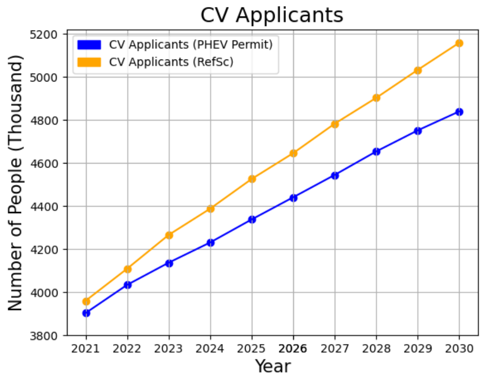
5.3.4 Scenario PHEVPermit: Exploring the Influences of PHEV Permit

In Beijing, PHEV license plate applicants need to compete for a limited number of the so-called CV license plates with general CV applicants, as PHEV is treated as one CV type. However, PHEV sale price tends to be much higher than that of CV, which appears to be one of the main reasons for the low adoption rate of PHEV in Beijing (Zhuge et al., 2020). In PHEVPermit, we investigated how a different license plate lottery policy in which PHEV was treated as one EV type, would influence the diffusion of EVs and V2G.

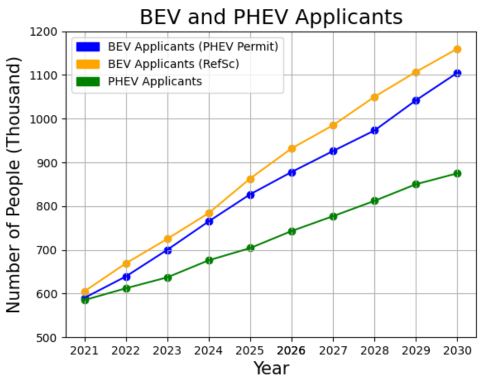
As shown by Fig. 16-(a), PHEVs were not competitive with CVs or BEVs, as evident from a much smaller number of PHEV owners (19,000) in 2030 (only accounting for 2.3% of EVs). It was likely because EV license plates were issued on a first-come-first-serve basis. As a result, those agents who had applied for EV license plates for BEVs before 2021 (when the lottery policy started to treat PHEV as an EV type) would be first issued with a license plate. Although they could choose PHEVs instead of BEVs in the simulation if their PHEV purchase intention was higher than that of BEV, only a few applicants did change their minds. However, PHEVs still would have a great potential market in Beijing, as the total number of PHEV applicants reached 875,000 in 2030, which is close to the number of BEV applicants (1,105,000), as shown in Fig. 16-(c). In addition, the increase in PHEV applicants decreased the numbers of both the CV and BEV applicants (see Fig.16-(b) and -(c) respectively) , because some of them became PHEV applicants in this scenario. Also, we found significant changes in the spatial patterns of CV and BEV applicants (see Appendix 3.5 in supplementary materials). In terms of V2G adoption, only 1000 PHEV owners adopt V2G in 2030, accounting for 5% of the total number of PHEV owners. On the other hand, the total number of V2G adopters did not change a lot, because the number of BEV owners only decreased slightly in PHEVPermit, and the number of V2G-BEV adopters (i.e., BEV owners adopting V2G) was almost not influenced by this different lottery policy.



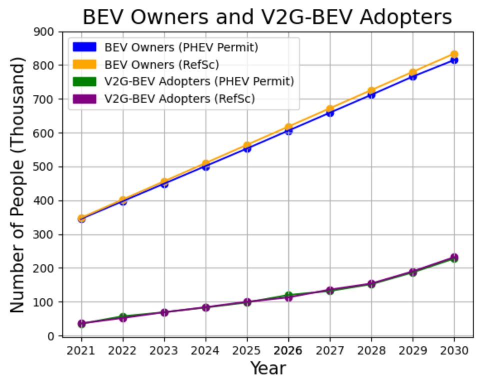
(a) PHEV Owners and V2G-PHEV Adopters



(b) CV Applicants



(c) BEV and PHEV Applicants



(d) BEV Owners and V2G-BEV Adopters

Fig. 16 Influence of the PHEV Permit on Diffusion of EV and V2G

5.4 Discussion on Scenario Analysis

We set up the reference scenario (i.e., baseline) to explore the future of EVs and V2G in Beijing with an assumption that both EVs and V2G would diffuse as before (see Section 5.2), and further explored how different EV- and V2G- related policies would influence the diffusion of EV and V2G within several "what-if" scenarios (see Section 5.3), compared to the reference scenario.

In the reference scenario, we found that only 10.3% of BEV owners adopted V2G in 2021, but the proportion increased to 27.8% in 2030, indicating that the V2G diffused at a relatively higher rate than BEV. There were two possible reasons: first, there was only a specific number of BEV purchase permits allocated each year, due to the license plate lottery policy. As a result, the number of BEV adopters could only increase at a certain rate; while there was no constraint on the V2G adoption. Second, the social influences (particularly neighbor and friendship effects) became stronger over time, due to the increase in the number of V2G adopters. Specifically, when more and more BEV owners adopted V2G, their friends and neighbors would be increasingly influenced, and may finally adopt V2G as well.

Based on the "what-if" scenarios, we identified two possible ways to promote the adoption of V2G.

First, it would be possible to encourage BEV applicants to adopt V2G, given that the price of selling electricity back to the grid was 1.3 times of the original electricity price in the context of V2G. However, a higher selling price had little influence on the uptake of V2G. This was likely because the selling price was used as a condition to screen BEV adopters in the V2G model: only those BEV adopters whose expected selling price is lower than the selling price set by the power grid could become a potentially V2G adopter. This means that setting the selling price to be 1.3 times of the original electricity price could satisfy most of the BEV owners who would become a potential V2G adopter.

Another possible way to promote the adoption of new technologies is to get those potential adopters to become familiar with the technologies through advertising (i.e., global influence). Our scenario analysis suggested that advertising tended to be more effective to adoption of BEVs than that of V2G. Specifically, a higher percentage of agents exposed to V2G advertisement could help to promote the adoption of V2G to some extent at the early stage, but V2G advertisement became less influential later. This was likely because BEV owners' V2G adoption intention was quantified with both their willingness to adopt V2G and social influences, and global influence was just one type of social influences. For those scenarios with a lower percentage of agents exposed to V2G advertisement, their social influences could also become stronger with more and more their friends and neighbors adopting V2G. As a result, these scenarios could have more V2G adopters at a later stage. Therefore, stakeholders (e.g., power companies) are suggested to use advertising as a promotion approach only at the early stage of V2G development. Although a higher percentage of agents exposed to BEV advertisement could significantly increase the number of BEV applicants, but it had almost no influence on the number of final BEV adopters due to the purchase constraint (i.e., the license plate lottery policy), and thus had almost no influence on the V2G adoption either.

6 Conclusions

This study explored the diffusion of Electric Vehicles (EVs) and Vehicle-to-Grid (V2G) from both empirical and theoretical perspectives. According to the empirical findings, familiarity with EVs was a important factor in people's willingness to adopt EVs, especially for PHEVs. However, we found that 32.3% of respondents were not familiar with EVs. Furthermore, those people who were familiar with EVs and had EV driving experience tended to be more willing to buy EVs. Therefore, the EV-related stakeholders, such as local authorities and vehicle manufacturers, are suggested to get citizens to become familiar with EVs. For example, citizens should be provided with more information about EVs, such as vehicle's profiles and benefits, so that they could become familiar with EVs. Also, citizens should be offered more opportunities to drive EVs, for example, in demonstration projects, as real-world EV driving experience could increase the probability of buying EVs. For the adoption of V2G, the survey suggested that only a small fraction of people in Beijing (3.3%) were familiar with V2G, and 25.7% of them had heard V2G before, but knew little about it. Also, we found that most of the respondents might/would try V2G if they had an EV (either BEV or PHEV), indicating a promising V2G market in Beijing. From a theoretical perspective, we developed an agent-based EV-V2G joint model to simulate the diffusion of EVs and V2G over time, with the empirical findings from the Beijing survey data. In the Reference Scenario (RefSc), we found that the number of CV applicants was 6.19 times that of BEV applicants, and only 27.8% of BEV users adopted V2G. Furthermore, V2G selling price, EV/V2G advertisement and dedicated PHEV purchase permits were not very influential to the diffusion of V2G.

In the future work, we will further improve the joint EV-V2G model in the following two aspects: First, we will further improve the V2G model by considering different V2G contract types. Specifically, EV users' willingness to adopt V2G is associated with the specific requirements (e.g., plug-in time and reward) in the agreement (or contract) signed with the power grid company. Therefore, in the improved V2G model, we can further simulate how EV users' choose between different V2G contract types if they are interested in V2G. Second, we will incorporate a more realistic social network model into the EV-V2G joint model to consider the heterogeneous influences between the linked agents. Specifically, we will distinguish between strong and weak social ties in their influences on the diffusion of information on EV and V2G adoption. In general, a pair of friends which are connected with a strong tie tend to contact more frequently, and thus would have a higher chance to receive the adoption information from their friends. Furthermore, we will also consider agents' sensitivity to the adoption information, as some of agents would be more likely to be influenced by the information received. Third, we will further test the joint model through more "what-if" scenarios, and explore how different EV- or V2G- related policies, technologies, and infrastructures could influence the adoption of V2G.

Acknowledgement

This research was supported by the Hong Kong Polytechnic University [1-BE2J; P0038213], and the National Natural Science Foundation of China (52002345).

References

Adepetu, A., Keshav, S. and Arya, V., 2016. An agent-based electric vehicle ecosystem model: San Francisco case study. Transport Policy, 46: 109-122.

Al-Alawi, B.M. and Bradley, T.H., 2013. Review of hybrid, plug-in hybrid, and electric vehicle market modeling studies. Renewable and Sustainable Energy Reviews, 21: 190-203.

Amamra, S. and Marco, J., 2019. Vehicle-to-Grid Aggregator to Support Power Grid and Reduce Electric Vehicle Charging Cost. IEEE Access, 7: 178528-178538.

Axsen, J., Orlebar, C. and Skippon, S., 2013. Social influence and consumer preference formation for pro-environmental technology: The case of a UK workplace electric-vehicle study. Ecological Economics, 95: 96-107.

Beijing Municipal Bureau of Statistics, 2019. Beijing Statistical Yearbook 2019. China Statistics Press.

Beijing Transport Institute, 2020. Transport Development Annual Report 2020.

Bollobás, B., 1985. Random Graph. Random Graph.

Brown, M., 2013. Catching the PHEVer: simulating electric vehicle diffusion with an agent-based mixed logit model of vehicle choice. Journal of Artificial Societies and Social Simulation, 16(2): 5.

Chen, C.-f., de Rubens, G.Z., Noel, L., Kester, J., Sovacool, B.K.J.R. and Reviews, S.E., 2020. Assessing the socio-demographic, technical, economic and behavioral factors of Nordic electric vehicle adoption and the influence of vehicle-to-grid preferences. Renewable Sustainable Energy Reviews, 121: 109692.

Chen, X., Zhang, H., Xu, Z., Nielsen, C.P., McElroy, M.B. and Lv, J., 2018. Impacts of fleet types and charging modes for electric vehicles on emissions under different penetrations of wind power. Nature Energy, 3(5): 413-421.

Criminisi, A., Shotton, J. and Konukoglu, E., 2011. Decision forests for classification, regression, density estimation, manifold learning and semi-supervised learning. Microsoft Research Cambridge, Tech. Rep. MSRTR--114, 5(6): 12.

Eppstein, M.J., Grover, D.K., Marshall, J.S. and Rizzo, D.M., 2011. An agent-based model to study market penetration of plug-in hybrid electric vehicles. Energy Policy, 39(6): 3789-3802.

Freeman, G.M., Drennen, T.E. and White, A.D., 2017. Can parked cars and carbon taxes create a profit? The economics of vehicle-to-grid energy storage for peak reduction. Energy Policy, 106(JUL.): 183-190.

Hidrue, M.K. and Parsons, G.R., 2015. Is there a near-term market for vehicle-to-grid electric vehicles? Applied Energy, 151(aug.1): 67-76.

Ho, T.K., 1995. Random decision forests, Proceedings of 3rd international conference on document analysis and recognition. IEEE, pp. 278-282.

International Energy Agency, 2020. Global EV Outlook 2020: Entering the decade of electric drive?

Kempton, W. and Letendre, S., 1997. Electric vehicles as a new power source for electric utilities. Transportation Research Part D: Transport and Environmental Research Letters, 2(3): 157-175.

Kempton, W. and Tomić, J., 2005. Vehicle-to-grid power implementation: From stabilizing the grid to supporting large-scale renewable energy. Journal of Power Sources, 144(1): 280-294.

Kempton, W., Tomic, J., Letendre, S., Brooks, A. and Lipman, T., 2001. Vehicle-to-grid power: battery, hybrid, and fuel cell vehicles as resources for distributed electric power in California. UC Davis: Institute of Transportation Studies.

Krejcie, R.V. and Morgan, D.W., 1970. Determining sample size for research activities. Educational and Psychological Measurement, 30(3): 607-610.

Lee, C.Y., Jang, J.W. and Lee, M.K., 2020. Willingness to accept values for vehicle-to-grid service in South Korea. Transportation Research Part D: Transport and Environmental, 87: 102487.

Liao, F., Molin, E. and van Wee, B., 2017. Consumer preferences for electric vehicles: a literature review. Transport Reviews, 37(3): 252-275.

Lu, T., Yao, E., Jin, F. and Pan, L., 2020. Alternative Incentive Policies against Purchase Subsidy Decrease for Battery Electric Vehicle (BEV) Adoption. Energies, 13(7): 1645.

Markewitz, P., Kuckshinrichs, W., Leitner, W., Linssen, J., Zapp, P., Bongartz, R., Schreiber, A. and Müller, T.E., 2012. Worldwide innovations in the development of carbon capture technologies and the utilization of CO2. Energy and Environmental Science, 5(6): 7281-7305.

Müller, K. and Axhausen, K.W., 2010. Population synthesis for microsimulation: State of the art. Arbeitsberichte Verkehrs-und Raumplanung, 638.

Noel, L., Carrone, A.P., Jensen, A.F., De Rubens, G.Z., Kester, J. and Sovacool, B.K., 2018. Willingness to pay for electric vehicles and vehicle-to-grid applications: A Nordic choice experiment. Energy Economics, 78: 525-534.

Pal, M., 2005. Random forest classifier for remote sensing classification. International journal of remote sensing, 26(1): 217-222.

Parsons, G.R., Hidrue, M.K., Kempton, W. and Gardner, M.P., 2014. Willingness to pay for vehicle-to-grid (V2G) electric vehicles and their contract terms. Energy Economics, 42(1): 313-324.

Pettifor, H., Wilson, C., Axsen, J., Abrahamse, W. and Anable, J., 2017. Social influence in the global diffusion of alternative fuel vehicles–A meta-analysis. Journal of Transport Geography, 62: 247-261.

Raines, G.B., 2009. Electric vehicles: technology, research and development. Nova Science.

Shafiei, E., Thorkelsson, H., Ásgeirsson, E.I., Davidsdottir, B., Raberto, M. and Stefansson, H., 2012. An agent-based modeling approach to predict the evolution of market share of electric vehicles: a case study from Iceland. Technological Forecasting and Social Change, 79(9): 1638-1653.

Shi, T. and Horvath, S., 2006. Unsupervised learning with random forest predictors. Journal of Computational and Graphical Statistics, 15(1): 118-138.

Silvia, C. and Krause, R.M., 2016. Assessing the impact of policy interventions on the adoption of plug-in electric vehicles: An agent-based model. Energy Policy, 96: 105-118.

Sovacool, B.K., Noel, L., Axsen, J. and Kempton, W., 2018. The neglected social dimensions to a vehicle-to-grid (V2G) transition: a critical and systematic review. Environmental Research Letters, 13(1): 013001.

Steinberg, D. and Colla, P., 2009. CART: classification and regression trees. The top ten algorithms in data mining, 9: 179.

The People's Government of Beijing Municipality, 2019. Notice on adjusting the relevant contents of the administrative measures of Beijing Municipality on the promotion and application of new energy vehicles. . In: B.M.C.o.S.a. Technology, B.M.B.o.E.a.I. Technology, B.M.B.o. Finance, B.M.C.o.U. Administration and B.M.C.o. Transportation (Editors).

Tisue, S. and Wilensky, U., 2004. Netlogo: A simple environment for modeling complexity, International conference on complex systems. Boston, MA, pp. 16-21.

V2G Hub, 2020. V2G around the world.

van der Steen, M., Van Schelven, R., Kotter, R., Van Twist, M. and Peter van Deventer, M., 2015. EV policy compared: an international comparison of governments' policy strategy towards E-mobility, E-mobility in Europe. Springer, pp. 27-53.

Wang, T., 2020. 2819 charging piles will be built in Beijing. , Beijing Daily.

Wehinger, L.A., Galus, M.D. and Andersson, G., 2010. Agent-based simulator for the German electricity wholesale market including wind power generation and widescale PHEV adoption, 2010 7th International Conference on the European Energy Market. IEEE, pp. 1-6.

Wolf, I., Schroeder, T., Neumann, J. and de Haan, G., 2015. Changing minds about electric cars: An empirically grounded agent-based modeling approach. Technological Forecasting and Social Change, 94: 269-285.

Wolinetz, M., Axsen, J., Peters, J. and Crawford, C., 2018. Simulating the value of electric-vehicle–grid integration using a behaviourally realistic model. Nature Energy, 3(2): 132.

Wu, W., Zhang, W. and Dong, G., 2013. Determinant of residential location choice in a transitional housing market: Evidence based on micro survey from Beijing. Habitat International, 39: 16-24.

Yilmaz, M. and Krein, P.T., 2013. Review of the Impact of Vehicle-to-Grid Technologies on Distribution Systems and Utility Interfaces. IEEE Transactions on Power Electronics, 28(12): 5673-5689.

Zhuge, C. and Shao, C., 2019. Investigating the factors influencing the uptake of electric vehicles in Beijing, China: Statistical and spatial perspectives. Journal of Cleaner Production, 213: 199-216.

Zhuge, C., Shao, C., Gao, J., Dong, C. and Zhang, H., 2016. Agent-based joint model of residential location choice and real estate price for land use and transport model. Computers, Environment and Urban Systems, 57: 93-105.

Zhuge, C., Wei, B., Dong, C., Shao, C. and Shan, Y., 2019. Exploring the future electric vehicle market and its impacts with an agent-based spatial integrated framework: A case study of Beijing, China. Journal of Cleaner Production, 221: 710-737.

Zhuge, C., Wei, B., Shao, C., Shan, Y. and Dong, C., 2020. The role of the license plate lottery policy in the adoption of electric vehicles: A case study of Beijing. Energy Policy, 139: 111328.