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Exploring the future electric vehicle market and its impacts with an agent-based spatial integrated framework: A case study of Beijing, China

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A B S T R A C T

This paper investigates the potential expansion and impacts of Electric Vehicle (EV) market in Beijing, China at the micro level with an agent-based integrated urban model (SelfSim-EV), considering the interactions, feedbacks and dynamics found in the complex urban system. Specifically, a calibrated and validated SelfSim-EV Beijing model was firstly used to simulate how the EV market might expand in the context of urban evolution from 2016 to 2020, based on which the potential impacts of EV market expansion on the environment, power grid system and transportation infrastructures were assessed at the multiple resolutions. The results suggest that 1) the adoption rate of Battery Electric Vehicle (BEV) increases over the period, whereas the rate of Plug-in Hybrid Electric Vehicle (PHEV) almost remains the same; Furthermore, the so-called neighbour effects appear to influence the uptake of BEVs, based on the spatial analyses of the residential locations of BEV owners; 2) the EV market expansion could eventually benefit the environment, as evident from the slight decrease in the amounts of HC, CO and CO_2 emissions after 2017; 3) Charging demand accounting for around 4% of total residential electricity demand in 2020 may put slight pressure on the power grid system; 4) the EV market expansion could influence several EV-related transport facilities, including parking lots, refuelling stations, and charging posts at parking lots, in terms of quantity, layout and usage. These results are expected to be useful for different EV-related stakeholders, such as local authorities and manufacturers, to shape polices and invest in technologies and infrastructures for EVs.

1. Introduction

1.1. Background

Electrification of transport in cities has received increasing attention over the past few years. Many countries, including China (Cazzola and Gorner, 2016), the UK (The-Guardian, 2017) and Norway (Mersky et al., 2016), have tried to promote both the usage and purchase of Electric Vehicles (EVs) mainly through policies (e.g., subsidies) (Hao et al., 2014), technologies (e.g., on-board batteries) (Chéron and Zins, 1997) and infrastructures (e.g., charging posts) (Bakker et al., 2011). In is hoped that EV could become an alternative to Convectional Vehicle (CV), so as to benefit the environmental and energy systems at both local and global levels (Zhuge and Shao, 2019). Note that in this paper EV particularly refers to Battery Electric Vehicle (BEV) and Plug-in Hybrid Electric Vehicle (PHEV), as both of them have an on-board battery that can be recharged through charging posts (Zhuge and Shao, 2018a, 2019). In order to provide EV-related stakeholders, such as local authorities and vehicle manufacturers, with tools, information and evidence to support their policy marking and investment in

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technologies and infrastructures, a great deal of research has been conducted, primarily involving in the adoption of EVs (see Section 1.2 below) and the potential impacts of the EV adoption on the environment, power grid system and urban infrastructures (see Section 1.3 below).

1.2. Previous studies of the EV adoption

Essentially, the studies of the adoption of EVs were focused on the two aspects: 1) the factors that might influence the purchase behaviour and 2) the ways to predict the adoption rate.

The EV purchase behaviour could be influenced by a wide variety of factors, including vehicle price (Sun et al., 2017), driving experience (Degirmenci and Breitner, 2017; Matthews et al., 2017), social influences (Li et al., 2013), and the environmental awareness (Degirmenci and Breitner, 2017; Smith et al., 2017), as recently reviewed in (Biresselioglu et al., 2018; Li et al., 2017; Zhuge and Shao, 2019). Identifying these influential factors could help to develop methods and models to predict the EV penetration rates, as the factors can be used as the independent variables of an EV market model.

As reviewed by Al-Alawi and Bradley (2013), agent-based model, discrete choice model (e.g., multinomial logit model) and diffusion rate model (e.g., the Bass model) have tended to be the three of the most-used approaches to the EV market forecasting (or predicting the market share). The former two try to simulate the decision-making of individuals at the micro scale; while the latter tries to predict the EV penetration rate at the macro level. Agent-based modelling has been increasingly viewed as a promising approach to investigating complex dynamic systems (Farmer and Foley, 2009; Heppenstall et al., 2011; Waldrop, 2018). The EV market is such a complex system in which several EV-related stakeholders interact with each other, including consumers (Eppstein et al., 2011; McCoy and Lyons, 2014), governments (Zhang et al., 2011), manufacturers (Zhang et al., 2011), fuel suppliers (Sullivan et al., 2009) and urban planners (Adepetu et al., 2016), and therefore agent-based modelling has been widely used to investigate the EV market (Al-Alawi and Bradley, 2013). In the agent-based EV market models, consumer tends to be the core agent type, as it makes decision on vehicle purchase, and can also directly or indirectly interact with the other EV-related stakeholders. Utility maximization theory (Aleskerov et al., 2007) appears to be one of the most-used approaches to simulating the behaviour of agents in the EV market models with the assumption that consumer agents always choose their vehicles with the highest utilities. For example, Adepetu et al. (2016) used a utility function that considered the vehicle attributes (e.g., driving range) as variables to simulate the decision-making of consumer agents on vehicle purchase; Similarly, Brown (2013) used a discrete choice model (specifically a mixed logit model), which incorporated the utility maximization theory, to predict the vehicle choices of consumer agent.

As reviewed above, although a wide variety of models and methods have been developed to investigate the EV market expansion at both the micro and macro levels, these models were generally only focused on the EV market, paying little attention to the interactions or connections between the EV market and those associated urban elements, such as population system and land use. This could lead to an inaccurate estimation of the EV market penetrate rate from a dynamic perspective, as the changes in those associated urban elements could also influence the EV market expansion. For example, as the population system evolves over time, the demographic characteristics of individuals could change, which would further give rise to the change in the purchase behaviour of EV. More importantly, all of these urban elements above interact with each other and evolve over time, making the studies of the EV market expansion more complex than generally expected. Therefore, an integrated urban model would be useful here for a better estimation of the EV penetration rate, considering the interactions, feedbacks and dynamics found there.

1.3. Previous work on assessing the impacts of the EV adoption

The EV market expansion may benefit the environment at both global and local levels (Zhuge and Shao, 2019). The rising market share of EVs may reduce the CO_2 emissions, but the potential reduction depends on the electric power plant fleet. For example, Casals et al. (2016) found that some EU counties, such as Germany and the UK, could not benefit immediately from the uptake of EV, as these countries needed to put more efforts into decarbonizing their power plant fleet. Similarly, Doucette and McCulloch (2011)'s findings also suggested that the reduction in the CO_2 emissions might not occur until those highly CO_2 intensive countries, such as China, could decarbonize their power plant fleet. Coupling renewable energy (e.g., solar and wind energy) with EVs appears to a promising way to reduce the CO_2 emissions (Lund and Kempton, 2008), as the electricity generation would produce significantly less CO_2 emissions. For example, Chen et al. (2018) found that a significant reduction in CO_2 emissions could be expected at several levels of wind penetration, using China as a case study. At the local level, the widespread adoption of EVs may improve the local air quality and thus benefit human health. As found by Ferrero et al. (2016), only a high EV market share (e.g., 50%) could have a substantial reduction in the pollutant concentrations. However, a lower EV penetration rate was still helpful especially during those intense pollution episodes. In addition, Holland et al. (2016)'s work suggested that people with different incomes and EV subsidies could receive different local environmental benefits from EVs.

Integrating EVs into the power grid system could increase the demand for infrastructures and equipment for generating and transmitting the electricity (Muratori, 2018), as the grid system needs to accommodate the additional charging demand from EVs. In general, the potential impacts of the EV market expansion on the power grid system were assessed within various “what-if” scenarios, including wind power scenario (Chen et al., 2018), price- and incentive-based demand response scenario (Shafie-khah et al., 2016), Vehicle-to-Grid (V2G) scenario (Lund and Kempton, 2008), and dumb grid scenario (Galus et al., 2010; Qian et al., 2011). For example, Qian et al. (2011) found that 10% and 20% market shares of EV could result in 17.9% and 35.8% increases in peak load in a dumb grid scenario (where no measures were taken to optimize the integration of EV), respectively. V2G (Pillai and Bak-Jensen, 2011), which enables EVs to sell electricity back to the grid, has been increasingly viewed as a promising technology to address some critical issues in the dumb grid system, such as voltage problems (Clement-Nyns et al., 2011). Also, V2G could economically benefit EV owners through the reduction in electricity prices (Wolinetz et al., 2018).

In addition, the rising EV market share could also give rise to the increase of the demand for charging facilities, but the decrease of the demand for refuelling stations, due to the potential competitions and interactions between charging and refuelling facilities (Zhuge and Shao, 2018a). Previous studies have looked at several different charging facilities, including charging lanes (Chen et al., 2016), battery swap stations (Hof et al., 2017; Yang and Sun, 2015), enroute fast charging stations (Bae and Kwasinski, 2012), charging stations for electric taxis (Asamer et al., 2016), and show charging posts at parking lots (Chen et al., 2013). These studies generally tried to locate the charging facilities with several different objectives, including minimizing the total number of the missed trips of EV drivers (Dong et al., 2014), minimizing the social cost (Chen et al., 2016), minimizing the total cost of charging facility, and satisfying as much charging demand as possible (Asamer et al., 2016; Cavadas et al., 2015). Also, some constraints were also imposed on the deployment of charging facilities, including a limited budget (Cavadas et al., 2015; Chen et al., 2016) and a fixed number of charging stations to be added (Asamer et al., 2016).

Since the EV market expansion and its impacts are closely linked, some attempts have been made to simultaneously investigate the EV adoption and its potential impacts. For example, Wolinetz et al. (2018) pointed out that the consumer behaviour might influence the magnitude of the impact of V2G, and therefore tried to assess the impact within an integrated framework, which combined a vehicle adoption model, a charging behaviour model and an electricity system model. However, these studies still did not fully connect the EV market expansion to its impact assessment, and thus were not able to provide the EV-related stakeholders (e.g., local authorities, utility companies and vehicle manufacturers) with full information for their decision-makings. Therefore, this paper attempts to simultaneously investigate the potential expansion and impacts of EV market within an integrated framework. Here, the potential impacts of market expansion on the environment, power grid system and urban infrastructures will be fully assessed in a dynamic way, as the EV market expands.

1.4. Comments on previous work

As reviewed and discussed in Sections 1.2 and 1.3, the existing studies of EV market expansion and its impacts were limited in 1) ignoring the interactions and linkages between the EV market and those associated urban elements, such as land use and population systems and 2) investigating the expansion and impacts of EV market separately. These limitations could lead to an inaccurate estimation of the EV penetration rate through time and also a limited understanding of the impacts of the EV market. In response to these limitations, this paper attempts to simultaneously explore the future EV market and its impacts with an agent-based integrated urban model (SelfSim-EV) (Zhuge and Shao, 2018a, 2018b; Zhuge et al., 2016), involving in six EV-related urban sub-systems, namely transportation, land use, population, economy, energy and environment systems, so as to take into account the feedbacks, dynamics and interactions found there. It is expected that the model outcomes could be more systematic and comprehensive and thus would be more useful for those EV-related stakeholders involved, such as local authorities and vehicle manufacturers.

The capital of China, Beijing, will be used as a case study, as the Beijing government appears to act actively in promoting both the purchase and usage of EVs (Sun et al., 2017; Zhang et al., 2018; Zhuge and Shao, 2019). This paper will be focused on one specific scenario with the assumption that the Beijing urban system (including the EV market and its associated urban sub-systems) would evolve as before during the period from 2016 to 2020. Such a scenario could be viewed as a reference scenario (or baseline), which can be further compared to various “what-if” scenarios, which investigate how different factors, such as the EV-related policies, technologies and infrastructures, may influence the EV market expansion and its impacts.

2. An agent-based integrated urban model (SelfSim-EV) for investigating the expansion and impacts of EV market

2.1. Framework of SelfSim-EV

Fig. 1 shows the framework of SelfSim-EV, which is updated from an agent-based land use and transport model, SelfSim (Zhuge et al., 2016), by incorporating several EV-related modules, including an EV market model, a social network evolution model and a transport facility development model. Essentially, SelfSim-EV is composed of initialisation and simulation modules: the initialisation module actually is a virtual city creator, which is used to generate an agent- and GIS-based virtual city containing individuals, households and facilities, as well as their attributes (e.g., sex and facility capacity) and relationships (e.g., social networks): see Zhuge et al. (2018b) and Zhuge et al. (2018a)'s work for more details; the simulation module comprises several spatial explicitly urban models, including a demographic evolution model (Zhuge and Shao, 2018b), a joint model of Residential Location Choice and Real Estate Price (RLC-REP) (Zhuge and Shao, 2018b), a social network evolution model, an EV market model, an activity-based travel demand model (MATSim-EV) (Horni et al., 2016; Zhuge and Shao, 2018a; Zhuge et al., 2017), an activity facility development model and a transport facility development model (Zhuge and Shao, 2018a), which form an annual loop to simulate how the urban system evolves over time, with a particular focus on the EV market expansion and its impacts on the environment, power grid system and transport infrastructures.

Given a virtual city generated by the creator, SelfSim-EV works in the following way: first, the demographic evolution model is used to simulate some typical demographic transitions such as birth, employment, marriage and immigration (see Zhuge and Shao (2018b)'s work for model specification and test); then the joint model of RLC-REP is used to simulate how purchaser, renter, investor, landlord and seller agents interact with each other in the dynamic housing market, resulting in new residential locations and also selling prices and rents of houses (see Zhuge and Shao (2018b)'s work for model specification and test); Next, the social network evolution model, which is updated from a static social network generator proposed by Zhuge et al. (2018b), is used to simulate how individuals build and dissolve their friendships at the micro level, using a utility function considering the similarity in individual attributes (e.g., income) and spatial closeness of their residential location and workplaces (Zhuge et al., 2018b); further, the EV market model is used to simulate how consumer agents make decision on vehicle purchase, considering the interactions among consumer, government and manufacturer agents (see Section 2.2 below); Then the activity-based model, MATSim-EV, which is an EV version of MATSim (Multi-Agent Transport Simulation) (Horni et al., 2016), is used to simulate how people perform their daily activities (e.g., shopping and work) and travel from one activity location to another using different transport modes, including both EVs and CVs (Zhuge and Shao, 2018a). More detailed introduction to MATSim can be found in (Horni et al., 2016); Finally, the activity facility development model and transport facility development model are used to develop (add or remove) activity and transport facilities, respectively. Note that the activity facility development model has not been implemented yet, so the activity facilities for each simulation will be input when SelfSim-EV is initialised. A detailed introduction to the transport facility development model can be found in the work of Zhuge and Shao (2018a).

The key roles of these SelfSim-EV sub-models in the investigation of the EV market expansion and its impacts are described as follows: 1) the outputs from the demographic evolution model are some key socio-demographic characteristics (e.g., age and income), which are associated with several behavioural rules of agents (e.g., vehicle consumer and EV driver) in SelfSim-EV. For example, some socio-demographic attributes have been used as the variables of discrete choice models (e.g., multinomial logit model) (Bierlaire, 1998) for the simulation of parking and charging behaviours of both BEVs and PHEVs in the MATSim-EV simulation; 2) the household residential locations can be obtained from the RLC-REP

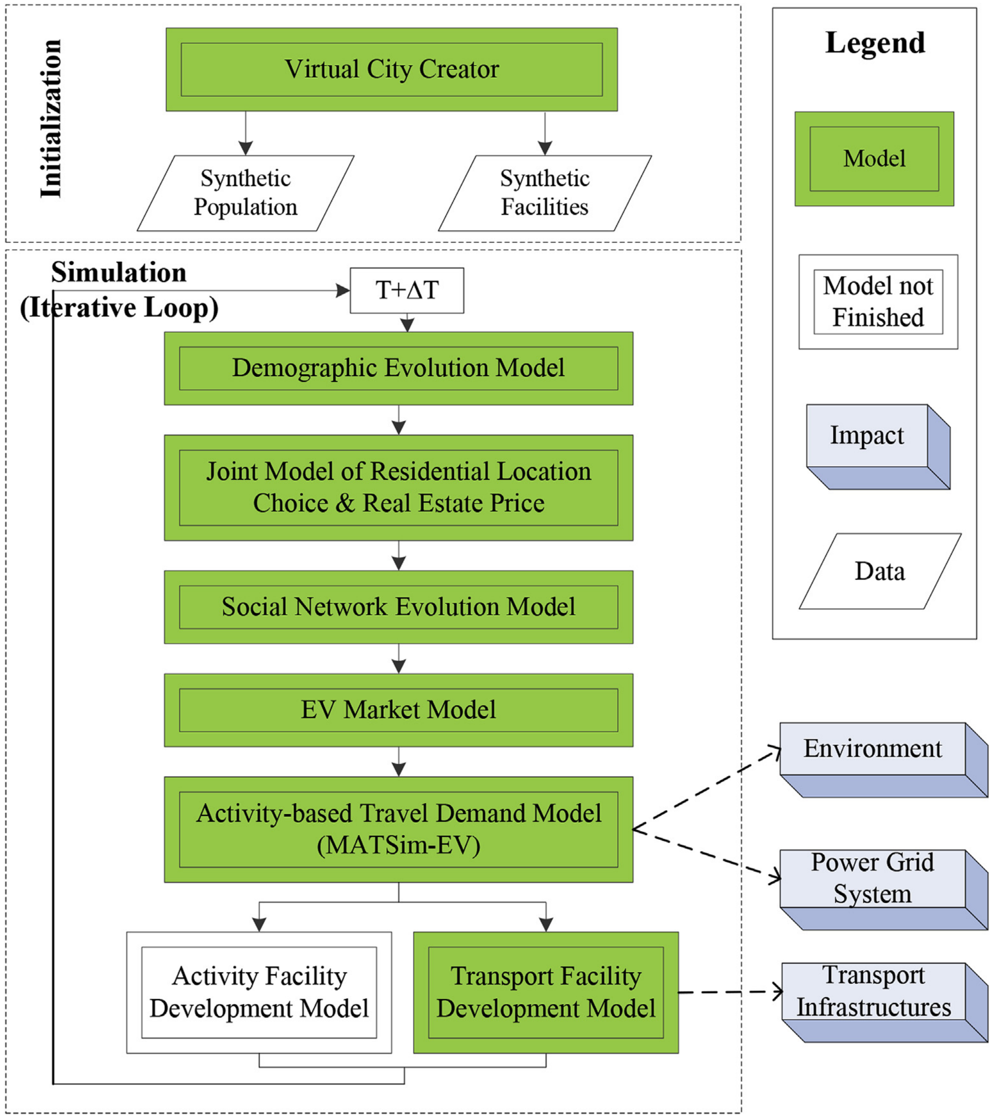


Fig. 1. Framework of the SelfSim-EV model (Zhuge and Shao, 2018a, 2018b; Zhuge et al., 2018a).

model and can be further used for, for example, the spatial analysis of EV owners and charging demand. Also, the potential neighbour effects in the adoption of EVs (Axsen et al., 2009; Mau et al., 2008) can also be quantified with the residential locations; 3) the outputs from the social network evolution model can be further used to quantify the potential social influence on the adoption of EVs through individual social networks (Axsen and Kurani, 2012; Axsen et al., 2013; Pettifor et al., 2017), as the social influence is considered as a utility term associated with the decision-making of consumer agents in the EV market (see Equation (1) below). The EV market, MATSim-EV and transport facility development models are directly used for simulating the EV maker expansion and assessing its impacts, which will be introduced in more details in Sections 2.2 and 2.3 below.

2.2. Simulation of the EV market expansion

As aforementioned, the agent-based EV market model is used to simulate whether consumer agents would purchase vehicles or not, and if yes, which vehicle type to purchase, considering the interactions with the government and vehicle manufacturer agents in the vehicle market. The market is assumed to have three vehicle types, namely BEV, PHEV and CV. As shown by Fig. 2, the EV market model is composed of two stages: At Stage 1, each agent in the population will be firstly screened and only those agents passing all of the three conditions (e.g., driving license) can become the consumer agents entering the vehicle market; At Stage 2: these consumer agents will interact with the other EV-related stakeholders in the vehicle market: first, consumer agents will decide which vehicle type to purchase using a utility function considering four key factors, namely, social influence ($U_{SocialInfluence}$), driving experience ($U_{DailyPlan}$), vehicle purchase price ($U_{PurchasePrice}$) and environmental awareness ($U_{Environment}$), as well as a random term (U_{Random}), as presented by Equation (1); then the government agent will update the EV subsidies according to the EV adoption rate, and the vehicle manufacturer agents will update their EV and CV prices according to the purchase demand (or market penetration rate). The EV subsidies and vehicle sale prices will be fed back to consumer agents in the next simulation year, and the difference between the subsidy and sale price will be the purchase price ($U_{PurchasePrice}$).

In the utility function for the decision-making of consumer agents, $U_{DailyPlan}$ and $U_{Environment}$ are calculated based on the activity-based travel demand model (MATSim-EV), which executes and scores the daily plans of each agent in the population, resulting in the moving trajectories of each agent throughout the whole day: see Horni et al. (2016)'s work for more details. A daily plan contains the detailed information on how the agent performs its daily activities (e.g., shopping) and travels from one activity location to the next using different transport modes (e.g., EVs and public transport). MATSim-EV uses a utility function of travel and activity to score daily plans (see Horni et al. (2016) for a detailed introduction to the utility function). Therefore, consumer agents can compare the utilities of their daily plans ($U_{DailyPlan}$) with different vehicle types. It is worth noting that the limited driving range of EVs is considered in $U_{DailyPlan}$: those BEV drivers, who use up electricity before they reach their trip destinations where charging facilities are available, would receive very high negative utilities. As a result, the BEV drivers will have very low $U_{DailyPlan}$, and thus will be discouraged to purchase or use BEVs. For PHEV drivers, they will receive very low $U_{DailyPlan}$ only when they use up both electricity and petrol. In addition, social influence has been found as an important factor to the uptake of EVs (Axsen et al., 2013; Pettifor et al., 2017; Zhuge and Shao, 2019), and thus are also considered as a utility term ($U_{SocialInfluence}$), which is calculated based on the social network evolution model, as mentioned before.

$$U_{Vehicle} = U_{SocialInfluence} + U_{DailyPlan} + U_{PurchasePrice} + U_{Environment} + U_{Random} \tag{1}$$

2.3. Ways to assess the impacts of EV market expansion with SelfSim-EV

The potential impacts of EV market expansion on the environment (see Section 2.3.1), power grid system (see Section 2.3.2) and transport infrastructures (see Section 2.3.3) can be assessed with SelfSim-EV in the following ways:

2.3.1. Impact on the environment

The environmental impact can be assessed based on the simulation of individual travel behaviour (or the MATSim-EV simulation) (Horni et al., 2016). Specifically, the energy state of each vehicle is traced in the simulation when they move from one activity location to another in order to perform their daily activities (e.g., shopping and work) at different places, as illustrated by Fig. 3. An energy consumption factor, which is the function of travel speed, is used here to calculate the real-time electricity or petrol consumption for each vehicle when they are moving on the road network (Yao and Song, 2013; Yao et al., 2013). Similarly, a vehicular emission factor, which is also a function of travel speed (Yao and Song, 2013), is used to calculate the amount of vehicular emissions when vehicles consume fuel (Zhuge and Shao, 2018a). SelfSim-EV considers four typical types of vehicular emission, namely HC, CO, CO2 and NOx. The energy consumption factor and emission factor in MATSim-EV are from the work of Yao and Song (2013) and Yao et al. (2013). In addition, the street-level emissions from the model can be aggregated at the traffic zone-, district- and city-levels, so as to understand the environmental impacts at multiple spatial resolutions.

2.3.2. Impact on power grid system

As mentioned above, the energy state of each vehicle can be traced within the activity-based travel behaviour simulation (or the MATSim-EV simulation) (Horni et al., 2016), based on which the charging demand of each EV can be estimated at both the enroute fast charging stations and the parking lots with charging posts established (at trip destinations), as shown by Fig. 3. The spatially and temporally disaggregate charging demand can be further aggregated at the traffic zone-, district- and city-levels. Such information can be used to assess the potential impacts of the integration of EVs on the power grid system at both micro and macro scales, and should be useful, for example, for electricity management and planning on charging facilities.

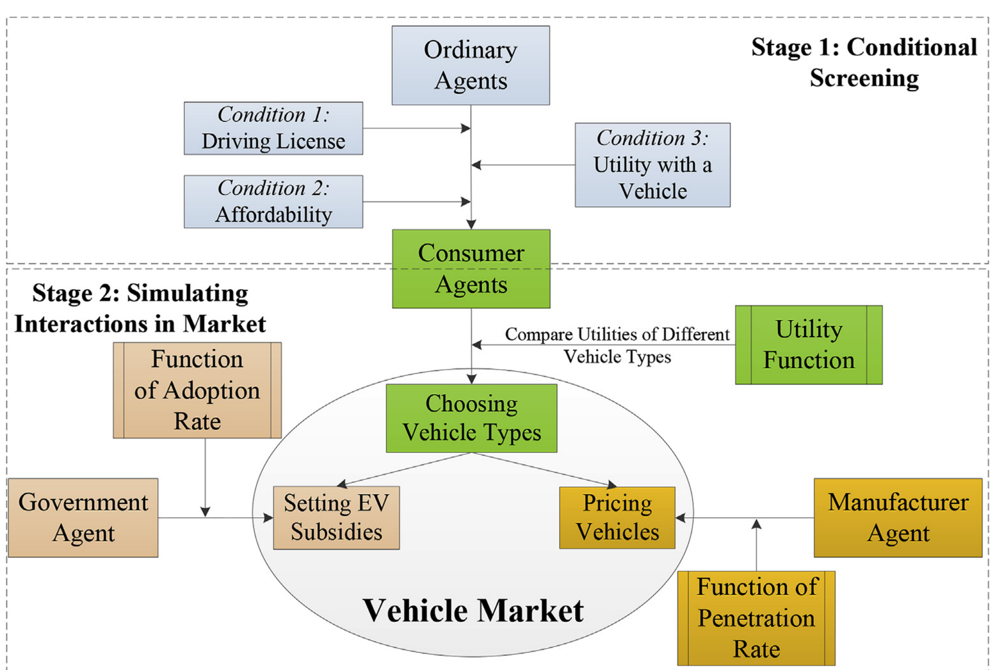


Fig. 2. Framework of the EV market model.

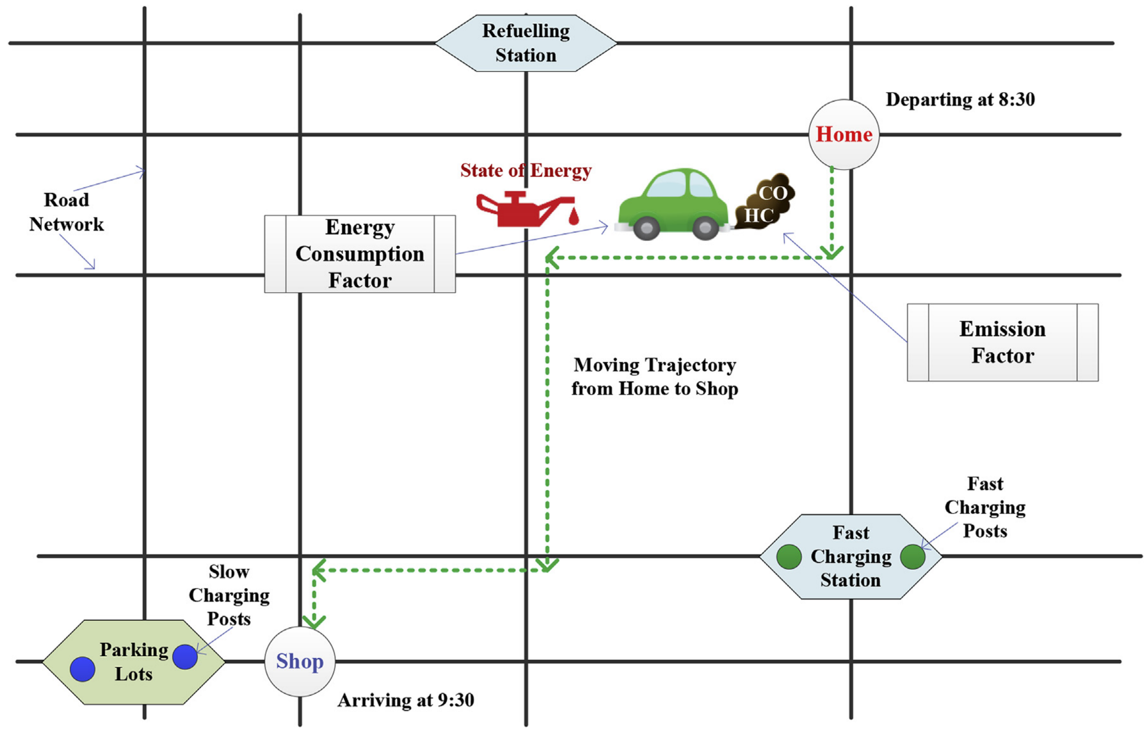


Fig. 3. An Example Illustrating the Moving Trajectory of a Vehicle Agent and its Energy Consumption and Emission in MATSim-EV (Zhuge et al., 2018a).

2.3.3. Impact on transport infrastructures

The increasing adoption of EVs may give rise to the increase in the demand for charging facilities, such as enroute fast charging stations and slow charging posts at trip destinations (or parking lots). Meanwhile, the demand for refuelling stations may decrease because of replacing CVs with EVs (Zhuge and Shao, 2018a). In other words, the interactions and competitions between refuelling and charging facilities may occur, as the widespread adoption of EVs. In order to quantify the potential influence of the EV market expansion on those EV-related transportation facilities with the consideration of the interactions and competitions, the transport facility development model developed by Zhuge and Shao (2018a) is used here. The model considers four types of EV-related transport facilities, namely parking lots, refuelling stations, enroute fast charging stations and slow charging posts at parking lots, as shown by Fig. 3. The model results, which can also be presented at station-, parking lot-, traffic zone-, district- and city-levels, should be helpful for local authorities and urban planners to locate and optimize the EV-related transport facilities, so as to promote the purchase and usage of EVs.

3. Case study of Beijing, China

3.1. Scenario description

The capital of China, Beijing was used as a case study. The scenario used 2015 as the base year, and simulated the EV market expansion during the period from 2016 to 2020 (which is the planning period of the China's thirteenth Five-Year Plan), with a calibrated and validated SelfSim-EV Beijing model. Specifically, SelfSim-EV was calibrated in two ways: 1) several behaviour types of individual and household agents, including the purchase behaviour of consumer agents, and the parking and refuelling/charging behaviours of CV, PHEV and BEV, were calibrated with the data collected in two questionnaire surveys in Beijing from September 2015 to March 2016. For example, the empirical findings from the survey on vehicle purchase (see (Zhuge and Shao, 2019) for more details) was used to calibrate the utility function of consumer agents (see Equation (1)), which was used to simulate their decision-makings on vehicle type; 2) SelfSim-EV was also calibrated by fitting some macro data from 2011 to 2014 on vehicle prices, vehicle sales, EV subsidies, the numbers of different transport facilities (e.g., parking lots) and real estate prices at both district- and city-levels, using a Sensitivity Analysis (SA)-based method (Zhuge and Shao, 2018a, 2018b). Further, the calibrated model was validated in 2015 using the same data type. The Mean Absolute Percentage Errors (MAPEs) for model calibration and validation were 5.5% and 9.6%, respectively, exhibiting a relatively satisfactory performance.

The scenario in this paper continued to run the calibrated and validated SelfSim-EV Beijing model from 2016 to 2020, with the assumption that the Beijing urban system would evolve as before. The results would be useful for attaining the goal of promoting EVs, as established in the thirteenth Five-Year Plan of China. Note that the scenario here is not to exactly predict the future EV market, but is to explore the likely EV market in the near future, as well as its potential impacts on the environment, power grid system and transport infrastructures, as the future of such a complex urban system is rather difficult to predict. It is also worth noting that the SelfSim-EV model was run ten times and the averages of these ten simulations were used as the final results, in order to take into account the potential stochastic effects (or model variability). In addition, the model performance was examined again by comparing the predicted and observed data on the EV market and the EV-related transport facilities in 2016, suggesting that the ability to predict is satisfactory with a MPAE of 6.3% (see Table 5 in Appendix 2.1 for more details).

The outputs of SelfSim-EV simulation in 2015 were used as the inputs of the Beijing scenario here, and can be viewed as an agent- and GIS- based virtual Beijing. Note that all of the facilities (including both transport and activity facilities) in SelfSim-EV are assumed to be located at road nodes (or interactions), meaning that agents need to travel from one node to another in order to perform activities in different node-based facilities (Zhuge and Shao, 2018a, 2018b; Zhuge et al., 2018a, 2018b). Fig. 4 shows a specific element in the virtual Beijing: each dot in the map, which is based on road node or interaction, represents a residential building with the capacity information attached.

Apart from the virtual Beijing in 2015, the future-year SelfSim-EV simulations need the macro-level constraints on demographical attributes and activity facilities, which are used to simulate the demographic evolution and the activity facility development, respectively. The constraints were forecast using the Autoregressive Integrated Moving Average (ARIMA) model (Box et al., 2015; Wei, 1994) with the time series data extracted from relevant statistical yearbooks. The forecasting was done within R software package (Shumway and Stoffer, 2010). The synthetic data on demographical attributes and activity facilities for future-year simulations can be found in Appendix 1.

3.2. Potential EV market expansion from 2016 to 2020

3.2.1. Aggregate results about the market expansion

Fig. 5 shows the aggregate data on the EV market expansion from 2016 to 2020, including EV subsidies, vehicle sales and vehicle prices. For vehicle sales, the CV sale decreases at the beginning and starts to level off after 2018, while the BEV sale rises at the beginning and starts to level off after 2018. This is mainly due to the constraints on both CV and BEV purchase permits (or the license plate lottery policy) (Yang et al., 2016; Zhang et al., 2018). Note that CV purchase permits mentioned in this paper refers to the permits for both CVs and PHEVs, as PHEVs are treated as CVs in Beijing in both the license plate lottery policy and the subsidy scheme for EVs (but PHEV purchasers do receive national subsidies). However, the number of PHEVs almost remains zero over the period, as PHEVs are significantly less competitive than CVs when they share a fixed number of vehicle purchase permits. One of the main reasons is probably that PHEVs have a relatively higher price, though some subsidies are provided by the national government. For vehicle prices, the CV and BEV prices level off from 2016 to 2017, due to the specific mechanism of the EV market model (specifically, the EV market model updates the vehicle prices based on the difference of market penetration rates in two consecutive years), but their prices start to goes down and up in 2017, respectively, and then level off again. The changes in the prices in 2017 are caused by the changes in their penetration rates. In addition, the PHEV price remains the same over the period due to its penetration rates of nearly zero. For EV subsidies, the BEV subsidy decreases gradually over time, due to the increasing BEV adoption rate; while the PHEV subsidy almost remains the same due to the almost unchanged PHEV adoption rate over the period. In order to further examine the stochastic effects, the standard deviations of the 10-run SelfSim-EV results about the EV market expansion from 2016 to 2020 are calculated, suggesting that the simulation outcomes of the 10 runs tend to be close to the averages, and the model stochastic uncertainty is unlikely to

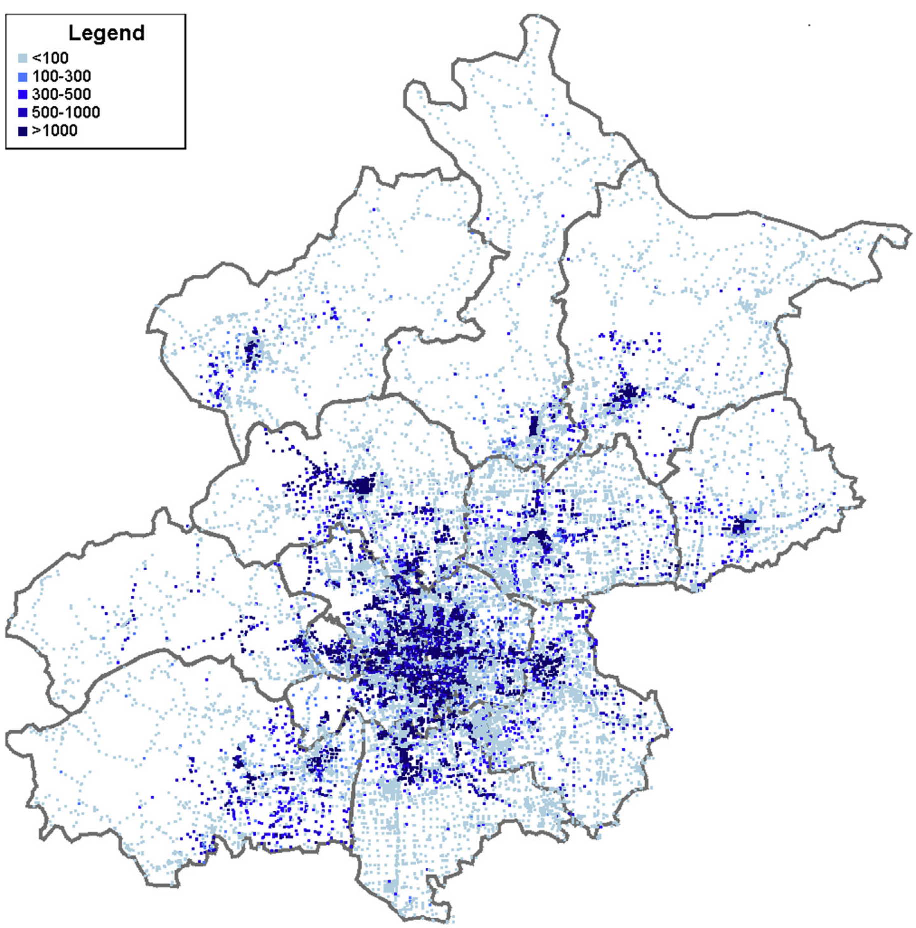
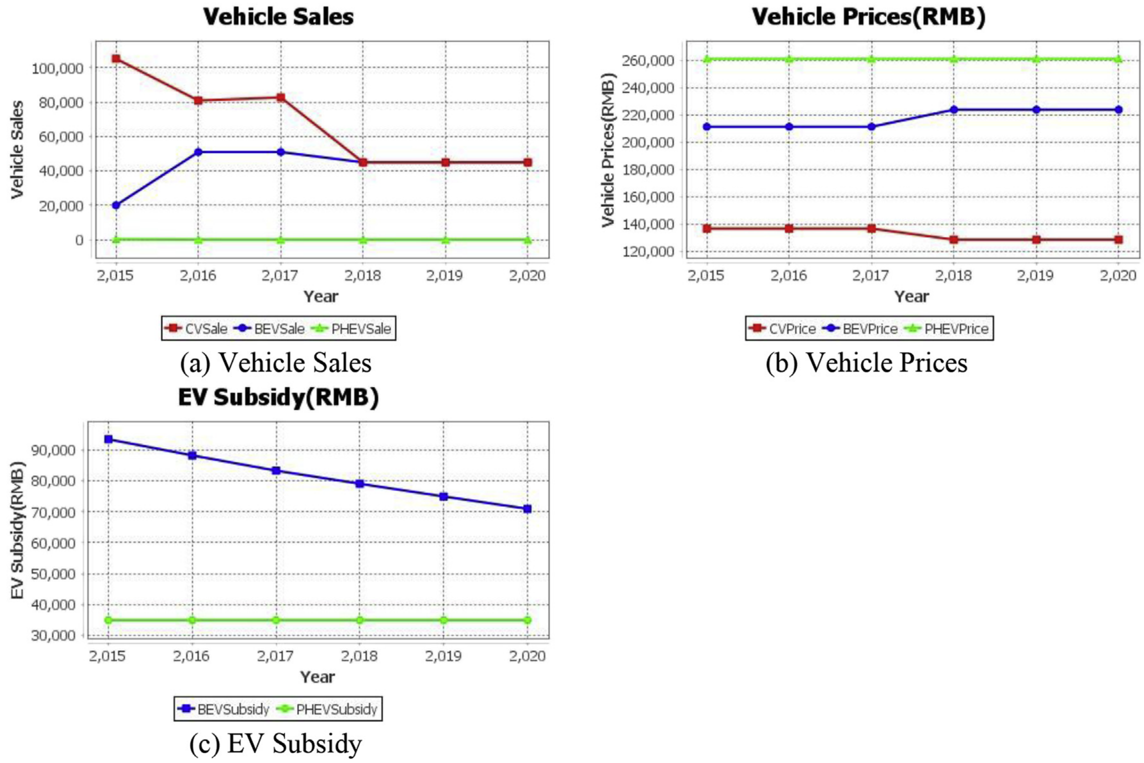


Fig. 4. Spatial distribution of residential buildings in the virtual Beijing in 2015.



(a) Vehicle Sales (b) Vehicle Prices (c) EV Subsidy

Fig. 5. The EV market expansion from 2016 to 2020.

heavily influence the outcomes: see Fig. 18 in Appendix 2.2.1 for more details.

In addition, the ability of the EV market model to predict is somewhat evaluated with the latest observed figures as follows: the numbers of BEV and CV purchase permits allocated in 2017 was 82,800 and 51,000, which are almost the same as the simulated BEV and CV sales, respectively; the observed BEV price in 2017 was 228,722 RMB (note that this was the average price of 25 BEV types sold in 2017), which is quite close to the simulated BEV price of 211,088 RMB; The simulated BEV subsidy in 2017 is 83,334 RMB, which was a little over the observed subsidy of 66,667 RMB. The predict ability in 2017 appears to become weaker, compared to that in 2016 (see Appendix 2.1). However, it should be noted that the scenario here was to explore the likely future EV market and its potential impacts, with the assumption that the urban system would evolve as before. Exact prediction tends to be impossible in such a dynamic complex system, and thus was not expected. The scenario here is planned to be used as a baseline and be further compared to "what-if" scenarios considering the influence of different EV-related policies (e.g., subsides), technologies (e.g., battery capacity) and infrastructures (e.g., battery swap station) on the uptake of EVs and further its impacts.

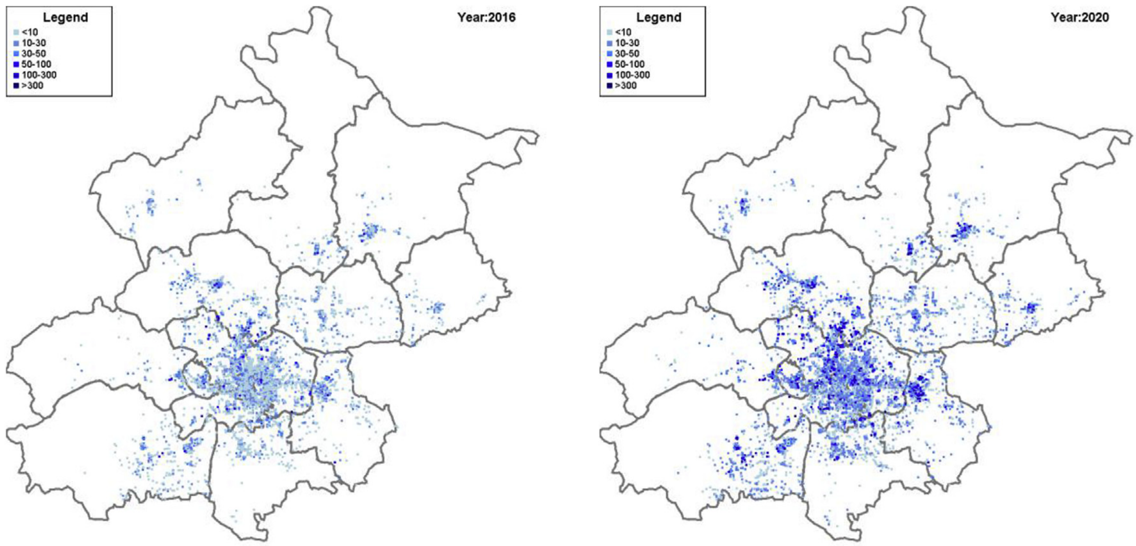
3.2.2. Spatial analysis of the EV market expansion: neighbour effects

The EV marker expansion is further analysed from a spatial perspective, based on the residential locations of vehicle owners, in order to examine the so-called neighbour effects: For an agent, it may be more likely to purchase an EV if its neighbours have EVs (Axsen et al., 2009; Mau et al., 2008; Zhuge and Shao, 2019). By comparing the spatial distributions in Fig. 6-(a) and -(b), it can be seen that some clusters become bigger from 2016 to 2020, due to new added dots (or BEV purchasers), suggesting that the so-called neighbour effects may influence the purchase behaviour of BEVs. Such neighbour influences can also be found in the adoption of BEVs at the district level, as shown by Fig. 7 that aggregates, groups and maps the numbers of vehicle owners for each district. Note that the numbers are grouped by a K-means clustering algorithm (Kanungo et al., 2002). Specifically, the BEV adopters in 2016 are mostly resident in the four districts (namely Chaoyang, Haidian, Shijingshan and Tongzhou) as highlighted in darker blue; whereas the number of districts highlighted in darker blue grows to nine in 2020 with the five new added districts (namely Dongcheng, Xicheng, Fengtai, Daxing and Fangshan), which are close to the four initial districts. However, such neighbour influences are not significant in the adoption of PHEVs. This is likely because PHEVs are not very attractive, compared to BEVs.

More details on the spatial distributions of PHEV and CV owners at the multiple resolutions can be found in Appendix 2.2.2. Such spatially explicit results could be useful for both local authorities and electricity utilities to shape policies and invest in private charging facilities for EVs.

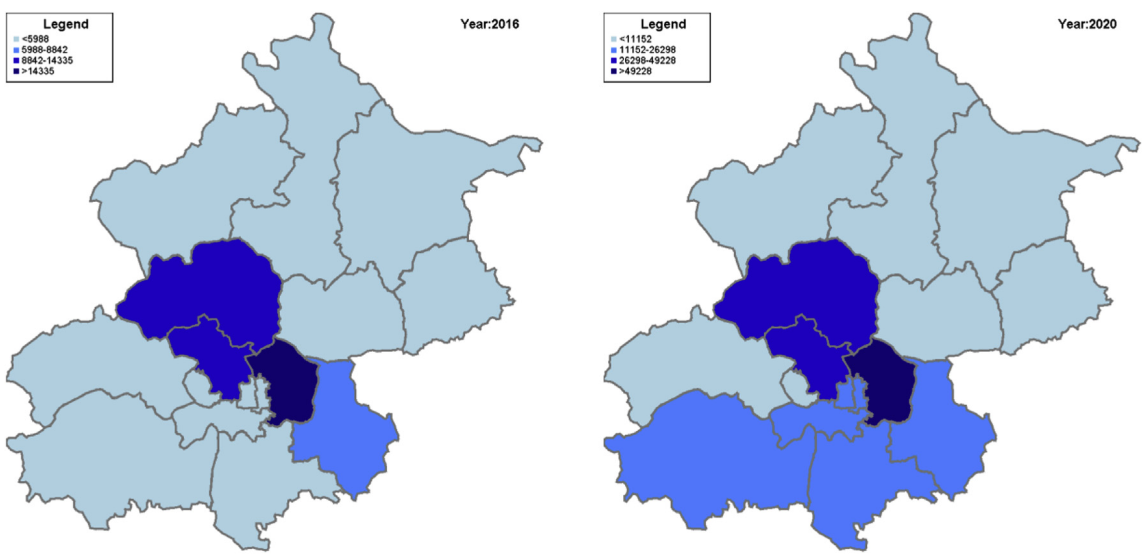
3.3. Impacts of EV market expansion on transport facilities: quantity, layout and usage

The market expansion has little impact on neither refuelling stations nor enroute fast charging stations (and thus the results are not presented here), in terms of quantity. This is very likely because the number of added vehicles (either CV or EV) decreases over time, with a limited and relatively small number of vehicle purchase permits allocated each year (according to the license plate lottery policy). For example, the number of vehicles sold in 2010 was around 748,000 without the constraint on the number of purchase permits; while the number of CVs sold in 2016 was around 80,000, which was only about 10% of the vehicle sale in 2010. Whereas the impacts of the market expansion on the public parking lots and public charging posts are very significant, as shown by Fig. 8. The



(a) BEV Owners in 2016 (b) BEV Owners in 2020

Fig. 6. Spatial distributions of BEV owners in 2016 and 2020 at the facility level.



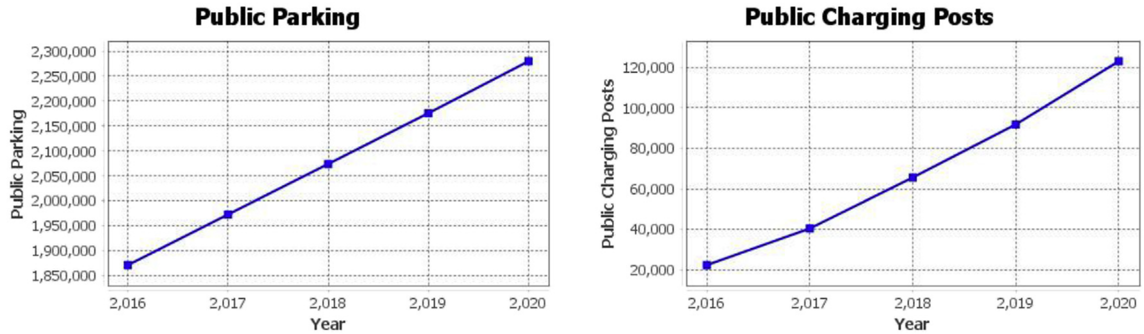
(a) BEV Owners in 2016 (b) BEV Owners in 2020

Fig. 7. Spatial distributions of BEV owners in 2016 and 2020 at the district level.

numbers of public parking spaces and charging posts rise dramatically over the period. It should be noted that the numbers of private charging posts and parking lots are not presented here because in the SelfSim-EV simulation, it is assumed that each vehicle owner is allocated with a private parking lot and each EV owner is extra allocated with a private charging post, once they purchase vehicles. This means the numbers are directly proportional to the numbers of vehicles added. As before, the standard deviations about the transport facilities are computed to investigate the model variability, suggesting that standard deviations are again relatively small as a fraction of the means (see Fig. 21 in Appendix 2.2.1 for more details).

In addition, the ability of the transport facility development model to predict is somewhat evaluated with the latest observed figures: the number of public parking spaces was 2,060,352 in 2017, which is quite close to the simulated number of 1,972,948; the simulated number of public charging posts in 2017 is 40,398, which is a little greater than the reported number of 30,805 in January 2018. This suggests that the predict ability of the transport facility development model also appears to become weaker, compared to that in 2016 (see Appendix 2.1).

In addition, the EV market expansion can also somewhat change the layout of public charging posts at the facility- and zone-levels (see Fig. 9 and Fig. 10), but it has little impact at the district level (see Fig. 22 in Appendix 2.3.2); while the EV market expansion has marginal impact on the layouts of the parking lots at the facility-, zone- or district-levels: one possible reason might be that those parking lots with higher number of parking spaces have also been



(a) Number of Public Parking Spaces (b) Number of Public Charging Posts

Fig. 8. Impacts of market expansion on the quantities of transport infrastructures.

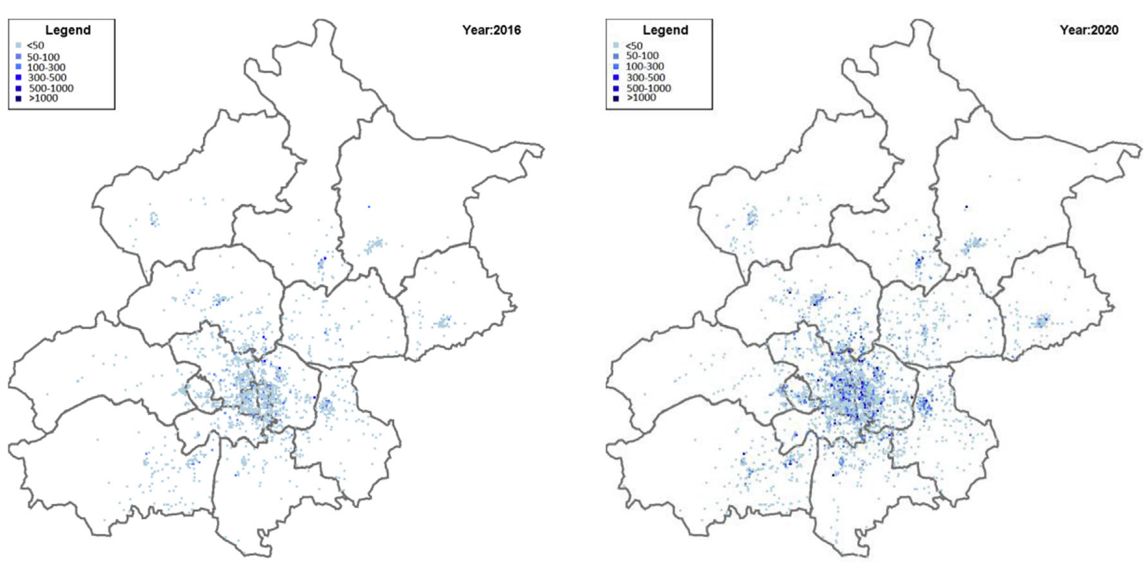
allocated with more parking spaces. As a result, the spatial distributions do not change significantly, though the number of parking spaces increases heavily over the period (as shown by Fig. 8-(a)).

In addition to the impact on the numbers and layouts of transport facilities, the EV market expansion could also influence the usage of the facilities, as evident from the changes in two indicators, namely the average number of vehicles served and average occupied time (see Appendix 2.3.3 for more details).

3.4. Impacts of EV market expansion on the environment

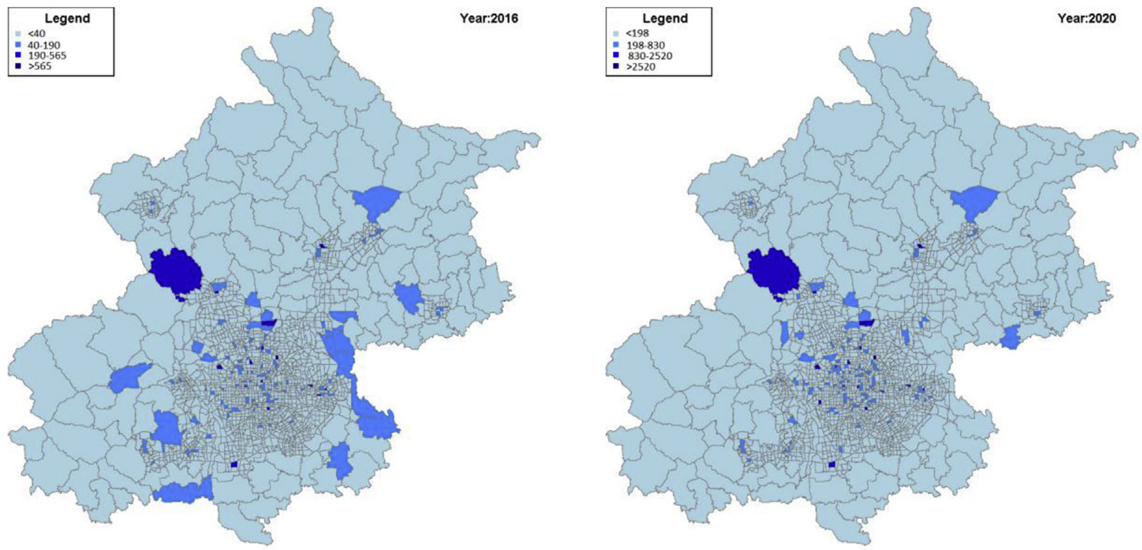
Fig. 11 shows the total amounts of petrol consumed and vehicular emissions in one particular weekday from 2016 to 2020. Overall, there are relatively slight changes in both amounts, primarily due to the constraint on the total number of CV purchase permits (or the license plate lottery policy). In addition, the total amounts of CO, CO_2 and petrol consumed have similar tends over the period which increase in 2017 and then go down until 2020; while the amount of HC rises from 2016 to 2018 and then levels off, but the amount of NOx goes up over the period. Although the numbers of CV and PHEV increase over time, the amounts of vehicular emissions change differently. This is because the amounts of emissions are associated with both travel speed and distance which vary over time and also across agents. In addition, for different types of vehicular emissions, the amount of emission has different relationships with travel speed. All of these can eventually change the total amount of emissions. Again, the stochastic effects are analysed with the standard deviations, suggesting that the stochastic effects are not significant (see Appendix 2.4.1 for more details). In addition, the environmental impacts are also assessed at the multiple resolutions: see Appendix 2.4.2 for more details.

It is worth noting that the amounts of vehicular emissions and petrol consumed are estimated for one particular weekday in Beijing, and the results cannot be linearly scaled up for one year, for example, by simply multiplying by the outcomes by 365. A promising approach to calculating the annual amounts is using a day-to-day activity-based travel demand model (Habib and Miller, 2008) instead of the current single-day activity-based model, so as to simulate the travel behaviour of each agent throughout the whole year. However, such day-to-day activity-based models, in general, require more disaggregate input data on travel demand and also take much longer computing time.



(a) Public Charging Posts in 2016 (b) Public Charging Posts in 2020

Fig. 9. Layouts of public charging posts in 2016 and 2020.



(a) Public Charging Posts in 2016 (b) Public Charging Posts in 2020

Fig. 10. Layouts of public charging posts in 2016 and 2020 at the zone level.

3.5. Impacts of EV market expansion on power grid system

Fig. 12 shows the total amounts of electricity provided by both private and public charging posts in one particular weekday from 2016 to 2020. The total amounts increase over the period due to the increase of the EV number, but the increasing rate gets smaller, which is likely caused by the decreasing number of EV purchasers (due to the decreasing number of vehicle purchase permits, see Fig. 5-(a)). In addition, EVs are mostly charged through private charging posts, as evident from the significantly higher amount of electricity provided by private charging posts. For example, in 2020, the private charging demand is estimated to be around 1,800,000 kW•h in one particular weekday, which is about 9 times of public charging demand that is around 200,000 kW•h per day. In addition, it is estimated that the total charging demand will account for 4% of total residential electricity demand in 2020 and thus may put slight pressure on the power grid system. As before, the standard deviations are not significant (see Fig. 29 in Appendix 2.5 in more details). In addition, the day-to-day activity-based travel demand model mentioned above (see Section 3.4) could also be used here to estimate the annual charging demand in a more accurate way.

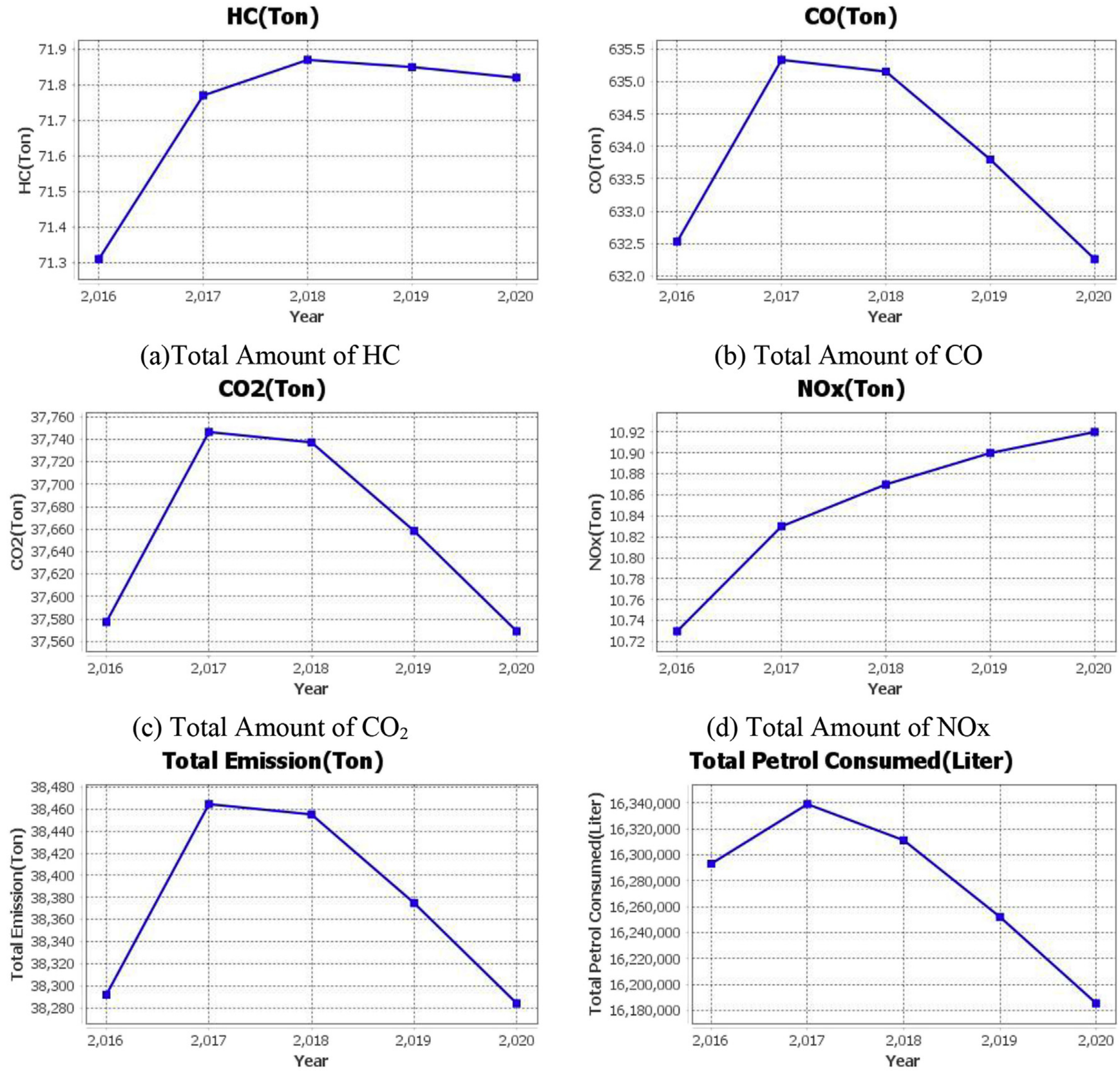
Fig. 13 further maps the spatial distributions of both private and public charging demand based at parking lots (as charging posts are established at parking lots), and Fig. 14 aggregates the demand at the district level. It can be found from the maps that most of charging demand either public or private is at the central districts or the central areas of the outer districts. In addition, the public charging demand in the central districts (e.g., Dongcheng and Xicheng districts) become relatively larger, as the EV market expands from 2016 to 2020 (see Fig. 14-(b) and (d); Note a K-means clustering algorithm was also used to group the data); while the private charging demand in the outer districts (such as Tongzhou district) tends to become relatively smaller from 2016 to 2020 (see Fig. 14-(a) and (c)). Again, these changes might be attributed to many factors discussed above, such as vehicle ownerships and travel patterns. Such spatially disaggregate results about the charging demand could be helpful for electricity utilities to invest in facilities and equipment for generating and transmitting electricity, so as to better accommodate the increasing electricity demand from EVs.

4. Discussion

The SelfSim-EV Beijing scenario explores the likely future EV market from 2016 to 2020, with the assumption that the urban system would evolve as before. The results suggest that the BEV sale will go up, but the CV sale will go down, mainly due to the constraint on the number of vehicle purchase permits (or the license plate lottery policy). The PHEV sale will almost remain over the period mainly due to a relatively higher price. Accordingly, the BEV subsidies decrease over the period, because of its increasing adoption rate; while the PHEV subsidies almost stay the same, as its sale almost remains. Another important finding in the EV market expansion is that the so-called neighbour effects appear to influence the adoption of BEVs, based on the spatial analyses of the residential locations of BEV owners at both facility- and district-levels. Both Axsen et al. (2009) and Mau et al. (2008) tried to investigate neighbour effects in the adoption of EV from a statistical perspective, but their results could not be presented spatially. With SelfSim-EV, the neighbour effects can be easily captured at multiple spatial resolutions, offering new insights into the neighbour effects from a spatial perspective.

Furthermore, the potential impacts of the EV market expansion on the environment, power grid system and transport infrastructures are assessed at the multiple resolutions:

1) Impacts on the environment: the amounts of HC, CO and CO_2 have tendencies to decrease from around 2018; while the amount of NOx increases over the period but at a diminishing rate. This suggests that introducing EVs appears to benefit the environment, though the benefit is marginal relative to the total amount of vehicular emissions. However, with the widespread adoption of EVs, the environmental benefits could become significant. Compared to the existing environmental assessments on the adoption of EV (Casals et al., 2016; Chen et al., 2018; Holland et al., 2016), the assessment here can not only provide aggregate information on the changes in several typical vehicular emissions, but also can present their spatial distributions. Such spatially disaggregate information could be particularly useful for assessing the local environmental impact of EV

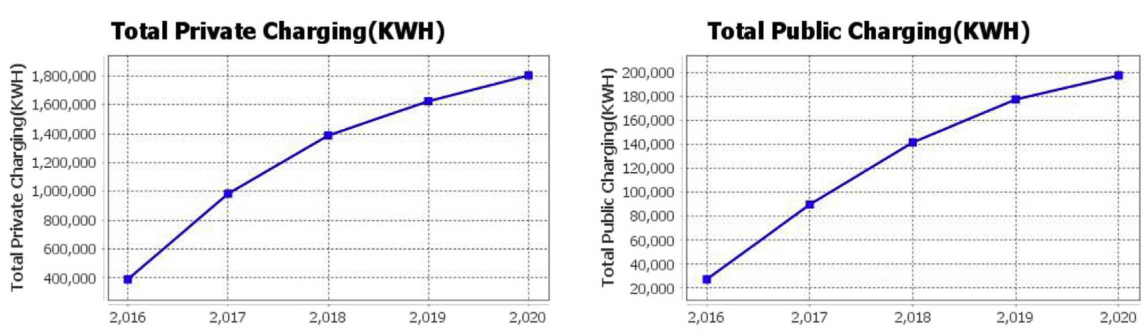


(a)Total Amount of HC (b) Total Amount of CO

(c) Total Amount of CO_2 (d) Total Amount of NOx

(e) Total Amount of Vehicular Emissions (f) Total Amount of Petrol Consumed

Fig. 11. Amounts of petrol consumed and vehicular emissions in one particular weekday from 2016 to 2020.



(a) Total Amount of Electricty Provided by Private Charging Posts (b) Total Amount of Electricty Provided by Public Charging Posts

Fig. 12. Total amount of electricty consumed with charging posts in one particular weekday from 2016 to 2020 (kW•h).

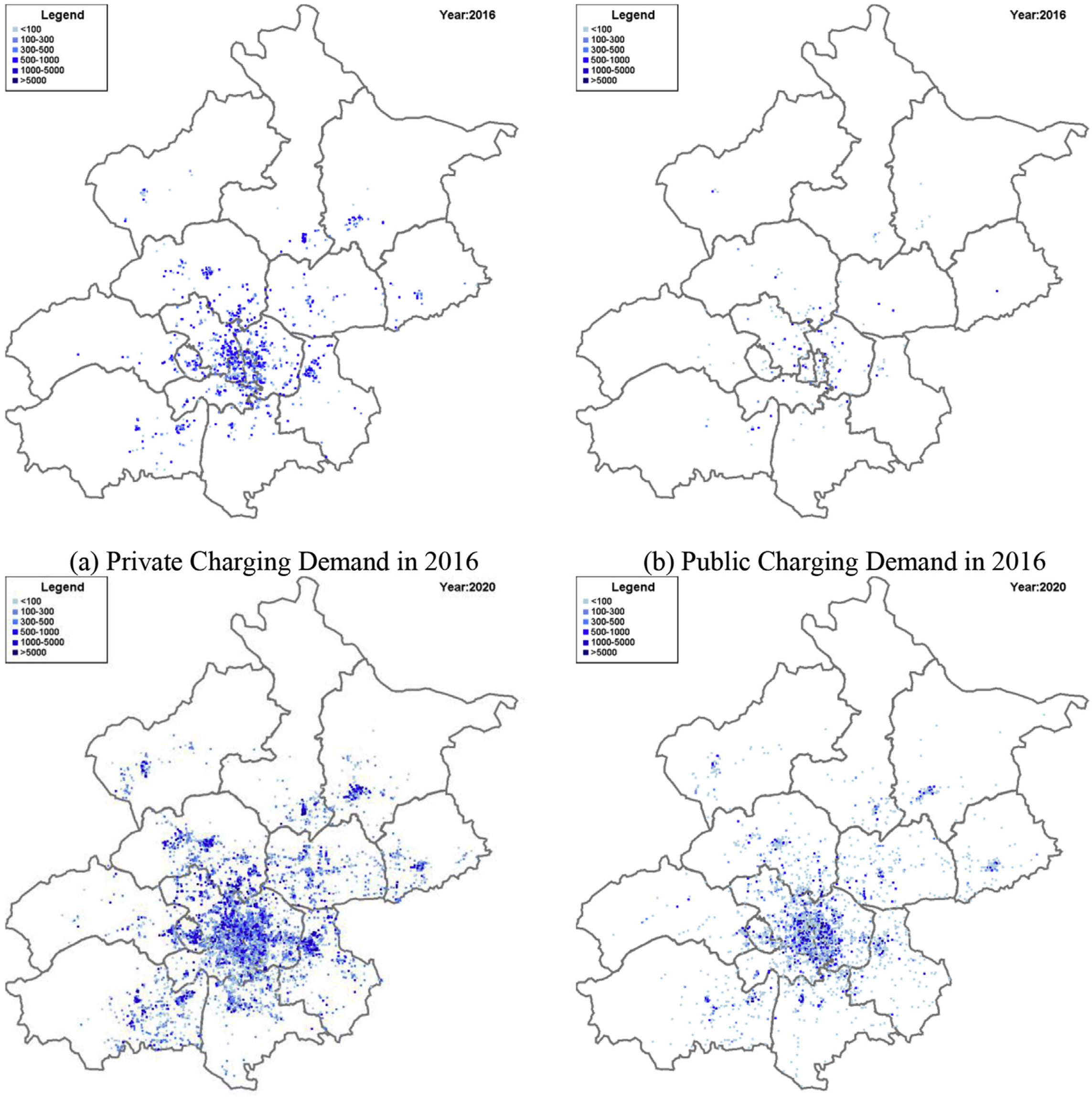
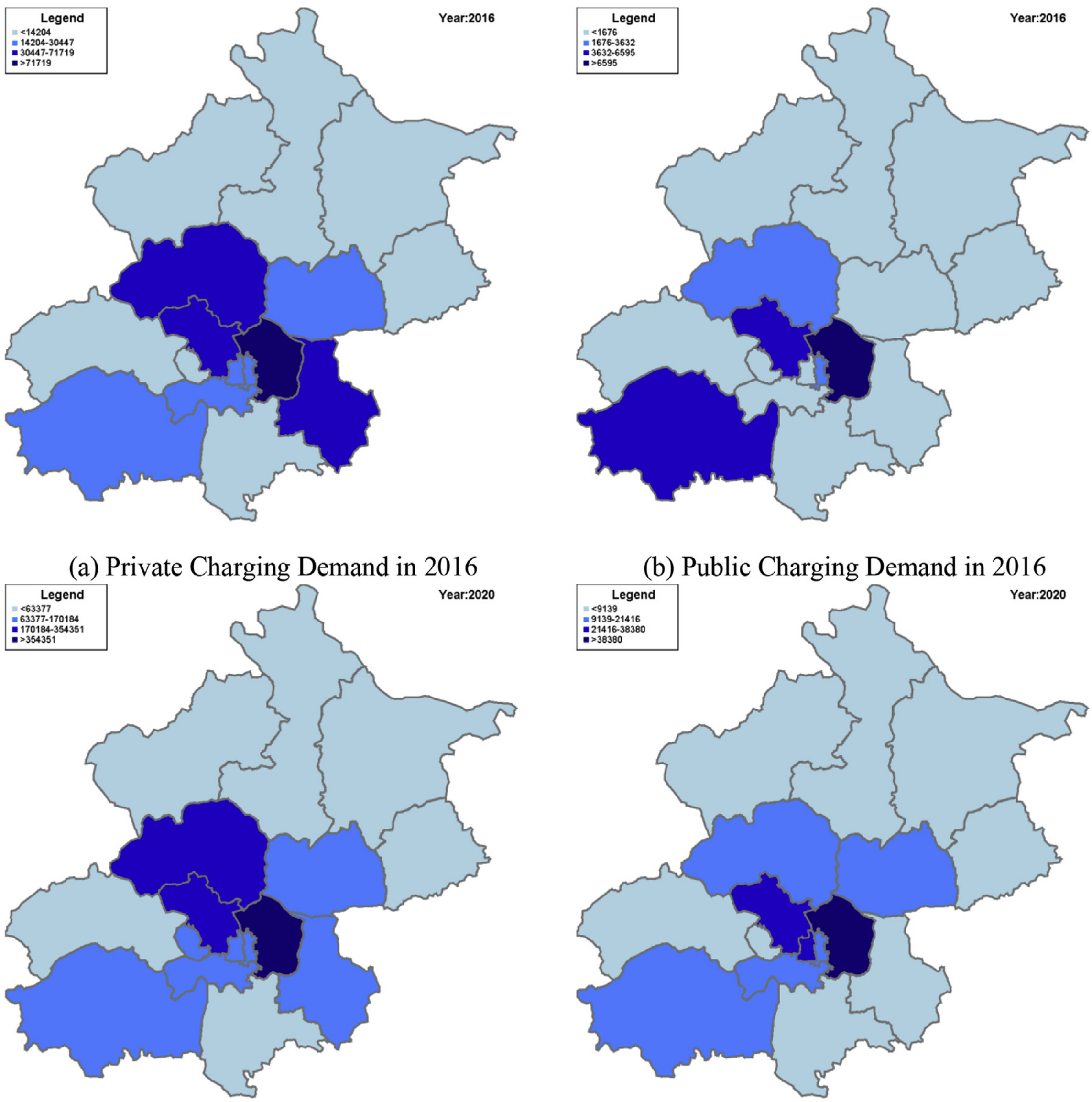


Fig. 13. Spatial distributions of charging demand in one particualr weekday in 2016 and 2020 at the facility level (kW•h).

market expansion: for example, with the moving trajectories of each agent in the population and also the spatiotemporal distributions of different vehicular emissions (which can be obtained from the MATSim-EV simulation, see Section 2.3.1), the time of each agent being exposed to vehicular emissions can be calculated and thus the human health effect can be further assessed.

2) Impacts on the power grid system: EV drivers tend to charge their vehicles using private charging facilities, and it is estimated that private charging demand in 2020 will be about 9 times of public charging demand. It is further estimated that the total charging demand will only account for around 4% of the total domestic electricity consumption in 2020. Therefore, the impact of EV market expansion might be slight, due to a relative small EV adoption rate in 2020 (because of the constraint on the vehicle purchase). The impact assessment here distinguished between the public and private charging demands and also the dynamic demands were presented at very high temporal (in second) and spatial (at the node level) resolutions, which have received relatively scant attention in the previous studies (Chen et al., 2018; Muratori, 2018; Wolinetz et al., 2018).

3) Impacts on transport infrastructures: the EV market expansion could influence several EV-related transport facilities, including parking lots, refuelling stations, and charging posts at parking lots, in terms of quantity, layout and usage. The numbers of charging posts and parking lots increase over time mainly because of the increasing number of both CVs and EVs; however, the number of vehicle purchasers increases slightly relative to the number of existing vehicle owners. As a result, both the quantity and layout of refuelling stations almost do not change, but the usage of station does change, as evident from the varying average number of vehicles served and occupied time. Previous studies of EV charging facilities were only focused on one type of charging facility (Asamer et al., 2016; Chen et al., 2016; Hof et al., 2017) and have generally ignored the interactions and competitions between those EV-related facilities, including charging posts,



(a) Private Charging Demand in 2016 (b) Public Charging Demand in 2016

(c) Private Charging Demand in 2020 (d) Public Charging Demand in 2020

Fig. 14. Spatial Distributions of Charging Demand in One Particualr Weekday in 2016 and 2020 at the District level (kW•h).

parking lots and refuelling station; Furthermore, these studies were mostly focused on the quantity and layout of charging facilities, paying little attention to their usage. The impact assessment in this paper tried to take into account the interactions and competitions above and quantify the impacts of EV market expansion on the quantity, layout and usage of four typical EV-related transport facilities, with an agent-based transport facility development model for both CVs and EVs (Zhuge and Shao, 2018a). Therefore, the results tended to be more comprehensive and accurate and thus should be more useful.

The spatially and temporally explicit results above could be very helpful for different EV-related stakeholders involved: 1) Electricity Utilities: Since the number of EVs will still be relatively small in 2020 (due to the license plate lottery policy), the charging demand may put slight pressure on the power grid system. The electricity utilities may do not need to invest in too many charging facilities at the current stage; on the other hand, the spatial distributions of charging demand may help the electricity utilities to better locate charging facilities; 2) Local Authorities: introducing EVs could somewhat benefit the environment. Therefore, local authorities may want to shape policies to promote the purchase and usage of EVs, so as to improve the local air quality; In addition, the adoption rate of PHEV will remain low over the period, likely due to the high sale price. More subsides may be needed to for PHEV purchasers, if local authorities would make PHEVs competitive to CVs and BEVs. In addition, the suggestions above may also be useful for other cities in both China and the other countries where the development of EV is staying at the early stage. For example, subsides have been identified as an influential factor in Beijing, and therefore the other cities are suggested to carefully design financial incentives. Furthermore, the agent-based integrated framework was also found as useful for investigating the EV market expansion and its impacts at multiple resolutions, and was thus recommended, especially in those cases where a comprehensive understanding of the EV market expansion and its impacts is needed.

5. Conclusions

This paper used a calibrated and validated agent-based spatial integrated urban model, SelfSim-EV to simulate how the Electric Vehicle (EV) market in Beijing, China might expand in the context of urban evolution at the micro scale, and then to assess the potential impacts of the market expansion on the environment, power grid system and urban infrastructures. As an EV version of SelfSim (an agent-based land use and transport model), SelfSim-EV is composed of several spatial sub-models, which form an annual loop to simulate how the urban system evolves over time, focusing on the EV market expansion and its impacts.

With the SelfSim-EV Beijing model, it was found that Battery Electric Vehicle (BEV) would be more favoured than Plug-in Hybrid Electric Vehicle (PHEV) from 2016 to 2020, and the so-called neighbour effects appeared to exist, as evident from the spatial differences between the residential locations of BEV owners in 2016 and 2020 at both facility- and district-levels. The adoption of EV would somewhat benefit the environment at the global level, as evident from the slight decrease in the amounts of HC, CO and CO_2 emissions after 2017; It was estimated that the electricity demand from EVs would only account for 4% of the total domestic electricity demand in 2020, suggesting that the impact of market expansion on the power grid system might be slight too; The EV market expansions appeared to have more significant impacts on the quantity, layout and usage of those EV-related transport infrastructures, including parking lots and charging posts.

The further work will be focused on the following aspects: 1) this paper explored the likely future EV market with the assumption that the urban system would evolve as before. However, it is impossible to exactly predict the future EV market with such a simple integrated model, compared with the complex and dynamic urban system. Therefore, it is necessary to explore the future EV market within different "what-if" scenarios, for example, considering various policies, technologies and infrastructures for EVs. Such "what-if" scenario analyses could help understand different possibilities about the future EV market and its impacts, using the scenario in this paper as a baseline; 2) the SelfSim-EV model can be further extended to incorporate a dispersion model that is capable of simulating the movement of vehicular emissions, so as to assess the potential human health effect of EV market expansion at the local scale, as discussed above; Furthermore, the SelfSim-EV model can also be further extended to integrate a smart grid model, so as to capture the interaction between the EV market expansion and the power grid system. Currently, the feedback from the power grid system has not been considered.

Acknowledgement

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Appendix 1. Synthetic Data for Future-Year Simulations

Appendix 1.1. Synthetic Data on Demographic Attributes for Future-Year Simulations

The demographic input data from 2010 to 2015 was extracted from the Beijing Statistical Yearbooks, and the data from 2016 to 2020 was predicted using the demographic time series data with the Autoregressive Integrated Moving Average (ARIMA) models. The forecast results and the specific ARIMA models used are shown by Fig. 15. The forecast demographic data from 2016 to 2020 is summarized in Table 1.

Table 1
Forecast Demographic Data for Simulation Years from 2016 to 2020

Year	2016	2017	2018	2019	2020
Marriage Rate	0.0076	0.0076	0.0075	0.0075	0.0074
Divorce Rate	0.0043	0.0050	0.0056	0.0063	0.0069
Unemployment Number	101181	107758	114859	121050	126914
Employment Number	425900	425600	425300	425000	424700
Death Rate	0.0049	0.0049	0.0049	0.0049	0.0049
Birth Rate	0.0087	0.0085	0.0086	0.0086	0.0086
Immigration Rate	0.0077	0.0077	0.0076	0.0076	0.0076
Emigration Rate	0.0041	0.0038	0.0035	0.0030	0.0025
Individual Yearly Income (RMB)	122,405	131,940	141,287	150,808	160,168

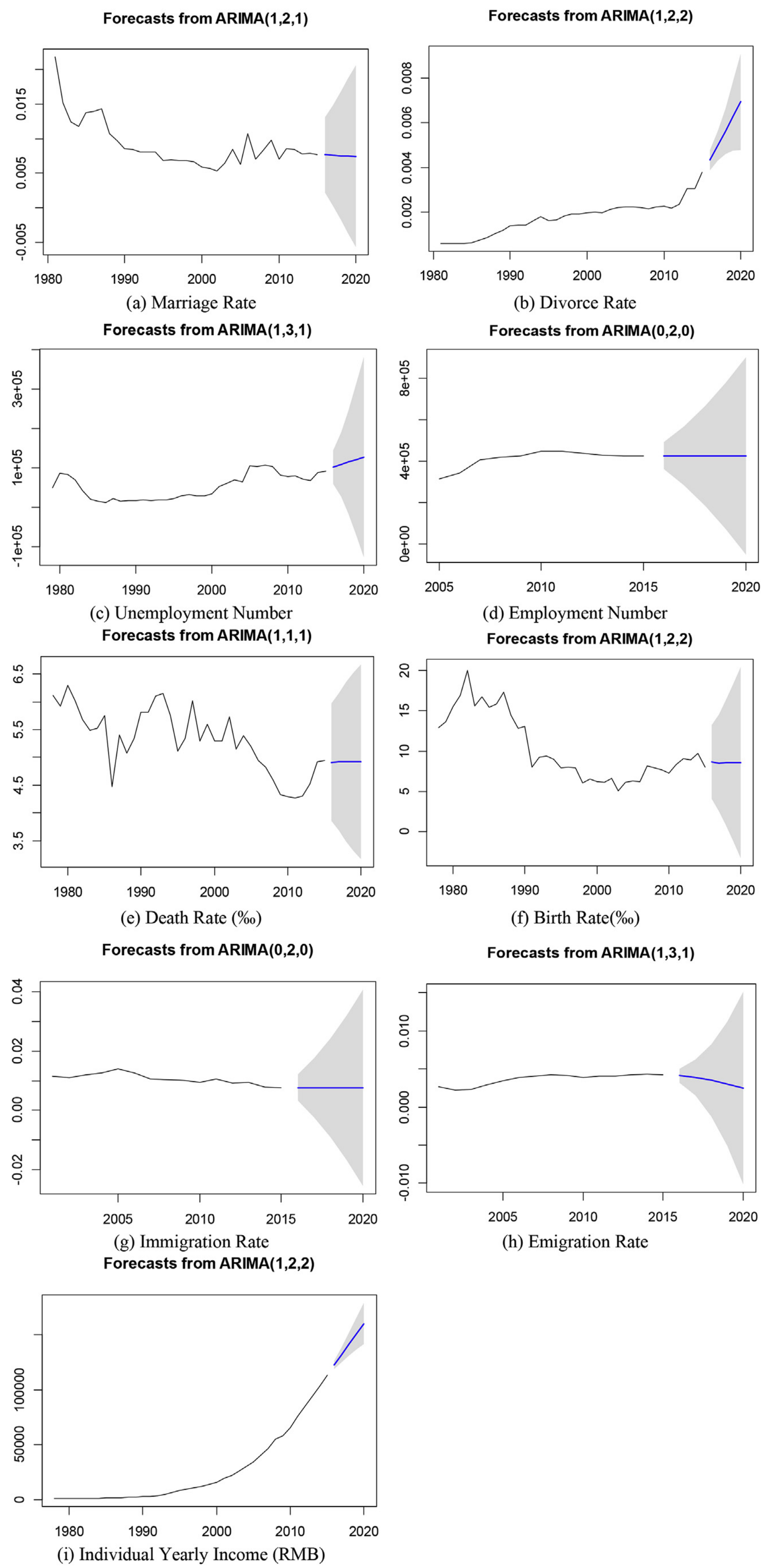


Fig. 15. ARIMA Models for Demographic Time Series Data

Appendix 1.2. Synthetic Data on Activity Facilities for Future-Year Simulations

As aforementioned, there are five basic activity facility types in SelfSim-EV, namely, home, work, education, leisure and shop. The work and education facilities were added based on the numbers of activity opportunities available that were the total numbers of students and jobs, respectively; the remainder were added based on the floor space which needed to be further converted into facility capacity.

(1) Work and Education Facilities

The work facilities were added based on the numbers of employment and unemployment that were forecast in Appendix 1.1. Specifically, the difference between these two numbers was used as the constraint and a specific number of work facilities were added or removed according to the difference. Similarly, the education facilities were added based on both the numbers of students and schools that were forecast with the time series data. Fig. 16 shows the ARIMA models that were used to forecast the number of education facilities, as well as their capacities (or the numbers of education opportunities available in the facilities). The education facilities were grouped into five types, namely Kindergarten, Primary, Middle School, High School, and College. Table 2 summarizes the forecast numbers of education facilities, as well as their capacities from 2016 to 2020.

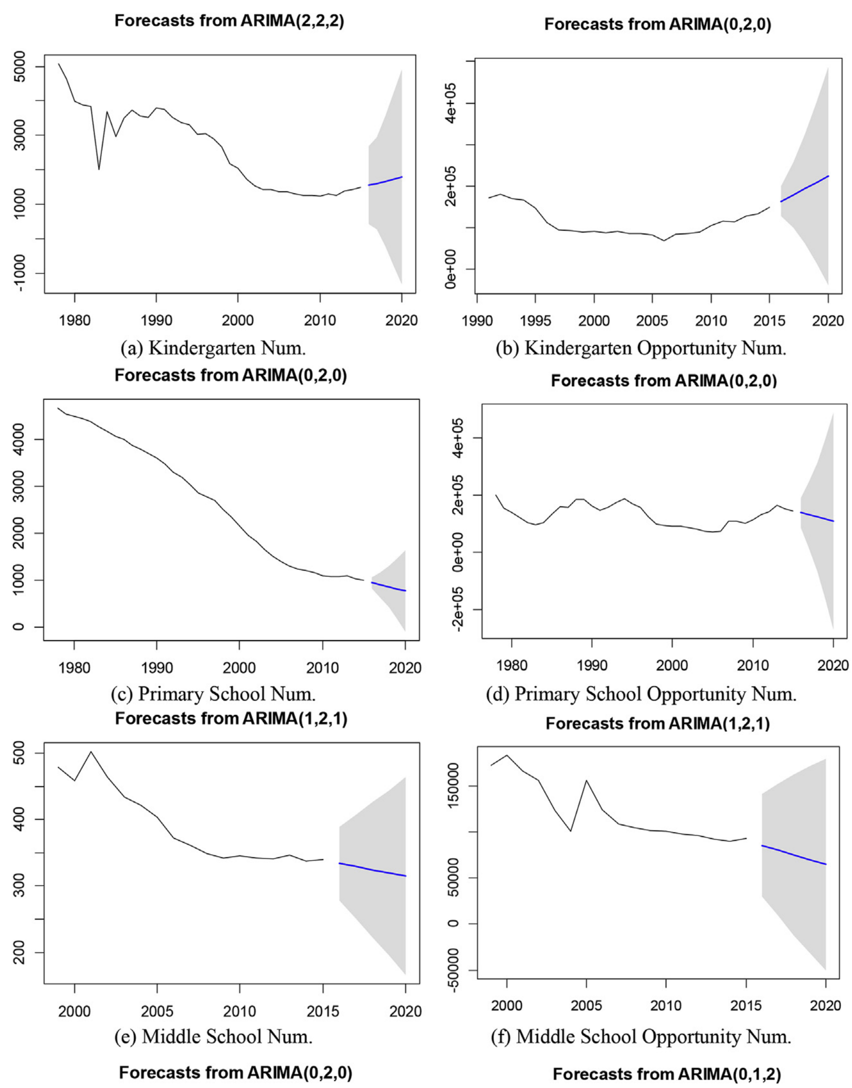


Fig. 16. ARIMA Models for the Time Series Data on Education Facilities

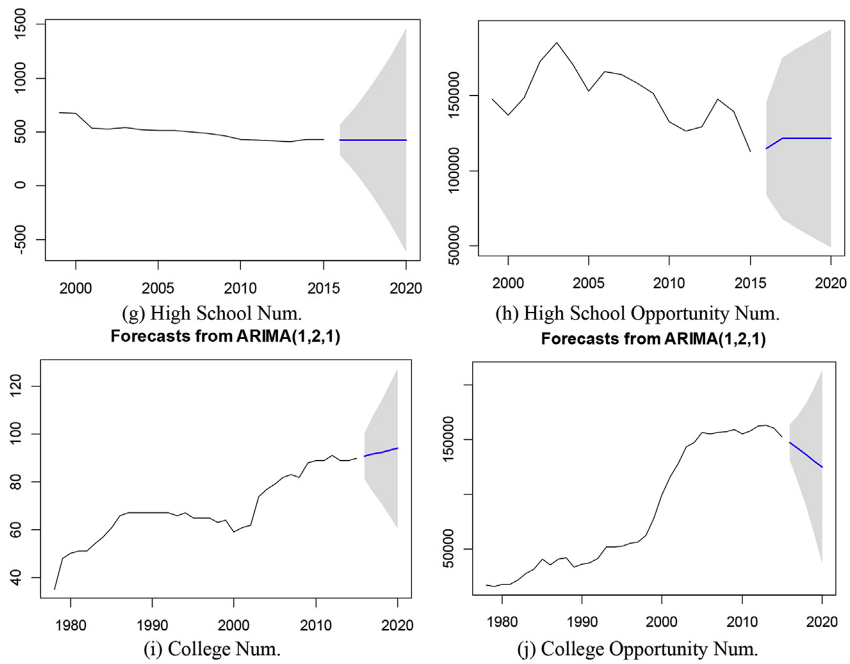


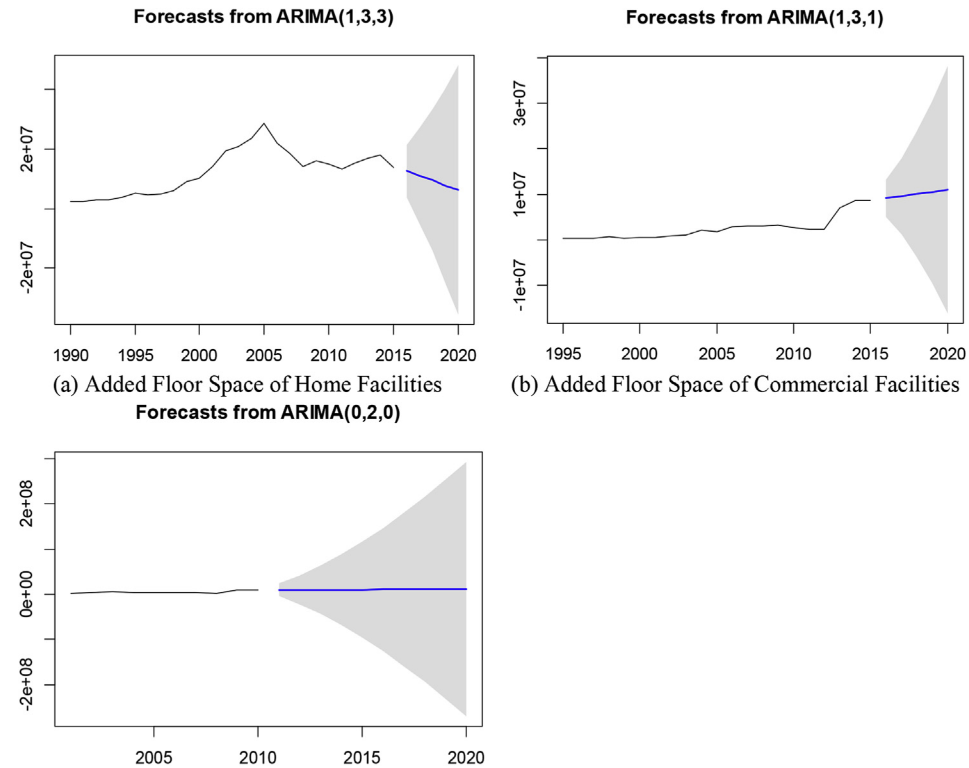
Fig. 16. (*continued*).

Table 2
Forecast Macro-Level Constraints on Education Facilities from 2016 to 2020

Year	2016	2017	2018	2019	2020
Kindergarten Num.	1550	1607	1669	1728	1788
Primary Num.	952	908	864	820	776
Middle School Num.	334	329	324	320	315
High School Num.	427	426	425	424	423
College Num.	91	92	92	93	94
Opportunity Num. of Kindergarten	164107	179172	194237	209302	224367
Opportunity Num. of Primary	138503	131130	123757	116384	109011
Opportunity Num. of Middle School	85380	80625	75175	69909	64594
Opportunity Num. of High School	114897	121480	121480	121480	121480
Opportunity Num. of College	147514	141724	136086	130407	124739

(2) Home, Shop and Leisure Facilities

The macro-level constraints on the home, shop and leisure facilities, which were the total numbers of activity opportunities available in the facilities, were forecast using the ARIMA models as well. Firstly, the added and removed floor space was forecast using the ARIMA models for each facility type; next, the forecast floor space was further converted into the number of activity opportunities (or facility capacity) with the ratio of floor space to activity opportunity number. The ratio varies across facility types and can be found in relevant statistical yearbooks. In Beijing, the ratio of floor space to home opportunity number was 19.49 square meters per person in 2010; the ratio for commercial opportunity (referring to both shop and leisure opportunities) was 1.5 square meters per person. More details on the ARIMA models, assumptions and calculations that were used to estimate are shown in Fig. 17 and Table 3. Table 4 briefly summaries the forecast numbers of activity opportunities added or removed from 2016 to 2020.



(a) Added Floor Space of Home Facilities (b) Added Floor Space of Commercial Facilities

(c) Removed Floor Space of Home Facilities

Fig. 17. ARIMA Models for the Time Series Data on Activity Facilities

Table 3
Forecast Macro-Level Constraints on Activity Facilities from 2016 to 2020 (Unit: Million Square Meters)

Year	2016	2017	2018	2019	2020
Added Floor Space of Home Facility	*12.57*	*10.94*	*9.56*	*7.79*	*6.24*
Added Floor Space of Commercial Facility	*9.17*	*9.58*	*10.04*	*10.51*	*11.00*
Removed Floor Space of Home Facility	*10.43*	*10.59*	*10.74*	*10.90*	*11.06*
Removed Floor Space of Commercial Facilities	*4.48*	*4.54*	*4.61*	*4.68*	*4.75*
Finally Added Floor Space of Home Facilities	*2.14*	*0.35*	*−1.18*	*−3.11*	*−4.82*
Finally Added Floor Space of Commercial Facilities	*4.69*	*5.03*	*5.42*	*5.83*	*6.26*
Finally Added Opportunity Num. of Home Facilities	*0.11*	*0.02*	*−0.06*	*−0.16*	*−0.25*
Finally Added Opportunity Num. of Commercial Facilities	*3.13*	*3.36*	*3.62*	*3.88*	*4.17*
Finally Added Opportunity Num. of Leisure Facilities	*1.56*	*1.68*	*1.81*	*1.94*	*2.09*
Finally Added Opportunity Num. of Shop Facilities	*1.56*	*1.68*	*1.81*	*1.94*	*2.09*

(Note: The forecast figures are highlighted in italics; In addition, due to the lack of time series data on the removed floor space of commercial facilities, it was assumed that the removed floor space of commercial facilities was associated with the removed floor space of home facilities, and the former varied according to the latter with a fixed ratio (the ratio of the removed floor space of commercial facilities) which was estimated based on relevant historical data. In the Beijing scenario, the ratio was 0.64. Another assumption here for the commercial facilities was that the shop and leisure facilities equally shared the total floor space of commercial facilities.).

Table 4
Forecast Macro-Level Constraints on Activity Facilities from 2016 to 2020 (Unit: Million)

Year	2016	2017	2018	2019	2020
Number of Home Opportunities Added	0.11	0.02	−0.06	−0.16	−0.25
Number of Leisure Opportunities Added	1.56	1.68	1.81	1.94	2.09
Number of Shop Opportunities Added	1.56	1.68	1.81	1.94	2.09

Appendix 2. Results about EV Market Expansion and Its Impacts

Appendix 2.1. Validating SelfSim-EV in 2016

The performance of the calibrated and validated SelfSim-EV model was further examined by comparing the simulated and observed data on the EV market and EV-related transport facilities in 2016, as shown by Table 5. The MAPE is 6.3%, suggesting that the performance is relatively satisfactory. In particular, the transport facility development model appears to have a relatively good ability to predict at the aggregate level.

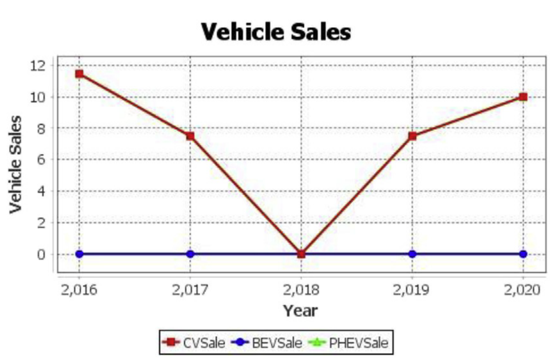
Table 5
Model Validation in 2016

Model Type	Data Type	2016		
		Observed Data	Simulated Data	Absolute Percentage Error (APE)
EV Market	**BEV Price**	254737	211088	17.1%
	BEV Subsidy	83333	88272	5.9%
	PHEV Subsidy	30000	34943	16.5%
	BEV Sale	51000	51000	0.0%
	CV Sale	81000	80993	0.0%
Transport Facility	**Number of Public Parking Space**	1931479	1871520	3.1%
	Number of Public Charging Posts	21940	22315	1.7%

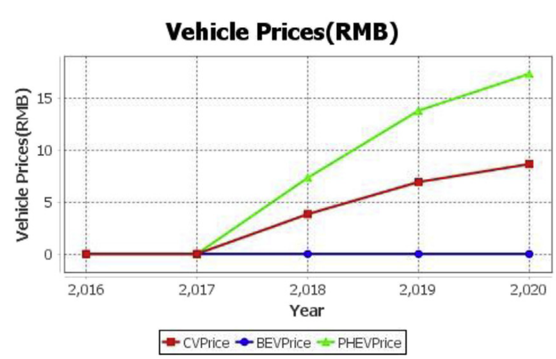
Appendix 2.2. EV Market Expansion from 2016 to 2020

Appendix 2.2.1. Stochastic Effects on the EV Market Model

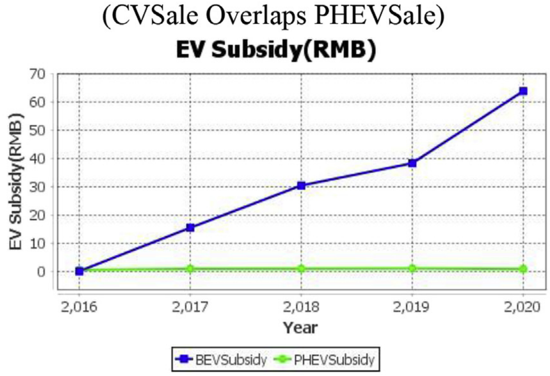
In order to further explore the stochastic effects, the standard deviations of the 10-run SelfSim-EV results about the EV market expansion from 2016 to 2020 are calculated and shown by Fig. 18. It should be noted that most of the standard deviations are relatively small and are difficult to present error bars in the figures about results, thus they are drawn with separate figures. The following conclusions can be drawn: 1) the standard deviations of vehicle sale, vehicle price and EV subsidy change over time. In addition, the standard deviations of vehicle price remain zero for the years of 2016 and 2017, due to again the pricing behaviour of manufacturer agents (in the EV market model) that is based on the difference of market penetration rates in two consecutive years; 2) the standard deviations of CV and PHEV sales are the same, this is because the total numbers of CV and PHEV sold remain the same across the 10 runs and are equal to the total numbers of the so-called CV purchase permits; Furthermore, they decrease to zero in 2018, because the number of CV purchase permits drops significantly and all of the permits are allocated to CV purchasers; 3) the three types of standard deviations are relatively low, suggesting that the simulation outcomes of the 10 runs tend to be close to the averages, and the model stochastic uncertainty is unlikely to heavily influence the outcomes.



(a) Vehicle Sales
(CVSale Overlaps PHEVSale)



(b) Vehicle Prices



(c) EV Subsidy

Fig. 18. Standard Deviations of the 10-Run Results about the EV Market from 2016 to 2020

Appendix 2.2.2. Spatial Distribution of Vehicle Owners

Figs. 19 and 20 show the spatial distribution of vehicle owners at the facility- and district-levels. Both CV and PHEV owners tend to live in the central districts and the central areas of the outer districts.

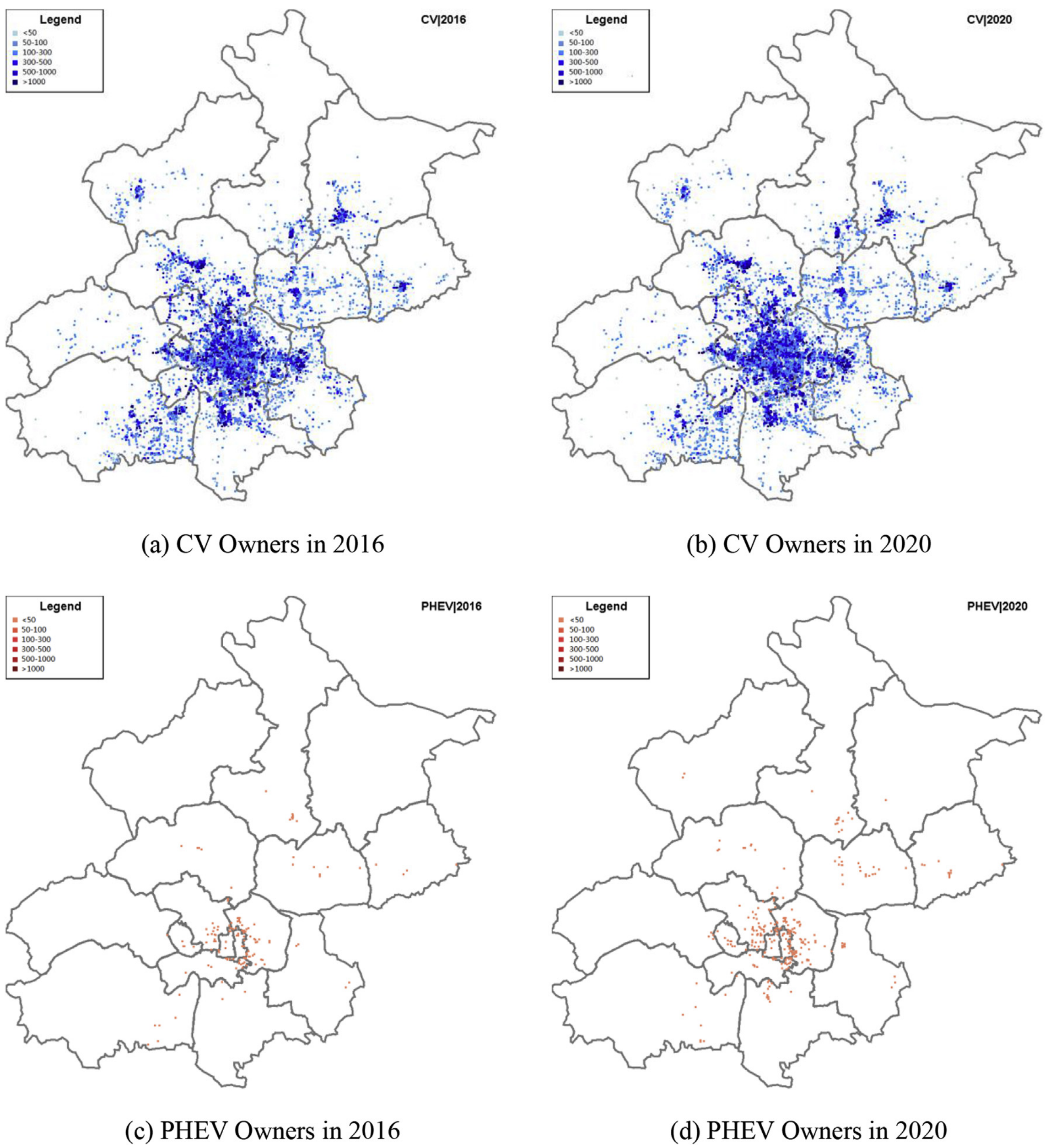


Fig. 19. Spatial Distributions of Vehicle Owners in 2016 and 2020 at the Facility Level

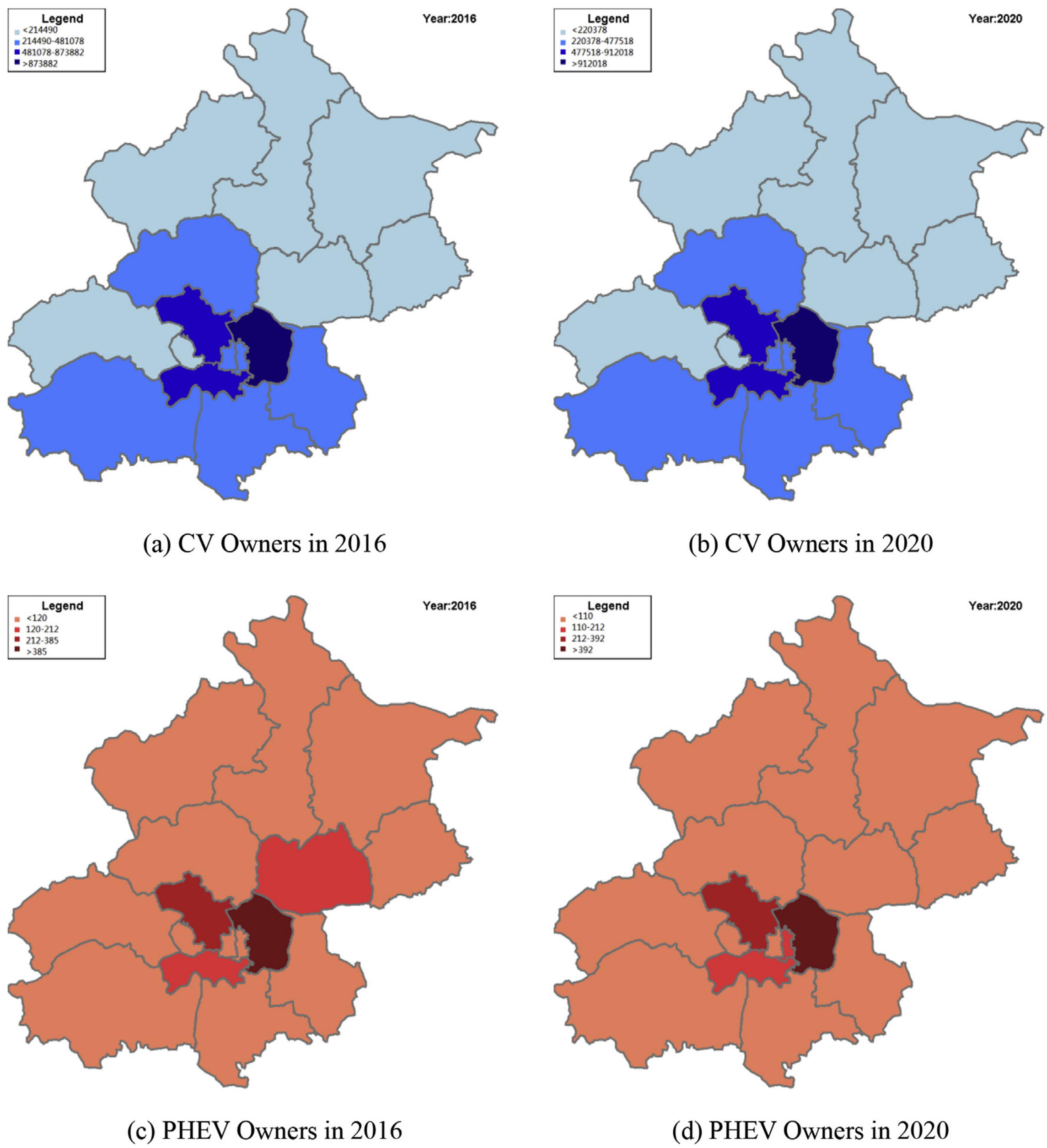
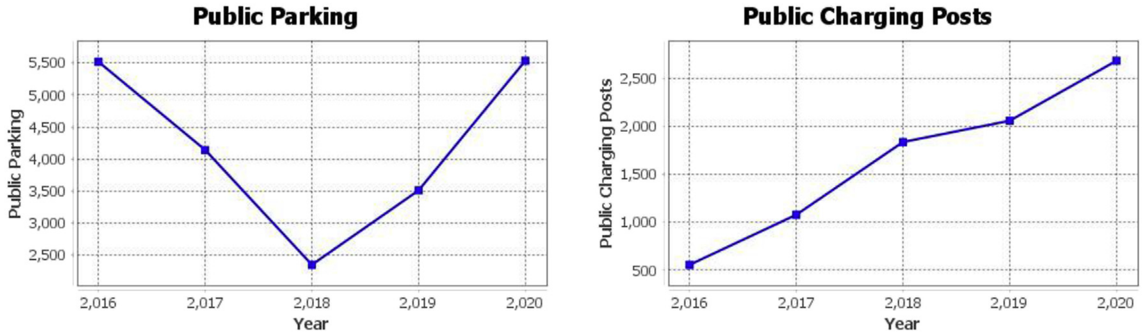


Fig. 20. Spatial Distributions of Vehicle Owners in 2016 and 2020 at the District Level

Appendix 2.3. Impacts of EV Market Expansion on Transport Facilities

Appendix 2.3.1. Standard deviations about the transport facilities

As before, the standard deviations about the transport facilities are computed to investigate the model variability (see Fig. 21): 1) the change in the standard deviation of public parking spaces over the period is quite similar to that of CV (and PHEV) sales (see Fig. 18-(a)). This is likely because the number of public parking spaces is directly associated with vehicle sales; 2) Standard deviations are again relatively small as a fraction of the means.



(b) Number of Public Parking Spaces (c) Number of Public Charging Posts

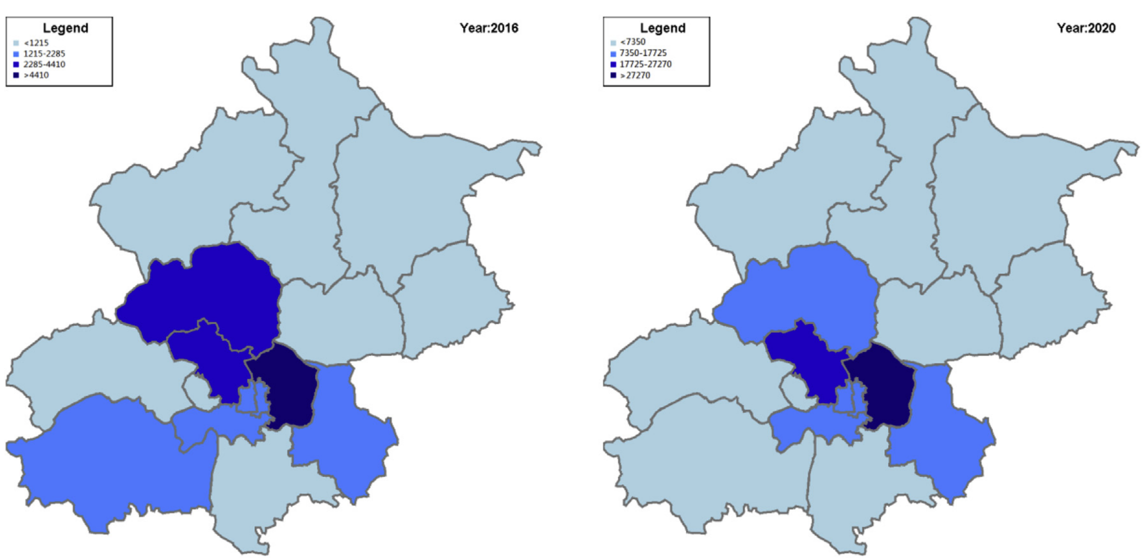
Fig. 21. Standard Deviations of the 10-Run Results about Transport Facilities from 2016 to 2020

Appendix 2.3.2. Impacts of EV Market Expansion on Layouts of Transport Facilities

The EV market expansion can impact the layout of several different EV-related transport facilities, including charging posts and parking lots. Here, public charging posts were used as an example to show the spatial impacts. Specifically, Fig. 22 compares the spatial distributions of public charging posts in 2016 and 2020 at the district level, suggesting that the spatial distributions change slightly over the period.

Appendix 2.3.3. Impacts of EV Market Expansion on the Usage of Infrastructures

In addition to the impacts on the number and layout of transport facilities, the impacts on the usage of transport facilities are further assessed using several indicators, such as average number of vehicles served and average occupied time. Next, charging post will be used as an example to show the impact on the usage of transport facilities.



(a) Public Charging Posts in 2016 (b) Public Charging Posts in 2020

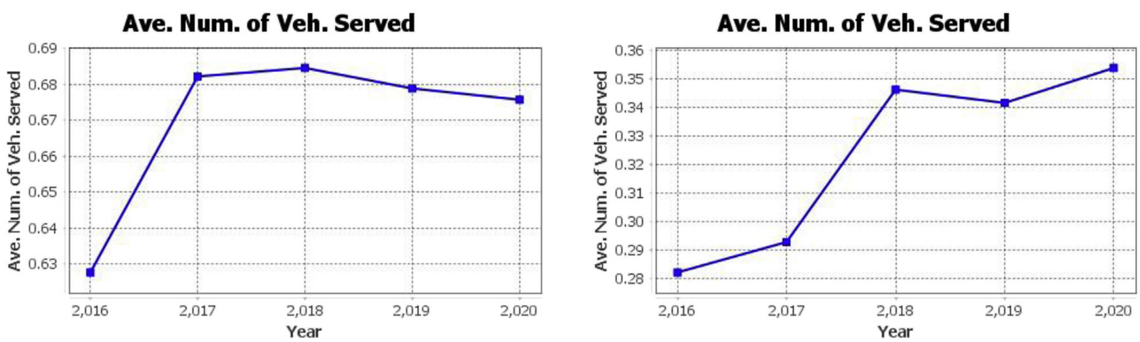
Fig. 22. Layouts of Public Charging Posts in 2016 and 2020 at the District Level

Figs. 23 and 24 show the impacts of the market expansion on the usage of charging posts using the indicators of average number of vehicles served and average occupied time. For private charging posts, these two indicators go up in 2017, but decrease over the remaining time; for public charging posts, these two indicators go up from 2016 to 2018 and fluctuate over the remaining period. The changes in these two indicators could be associated with many factors, as well as the interactions between them. For instance, the usage of charging posts could be influenced by both the number of charging posts added and the layout of charging posts. In addition, private charging posts tend to serve more vehicles than public ones, as evident from the higher number of vehicles served and longer occupied time of private ones.

Appendix 2.4. Impacts of EV Market Expansion on the Environment

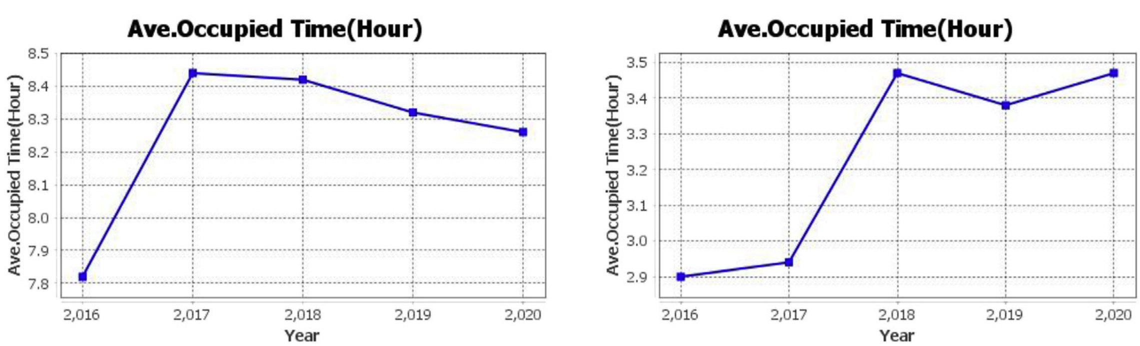
Appendix 2.4.1. Standard deviations about the environmental impact

Again, the stochastic effects are analysed with the standard deviations (Fig. 25): all of the standard deviations increase over time, suggesting that uncertainty is on the rise, but the standard deviations are small relative to the total amounts, suggesting that the stochastic effects are not significant. Note that the variability between runs tends to increase even when mean values are falling, suggesting the increases have more to do with increase in model uncertainty over time, rather than just an increase in line with upward trending mean values.



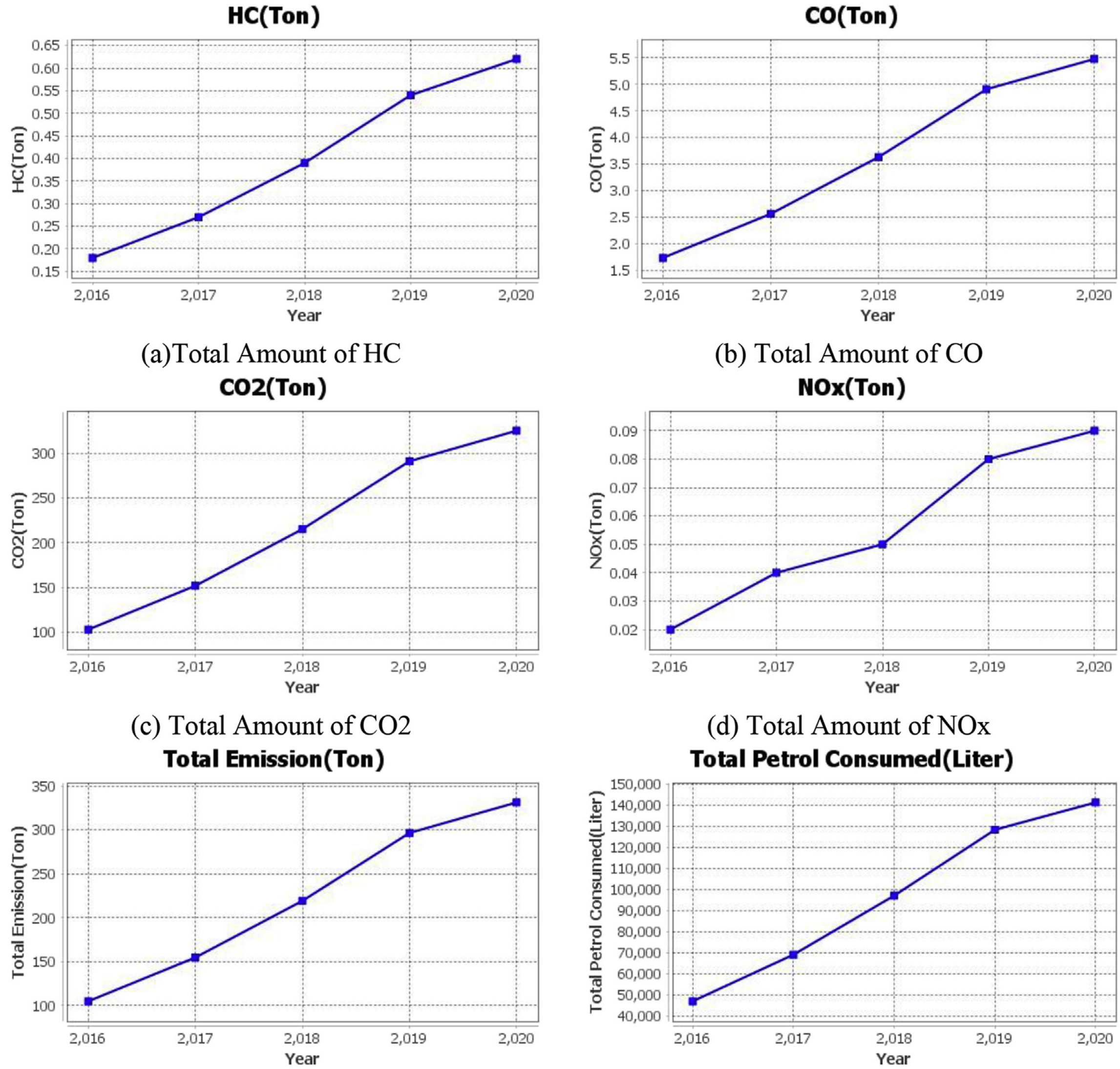
(a) Private Charging Posts (b) Public Charging Posts

Fig. 23. Average Numbers of Vehicles Served with Charging Posts from 2016 to 2020



(a) Private Charging Posts (b) Public Charging Posts

Fig. 24. Average Occupied Time of Charging Posts from 2016 to 2020



(a)Total Amount of HC (b) Total Amount of CO

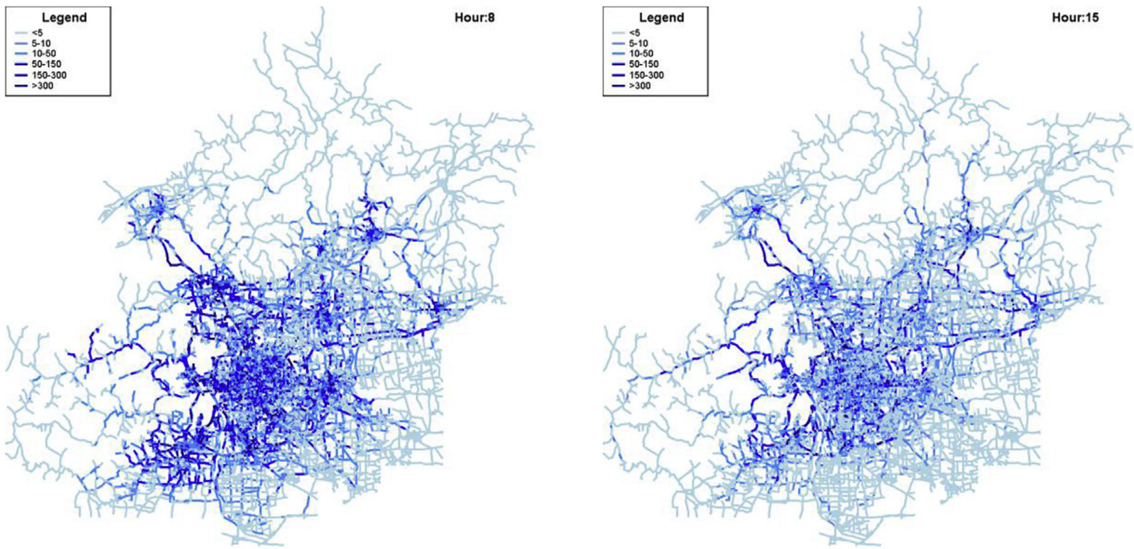
(c) Total Amount of CO2 (d) Total Amount of NOx

(e) Total Amount of Emissions (f) Total Amount of Petrol Consumed

Fig. 25. Standard Deviations of the 10-Run Results about Petrol Consumed and Vehicular Emissions from 2016 to 2020

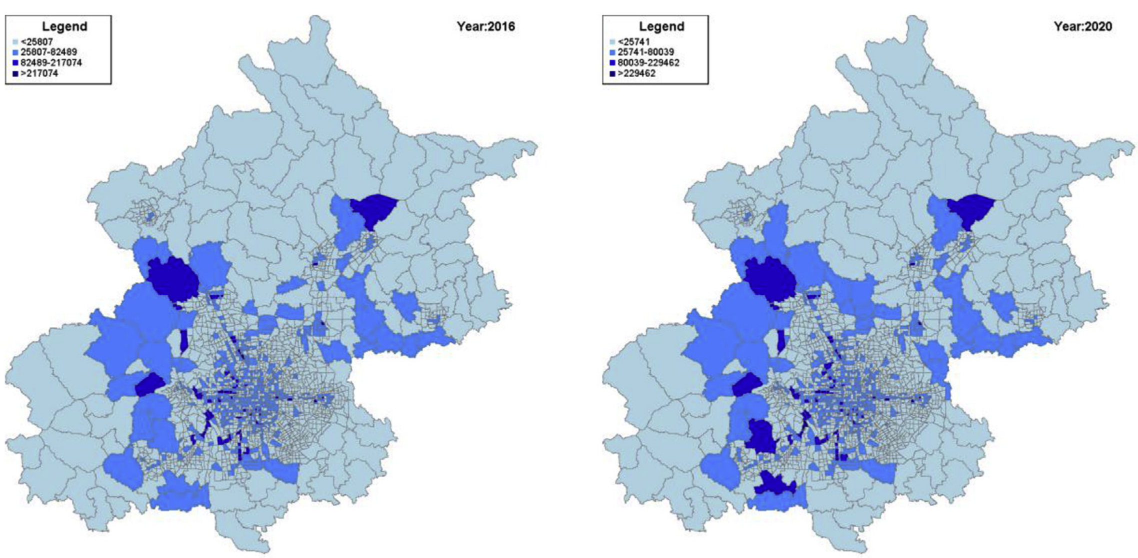
Appendix 2.4.2. Spatial Distributions of Vehicular Emissions

Fig. 26 compares the spatial distributions of hourly link-based vehicular emissions in one particular weekday in 2020 at both peak and off-peak hours (one morning peak hour from 7 to 8AMand one off-peak hour from 2 to 3 PM), suggesting that the morning peak hour tends to have more vehicular emissions, and the central districts and the central areas of the outer districts tend to have bigger amounts of vehicular emissions. This is very likely because the traffic flow either at peak hours or at the central districts, tend to be much heavier. According to Fig. 27 that aggregates, groups and maps the vehicular emissions at the zone level, the spatial distribution of emissions also somewhat changes over the period. This could be attributed to many factors, as discussed above, such as the travel patterns, vehicle ownerships and activity locations. Note that the spatial distributions do not change at the district level, as shown in Fig. 28. In addition, such spatially and temporally disagree results could be helpful for local authorities to shape policies and invest in infrastructures to reduce the emissions effectively. For example, those areas (or zones) with higher amounts of vehicular emissions can put forward congestion charge policies: CV drivers need to pay a fee during a specific period, but it is free to EV drivers.



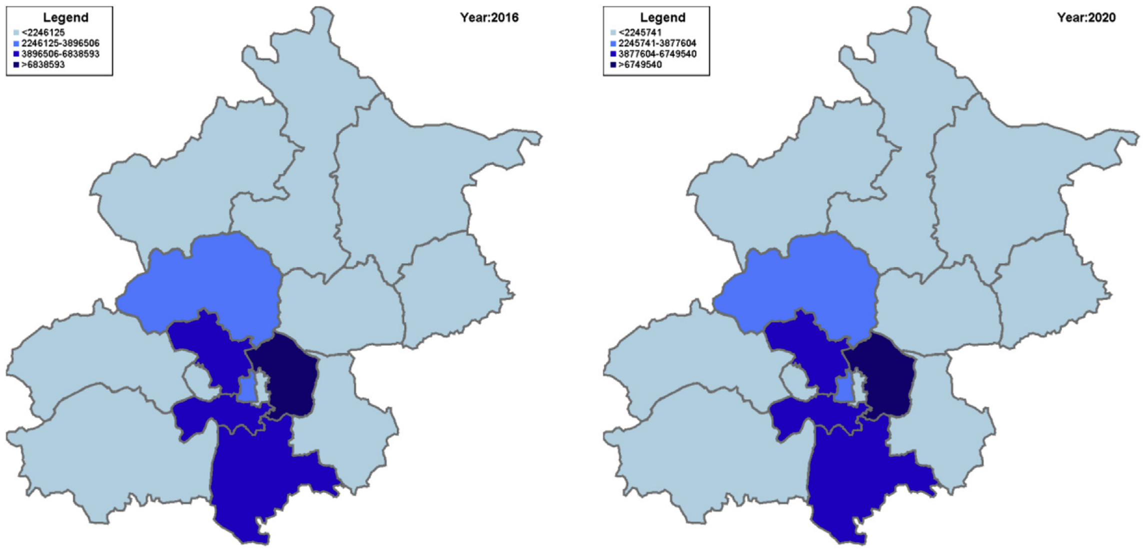
(a) 7-8 AM (b) 2-3 PM

Fig. 26. Link-based Vehicular Emissions in One Particular Weekday in 2020 (Kilogram)



(a) Total Emissions in 2016 (e) Total Emissions in 2020

Fig. 27. Zone-based Vehicular Emissions in One Particular Weekday in 2016 and 2020 (Kilogram)

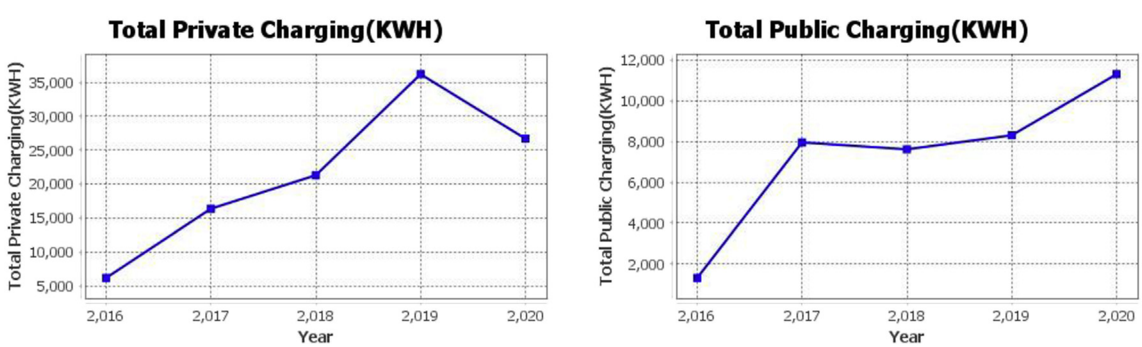


(a) Total Emissions in 2016 (e) Total Emissions in 2020

Fig. 28. District-based Vehicular Emissions in One Particular Weekday in 2016 and 2020 (Kilogram)

Appendix 2.5. Impact on the Power Grid System

As shown by Fig. 29, the standard deviations are also relatively small, suggesting that model uncertainty (or stochasticity) may not heavily influence the simulation results about the amount of electricity provided.



(a) Total Amount of Electricty Provided by Private Charging Posts (b) Total Amount of Electricty Provided by Public Charging Posts

Fig. 29. Standard Deviations of the 10-Run Results about Total Amount of Electricty Provided by Charging Posts from 2016 to 2020 (kW•h)

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