Electric vehicle charging station diffusion: an agent-based evolutionary game model in complex networks

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Acknowledgements
This study is supported by the Chinese National Funding of Social Science (Grant No. 18BJY066) the Fundamental Research Funds for the Central Universities (Grant No. 2021CDJSKJC14).

Abstract

The "chicken-and-egg" link between charging infrastructure and electric vehicle adoption complicates charging station investment, yet existing research lacks significant understanding of this relationship, particularly in complex network settings. To this end, our research designs a novel agent-based evolutionary game model that incorporates consumers' microscopic behavior into the dynamics of charging station diffusion. Based on a case study, the diffusion of charging stations and electric vehicles under current market conditions is simulated and the impact of the network topology is investigated. Results show that: (1) combined with existing policies, the carbon tax policy could increase the charging station proportion by 17.06%; (2) there is an inverted U-shaped effect between electricity prices and the proliferation of charging stations and electric vehicles; (3) the negative impact of electric vehicle social networks can be transferred to charging station proliferation; (4) there are two priorities for the proliferation of the two industries: prioritizing increasing the clustering coefficient, followed by decreasing the average path length, and increasing the clustering coefficient is better than increasing the individual degree; (5) relevant factors (e.g., construction subsidies, carbon taxes, early high electricity prices, high clustering factor networks) contribute to the conversion of plug-in electric vehicles to battery electric vehicles.

Keywords: consumer adoption behavior, charging station diffusion, government intervention, agent-based evolutionary game model, complex networks, China

Nomenclature

Sets and indices	
$G(V,E)$	the charging station diffusion network
V	all nodes in the charging station diffusion network
E	all edges in the charging station diffusion network
Parameters	
ce	the cost effectiveness of BEV
pre_{BEV}	the BEV price premium
sav_{BEV}	the lifetime operational cost savings of BEV
yer_{BEV}	the assigned lifespan of BEV
p_{BEV}, p_{CV}	sales price of BEVs and CVs
p_{oil}, p_e	the unit oil price and the unit electricity price
m_{BEV}, m_{CV}	the energy consumption per unit kilometer of CVs and BEVs
VKT	average annual vehicle kilometers traveled
w_k	consumer preference weights
EM	expert assessment matrix
S_k	customer preference matrix
α	social network strength
β	a parameter that reacts to the technology's learning ability.
L_k	neighbor number of consumer k
C_{csc}, C_{gsc}	annual cost of investing in a charging station and a gas station
$\varphi_{cs}, \varphi_{gs}$	the installing profits for a charging station and gas station
v, mpg	energy consumption per kilometer for EVs and CVs
θ_k	social network influence
$\overline{x}_{ij0}^{k}, \overline{x}_{ij}^{k}$	normalization vectors of consumer choices not influenced by social networks and those influenced by social networks
$\overline{x}_{ij}^{l}$	the normalization vector of neighbors for consumer choice
C_i^k	the closeness of individual i about product k
$c_{BEV}(Q)$	the unit production cost when the BEV scale reaches Q
C_{cs}, C_{gs}	initial investment cost per charging station or gas station
RV_{csc}, RV_{gsc}	annual residual value of charging station or gas station
RV_{cs}, RV_{gs}	residual value at the end of life of the charging station or gas station
L_{cs}, L_{gs}	the service life of a charging station and gas station
C_{cso}, C_{gso}	the cost of operating a charging station and gas station
p_{ec}, p_{oc}	energy purchasing cost of charging stations and gas stations
s_{cs}	the government subsidy for installing a charging station annually
N	the number of energy stations
n_{CS}, n_{GS}	number of charging stations in a station neighborhood vs. number of gas stations
ω	average number of vehicles around an energy station
U_i^{CS}, U_i^{GS}	expected payoffs being invested in charging stations and gas stations
T_{gs}	the government taxation for installing a gas station
A_i, A_j	the strategy choice of the node i and j
$\tau(A_i \leftarrow A_j)$	probability of node j imitating node i strategy
k	the noise intensity of the external environment
Variables	
$y_{BEV}, y_{PHEV}, y_{CV}$	market share of BEVs, PHEVs, and CVs
z_{CS}, z_{GS}	market share of charging stations and gas stations
Acronyms	
BEV(s)	battery electric vehicle(s)
CV(s)	conventional vehicle(s)
F-TOPSIS	fuzzy technique for order preference by similarity to an ideal solution
BYD Qin	a vehicle model from a Chinese electric vehicle manufacturer (BYD)
RMB	national legal tender unit of the People's Republic of China

1. Introduction

The availability of charging infrastructure is critical for the adoption of electric vehicles (EVs), as users need to be able to use public charging stations for longer periods of time [1, 2]. As a key aggregator of charging infrastructure, charging stations provide up new options for producing long-term benefits. First, charging stations will have a significant impact on future social transportation networks and have the potential to generate significant market economic benefits. For example, EVs accounted for only 1.37% of total charging volume in China in 2019, but cumulative charging volume was 6.963 billion units [3]. Second, charging stations may be an effective way to ease EV users' charging stress and attract more potential purchasers to acquire EVs [4-6]. Despite the importance of charging stations, China's public charging stations continue to lag behind the EV sector, with a vehicle-to-pile ratio of 3.3:1 until 2020 [1, 3, 7]. This vehicle-to-pile ratio is far lower than the international requirement of 1.5:1 and China's targeted ratio of 1.2:1, resulting in a charging dilemma [8]. This phenomenon has been observed in countries all across the world, not only in China. According to the European Commission, by the end of 2016, there were only 1,052 fast chargers in Norway, 1,403 in Germany, and 523 in Sweden [9]. In this context, boosting charging stations becomes critical, especially for potential buyers who routinely request public charging outlets before purchasing an EV [7, 9, 10].

Academics and practitioners are now focused on charging station investment and market diffusion, since the adequacy of charging stations is important to the spread of green vehicle technologies (e.g.,Gnann et al. [9]; Fang et al. [11]; Li et al. [8] and Huang et al. [1]). Existing research, however, has mostly concentrated on the empirical investigation of investment determinants for charging stations (e.g.,Neaimeh et al. [4]; Hardman et al. [12]; Globisch et al. [13]). Despite the fact that these studies give a good foundation of knowledge, they rarely address the dynamics of charging station diffusion. It should be noted that evolutionary game theory is a method for gaining dynamical insights into charging station diffusion [1, 14, 15]. With the advent of network science in recent years, the combined approach of complex networks and evolutionary games has gained popularity among scholars. For example, Li et al.

[16] designed a complicated network evolutionary game model to study the impact of various government policies on EV uptake. Fang et al. [11] designed a complex network evolutionary game model to boost charging infrastructure that integrates policy incentives and consumer preferences. Shi et al. [14] developed a network-based evolutionary game model to investigate the dynamics of low-carbon technology diffusion across enterprises. Their research includes two types of networks that establish various group network linkages for enterprises and consumers. Zhao et al. [17] presented a three-stage evolutionary game model to explore how to promote new energy vehicle diffusion in the complex network context. Their study analyzed impact of four kinds of network topologies, including nearest-neighbor coupled network, WS small-world network, BA scale-free network and ER random network. It should be noted that the four networks mentioned above are the most commonly used network topologies in complex network science, with the nearest-neighboring coupled network being a regular network with the highest clustering coefficient and the shortest average path length, followed by the WS small world network, the BA scale-free network, and the ER random network. Li et al. [18] built a complex network-based evolutionary game model to analyze the potential impact of punitive measures on the clean transition behavior of enterprises. Punitive measures are decomposed into multiple policy combinations in their study, including punishment intensity variation, punishment coverage variation, and punishment accuracy variation, with the goal of improving the actual performance of punitive policies based on three key attributes: coverage, intensity, and accuracy.

The network-based evolutionary game models provide an effective means to gain knowledge on promoting public charging stations. However, there are two shortcomings for this research stream. First, the dynamics of charging station diffusion on the demand side is unexplored in the literature. A complete market necessarily consists of two side markets, namely the supply side and demand side, and consumer adoption behavior on the demand side could critically influence firms' operation decisions in evolutionary games [14]. Thus, describing the dynamic feature of consumer purchase decision is of equal significance when designing a complete dynamics of charging station investment, specifically using the network-based evolutionary game models. Actually, for existing literature that ignore the diffusion dynamics on the demand side by using an evolutionary game model, such a dynamics is implicitly considered in a hypothesis, that is, consumers purchase behaviors happen every time unit [14, 15]. However, such an assumption is just applicable for fast-consuming goods. In our study, consumer adoption behavior refers to when a new automobile is used or acquired, which is not a short-term or rapid behavior, therefore a relatively lengthy behavioral lifespan is required and more realistic.

Second, most studies have largely ignored the effect of network topology on the findings when using complex network game models, and have used only a general network [11, 16, 19], such as WS small-world network or BA scale-free network. This phenomenon also exists in the field of charging infrastructure diffusion. Varied network topologies have different priority levels in complex network science, which influences target market spread [17]. The charging station diffusion in our study is a typical systematic topological structure connected by several node firms and has typical complicated network features. However, we do not know the real network structure of the industry and how to improve the network structure to help the industry grow. Thus, it is necessary to use more network topologies to reflect the real network connection, thereby gaining the knowledge on the real impact of related factors on charging station diffusion to the greatest extent.

To this end, our study aims to fill the above research gap by developing a novel agent-based evolutionary game model for promoting charging stations. Our analytical framework mainly consists of two-part dynamics of supply and demand sides, and integrate the impact of social network, given in Figure 1. The supply-demand relationship of charging stations and EV users belongs to the “chicken-egg” relationship that are influenced by each other. It should be noted that our study uses the WS small-world network to construct two-level network among energy stations and vehicle users in diffusion benchmark scenario, as this network provides a stronger power for network connection in the real world [20]. In the extensions, we compare the impact of other three network topologies, including BA scale-free network, nearest-neighbor coupled network and ER random network. Specifically, on the demand side, consumers periodically repeatedly purchase their desired vehicles based on the assigned vehicle lifespan, i.e., an EV or a CV. When they need to make purchasing decisions, such decisions are influenced not only by their own preferences, but also by their neighbors, such as parents, friends and other important persons for them, and physical environment, such as charging station supply. While on the supply side, energy stations play evolutionary games between their neighbors to decide whether to invest in charging stations. Unlike the latest studies that uses network-based evolutionary game models [11, 14, 17], our study redesigns consumer decision logic on the demand side using an agent-based model and a complex network, and integrates it into the dynamics of charging station investment. These dynamic features allow us to not only investigate the impact of carbon taxes, construction subsidies, and demand preferences on public charging station investment, but also to gain a better understanding of the microscopic mechanisms that govern how energy stations respond to demand and policies.

Our study is interested in following questions. (1) What impact does the integration of charging station demand-side dynamics have on its market proliferation? (2) How network topology affects charging station and EV diffusion and which network performs best: depth of diffusion versus speed? (3) How to facilitate the transformation of the EV market from PHEVs to BEVs? Besides, our study contributes to the existing literature from three aspects. (1) Designing a novel agent-based evolutionary game model that integrates simultaneously the charging station investment on the supply side and EV diffusion on the demand side. Such a novel analytical framework makes the proposed model different from the models that include only one side in the existing literature, thus filling the research gap. (2) Bridging the gap between the microscopic adoption behavior of consumers and charging station investment emerging on the system level. (3) Exploring the impact of complex network topologies on charging station and EV diffusion. We run the simulation experiments in different network topology structures and found the network structure exhibiting the best performance in charging station diffusion.

The rest of study is organized as follows. Section 2 reviews related research. Section 3 proposes an agent-based evolutionary game analytical framework and constructs a complete dynamics of charging station diffusion on supply and demand sides. By using the proposed model, Section 4 simulates the charging station diffusion considering different influencing factors in different network topologies. Finally, the discussion is presented in Section 5. And policy recommendations and limitation are given in Section 6.

2. Literature review

The question of how to promote the diffusion of charging infrastructure has become a hot topic, as the disparity in charging facility supply and demand is a significant psychological barrier to EV adoption. The literature relevant to our study can be divided into three categories.

2.1 Policies on charging infrastructure diffusion

Green technology evolution will be impossible without government intervention, such as solar panels, EVs, and charging infrastructure [7, 10, 11, 21, 22]. Subsidies and carbon taxes are two types of government interventions. Government interventions play a similar role in the charging station sector, but a new concern has been raised: how government interventions can adapt to the charging station market's development [23]. Regarding this query, Fetene et al. [24] indicated that subsidies can help alleviate the investment pressure on public charging infrastructure while also increasing their willingness to collaborate. Zhang et al. [25] believed that the public-private partnership cooperation (PPP) model formed through government subsidies will not only help ease the government's financial pressures, but will also lower the price of charging services and promote the business model's success. Yang et al. [26] and Marion and Muehlegger [27] argued that taxation policy is an effective market-regulatory tool in the charging infrastructure industry. Fang et al. [11] investigated the role of balanced subsidy and tax policies in charging station rollout and discovered that this balanced strategy has benefits for charging station rollout. However, unlike previous studies, which are based on a unilateral dynamics model, charging station diffusion happens in the context of a complex reality of multi-agent interaction, and this discrepancy leads to a gap between the influence of key parameters and reality. To that aim, our study adds to the body of knowledge by broadening the research framework into the complex network context and demonstrating the real influence of government regulations on charging station diffusion. The findings give a new viewpoint on the influence of policies on the diffusion of charging stations.

2.2 Consumer preferences

Significant customer preferences drive consumer choice behavior. Numerous empirical and experimental research studies on clean technology diffusion have been published in order to discover relevant variables., e.g., Hardman et al. [12], Globisch et al. [28] and Huang et al. [10]. Charging station diffusion are no exception. Globisch et al. [13] , for example, found that most automobile drivers are unwilling to pay the minimal service price for utilizing public charging stations. Tan and Lin [6] argued that customers' environmental opinions have a major impact on their willingness to pay for public charging stations. As for consumer preferences regarding EV adoption, Huang et al. [10] and Herberz et al. [29] indicated that product features (price, acceleration, charging time, etc.) and knowledge and attitude traits (environmental awareness, technological interestingness, etc.) of EVs are indications of customer preferences. What's more, waste battery recycling policies also significantly affect consumers' willingness to adopt EVs, as consumers fear that in the absence of a comprehensive waste battery recycling system, their adoption behavior will lead to greater environmental and social pollution [30]. When customers are willing to use EVs, their demand for charging stations grows [11]. Although this body of work provides a sound theoretical foundation, few of them examine how consumer preferences for EV adoption impact charging station diffusion, such as diffusion speed vs. diffusion depth. In this regard, our research incorporates consumer choice logics based on their preferences into the dynamics of charging station diffusion and examines the influence of these preferences on charging station diffusion in a complex network setting.

2.3 The research method of charging station diffusion

As a form of technology/innovation diffusion, charging station diffusion is a dynamic process in nature, but most related studies lack of attention to its dynamics. Zhang et al. [25], for example, used the system dynamics technique to illustrate how charging price might help with charging infrastructure. Li et al. [8] created a multi-sectorial stochastic evolutionary game model to assist charging infrastructure in overcoming the construction dilemma. Based on an evolutionary game model, Huang et al. [1] created novel evolutionary dynamics for promoting charging infrastructure. Their dynamics are based on the PPP concept, but the model mechanism is also reproduced using differential equations. Clearly, one limitation of these studies is that their model dynamics belong to the macro level, which is an up-bottom system and cannot capture the interaction between agents and environment, particularly in complex networks. This is not unexpected given that traditional approaches, such as differential equations and system dynamics, lack the ability to combine the microscopic behavior of individuals with the macroscopic behavior of a system [14]. Because charging station diffusion is a complex adaptive system that occurs through self-organization interaction among agents and between agents and the environment, the combination of these two features is critical. Agent-based modeling is a strong tool for bridging the micro-macro gap.

Agent-based modeling (ABM) is a bottom-up technique that microscopically creates the operation logic of every system component while integrating the macro-level system performance, allowing macro-level patterns to emerge spontaneously [31]. The ABM approach has been widely used to assess, explain, and forecast the dissemination of new products and technologies (e.g., Huang et al. [7], Shi et al. [14], Pagani et al. [31], Ning et al. [32], Sun et al. [33], Silvia and Krause [34], Eppstein et al. [35]). An key evolutionary element of the ABM method in recent years has been the emphasis on the design of comprehensive dynamics, particularly demand-side dynamics [14]. Pagani et al. [31] introduced an agent-based evaluation model that takes into account EV user behavior as well as spatial distributions of EVs in order to predict and adjust future development of EV charging infrastructure. Shi et al. [14] used an evolutionary game model on a two-level heterogeneous social network to investigate low-carbon spread across companies. Their model incorporates demand-side dynamics with a complex network feature in the form of game payoffs. However, such studies with entire market dynamics are rare, and the majority of research only address just one-side dynamics, either supply or demand side dynamics.

To the best of our knowledge, our work is the first to use a sophisticated agent-based evolutionary game model to design the whole market dynamics for encouraging charging station diffusion. In our approach, the evolutionary game model gives the rule of investing in charging stations to energy station firms, whilst the ABM describes consumer choice logic on the demand side and simulates the interaction mechanism of a system's adaptive components. Our model is similar to those of Fang et al. [11] and Huang et al. [7], who construct charging station investment decisions and customer purchase decisions for EVs, respectively. Their models, however, are both one-sided dynamics models that ignore the interplay between charging stations and EV adoption in complex networks. In this regard, our study aims to bridge a knowledge gap by creating new comprehensive dynamics for charging station diffusion.

3. Methods

To facilitate comprehension of the research, this section discusses the research topics and mathematical formulations.

3.1 Model description

Figure 1 depicts an analytical framework for the diffusion of charging stations. We examine two categories of agents in our analytical framework: customers (or vehicle users) and energy station enterprises. On the demand side, consumers have their own decision logic, which is impacted not only by their personal preferences, but also by macroeconomic issues such as oil prices, power prices, and the charging environment. Consumers will choose between battery electric vehicles (BEVs), plug-in hybrid electric vehicles (PHEVs), and conventional vehicles (CVs) based on this selection method. On the supply side, energy station firms attempt to satisfy the vehicle market's energy demands by making appropriate investment decisions. Of course, energy station businesses are profit-driven, especially in the competitive environment of regional energy networks. Any strategy chosen by energy station enterprises is influenced by customer behavior, neighbor strategy selection, and policy limits. The government functions as the primary market regulator by imposing subsidies or carbon taxes.

It is important to remember that our model is dynamic. Following the initialization of charging stations and various forms of vehicle occupancy, energy station enterprises and consumers will make appropriate strategy choices over time. These decisions alter the system environment, which in turn influences the strategy choices of relevant agents. Their interactions continue until the simulation ends. Our model is obviously a typical nonlinear dynamic complex system, and to simulate it, we developed a unique agent-based evolutionary game model to simulate charging station diffusion in complex networks.

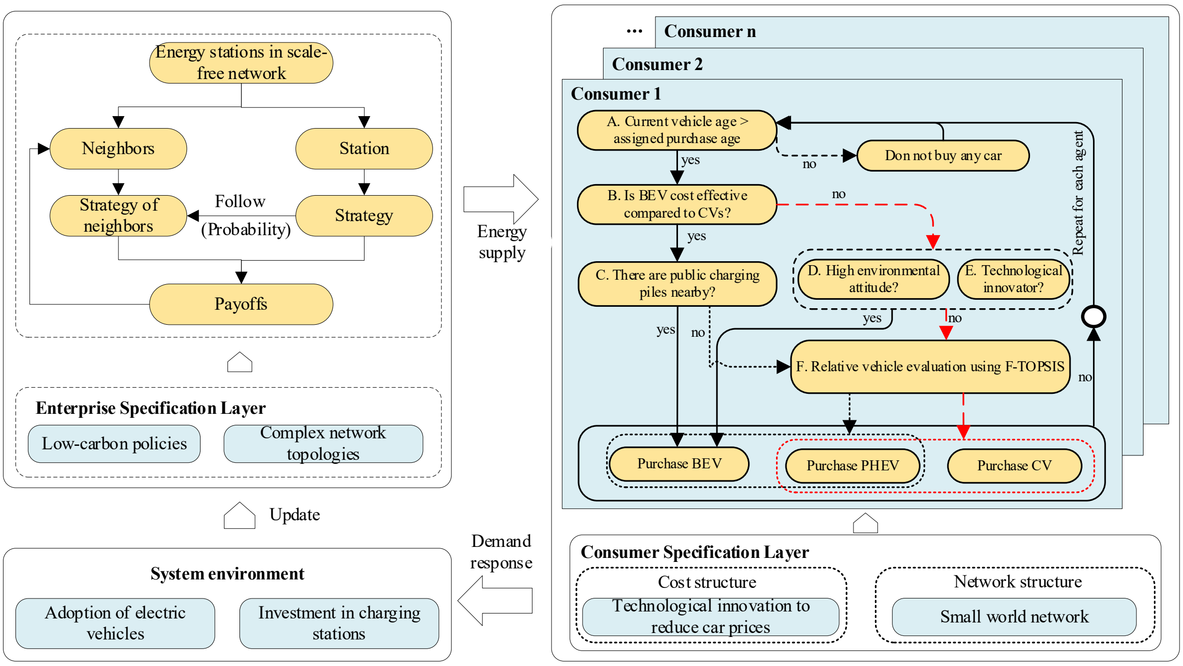

Figure 1. Analytic framework for charging station diffusion.

3.2 Agent-based evolutionary game model

3.2.1 Consumer adoption behavior

In our model, consumers are heterogeneous and bounded rational, and they aim to choose their desired vehicle among BEVs, PHEVs and CVs. Following the literatures, i.e., Kim et al. [36], Silvia and Krause [34] and Huang et al. [7], our study redesigns a consumer decision logic to describe their heterogeneous preferences. Assume that every consumer has one vehicle at least, and will replace their car when it dies. Consumer purchasing decision obeys the following rules: 1) they will buy the BEV if it is more cost-effective than the CV and there are charging stations nearby, or if they are environmentalists or technophiles; 2) they will make choice between the BEV and PHEV to maximize utility if the BEV is more cost-effective and there are no charging stations around; 3) they will make choice between PHEV and CV options if the CV is more cost-effective, or their environmental attitude and technology preference are general. Such decision logic implies the importance of charging facilities and is consistent with the decision logic of real consumers.

Five important aspects are developed to quantify the customer decision based on the aforementioned guidelines. Individuals often make purchase decisions by carefully considering various significant elements of a product; however, there is no defined sequence in which the corresponding assessment items are equally relevant [7]. The basis of obtaining or replacing a car is question A. When it comes time for consumers to make adoption decisions, a BEV may not be the best solution because their choices are based on the remaining four questions. Question B is about the BEV's cost effectiveness, and it's calculated using Eq (1), where ce is the cost effectiveness of the BEV, pre_{BEV} refers to the BEV price premium, sav_{BEV} is the lifetime operational cost savings of BEV, and $\mathrm{y}er_{BEV}$ is the assigned lifespan of a BEV. The price premium of BEV is shown in Eq. (2), where p_{BEV}, p_{CV} are sales price of BEVs and CVs, respectively. The lifetime operational cost savings is shown in Eq. (3), where p_{oil}, p_e are the unit oil price and the unit electricity price, m_{BEV}, m_{CV} are the energy consumption per unit kilometer of CVs and BEVs, and VKT is annual vehicle kilometers traveled.

$$ce = pre_{BEV} - sav_{BEV} \cdot \mathrm{y}er_{BEV} \tag{1}$$

$$pre_{BEV} = p_{BEV} - p_{CV} \tag{2}$$

$$sav_{BEV} = \left(p_{oil} \cdot m_{CV} - p_e \cdot m_{BEV} \right) VKT \tag{3}$$

It's worth noting that all users are considered "potential BEV adopters." Because charging infrastructure is becoming more important, customers are more likely to buy or replace their car with a BEV if and only if their charging demands are met. This demand is contingent on the availability of charging stations. If the BEV is more cost-effective but there is no charging infrastructure accessible, they will choose between BEVs and PHEVs using the fuzzy technique for order preference by similarity to an ideal solution (F-TOPSIS). Consumers are driven to embrace BEVs regardless of whether they are cost effective, according to questions D and E. Assume that 2.5% prospective consumers are innovators and 16% are environmentalists, respectively [34, 37]. Consumers will choose between PHEVs and CVs based on the same assessment process if the aforesaid requirements are not satisfied.

Question F specifies the customer multi-vehicle choice assessment approach by using F-TOPSIS. In order to configure F-TOPSIS, we must first gather consumer preference weights $w_k = \left(w_{1k}, w_{2k}, \cdots, w_{nk}\right)^T$ and an expert assessment matrix EM for three vehicle qualities. Using the two matrices, we could create a customer preference matrix S_k, where $S_k = EM \cdot w_k$. In this regard, the specific decision steps are as follows:

Step 1: Constructing multi-product attribute evaluation matrix EM from expert group, and use e_{ij} to represent the j attribute value of the i product.

$$EM = \begin{bmatrix} e_{11} & e_{12} & \cdots & e_{1n} \\ e_{21} & e_{22} & \cdots & e_{2n} \\ \vdots & \cdots & \vdots & \vdots \\ e_{m1} & e_{m2} & \cdots & e_{mn} \end{bmatrix} \tag{4}$$

Step 2: Constructing consumer matrix S_k based on the consumer product attribute matrix $w_k = \left(w_{1k}, w_{2k}, \cdots, w_{nk}\right)^T$, where $S_k = E \cdot w_k$.

In reality, consumers often make purchase decisions based on their ambiguous perceptions. In this study, 7-point Likert scale is used to measure consumers' fuzzy perception and two types of language variable sets are used for evaluation: namely performance variable set and social network impact sensitivity variable set, as shown in Table 1. Noted that these variable sets were also used in the perceptual evaluation of the expert group in step 1.

Table 1 linguistic variable set and triangular fuzzy number mapping.

Variable	Linguistic term						
Performance	Very Poor (VP)	Poor (P)	Mid-Poor (MP)	Fair (F)	Mid-Fair (MF)	Good (G)	Very Good (VG)
Social influence	Very Weak	Weak	Mid-Weak	Fair	Mid-High	High	Very High

Triangular fuzzy number	(0, 0,.1)	(0, .1, .3)	(.1, .3, .5)	(.3, .5, .7)	(.5, .7, .9)	(.7,.9,1)	(.9, 1, 1)

Among them, the membership function $\mu_{\tilde{a}}(x): R \to [0,1]$ of triangular fuzzy numbers is in (5), where the number of rows $\mu_{\tilde{a}}(x)$ indicates the degree to which element x belongs to fuzzy set $\tilde{a}$ and $a_1 \le a_m \le a_n$. The cascade average comprehensive representation is used to transform the fuzzy number into the exact value $P(\tilde{a})$, as shown in (6) and (7), where $\tilde{a} = (a_1, a_m, a_n), \tilde{b} = (b_1, b_m, b_n)$.

$$\mu_{\tilde{a}}(x) = \begin{cases} \dfrac{x-a_1}{a_m-a_1}, & a_1 \le x \le a_m \\ \dfrac{x-a_n}{a_m-a_n}, & a_m \le x \le a_n \\ 0, & other \end{cases} \tag{5}$$

$$P(\tilde{a}) = (a_1 + 4a_m + a_n)/6 \tag{6}$$

$$P(\tilde{a} \otimes \tilde{b}) = [(a_1 + 4a_m + a_n)/6] \times [(b_1 + 4b_m + b_n)/6] \tag{7}$$

Based on the above rules, the independent consumer k establishes a weight matrix $s^k = (x_{ij}^k)_{m \times n}$ for the weight $w_k = (w_{1k}, w_{2k}, \cdots, w_{nk})^T$ of n attributes $A_1, A_2, \cdots, A_n$ of the product automobile agent. Thus, the consumer weight is denoted in (8), where $x_{ij}^k = P(e_{ij} \otimes w_{jk}) = \frac{1}{6}(e_{ij}^1 + 4e_{ij}^2 + e_{ij}^3) \times \frac{1}{6}(w_{jk}^1 + 4w_{jk}^2 + w_{jk}^3), e_{ij} = (e_{ij}^1, e_{ij}^2, e_{ij}^3)$ refers to the expert evaluation information for the j attribute of product i; $w_{jk} = (w_{jk}^1, w_{jk}^2, w_{jk}^3)$ refers to the preference of consumer k on product attribute j.

$$S_k = \begin{bmatrix} x_{11}^k & x_{12}^k & \cdots & x_{1n}^k \\ x_{21}^k & x_{22}^k & \cdots & x_{2n}^k \\ \vdots & \cdots & \vdots & \vdots \\ x_{m1}^k & x_{m2}^k & \cdots & x_{mn}^k \end{bmatrix} \tag{8}$$

Step 3: Standardizing the consumer perception weight matrix, getting the normalization vector $\overline{x}_{ij0}^k$, and the normalized matrix is calculated in (9), where $i = 1, 2, \cdots, m$ and $j = 1, 2, \cdots, n$.

$$\overline{x}_{ij0}^k = \frac{x_{ij}^k}{\sqrt{\sum_{i=1}^m \left(x_{ij}^k\right)^2}} \tag{9}$$

Noted that the normalization matrix of the small-world network model was used to establish the influence of the social network on consumer adoption decisions, as shown in (10), where α_k indicates the consumer's sensitivity to the social network influence; L_k indicates the number of directly connected neighbors of the consumer k; and $\overline{x}_{ij}^l$ is the normalized vector of the neighbor.

$$\overline{x}_{ij}^k = \left(1 - \alpha\theta_k\right)\overline{x}_{ij0}^k + \alpha\theta_k \sum_{l \in L_k} \frac{\overline{x}_{ij}^l}{\left|L_k\right|} \tag{10}$$

Step 4: Determining each consumer's ideal solution p^{k+} and anti-ideal solution p^{k-} by using equation (11) and (12), where J_1 is the profitability index set, representing the optimal value on the i index; J_2 is the wastage index set, representing the worst value of the i index.

$$p^{k+} = \left\{\overline{x}_1^{k+}, \overline{x}_2^{k+}, \cdots, \overline{x}_n^{k+}\right\} = \left\{\left(\max \overline{x}_{ij}^{k+} \middle| j \in J_1\right), \left(\min \overline{x}_{ij}^{k+} \middle| j \in J_2\right), \middle| i = 1, 2, \cdots, m\right\} \tag{11}$$

$$p^{k-} = \left\{\overline{x}_1^{k-}, \overline{x}_2^{k-}, \cdots, \overline{x}_n^{k-}\right\} = \left\{\left(\max \overline{x}_{ij}^{k-} \middle| j \in J_1\right), \left(\min \overline{x}_{ij}^{k-} \middle| j \in J_2\right), \middle| i = 1, 2, \cdots, m\right\} \tag{12}$$

Step 5: Calculating the distance scale through the n dimensional Euclidean distance formula. The distance from the target to the ideal solution p^{k+} is d_i^{k+}, and the distance to the anti-ideal solution p^{k-} is d_i^{k-}, where $i = 1, 2, \cdots, m$.

$$d_i^{k+} = \sqrt{\sum_{j=1}^{n} \left(\overline{x}_{ij}^{k} - \overline{x}_{j}^{k+} \right)^2} \tag{13}$$

$$d_i^{k-} = \sqrt{\sum_{j=1}^{n} \left(\overline{x}_{ij}^{k} - \overline{x}_{j}^{k-} \right)^2} \tag{14}$$

Step 6: Calculating the closeness of the ideal solution, as shown in equation (15), where $0 \le C_i^k \le 1$. Noted that the goal is the worst if $C_i^k = 0$ and $p_i = p^{k-}$, and the goal is the best if $C_i^k = 1$ and $p_i = p^{k+}$.

$$C_i^k = \frac{d_i^{k-}}{d_i^{k+} + d_i^{k-}},\ i = 1, 2, \cdots, m \tag{15}$$

Step 7: Sorting the closeness of the ideal solution C_i^k. The larger the value of closeness C^* is, the better the goal is. And the one with the largest value of C_i^k is the optimal decision-making goal.

It should be noted that question B focuses on the sales and manufacturing costs of BEVs. In reality, as EV technology advances, the cost of creating BEVs will fall [7]. To model this process, we use the technical learning curve to show the cost-cutting tendency of BEVs. The technical learning curve is represented by (16).

$$c_{BEV}\left(Q\right) = c_{BEV}^{0} Q^{-\beta} \tag{16}$$

where $c_{BEV}\left(Q\right)$ is the unit production cost when the BEV scale reaches Q, c_{BEV}^{0} is the beginning BEV production cost, and β is a parameter that reacts to the technology's learning ability. As a result, the learning rate is $1 - 2^{-\beta}$, which is the proportion of production expenses that will be reduced when the production size is doubled. In terms of product pricing, we employ the cost-plus pricing approach, which allows us to designate the sale price of BEVs in (6), where $\mu > 0$ is the mark-up on the product.

$$p_{BEV} = (1 + \mu) c_{BEV} \tag{17}$$

3.2.2 Energy station decision behavior

The network-based evolutionary game model is used to describe the decision behavior of energy station enterprises, which are profit-seeking. Several assumptions are stated below in this respect.

(1) N stations are established in this game model, and each station has two options: invest in charging stations or invest in gas stations.
(2) The information can be exchanged between neighbors; that is, the station has access to their neighbors' payoffs. A station's neighbors include n_{CS} charging stations and n_{GS} gas stations.
(3) In the market, there are three categories of vehicles: BEVs, PHEVs, and CVs. The cars are scattered evenly around each station, with the average number given as ω. Furthermore, the PHEV is equivalent to 0.17 unit BEV and 0.83 unit CV[1].
(4) The cost and profit are calculated across the life cycle.

In our model, energy station profit is made up of two components: operational profit and policy profit. The operational profit is the difference between the revenue from energy sales and the cost of building the energy station. Subsidies or taxes on energy stations are examples of policy profit. In (18) and (19), the yearly expenses of investing in a charging station and a gas station are determined. (20) and (21) illustrate their yearly residual values, respectively.

$$C_{csc} = C_{cs} * \frac{r(1+r)^{L_{cs}}}{(1+r)^{L_{cs}} - 1} \tag{18}$$

$$C_{gsc} = C_{gs} * \frac{r(1+r)^{L_{gs}}}{(1+r)^{L_{gs}} - 1} \tag{19}$$

$$RV_{\mathrm{csc}} = RV_{cs} * \frac{r(1+r)^{L_{cs}}}{(1+r)^{L_{cs}} - 1} \tag{20}$$

$$RV_{gsc} = RV_{gs} * \frac{r(1+r)^{L_{gs}}}{(1+r)^{L_{gs}} - 1} \tag{21}$$

Despite the fact that energy station investment decisions follow the utility maximization theory, an energy station's strategy is impacted by the proportion of BEV consumers and the strategies of its neighbors in complex networks. If there are numerous charging stations in the same region, for example, the charging demand will be distributed equally among them. Instead, when there is only one charging station in the region and all others are gas stations, all charging demand will be diverted to this one charging station. We get 12 approach options based on neighbor and customer preferences, as shown in Table 2. The payoff matrixes for the majority of strategy combinations are simple to grasp, but we need to offer extra information for cases (1,0,1), (1,1,2), and (1,0,2). In case (1,0,1), if the station i is a charging station and all of its neighbors are gas stations, yet all consumers in the local network around the station are EV

[1] According to the BYD Qin family that the most popular EV in China in 2021, the PHEV has a electric capacity of 9.03kWh, and the BEV's is 53.1kWh. This means that the PHEV is is equal to 0.17 unit BEV or 0.83 unit CV.

users, the station will get all earnings, including those from its neighbors. Thus, operational profit of station i is $(p_e - p_{ec})\omega m_{BEV}VKT \cdot (n_{GS}+1)$. In case (1,1,2), if station i is a charging station and all of its neighbors are charging stations, and all customers are PHEV users, the station will share the operational profit with their neighbors equitably, thus the profit is $(p_e - p_{ec})\omega m_{BEV}VKT \cdot 0.17$. In case (1,0,2), If station i is a charging station and all of its neighbors are gas stations, and all of its customers are PHEV users, the station will get all operational earnings $(p_e - p_{ec})\omega m_{BEV}VKT \cdot (n_{GS}+1)\cdot 0.17$, including PHEV profits from its neighbors.

Table 2. Payoff matrix, where 1 represents investing in a charging station or becoming a BEV user, and 2 represents being a PHEV user.

Strategies			
Station i	Neighbors	Consumer	Payoff matrix of station
1	1	1	$case1 = (p_e - p_{ec})\omega m_{BEV}VKT + s_{cs} - C_{csc} - C_{cso} + RV_{cs}$
1	1	0	$case2 = s_{cs} - C_{csc} - C_{cso} + RV_{cs}$
1	1	2	$case3 = (p_e - p_{ec})\omega m_{BEV}VKT \cdot 0.17 + s_{cs} - C_{csc} - C_{cso} + RV_{cs}$
1	0	1	$case4 = (p_e - p_{ec})\omega m_{BEV}VKT \cdot (n_{GS}+1) + s_{cs} - C_{csc} - C_{cso} + RV_{cs}$
1	0	0	$case5 = s_{cs} - C_{csc} - C_{cso} + RV_{cs}$
1	0	2	$case6 = (p_e - p_{ec})\omega m_{BEV}VKT \cdot (n_{GS}+1)\cdot 0.17 + s_{cs} - C_{csc} - C_{cso} + RV_{cs}$
0	1	1	$case7 = -t_{gs} - C_{gsc} - C_{gso} + RV_{gs}$
0	1	0	$case8 = (p_{oil} - p_{oc})\omega m_{CV}VKT \cdot (n_{CS}+1) - t_{gs} - C_{gsc} - C_{gso} + RV_{gs}$
0	1	2	$case9 = (p_{oil} - p_{oc})\omega m_{CV}VKT \cdot (n_{CS}+1)\cdot 0.83 - t_{gs} - C_{gsc} - C_{gso} + RV_{gs}$
0	0	1	$case10 = -t_{gs} - C_{gsc} - C_{gso} + RV_{gs}$
0	0	0	$case11 = (p_{oil} - p_{oc})\omega m_{CV}VKT - t_{gs} - C_{gsc} - C_{gso} + RV_{gs}$
0	0	2	$case12 = (p_{oil} - p_{oc})\omega m_{CV}VKT \cdot 0.83 - t_{gs} - C_{gsc} - C_{gso} + RV_{gs}$

According to section 3.2.1, we could calculate the market share of BEVs, PHEVs, and CVs and label them as y_{BEV}, y_{PHEV} and y_{CV}. Based on Table 3, we could obtain the expected payoffs of station i being invested in charging stations, marked as U_i^{CS}, and U_i^{GS} for gas stations.

$$U_i^{CS} = \begin{pmatrix} \frac{n_{CS}}{n_{CS}+n_{GS}} & \frac{n_{GS}}{n_{CS}+n_{GS}} \end{pmatrix} \begin{pmatrix} case1 & case2 & case3 \\ case4 & case5 & case6 \end{pmatrix} \begin{pmatrix} y_{BEV} \\ y_{PHEV} \\ y_{CV} \end{pmatrix} \tag{22}$$

$$U_i^{GS}=\begin{pmatrix}\frac{n_{CS}}{n_{CS}+n_{GS}} & \frac{n_{GS}}{n_{CS}+n_{GS}}\end{pmatrix}\begin{pmatrix}case7 & case8 & case9\\ case10 & case11 & case12\end{pmatrix}\begin{pmatrix}y_{BEV}\\ y_{PHEV}\\ y_{CV}\end{pmatrix} \tag{23}$$

3.2.3 Rulemaking of network evolution dynamics

The population of energy station enterprises evolves in a network with a certain topology. After receiving the payoffs, each station may alter its strategy by comparing profit with a neighbor chosen at random in complex networks. If its payoff is smaller than the payoff of a selected neighbor, it will replicate the neighbor's strategy with a probability given by (24) [38, 39]. This update rule is often employed in the literature of complex network evolutionary games, for example, by Fang et al. [11], Li et al. [16] and Hu et al. [19].

$$\tau(A_i \leftarrow A_j)=\frac{1}{1+exp\left[(U_i-U_j)/k\right]} \tag{24}$$

where the player j will take the strategy of the player i who receives a bigger payoff with the probability τ, and k is the degree of noise effects that describes the uncertainties in the decision-making process such as fluctuations and mistakes. In our study, k is set to 0.1, as it is in the work [40].

In this study, we employ the WS small-world network to link agents, which is applicable to both energy station enterprises and consumers. The primary rationale for this configuration is that the vast majority of real-world network connections can be described by the WS small-world network topology [20]. The network structure is specifically characterized as $G(V,E)$, where $V=v_1,v_2,...,v_n$ signifies n energy station enterprises and $E=E_1,E_2,...,E_m$ denotes m edges linking the nodes. The small world network has two distinguishing characteristics: neighbor set and randomized reconnection. A neighborhood set is a group of proxy-connected nodes, the number of which is referred to as a network degree. With a given probability, the agent gets reconnected to its neighbors at random. Furthermore, because we do not know the difference between theory network topologies and real-world energy station connections, we employ additional network topologies, such as BA scale-free network, EA random network, and NN coupled network, to investigate the impact of their network topology on charging station diffusion. Section 4.4 contains network descriptions, and extension experiments give more insights into the real-world energy station network.

3.3 Simulation environment

Our research is being conducted in a virtual metropolitan environment with 100 energy stations and a volume of approximately 20000 vehicles, which is based on Chongqing, China. Chongqing is a significant car production center in China, with 14 vehicle manufacturers, 8 major auto brands, and 1,000 auto parts and accessories manufacturers [7]. Furthermore, Chongqing is among the first pilot cities to promote EVs (published in 2013), thus the general public has a solid understanding of EVs when compared to other cities in China. As a result, Chongqing is a fantastic starting point for developing the virtual simulation environment. Our simulation setting is equivalent to a virtual metropolis of 1.2 million people, based on the 0.168 automobiles per capital in Chongqing. Because the model is sized at 1:10, 20,000 cars represent the entire 200,000. It is worth noting that the number of energy stations is significantly higher since charging stations have a lower service capacity than gas stations, but our setting is appropriate on the premise that a charging station services roughly 200 EVs on average. Figure 2 depicts the simulated environment, in which green buildings and dots represent charging stations and EVs (comprised of BEVs and PHEVs), respectively, and gray houses and dots represent gas stations and CVs.

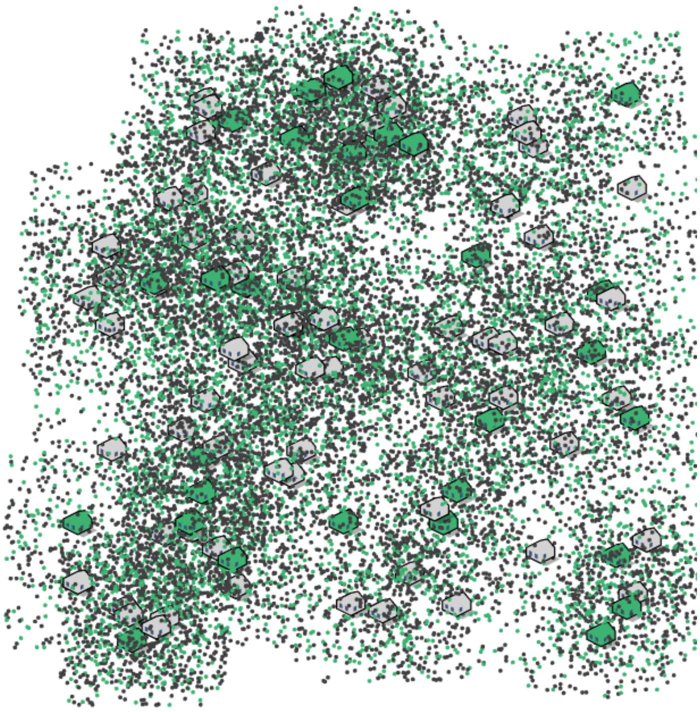

Figure 2. Example simulation environment.

4. Case study

Our research is based on a real-world scenario. The model's data is mostly obtained from BYD's official website, China's annual charging infrastructure development report, regulatory announcements, and related research. The potential rule of charging station diffusion in complex networks is revealed by simulation findings.

4.1 Parameter initialization

The parameterization of our model is divided into two parts. The first is for energy station enterprises. A charging station's cost is divided into two parts: the cost of basic equipment and the cost of operation. A city charging station typically serves at least 100 vehicles per day and requires 10 chargers [11]. According to the data of Annual Development Report of China Charging Infrastructure[3], the price of 10 chargers is around RMB 1.61 million (USD 0.25 million) and the cost of power distribution equipment including the transformer, power distribution cabinet, cable, and active filter package is around RMB 1.94 million (USD 0.3 million). Thus, the basic investment cost of the charging station is 3.55 million (USD 0.55 million). The total operating costs, including maintenance and labor, are around RMB 0.26. (USD 0.04 million). Gas stations in China are similar in size to charging stations. The cost of gas station equipment, which includes a tanker truck, a tank, and a level gauge, is around RMB 2.26 million (USD 0.35 million), while the cost of operation is approximately RMB 0.19 million (USD 0.03 million). In most provinces in China, subsidies for the building of charging stations account for 20% of overall investment [23], hence s_{cs} is RMB 0.71 million (USD 0.11 million). Because carbon taxes on gas stations appear to be a topic of debate, we set the initial value of carbon taxes to 0. In general, the service life of a gas station or a charging station (slow charging, rapid charging, or super charging facility) is at least 10 years. In terms of electricity pricing, the sales tariff and purchased cost of electricity for charging facilities are 1.5 RMB/kWh and 0.54 RMB/kWh, respectively, while the sales price and purchased cost of gasoline for gas stations are 7.5 RMB/liter and 5.13 RMB/liter, respectively [3]. The facility depreciation rate is 5%, according to the guideline "State-owned Assets Law of the People's Republic of China."

To initialize the vehicle users, we choose the BYD Qin Pro EV as a representative model of the Chinese EV market since it was not only the highest rated car in the top 10 sales in 2020, but it also features three vehicle types, including BEVs, PHEVs, and CVs [7, 17]. The BEV version costs around RMB 0.1499 million (USD 23753), whereas the CV version costs around RMB 0.0798 million (USD 12645). The electricity consumption per unit kilometer is set at 0.1324, which corresponds to an EV with a range of 400 kilometers and a battery capacity of 53.1 kWh. CVs have an oil consumption of 0.062 liters per kilometer. According to [41], the average vehicle kilometers traveled per capita in China is 17,213 km. EVs will have a cumulative market share of 2.6% by 2021, with BEVs accounting for 2.17% and PHEVs accounting for 0.53%. The market share of charging stations is 0.79% in 2021, based on the vehicle-pile rate of 3.3:1. We use a technical learning rate of 0.18 to explain the declining trend in BEV manufacturing costs, and use the same configuration for consumer decision parameters, as in work of [7]. Tables 3 indicate the expert group's product evaluation. Regarding consumer attribute weights (see Table 4) and consumer social sensitivity (see Table 5), we collected 685 valid (all data 750, effective rate 91.33%), whose questionnaire constructs and demographic characteristics are shown in Appendix Table B1 - Table B2.

Table 3. Vehicle attribute evaluation from the expert group.

Model	Attributes						
	Purchase price	Maintenance cost	Security	Technology integration	High power	Low noise	Carbon dioxide emission
BEV	F	F	F	G	MF	G	G
PHEV	F	MF	MF	MP	G	MF	F
CV	G	MF	MF	MP	F	F	MP

Notes: P, Poor; MP, Mid-Poor; F, Fair; MF, Mid-Fair; G, Good.

Table 4. Consumers' weights on seven attributes.

Weight	Attributes						
	Purchase price	Maintenance cost	Security	Technology integration	High power	Low noise	Carbon dioxide emission
Very Poor	.0029	.0015	0	.0088	.0073	.0058	.0204
Poor	.0044	.0102	0	.0380	.0438	.0277	.0496
Mid-Poor	.0146	.0569	.0015	.0715	.1139	.0628	.1036
Fair	.0599	.1197	.0190	.1401	.1825	.1314	.1606
Mid-Fair	.2628	.3460	.1051	.3051	.3212	.2788	.2613
Good	.3547	.3533	.2526	.3241	.2642	.3635	.2248
Very Good	.3007	.1124	.6219	.1124	.0672	.1299	.1796

Table 5. Consumer's sensitivity levels of social influence.

Sensitivity level	Very High	High	Mid-High	Fair	Mid-Weak	Weak	Very Weak
Relative frequency	.0788	.2934	.4307	.1241	.0511	.0131	.0088

4.2 Results of charging station and electric vehicle diffusion

After getting all model parameters, we run simulation experiments in ANYLOGIC 8.5.2 Professional, including baseline simulation experiments and sensitivity analyses of related factors. To eliminate error interference, these experiments were run 300 times on average. The baseline scenario is utilized specifically to highlight the diffusion outcomes of charging stations and EVs, which are backed by the experiment driven by base parameters, as shown in Figure 3. For both charging station and EV diffusion, the entire evolutionary process is an S-shaped growth curve, which is compatible with the diffusion curve of new product diffusion theory by [37]. Under present policy conditions, the energy market consists of 62% charging stations and 38% gas stations when it reaches equilibrium. In terms of EV diffusion, CVs will eventually be replaced by BEVs (75% market share) and PHEVs (25% market share), with PHEVs being the only models with fuel attributes, but BEVs not completely replacing PHEVs, as shown in Figure 3. This finding is compatible with China's present EV industry growth strategy since there is a possible pattern between CVs, BEVs, and PHEVs: PHEVs will replace CVs, followed by BEVs replacing PHEVs, until the whole market belongs to BEVs. If CV is removed from the market, consumers who favor fuel attributes between BEV and PHEV are more likely to pick PHEV, increasing PHEV's market share and supporting the establishment of gas stations. These findings also suggest that BEVs will continue to be favored over PHEVs until market conditions alter.

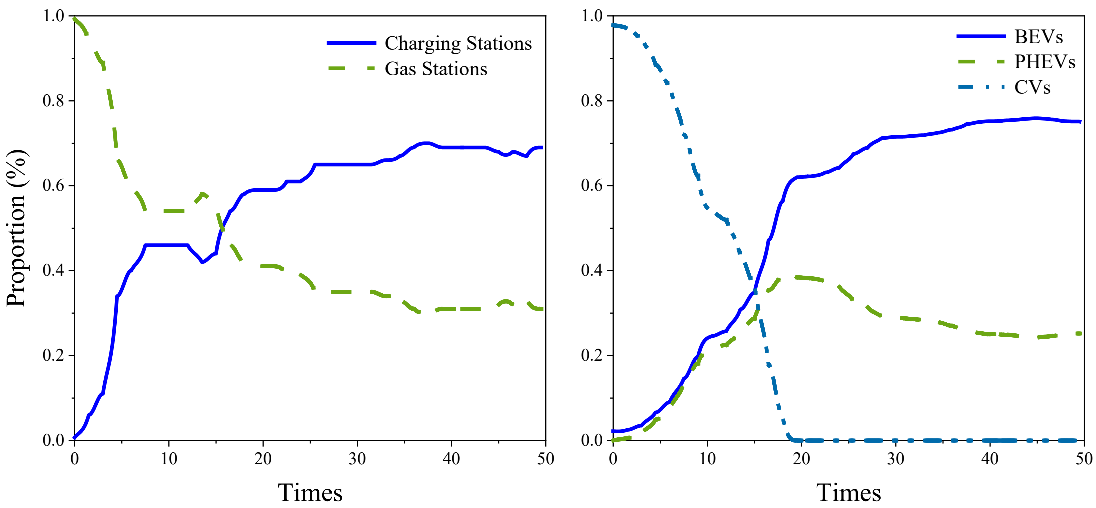

Figure 3. Proportion of charging stations and EVs in baseline scenario.

4.3 Sensitivity analysis

4.3.1 Impact of construction subsidy and carbon tax policy

Policies like as carbon taxes and construction subsidies are still major incentives for the growth of charging stations [1, 8]. Currently, construction subsidies account for around 20% of overall investment costs; however, China lacks a comprehensive carbon tax policy framework for gas stations. Under present policy settings, Figure 4 depicts the impact of various construction subsidy schemes on charging station, PHEV and BEV diffusion. The findings show that when construction subsidies grow, the share of charging stations and BEVs is growing and that of PHEVs is declining. This finding is consistent with existing knowledge, and an interesting phenomenon is that subsidies for charging station construction contribute to the conversion of PHEVs to BEVs. When the market reaches equilibrium under the 20% construction subsidy incentive, the market share of charging stations is 62%, while the market share of BEVs is 64.98% and that of PHEVs is 35.02%.

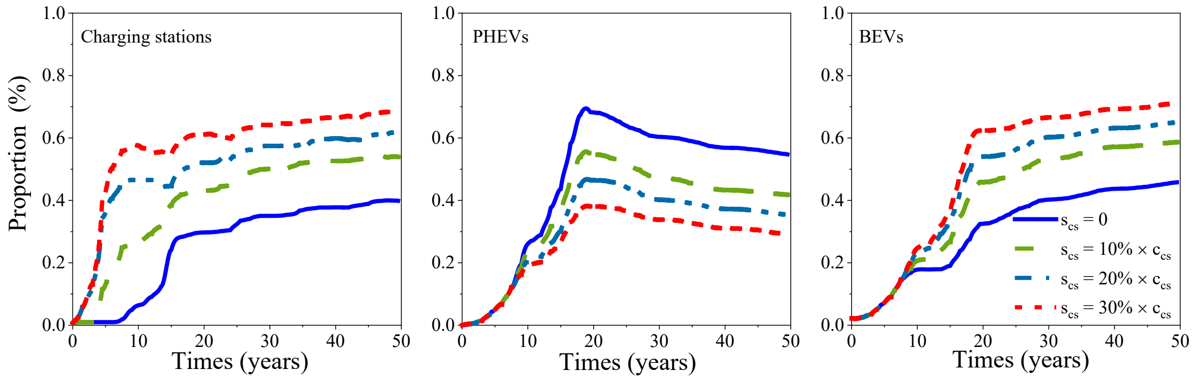

Figure 4. Impact of construction subsidy policy on charging station, PHEVs and BEV diffusion.

Figure 5 depicts the effect of various carbon tax policies on charging station, PHEV and BEV adoption under current policy settings. Similar impact might be found in construction subsidy schemes. When the same setting is applied to construction subsidies, the policy intervention becomes balanced. When the equalization policy is implemented, the market share of charging stations is 77.6%, while the market share of BEVs is 79.06% and that of PHEVs is 20.94%. By comparing Figure 4 and Figure 5, we can see that the market share of charging stations can increase by 17.06% when the equalization policy is implemented, while the market share of PHEVs to BEVs transforms by 14.08%. This is an important finding, and our research demonstrates the importance of carbon tax policies, both for the diffusion of charging stations with BEVs and the conversion of PHEVs to BEVs.

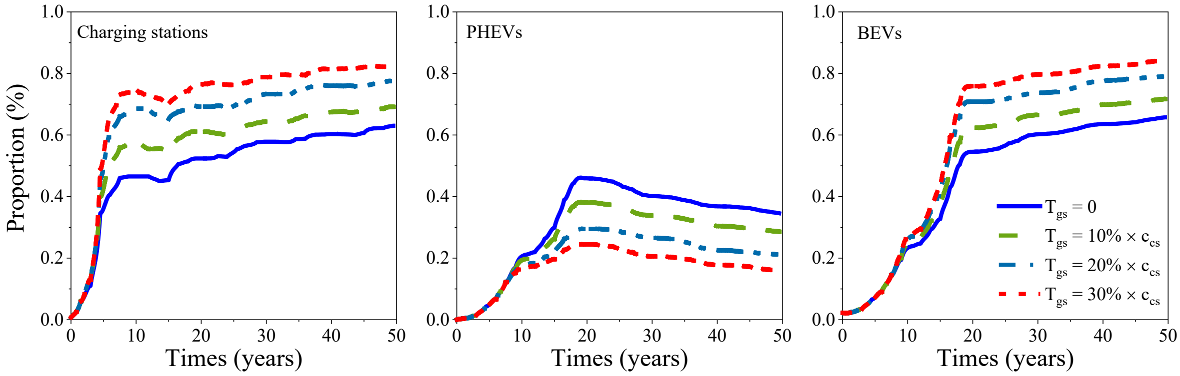

Figure 5. Impact of carbon tax policy on charging station, PHEV and BEV diffusion

4.3.2 Impact of electricity price

The role of electricity prices in encouraging charging stations and BEVs appears to be obvious: high electricity prices boost charging station construction while inhibiting BEV uptake. Adjusting electricity pricing is still an effective instrument for governments to use to manage the market. Figure 6 depicts the effect of electricity pricing on charging station, PHEV and BEV diffusion. Existing studies show that it is difficult for the charging station industry to diffuse when electricity prices are low, and that high electricity prices significantly increase the rate and level of charging station diffusion [11]. However, unlike the above perceptions, our research shows that there is an inverted U-shaped effect between electricity prices and charging station proliferation rather than a pure growth effect: appropriately high electricity prices can fuel charging station development, but too high electricity prices can inhibit charging station diffusion. This is also easy to explain, because early on the price of electricity is high, charging stations can get more revenue from the limited charging demand, the industry can develop, but the price of electricity is too high, charging demand will significantly decline and thus affect the charging station.

An interesting conclusion for the EV industry is that early high electricity prices benefit the EV industry and do not hinder its industrial development, contrary to common perceptions. This may be because higher electricity prices benefit the development of charging stations and promote their market proportion, which offsets the negative impact brought to BEV during the early diffusion. Of course, if the electricity price is too high, e.g., $1.7-2/kWh, the BEV industry proliferation will be difficult. If this is the case, charging stations are currently stifled and their popularity is much lower than when electricity prices are cheap, as shown in Figure 6. This is a very fascinating finding, as it is the first time this phenomenon has been found in a model, and it provides evidence for independent pricing of charging stations, which also demonstrates the sophistication and validity of our simulation model. Finally, we find that higher electricity prices can only be bad for the PHEV market. This may be because when electricity prices were higher early in the market, more charging stations led to more BEV market growth and also contributed to the conversion of PHEVs to BEVs; however, when electricity prices were higher, CVs were more favorable compared to PHEVs, which also led to a shrinking PHEV market.

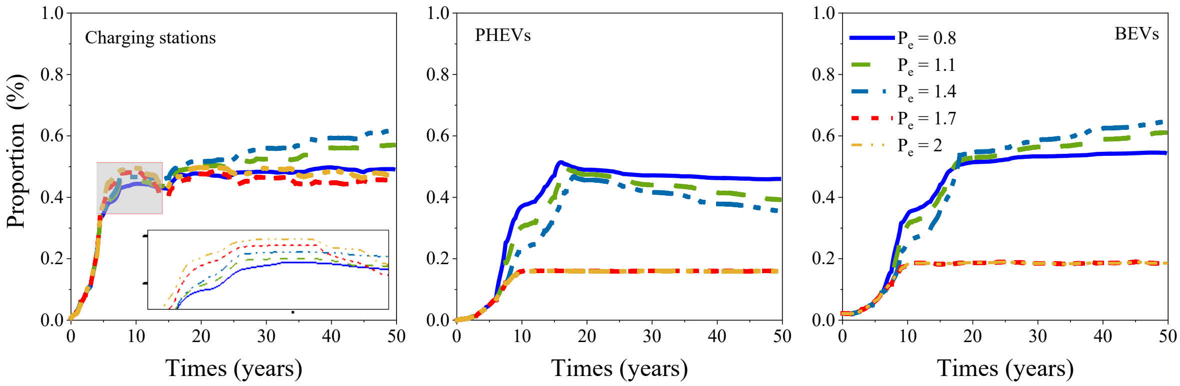

Figure 6. Impact of electricity price on charging station, PHEV and BEV diffusion

4.3.3 Impact of consumer social network strength and technical learning rate

Consumers do not exist in a vacuum, and their decisions are frequently impacted by social networks [7]. Scholars in the field of consumer research argue that social networks significantly influence consumer adoption behavior, such as friend recommendations and product "word of mouth" [32]. Figure 7 depicts the influence of social network strength on charging station, PHEV and BEV diffusion under current customer knowledge. An interesting finding is that the higher the strength of the social network, the lower the level of diffusion for charging stations and BEVs, but the higher the level of diffusion for PHEVs. In other words, consumer social networks are not conducive to the diffusion of charging stations and BEVs and favor the diffusion of PHEVs. This is also in line with current market conditions in China, as the general public is less willing to accept BEVs and prefers PHEVs when purchasing a vehicle between PHEVs and BEVs [7]. This may be due to the immaturity of EV technology and the imperfection of supporting industries (such as insufficient charging facilities), resulting in negative consumer perceptions of the EV industry and the charging station industry.

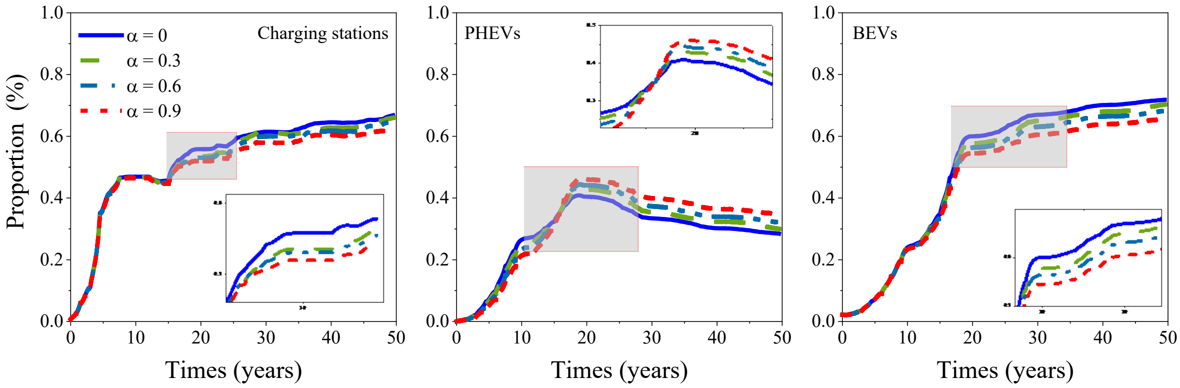

Figure 7. Impact of consumer social network on charging station and BEV diffusion.

The influence of technical learning rate on charging station, PHEV and BEV diffusion is seen in Figure 8. Technology learning curve attempts to reduce the manufacturing cost of BEVs and is positively correlated with the proliferation of charging stations, PHEVs and BEVs, and to a lesser extent can facilitate the conversion of PHEVs to BEVs. First, it is worth noting that when $\beta = 0.15$ the learning rate of the technology is too low resulting in a higher purchase price of BEVs and thus consumers prefer to buy CVs, making it difficult for both charging stations and the EV industry to proliferate. Second, in comparison to charging station diffusion, technical learning rate has a greater impact on PHEV and BEV diffusion, particularly in the early stages. This is because a faster rate of technical learning results in BEVs being a more cost-effective product earlier, causing more prospective customers to purchase PHEVs and BEVs. However, despite a minor rise in charging station market share, a comparable impact to charging station diffusion appears to be ineffective. This may be because the charging station industry has reached a relatively high market level supported by subsidy policies and the EV market (as in Figure 8, when Times=10). The higher proportion of charging stations can accommodate more demand for EVs due to lower costs as a result of technological learning, offsetting the potential impact of technological learning. As a result, the charging station industry is less dependent on technological learning from EVs than the EV industry. This finding also provides new knowledge to understand the relationship between charging stations and the EV industry.

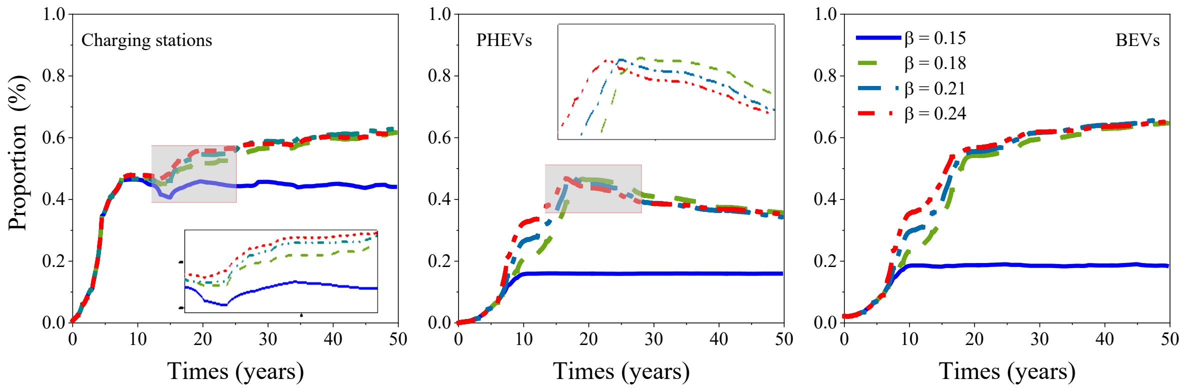

Figure 8. Impact of technical learning rate on charging station, PHEV and BEV diffusion.

4.4 Extensions

To standardize the research, we use the regular network and random network as extensions to evaluate the influence of different network topologies on charging station and BEV diffusion. Our research employs four popular topologies: nearest-neighbor coupled network, WS small-world network, BA scale-free network, and ER random network.

Complex networks have evolved through three stages: regular networks, random networks, and complex networks, where regular networks are nearest-neighbor coupled networks and complex networks are WS small-world networks and BA scale-free networks. The nearest-neighbor coupled network is best understood as a sensor network, in which each sensor only communicates with the sensors within its detecting range, and the charging station only interacts with the energy stations within its range. Of course, if charging station communication is not limited by range and may collaborate and compete with any energy station at any time, it is a random network. It is a complicated network if it is not any of the aforementioned. Complex networks feature three primary properties: small-world, scale-free, and high clustering, and are usually referred to as WS small-world networks and BA scale-free networks. The WS small world network can simulate most networks in the actual world, with the global village having the greatest image understanding and reflecting the features of tiny world and high clustering. If a charging station industry alliance or information platform is developed, this network may be thought of as a small world network. BA scale-free networks highlight the scale-free property, which means that a small number of nodes in the network have a higher degree, such as super-spreaders in an epidemic or leading technology corporations. If the charging station market is dominated by a few oligopolies, this network may be thought of as a BA scale-free network. The nearest-neighbor coupled network, complex networks (WS small world network and BA scale-free network), and random networks, in general, follow the law that the agglomeration coefficient is from big to small and the average particle length is from small to large. Real-world networks are neither regular nor random, but rather a complex network structure weighted by both.

The nearest-neighbor coupled network is a regular network with N nodes organized in a ring topology, and each node is linked to its closest $2d$ neighbor nodes ($d=2$) [42]. BA scale-free network begins with a linked network of m_0 nodes and adds a new node to connect to $m\left(m \le m_0\right)$ old nodes at each time step [17]. The connection probability is proportional to its degree, namely $\Pi\left(k_i\right)=k_i \Big/ \sum_{j=1}^{N-1} k_j$, where k_i is the degree of old node i. ER random network contains a total N nodes, and all possible $N\left(N-1\right)/2$ connections are connected with a certain random probability $p=\dfrac{2n}{N\left(N-1\right)}$, where n is the given edge number ($n<N\left(N-1\right)/2$) [43]. We use the same parameter settings as the baseline scenario in our analysis to examine the influence of different network topologies on charging station and BEV diffusion.

Figure 9 shows that charging stations and BEVs have similar diffusion trends, with the nearest-neighbor coupled network having the fastest diffusion, followed by WS small-world networks, BA scale-free networks, and ER random networks, while the PHEV market diffusion is just the opposite. According to the network topology theory, the nearest-neighbor coupled network has the largest clustering coefficient minimum mean path length, and the ER random network has the smallest clustering coefficient maximum mean path length, thus the nearest-neighbor coupled network has a significantly higher information exchange rate than the ER random network [17]. Figure 9 shows that the effect of network topology on the proliferation of charging stations and BEVs can be divided into two priorities: prioritizing increasing the clustering factor followed by decreasing the average path length. This means that in reality, the government and enterprises should prioritize to enhance the strength of the network connection of charging stations (or BEVs), such as establishing industrial alliances or information platforms, and secondly expanding the industry scale. In addition, Moreover, we can find that this impact is just the opposite for PHEVs, which means that the network science theory can effectively guide the transformation of the EV industry from PHEVs to BEVs.

As for the WS small-world network and BA scale-free network, the diffusion speed and evolution level of these two network topologies are intermediate between that of the nearest-neighbor coupled network and that of the ER random network. This is because their average path length is shorter than that of the ER random network and their clustering coefficient is lower than that of the nearest-neighbor coupled network, their information propagation path is shorter than that of the ER random network and their node connection is looser than that of the nearest-neighbor coupled network [17]. Furthermore, we discover that the WS small-world network outperforms the BA scale-free network. In other words, increasing the clustering coefficient is better than increasing the individual degree for both industry diffusion. Based on the topological features of the two networks, this means that the government and enterprises should prioritize supporting charging station alliances or information platforms for the charging station industry, followed by assisting the leading charging station technology firms.

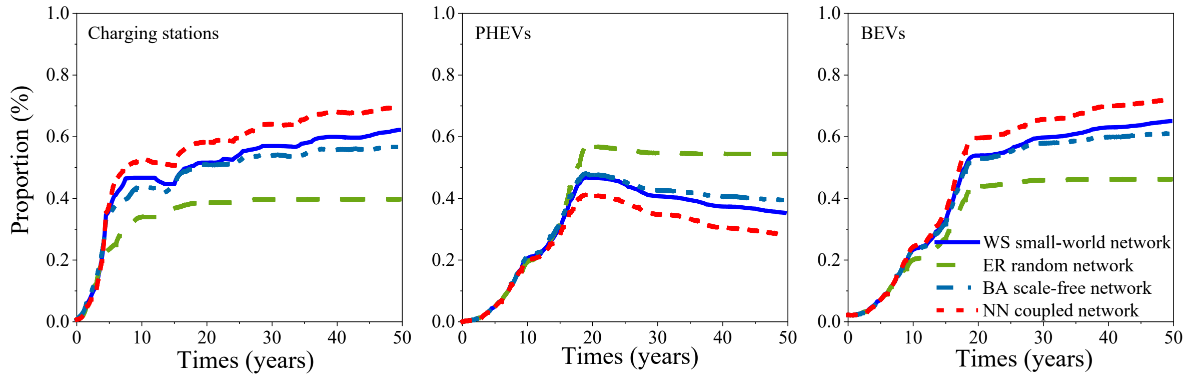

Figure 9. Impact of different network topologies on charging station and BEV diffusion.

5. Discussion

5.1 Theoretical contributions

Our research adds to the body of knowledge by developing a novel agent-based evolutionary game model that incorporates both charging station investment on the supply side and EV diffusion on the demand side. It highlights the importance of demand adoption behavior for the proliferation of charging stations. A full dynamics simulation model of this type can capture the influence of customers' microscopic adoption behavior on charging station diffusion arising at the system level. Based on this model, we found many interesting findings, such as an inverted U-shaped effect between electricity prices and the proliferation of charging stations and BEVs, where relevant factors (e.g., construction subsidies, carbon taxes, early high electricity prices, high clustering factor networks) contribute to the conversion of PHEVs to BEVs. To the best of our knowledge, no similar discoveries exist in the current literature, demonstrating the sophistication of our simulation model. In addition, our study is the first to consider the complete dynamics of charging stations and EV diffusion, extending the research boundary into the field of complex systems. Our study examines the influence of different network topologies on charging station diffusion, which is overlooked by most research when examining the diffusion of clean technology. The results of the study show that the impact of complex networks can be divided into two priorities: prioritizing increasing the clustering coefficient, followed by decreasing the average path length. Moreover, for the diffusion of both industries, increasing the clustering coefficient is better than increasing the individual degree. These new findings add to the understanding of two-industry diffusion and provide new knowledge on industrial diffusion.

5.2 Management implications

Our findings have implications for the diffusion of charging stations that incorporate customer behavior dynamics and are operated in complex networks. To summarize, BEVs remain the mainstream model, while PHEVs serve as a transitional replacement vehicle for CVs. We address five particular management implications based on such a demand, notably government policies, electricity prices, social networks, technical learning rates, and network topologies.

Government initiatives like as construction subsidies and carbon tax policies are effective instruments for promoting charging station diffusion. The most significant financial strain on the Chinese government is on the promotion of green technology [11]. Our study indicates that establishing a balanced approach may boost the market share of charging stations by 17.06% and BEVs by 14.08%. Currently, China does not have a carbon tax policy for gas stations, and our findings demonstrate the importance of implementing a balanced policy, especially when the government is under greater fiscal pressure. In addition, adjusting electricity prices can also aid in the proliferation of charging stations [25]. According to our research, high electricity prices do not necessarily impede the growth of BEVs, but rather stimulate the development of charging stations and EVs. Consider the "chicken-and-egg" link between EVs and charging stations, enabling high electricity prices early in the EV sector and gradually lowering them to avoid negative repercussions. This means charging stations should be given greater automated pricing authority, particularly early on.

In terms of social network influence, we find that it has a negative impact on BEV dissemination, which is consistent with the literature [7]. However, we also found that this negative impact can be passed on to the charging station industry and affect its proliferation.

Therefore, charging station enterprises should not overlook this influence, and they should actively participate in green customer nurturing operations to raise public awareness and enhance consumers' understanding of electric vehicles. In addition, we also discover that the impression of BEV technical learning rate has a minor influence on the proliferation of charging stations. This means that charging station development is important for electricity Therefore, instead of waiting for the development of BEV market, companies should plan ahead for investment in charging stations.

Finally, we look at how network topologies affect charging station and BEV diffusion. According to our findings, the influence of network topologies may be split into two priority levels: firstly clustering coefficient and secondly average path length. This means that in reality, the government and enterprises should prioritize to enhance the strength of the network connection of charging stations (or BEVs), such as establishing industrial alliances or information platforms, and secondly expanding the industry scale. In addition, Moreover, we can find that this impact is just the opposite for PHEVs, which means that the network science theory can effectively guide the transformation of the EV industry from PHEVs to BEVs. Furthermore, we discover that the WS small-world network outperforms the BA scale-free network. This means that the government and enterprises should prioritize supporting charging station alliances or information platforms for the charging station industry, followed by assisting the leading charging station technology firms.

6. Conclusions and policy implications

Our study presents an agent-based evolutionary game model to rethink the dynamics of charging station diffusion in a complex network to drive charging station diffusion. Unlike most previous research, this study incorporates the mechanism of customer adoption behavior into the dynamics of charging station diffusion, and the influence of network topologies is investigated. Meanwhile, the evolutionary game theory is proposed to simulate the boundedly rational decision-making process of energy station enterprises. A successful model should reproduce the fundamental features of target systems while also uncovering novel patterns that have not been recorded in earlier research [14]. Our work not only shows conclusions that are consistent with existing literature, such as the equilibriums coming from evolutionary games, but it also captures the influence of customers' microscopic adoption behavior on charging station diffusion emerging at the system level. We also utilize a case study to give more insights into management practices and to demonstrate the effectiveness of the proposed analytical framework.

Our research yielded the following results and implications. First, the carbon tax policy is a forward-looking policy that, when combined with existing policies, has the potential to increase the market share of charging stations by 17.06% and the conversion of PHEVs to BEVs by 14.08%. Second, there is an inverted U-shaped effect between electricity prices and the proliferation of charging stations and BEVs, and high electricity prices do not always hinder the development of BEVs or the construction of charging stations. We should give charging station enterprises greater automated pricing power, particularly in the early stages. Third, the detrimental impact of social networks on BEVs can be passed to charging station proliferation. Charging station enterprises should educate the public about the benefits of adopting a low-carbon lifestyle. Fourth, the rate of BEV technical learning has a minor influence on the expansion of charging stations. Rather than waiting for the BEV market to grow, enterprise investment in charging stations should be planned ahead of time. Firth, the impact of complex networks can be divided into two priorities: prioritizing increasing the clustering coefficient, followed by decreasing the average path length. Moreover, for the diffusion of both industries, increasing the clustering coefficient is better than increasing the individual degree. Therefore, the government and enterprises should give priority to establishing information platforms or industrial alliances, followed by supporting the development of leading technology enterprises and expanding the scale of the industry. Finally, relevant factors (e.g., construction subsidies, carbon taxes, early high electricity prices, high clustering factor networks) contribute to the conversion of PHEVs to BEVs.

Because of the complexities of practical problems, several limitations remain. First, the policies under consideration in the study are static policies, but dynamic policies may improve the flexibility of government control. Future study may attempt to assess their impact. Second, the study's consumer assessment knowledge is a short-term information that impacts customer car decisions and is largely stable throughout the cycle. Future study might look at the evolution of consumer knowledge in diverse technology environments to increase the efficacy of long-term decision-making.

Acknowledgements

Appendix: Questionnaire constructs and demographic characteristics

Table A1. Questionnaire constructs

Factors	Measurement items
purchase price	I think the price of a vehicle is very important to the decision I make to purchase the vehicle.
Maintenance cost	I think the maintenance cost is very important to the decision I make to purchase the vehicle.
Security	I think technology security is very important to the decision I make to purchase the vehicle.
Technology integration	I think technology integration (i.e. imbedding more vehicle technologies) is very important to the decision I make to purchase the vehicle.
High power	I think high power is very important to the decision I make to purchase the vehicle.
Low noise	I think low noise is very important to the decision I make to purchase the vehicle.
Carbon dioxide emission	I think low carbon dioxide emission is very important to the decision I make to purchase the vehicle.
Social network influence	I think the influence of the circle of friends (e.g., a friend's recommendation or a friend's decision to buy a car) is important to my car purchase decision.

Table A2. Demographic characteristics

Characteristics	Number	Ratio(%)	Characteristics	Number	Ratio(%)
Gender			10001-15000	122	17.81
Male	304	44.38	>15000	43	6.28
Female	381	55.62	*Occupation*		
Age (In years)			Student	128	18.69
18-24	108	15.77	Business	131	19.12
25-34	349	50.95	Public servant	101	14.74
35-44	174	25.40	Manufacturing and engineering	197	28.76
45-65	54	7.88	Other	128	18.69
Education level			*Marriage*		
High school or below	35	5.11	Unmarried	253	36.93
Bachelor	499	72.85	Married	432	63.07
Master	116	16.93	*Family size*		
Ph.D	35	5.11	1-2 memebers	97	14.16
Monthly income (RMB)			3 members	268	39.12
3001-5000	245	35.77	4 members	128	18.69
5001-10000	275	40.15	5 memebers and more than	192	28.03

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