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Electric Vehicles Scale Evolution Model Considering Social Attributes

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ABSTRACT Predicting the scale of electric vehicles at different time is the basis for the power grid to effectively accept charging loads. The development of electric vehicles is not only affected by economy, technology and policy, but also affected by the factors from social networks. This paper proposes the electric vehicle purchase decision model considering the influences of technology, economy and society. A two-dimensional space is used to characterize the random influences of related economic and social groups on consumer decisions, which can dynamically simulate the interaction between social environment and consumer decisions. Thus, based on such two-dimensional social space, an electric vehicle scale evolution model is established, so that it can be used to analyze the impact of the structural characteristics of social networks on the scale evolution. A large community in Changsha is taken as an example to analyze the scale development trend of electric vehicles under different social networks. Case studies demonstrate the feasibility and effectiveness of the proposed methodology.

INDEX TERMS Electric vehicles, scale evolution, social network, complex network, social evolution.

I. INTRODUCTION

Electric vehicles have become the main direction of developing new energy sources owing to the low pollution and the high environmental protection [1]. Because of the uncertain distribution of space and time of the electric vehicles, the grid is bound to lay out charging facilities for accepting the charging demand of electric vehicles according to the scale of electric vehicles [2], [3]. Therefore, it is important to predict the development scale of electric vehicles.

The facts are that the electric vehicle industry is in its infancy in China, thus, the poor historical data support for electric vehicles and the different policies of various countries lead to the low reference value of international data [4], [5], which bring challenges to the electric vehicle scale prediction [6], [7]. Current studies mostly use new product diffusion models to predict the development trend of electric vehicles [8]–[10]. There are mainly two kinds of the new product diffusion models: the macro diffusion models and the micro diffusion models.

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For the macro diffusion models, the classic diffusion Bass model was used to predict the annual market electric vehicle consumers by Zeng *et al.* [8]. Adopting the system dynamics, the scale development of electric vehicles was predicted by Xiang *et al.* [9]. Also, they pointed out that the early development of electric vehicles mainly depends on the government policy, while the later development depends on the technological innovation and the popularization of the charging facilities. The effects of media publicity and user satisfaction on the ownership of electric vehicles were considered by Yu *et al.* [10]. The macro diffusion models contribute a lot to the practical application of electric vehicle scale development, but it is difficult to examine the internal evolution of the market.

For the micro diffusion models: the factors of electric vehicle industry development were sorted out by Sierzchula *et al.* [11] and Egbue and Long [12], and the main point they mentioned is that the social factors are a non-negligible condition for the market diffusion of the electric vehicle. Shafiei subdivided the face of the social population from income level, family members, and social status [13]. As a coordinated integrated system [14], Multi-agent models were used to simulate the car purchase decision for different groups and to predict the development of electric vehicles in Iceland. Electric vehicle scale evolution based on multi-agent model was established by Yang [15]. Also, they analyzed the purchase process of electric vehicles based on consumer behavior. What the micro diffusion model focused on are individual differences and consumer interactions. However, how to simulate different types of consumers and analysis the consumer interactions under different networks were two difficult points in research works.

Social network is an important part of the micro diffusion model. The development of electric vehicles was affected by various factors such as the technological level, the economic attributes, and the policy propaganda [16], [17]. Note that, most of the factors affect the diffusion of electric vehicles through social networks. Social attributes play important roles in the policy promotion, the technological development, and the consumer decision-making [18]. Zhou *et al.* [19] considered the social network effect as a factor for product adoption. Shao and Chen [20] pointed out that the characteristics of social networks play key roles in consumers' opinion diffusion behavior. Kong [21] gave a vehicular social networks generation method based on floating car data.

This paper studies the influence of different social networks and social behaviors on the development of electric vehicles. The proposed method exploits the technical, economic and social cause and specifies the deterministic factors of consumers' purchase decision. The main contributions of this paper are highlighting as follows:

1) A two-dimensional space is used to characterize the random influences of related economic and social groups on consumer decisions, which can dynamically simulate the interaction between social environment and consumer decisions.
2) Propose an electric vehicle scale evolution model. The model is used to analyze consumer purchase behaviors in different social networks and network parameters.

The rest of the paper is organized as follows: In Section II, a framework for electric vehicle purchase decision models is established. In Section III, the specific formula and the calculation method are given. In Section IV, an electric vehicle scale evolution model considering social network structure is established. Test studies are presented in Section V, and conclusions are drawn in Section VI.

II. THE FRAMEWORK OF ELECTRIC VEHICLE PURCHASE DECISION BEHAVIOR

A. MACRO FACTORS FOR THE EVOLUTION OF ELECTRIC VEHICLE SCALE

The factors, which influence consumer decision-making from the perspective of social environment, are shown in Table 1.

1) Technical attributes refer to the technical parameters of electric vehicle products. Technical attributes are the basis for the diffusion of electric vehicles. e.g., the electric vehicle technology lags behind the fuel-powered vehicle technology.

TABLE 1. Macro-social factors for electric vehicle scale evolution.

Attributes	Factor set
Technical attributes	Technical parameters, endurance mileage, battery capacity, energy consumption, safety performance, power type, etc.
Economic attributes	Product prices, marketing strategies, government subsidies, etc.
Social attributes	Brand benefits, network effects, surrounding group preferences, electric vehicle penetration rate, social population income, etc.

2) Economic attributes refer to the economics of electric vehicle products, which are the key evaluation indicators for consumers to purchase, e.g. the high price is one of the reasons for restricting the rapid development of electric vehicles.
3) Social attributes generally refer to social factors affecting the scale development of electric vehicles. As an emerging novel product, electric vehicles are diffused and penetrated in social networks, e.g. low market share and insufficient user awareness of emerging products are the challenges of electric vehicle promotion.

B. THE FRAMEWORK OF CONSUMERS' PURCHASE DECISION

According to information processing theory [22], consumers' car purchase behavior is divided into information collection stage, social evolution stage and purchase decision stage shown in Fig. 1.

1) Information collection stage: Consumers collect relevant information and conduct a comprehensive evaluation of the products. The economic and social information of electric vehicles are provided for those evaluation.
2) Social evolution stage: Consumers' decisions not only are affected by individual preferences, but also have obvious network effects in the scope of decision-making influence [23], [24]. For example, consumers are influenced by friends or neighbors in social networks, and then adjust the preferences of electric vehicles. The occurrence of major social emergencies will also affect consumers' attitudes towards electric vehicles. Finally, they updates the evaluation results of electric vehicles based on their own characteristics.
3) Purchase decision stage: Consumers evaluate the technical attributes of electric vehicles and make purchase decisions. At the same time, the relevant people are affected by the purchase decision through social networks.

III. CONSUMER SOCIAL EVOLUTION IN A TWO-DIMENSIONAL SPACE

A. CONSUMER SOCIAL EVOLUTION

As shown in Fig. 2, consumers' attitudes towards the economic and social utility of electric vehicles can be reflected

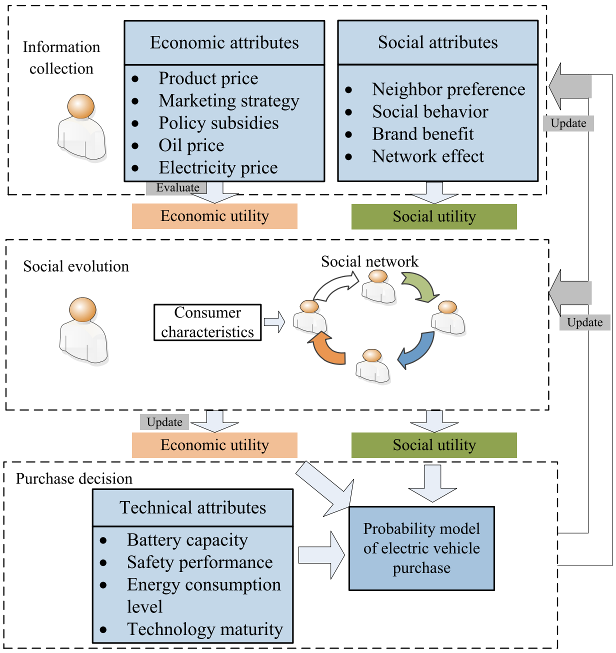

FIGURE 1. Consumer purchase decision model.

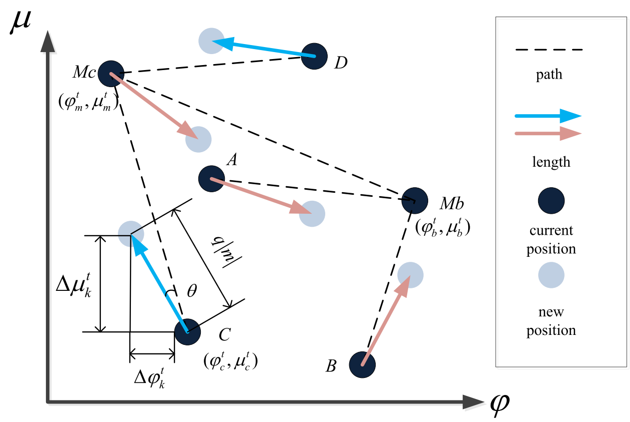

FIGURE 2. Consumer social evolution.

by moving in a two-dimensional coordinate. It is assumed that the social attitude space of all consumers is (φ, μ). The x-axis is defined as the social utility φ, which represents the degree to which consumers are affected by social networks when buying cars. The y-axis is defined as the economic utility μ, which means that consumers are affected by economy when buying a car.

The consumer's position in the two-dimensional space indicates his attitude for electric vehicles. The person who has contact with the consumer is defined as the relevant group. In the two-dimensional space, the connection between consumers and related groups is defined as a dotted line. Consumers have changed their attitudes towards electric vehicles after socializing with relevant groups. The change in consumer attitudes towards electric vehicles is manifested by moving a certain distance to a new location in a two-dimensional space. The direction of consumer movement is related to the influence of the relevant population and their own characteristics.

Consumer characteristics are divide into two types: volatile and conservative [25]. Volatile consumers are more susceptible to the influence of surrounding people and advertisements, so they pursue social utility. Conservative consumers are more susceptible to the value of products, so they pursue economic utility. In a social circle, a certain aspect of a product is most attractive to a consumer, and that consumer is called a typical consumer. The largest μ in a social circle (the economy is the most attractive to it) is called a typical conservative consumer. The individual with the largest φ in a social circle (the most attractive to society) is called a typical volatile consumer.

In the social circle, two types of consumers find and imitate typical volatile consumers and typical conservative consumers through social behavior. Simulate social evolution by moving consumers' positions in the attitude space. In a time period t (the period in the simulation is month), consumer attitude points (φ_k, μ_k) move a certain distance $|m|$ towards the typical consumer (φ_m, μ_m) to a new location. $|m|$ is defined as the intensity of social behavior. $|m|$ is positively correlated with the influence of consumers on typical consumers. The extreme social emergencies and other subjective accidents with small probability are defined as θ, to adjust the moving direction of the consumers in the space, such as COVID-19, Sino-US trade conflicts.

$$\Delta\mu_k^t = q\,|m|\sin\left(\arctan(\frac{\mu_m^t - \mu_k^t}{\varphi_m^t - \varphi_k^t}) + \theta\right) \tag{1}$$

$$\Delta\varphi_k^t = q\,|m|\cos\left(\arctan(\frac{\mu_m^t - \mu_k^t}{\varphi_m^t - \varphi_k^t}) + \theta\right) \tag{2}$$

where θ represents the impact of social emergencies on electric vehicles. If the individual difference is ignored and extreme events happened scarcely, θ is set as 1 in the simulation. Otherwise, θ ranges from -90 to 90 degrees.

$$q = 1 - e^{-\varepsilon l} \tag{3}$$

where q represents availability and social acceptability of charging facilities. l represents the coverage of charging facilities, which is approximately replaced by the penetration rate of electric vehicles [13].

The process of consumers' attitude update on economic utility and social utility is shown in Fig. 2. Suppose there are 6 consumers in this attitude space, and in a certain transaction cycle, M_b and M_c are typical variable consumers and typical conservative consumers, respectively. Volatile consumers A and B will move towards M_b, and conservative consumers C and D will move towards M_c. In the next cycle, if the characteristics of M_b are still volatile, the position will remain unchanged. If the characteristics of M_c become conservative, they will move towards M_b.

B. ECONOMIC UTILITY OF ELECTRIC VEHICLES

The economic value of electric vehicles is measured by the annual cost Ca of electric vehicles [13]. In equation (4), the annual cost includes the annual cost of selling price and the annual operating cost.

$$C_a = C_{pr} + C_{co} \tag{4}$$

where, C_{pr} is the annual cost of electric vehicle selling price [15], and C_{co} is the annual operating cost of electric vehicle.

The annual cost of the price of electric vehicles is described by the price of electric vehicles S_{ale}, the discount rate p, the government subsidy S_{ub}, the vehicle life T, the vehicle residual value R, and the vehicle depreciation rate a as shown in equation (5).

$$C_{pr} = p\frac{(S_{ale} - S_{ub})(1+p)^T - R}{(1+p)^T - 1} \tag{5}$$

In (5), the vehicle residual value R is expressed by the vehicle depreciation rate a and the vehicle life T:

$$R = (1-a)^T S_{ale} \tag{6}$$

The annual operating cost, the vehicle energy consumption rate re, the energy consumption price P_e, and the annual driving mileage D_a satisfy equation (7):

$$C_{co} = reP_eD_a \tag{7}$$

Based on equation (4)-(7), the economic utility of electric vehicles for user μ_i^t is defined as:

$$\mu_i^t = \frac{C_a^2 - (C_a^1 - C_a^2)}{C_a^2} \tag{8}$$

where ${C_a}^1$ and ${C_a}^2$ represent the cost of electric vehicles and fuel vehicles with the same performance. The annual cost of fuel vehicles is lower.

C. THE SOCIAL UTILITY OF ELECTRIC VEHICLES

The purchase decisions of the relevant people influence consumers' car purchases through social networks. The method of building a social network model is in Part A of Section IV. To characterize the impact of social networks, the definition is as follows:

1) Network effect φ is defined as the influence of consumers in the social network by the surrounding related groups. The network effect φ_i^t on the social network of consumer i at time t is the social utility of electric vehicles, as shown in equation (9):

$$\varphi_i^t = D_i^t g_i(d_i^t) \tag{9}$$

D_i^t is the network effect coefficient, d_i^t is the number of electric vehicles used by neighbors in the social network of consumers, $g_i(d_i^t)$ is the profit function of consumers' neighboring nodes to choose electric vehicles.

2) Network effect coefficient D^t reflects the degree to which different consumers are affected by neighboring nodes in the social network; Define the network effect coefficient to characterize the difference in the intensity of consumers affected by the relevant population. It can be expressed by the proportion of consumers' adjacent nodes adopting electric vehicles [26]. The network effect coefficient of consumer i at time t is D_i^t:

$$D_i^t = \frac{d_i^t}{N_i} \tag{10}$$

where N_i is the degree of social network, in which consumer i is located, and represents the total number of consumer-related groups.

3) Profit function $g(d)$: The profit function of the purchase decision of the relevant population on the consumer i is $g_i(d_i^t)$, The greater the number of consumers in the relevant consumer group who purchase electric vehicles is, the greater the profit function is [27].

$$g_i(d) = k_1 d + k_2 d^2 \tag{11}$$

k_1 and k_2 are parameters of the profit function.

IV. CONSUMER DECISION MODLE AND ELECTRIC VEHICLE SCALE EVOLUTION

A. CONSUMER DECISION MODEL

In addition to economic attributes, automotive technical attributes are important factors affecting user decisions. As shown in Fig. 1, technology maturity is used as the measure of car performance. The performance of electric vehicles improves with the development of technology. The closer to the technical bottleneck, the longer it takes. The development law of electric vehicle technology maturity is described by the logical growth curve model $\gamma(t)$ [15].

$$\gamma(t) = \frac{1}{1 + ae^{-bt}} \tag{12}$$

where a and b are model parameters. $a = 4$ and $b = 0.25$ in the simulation.

At this stage, the scale of electric vehicles is limited by the level of battery technology, which is likely to cause mileage anxiety. The improvement of battery technology will enhance the economics of electric vehicles and affect consumers' purchasing decisions [9]. Considering the impact of technology maturity on the economic and social utility of electric vehicles, technology attributes are integrated into the probability model of consumer purchase decisions. The probability P_i^t at the time t of consumer i buying an electric vehicle is:

$$P_i^t = \gamma(t)\,\mu_i^t + (1-\gamma(t))\varphi_i^t \tag{13}$$

where μ_i^t and φ_i^t are the economic value and social value of the electric vehicles of consumer i at time t.

B. ELECTRIC VEHICLE SCALE EVOLUTION MODEL UNDER SOCIAL NETWORKS

The process of the electric vehicle scale evolution model under the social network as follows:

First of all, calculate the consumers who need to buy cars annually. Then, refer to the relevant factors such as tax policy, subsidy mechanism, selling price, oil price and electricity price in the current year, calculate economic utility from equation (8); According to the social network location of consumers and the decision-making of neighboring groups, the social utility of consumers in the social network is calculated from equation (10); According to equation (1) (2), the social evolution of consumers to update the utility of electric vehicles is simulated; Based on the maturity model of electric vehicle technology, consumer car purchase decision behavior is simulated from equation (13). The simulation process is shown in Fig. 3:

1) Set model parameters, e.g. initial year, predicted year, current car volume, regional population, car scrap rate and growth rate, energy price, car type, etc. Consumers are divided into new users and old users. Old users buy new cars after the vehicles are scrapped. According to the annual car growth rate α and the car scrap rate β and the total number of cars N, the number of potential purchasers of electric vehicles $(\alpha + \beta)N$ is calculated.
2) Choose one kind of social networks model. According to the current number of cars, the node locations of electric vehicles are randomly assigned in the social network.
3) Collect the characteristics and decision-making information of consumers, including annual mileage, car prices, energy prices, location of social network nodes, typical vehicle type information, and its proportion.
4) Calculate the number of consumers and the utility of consumers in the month. Calculate economic utility and social utility according to equations (8), (10). Simulate consumer's social evolution behavior in the 2-d social space. Calculate the new economic and social utility of consumer.
5) Simulate the scale evolution of electric vehicles that year. According to the calculation results, the consumer's car purchase behavior in the current year is simulated and the car purchase results are counted.
6) Update the car purchase results of that year and send to the social network.
7) Determine whether the simulation target years have been reached, and if it is reached, the simulation will end, otherwise, update the social network scale and return to Step 3).

V. CASE STUDY

The development of electric vehicles in China is in its infancy [8]. Owing to the low ownership of electric vehicles and the high urban population base, the diffusion effect of social networks is not obvious. The case is a large community in Changsha. The case analyzes the evolution of the scale of electric vehicles in the region from 2018-2025. The community has 8220 households in 2018 with a community growth rate of 3%, private car ownership of 5165, and electric vehicle penetration rate of 9%. The annual growth rate of private cars is 8%, the scrap rate of private cars is 2%, the depreciation rate of cars is 20%, the discount rate is 5%, and the annual mileage of users follows a normal distribution N (12000, 3000^2). The electric vehicle charging price is assumed to be 1.0 Yuan/kw.h, and the fuel price is 8 Yuan/L. Through investigation and comparison, electric vehicles of the same product grade under the same brand are about 1.4 to 2.6 times the selling price of conventional vehicles. The overall classification of fuel vehicles and electric vehicles is shown in Table 2 [13], [15].

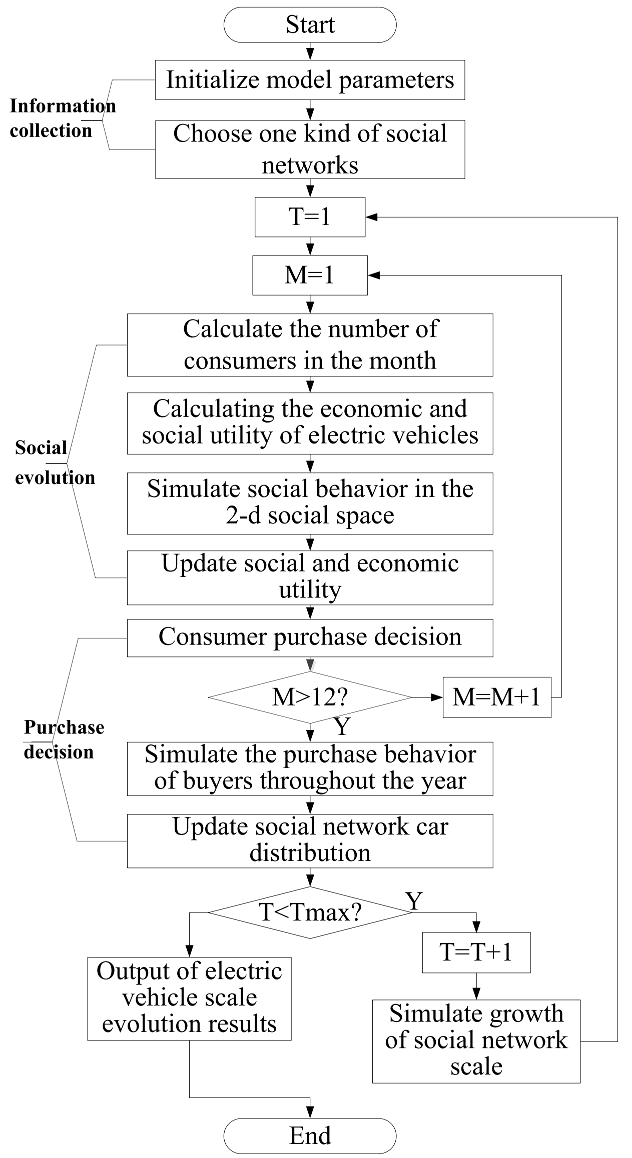

FIGURE 3. Electric vehicle scale evolution simulation flow chart.

TABLE 2. Car classification information [13], [15].

Type	price（Thousand yuan）	Fuel consumption（L/100km）	battery capacity	recharge mileage	Proportion
Minicar	30~100	5~7	15	155	22.8%
Small car	100~150	6~13	22	220	27.7%
Compact car	150~200	7~15	35	300	29.5%
Midsize car	200~400	8~15	52.5	370	13.3%
large cars	400~800	9~18	75	470	6.7%

TABLE 3. Basic parameters of complex social networks.

Network Type	Average distribution	Average path length	Clustering coefficient	Degree-degree correlation
Scale free network	12.0000	3.5140	0.0067	-0.0081
Small World Network	12.0000	1.8496	0.1507	-0.2119

The social network is typical complex network that exhibits typical complex network structure characteristics, such as small world characteristics and scale-free characteristics [28]. The evolution mechanism of electric vehicle scale is studied by simulating social networks composed of small world networks or scale-free networks. The typical structural parameters, i.e. average degree distribution, average path length, and clustering coefficient, are always taken to describe the probability distribution of node degrees in the social network, the number of intermediate consumers that consumers connect with other consumers, and the number of common neighbors among the neighbors of the connected groups respectively. Moreover, in social networks, degree-degree correlation means that consumers with high influence are more likely to contact consumers with high influence or consumers with less influence. The larger the clustering coefficient is, the deeper the clustering of network nodes are.

Thus, in this article, the initial social network is set to scale-free network and small world network with reconnection probability 0.5. In order to study the influence of social network structure parameters and focus on practical significance (the characteristics of the two online consumers are basically the same), the average distribution of generated networks is the same. The structural parameters are shown in Table 3.

The results in Table 3 show that the average path length of the small world network is shorter ($1.8496 < 3.514$), indicating that the consumers in the small world network are more closely connected; The large clustering coefficient means that consumers in the small world network have a greater degree of conglomeration; The degree-degree correlation is negative, indicating that nodes with high influence, such as community agency personnel, are more willing to conduct electric vehicle popularization activities to community residents (nodes with less influence).

A. ELECTRIC VEHICLE SCALE EVOLUTION UNDER THE INFLUENCE OF DIFFERENT SOCIAL NETWORKS

Considering two typical structural social networks, the growth rate of electric vehicle scale development is shown in Fig. 4.

From 2019 to 2022, electric vehicles are affected by government promotion and social propaganda effects. The number of electric vehicles is small, but the growth rate is fast. After 2022, the number of electric vehicles is going to expand, the annual growth rate of automobiles tends to be stable, and the annual growth rate of electric vehicles shows a steady development tendency. The policy subsidy for electric vehicles is declining. According to equation (13), advances in battery technology have gradually reduced the economic gap between electric vehicles and fuel vehicles with the same performance. Electric vehicles are becoming more competitive. At this time, electric vehicles have entered a stage of rapid rise, and the overall scale of electric vehicles is showing rapid development.

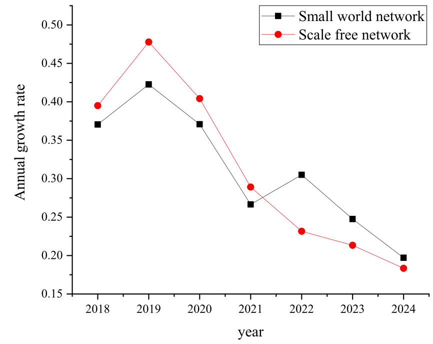

FIGURE 4. Annual growth rate of electric vehicles.

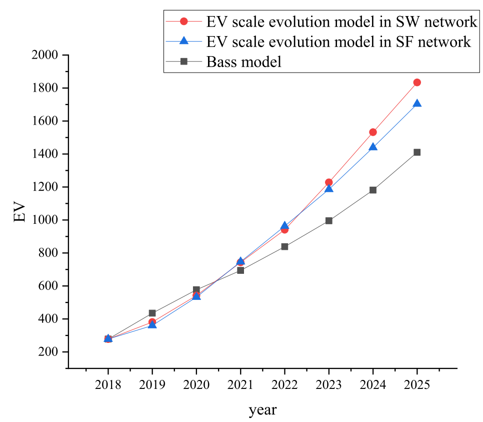

FIGURE 5. Electric vehicle scale growth chart.

The Bass model is used as a baseline model for the scale evolution of electric vehicles. The model parameters are set according to [8].

On the one hand, Fig. 5 shows the comparison results of the Bass model, electric vehicle scale evolution model in small world network and electric vehicle scale evolution model in scale free network. The development trend of electric vehicles of the two models is similar. Compared with the Bass model, the proposed model has more optimistic expectations for electric vehicles. Specifically, in the early stages of development, electric vehicles of the bass model developed faster. After 2021, the development speed of the proposed model begins to exceed the former. The number of electric vehicles in this community in 2019 is 370. The prediction result of the Bass model is 435. The prediction result of electric vehicle scale evolution model in small world

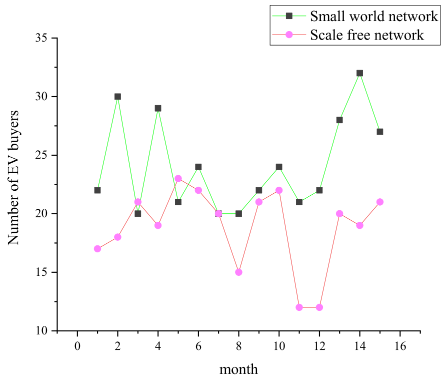

FIGURE 6. Monthly growth of electric cars at different social behavior intensities.

network and scale free network is 381 and 360 respectively. The electric vehicle scale evolution model is closer to the actual result. The fundamental reason is that the macro model and the micro model have different perspectives.

On the other hand, Fig. 5 shows the development of the number of electric vehicles under different social network types. In the early stage of the development of electric vehicles, because of the small base of electric vehicles, there is no obvious difference between the scale development of electric vehicles in the scale free network and the small world network. From 2022 to 2024, with the expansion of the base of electric vehicles, it can be clearly seen that the development of electric vehicles under the small world network is more rapid. Therefore, compared with the scale free network structure, the small world network structure is more conducive to the development of the number of electric vehicles.

B. CONSUMER SOCIAL BEHAVIOR ANALYSIS

In social networks, consumer decisions are influenced by the decisions of relevant nodes through social behavior. To study the impact of typical consumers on the development of electric vehicles, the simulation behavior is conducted when the social behavior intensity $m = 0.1$ and $m = 0.3$. The relationship between consumers' social behaviors and their decision to purchase electric vehicles is shown in Fig. 6:

Fig. 6 shows the number of car purchases per month in 2020. The number of car purchases with social behavior intensity $m = 0.3$ was only slightly less than that with $m = 0.1$ in March, May, and July. After August, the number of car purchases at $m = 0.3$ has been higher than that at $m = 0.1$, and the simulation has reached dynamic stability. When the influence of consumers' social behavior is greater, that is, when the influence of the people around the social network is greater, it is more conducive to the diffusion of electric vehicles.

C. ANALYSIS OF THE INFLUENCE OF NETWORK STRUCTURE PARAMETERS ON SCALE EVOLUTION

Further analysis of the evolution of the scale of electric vehicles in complex networks, combined with different

TABLE 4. Basic parameters of scale free networks.

Network Type	Average distribution	Average path length	Clustering coefficient	Degree-degree correlation
Scale-free network 1	12.0000	3.5140	0.0067	-0.0081
Scale-free network 2	15.9811	3.2372	0.0092	-0.0068

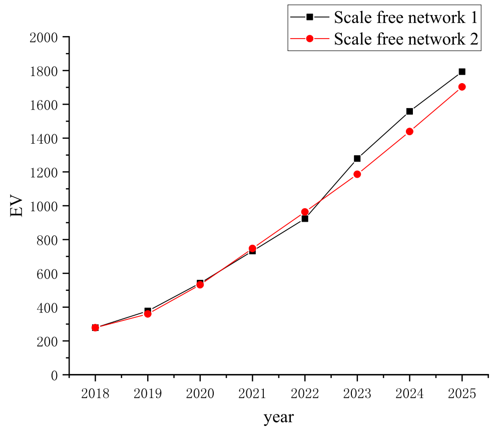

FIGURE 7. Scale evolution of electric vehicles under different scale-free networks.

topological structures in the network for in-depth research, scale free networks are prone to high level nodes, which can simulate community product promotion personnel. Take scale-free network as an example to discuss the influence of structural parameters on the evolution of electric vehicles. Table 4 shows the structural parameters of two scale free networks with different average distributions. Owing to the increase in the average degree distribution, the clustering coefficient of scale free network 2 is slightly larger than that of network 1, and the degree-degree correlation is negative.

Fig. 7 shows the evolution of electric vehicle scale under different scale free networks. The results show that social behavior of consumers through the social network can affect more consumers in a scale free network with a large average degree distribution, which also shows that the choice of the number of nodes in the network has a greater impact on the overall network. The scale free network 2 is more conducive to the development of electric vehicles. Shortening the average path length of social networks can promote consumer evolutionary behavior, and the development of electric vehicles depends on close social groups.

VI. CONCLUSION

Accurate prediction of the scale of electric vehicles is of great significance to power grid construction and safe operation. Considering the economics, social utility and technological maturity, this paper proposes a two-dimensional social space to characterize the random influences of related economic and social groups on consumer decisions, thus, to dynamically simulate the interaction between social environment and consumer decisions. An electric vehicle scale evolution model is proposed through modelling different kinds of social networks, namely small world social network and scale-free social network. Taking Hunan province as example, we found that:

1) The five-year development of electric vehicles in a large community in Hunan is predicted. The aggregation effect under the small world social network is more obvious, which is more conducive to the development of electric vehicles.
2) Consumers' purchasing decisions are affected by social behavior. When the social impact factor is large, the number of electric vehicle purchases increases significantly.
3) Different types of social networks lead to differences in the development of electric vehicles. Under the scale free network structure, the development of electric vehicles is more rapid when the average degree distribution is large enough. In the process of policy formulation, it is feasible to consider strengthening the degree of social membership and shortening the average path length of the social network to promote the development of electric vehicles.

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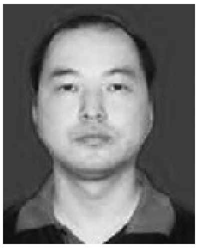

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