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Agent-Based Modeling for Scale Evolution of Plug-In Electric Vehicles and Charging Demand

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***Abstract*—Scale evolution pattern recognition f plug-in electric vehicles (PEVs) and charging demand modeling are essential for various involved sectors to promote PEV proliferation and integration into power systems. Considering that the market penetration development of PEVs will drive the evolution of charging demand, an integrated dynamic framework based on agent-based modeling technology is proposed in the paper by combining scale evolution model with charging demand model. Heterogeneous consumers presenting different preferences in making vehicle purchase decisions and the interactions with other consumers via social dynamics are taken into consideration in the scale evolution model. The driving patterns, charging behavior habits, and charging strategies are systematically incorporated into the charging demand model. Case studies demonstrate the feasibility and effectiveness of the proposed methodology. Furthermore, the factors that affect the market evolution of PEVs and the charging demand are also simulated and analyzed.**

Keywords—plug-in electric vehicle; charging demand; scale evolution; agent-based modeling

I. INTRODUCTION

Transportation electrification has been regarded as one of the most promising solutions for petroleum consumption reduction and environment protection because of the benefits associated with plug-in electric vehicles (PEVs). However, as an emerging industry, there are still significant barriers to widespread adoption of the new electrical vehicle technology, from both social and technical aspects [1]. On the other hand, the charging demand of PEVs is an additional burden on the power system, and the safety and reliability of power systems will be challenged with a large population of PEVs plugged in simultaneously [2]-[3]. In order to promote the proliferation of electric vehicles and friendly integrating PEVs into power systems, the scale evolution patterns of PEVs and charging demand profiles need to be analysed. It is also the essential foundational issue for charging electricity network planning and evaluating the impacts on power systems. These two issues are also interacting, and specifically, the scale evolution of PEVs will drive charging demand to evolve over time.

The PEVs diffusion pattern is so sophisticated to be accurately captured, as it is a long-term dynamic process jointly influenced by various factors, such as products attributes, consumers' preferences, policy incentives and social dynamics. In addition, at the early stage of PEVs development, the lack of precedent scale information is another challenge. Despite of these challenges, several studies have been conducted to address the issue [4]. The well-known Bass model was adopted in [5]-[6] to predict the scale of electric vehicles under the assumption that the social network is fully connected and homogenous. Gompertz growth and Logistic models were used in [7] to forecast the adoption rate of hybrid electric vehicles in the UK, where the life cycle net cost of technologies has taken into consideration. Considering the interactive and complicated relationship between different influence factors, the system dynamics approach was introduced in [8] for electric vehicle scale forecasting through modeling the multiple feedback loops of multivariable nonlinear systems. In general, the modeling techniques used by these models can be categorized as aggregated top-down model, which models the innovation diffusion procedure at macro market level without considering the heterogeneity of each consumer.

By contrast, the agent-based modeling (ABM) technique describes the automobile market by modeling consumers' vehicle purchasing behaviors at an individual level [4], [9]. The ABM holds the philosophy that macro-level patterns emerge with the aggregation of micro-level behavior of individuals and their interactions and thus it is convenient to integrate individual characteristics, needs, preferences and social networks. Hence, ABM has drawn increasing attention in the innovation diffusion field [10]. A probabilistic multi-agent model was constructed in [11] for studying people's willingness to buy electric vehicles based on a limited number of relevant questionnaires. In [12], an agent-based model was developed to study the market share evolution of passenger vehicles in Iceland. The vehicles compete for market penetration through a vehicle choice algorithm that accounts for social influences and consumers' attractiveness for vehicle attributes. A spatially explicit agent-based vehicle consumer choice model was designed in [13] to explore sensitivities and nonlinear interactions between various potential influences on plug-in hybrid vehicle market penetration.

As for the charging demand of PEVs, numerous studies have been conducted and various techniques have been adopted to deal with the properties of charging demand profiles. In [14]-[15], based on the probability density functions (PDFs) of driving patterns derived from travel statistics, Monte Carlo Simulation was conducted to model the stochastic charging load. Besides, fuzzy-logic inference systems were designed in [16]-[17] to emulate the decision-making processes of charging

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and characterize the charging behavior of drivers. Furthermore, a stochastic model for charging behavior of EVs was established in [18] based on non-homogeneous semi-Markov processes. In addition, queuing theory was widely employed in [19]-[21] to describe the charging behavior of multiple PEVs in charging station and residential community. In addition, various charging strategies were proposed in [22]-[25] to alleviate the adverse impact due to PEVs integration on the power system through changing charging load profiles. However, few studies have considered the scale evolution pattern of PEVs when modeling charging demand, which is inadequate for long-term implementation as charging demand dynamically evolves with the development of PEVs. Hence, it is necessary to study the charging demand characteristics from the perspective of evolution.

To effectively understand and quantify the interdependent relationship between PEVs scale and charging demand, an integrated dynamic framework combing scale evolution model and charging demand model is proposed in this paper. Individual agents are used to emulate consumers' vehicle purchasing decision processes in the scale evolution model. In the model, the annual total cost of ownership, technology maturity, social effect, environment benefits and the charging infrastructure deployment are incorporated in the choice algorithm. Additionally, consumer daily driving patterns, PEVs drivers' charging behavior habits, and the charging strategies are taken into consideration in the charging demand model.

The rest of this paper is organized as follows: In Section II, the integrated framework of the proposed model is presented. The scale evolution model is proposed in Section III. The charging behavior model and charging strategies are developed in Section IV. In Section V, case studies are performed and analyzed. Finally, conclusions are given in Section VI.

II. Framework of Proposed Model

Considering the interactive relationship between PEVs scale and charging demand, the integrated analytic framework proposed in this paper is depicted in Fig. 1.

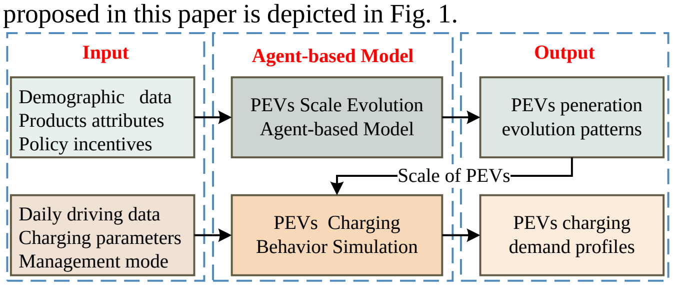


Fig. 1 Integrated analytic framework of the proposed model

At the upper level , the associated attributes for consumer agents of the study area are obtained according to demographic information, including current vehicle states, consumer preferences, typical years of car ownership, annual vehicle miles travelled, et al. Then, synthetic heterogeneous consumer agents are created to act vehicle purchasing behavior under the condition of known vehicle attributes and policy environment, with the interaction between consumers considered. Finally, the market evolution of PEVs can be achieved through aggregating each of agents purchasing decisions each year. at the lower level, after the scale of PEVs is obtained from previous procedures, the synthetic driving profiles of all PEV drivers are generated with Monte Carlo simulation based on travel statistics. In addition, the charging rules according to different charging strategies are set to model the charging behavior of each PEV agent. Finally, by aggregating all PEVs' charging demand in the district, the charging demand profiles can be obtained. The simulations can be implemented over time to explore the long-term evolution patterns.

III. Scale Evolution Model of PEVs

A. Consumer behaviour modeling

The purchase decision model of consumer agents is demonstrated in Fig. 2. Each individual consumer agent has its own personality traits towards products, which are mainly determined by socio-demographic attributes, such as income, education level and social status [26]. Consumers are heterogeneous with respect to their preferences and purchase decisions. For example, agents with low income are more sensitive to product price, whereas, agents with higher income might be less sensitive price but more concerned with performance. According to consumer behavior theory, after need recognition, consumer agents would comprehensively evaluate all the products available under the current decision environment to decide which product to choose. Here, the interactions with reference groups should also be taken into consideration, such as the recommendation of friends and neighbours. The assessment criteria and selection methodology will be specified in the following subsection.

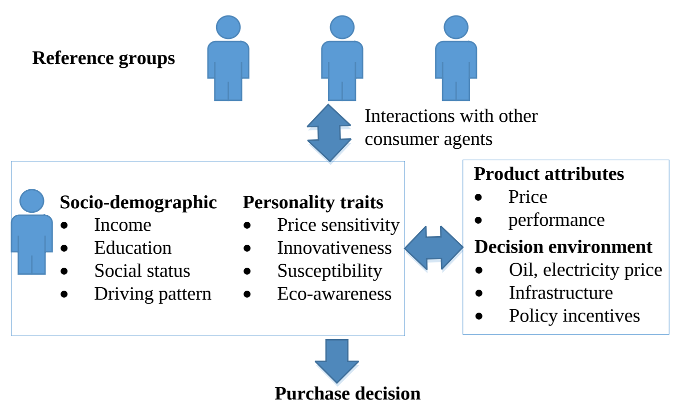


Fig. 2 The purchase decision model

B. Consumer choice probability

The involvement of consumers when buying durable product like vehicles is always relatively high due to high costs. Apart from cost-benefit analysis and performance evaluation, many factors play a role in buying decisions for prospective consumers, particularly attributes attached with vehicles, such as environment benefits. Additionally, as discussed previously, the purchasing behavior of other consumers will also affect the final decision due to social dynamics and peer effect. By taking various factors into consideration, the comprehensive utility for consumers purchasing different vehicle options is formulated as:

$$U_{ij}=\alpha_i U_{ij}^C+\beta_i U_{ij}^T+\gamma_i U_{ij}^S+\delta_i U_{ij}^E \quad (1)$$

Where, U_{ij} denotes the utility of purchasing vehicle j by consumer agent i; U_{ij}^C, U_{ij}^T, U_{ij}^S and U_{ij}^E are the economical utility, technological utility, social utility and environmental utility of purchasing vehicle j by consumer i, respectively; and $\alpha, \beta, \gamma, \delta$ are consumer preferences for each attribute.

(1) Economical utility

The annual total cost of ownership is adopted to evaluate the economic potential of each alternative, which consists of the discounted cash-flow of capital expenditure C_{inv} and annual operating expenditure C_{ope} [27]-[28]. It is formulated as follows:

$$C_{\mathrm{aTCO}}=C_{\mathrm{inv}}+C_{\mathrm{ope}} \quad (2)$$

$$C_{\mathrm{inv}}=p\frac{(P_{\mathrm{veh}}+T_{\mathrm{pur}}-S_{\mathrm{sub}})(1+p)^T-RV}{(1+p)^T-1} \quad (3)$$

$$RV=(1-r_{\mathrm{dep}})^T P_{\mathrm{veh}} \quad (4)$$

$$C_{\mathrm{ope}}=C_{\mathrm{energy}}+C_{\mathrm{m}}+T_{\mathrm{use}}+C_{\mathrm{Is}} \quad (5)$$

$$C_{\mathrm{energy}}=r_{\mathrm{e}}P_{\mathrm{e}}D_{\mathrm{veh}} \quad (6)$$

$$C_{\mathrm{Is}}=0.01k_{\mathrm{Is}}P_{\mathrm{veh}}+950+1480k_{\mathrm{Is}} \quad (7)$$

Where, C_{aTCO} is the annual total cost of ownership of evaluated vehicle by consumer agent i; P_{veh}, T_{pur} and S_{sub} are the vehicle retail price, purchase tax and subsidy provided by government, respectively; RV is the resale value considering the annual depreciation rate r_{dep} after T years; the annual operating cost includes energy consumption cost C_{energy}, maintenance cost C_{m}, use tax T_{use} as well as insurance cost C_{Is}; r_{e} is the energy consumption rate of the vehicle (L/100km or kWh/100km), P_{e} is the energy price (CHY/L or CHY/kWh), D_{veh} is the annual distance traveled by the vehicle; and the insurance cost is calculated according to empirical formula (7), k_{Is} is used to represent the effect of non-mandatory part and discount.

The economical utility of purchasing vehicle j by consumer i is defined as

$$U_{ij}^C=1-\frac{C_{\mathrm{aTCO}}^j-\min\left\{C_{\mathrm{aTCO}}^k\right\}}{\min\left\{C_{\mathrm{aTCO}}^k\right\}} \quad (8)$$

Where, C_{aTCO}^j is the annual total cost of owning vehicle j by consumer i.

(2) Technological utility

Due to lack of actual statistics about PEVs and its rapid development pace, the technological maturity is used as a comprehensive indicator for reflecting vehicle performance instead of various specific attributes, such as acceleration, capacity, etc. Conventional internal combustion engine (ICE) vehicle technologies have been tested for many years and thus the technological utility of ICE is set as 1. According to the basic chemical and physical laws, the more close to the limit, the longer it is required to improve the technology level. Thus, the logistic growth curve model is used to describe the evolution pattern of electric vehicle technology maturity, which is formulated as:

$$U^T=\frac{1}{1+ae^{-bt}} \quad (9)$$

Where, a and b are the parameters.

(3) Social utility

As stated before, consumers are linked with reference groups through the social network, and the purchase 3ehaviour of friends or neighbours are valued when making the purchase decisions. Thus, social utility is presented to reflect the "peer effect", which is defined as the vehicle penetration within reference groups:

$$U_{ij}^S=\frac{1}{K_i}\sum_{k=1}^{N}A_{ik}x_{kj} \quad (10)$$

Where, K_i is the number of agents linked with agent i in social network; N is the total number of agents; A is the adjacency matrix indicating the relationship among agents, if agent i links with agent k, then $A_{ik}=1$, else $A_{ik}=0$; x represents the adoption status, if agent k adopts vehicle j, then $x_{kj}=1$, else $x_{kj}=1$. A small-world network is generated randomly according to the method in [29], which is used to describe the connection relation.

(4) Environmental utility

As environmental friendly innovative products, electric cars have significant non-monetary value advantages compared to conventional cars. Some users are willing to pay a premium for these positive attributes of PEV, which can be reflected in a willingness-to-pay-more (WTPM) manner [27]. According to Rogers' "Diffusion of Innovations", different adopter groups in the adoption of PEVs can be characterized, e.g. innovators, early adopters, majority and laggards. The empirical value of WTPM for each group can be obtained through survey. In this paper, the environmental utility is presented to describe this aspect, and the environmental utility of PEVs is set as 1 due to zero emissions while operation. The environmental utility of ICE is formulated as:

$$U^E=1-\mathrm{WTPM} \quad (11)$$

(5) Recharging effect

The imperfection of charging facilities and relatively low range are important factors constraining the development of electric vehicles. Thus, the charging convenience index is constructed to indicate the recharging effect during purchase behaviors. It is determined by the installation of household charging facilities, the configuration of public charging facilities, the average daily driving distance of users and the range of electric vehicles, expressed as:

$$r=1-\frac{d}{L}\times e^{-\varepsilon(h+c)} \quad (12)$$

Where, r is the charging convenience; d is daily driving distance; L is the battery range of PEV; h is the difficulty factor of household charging facility installation; c is the coverage of public charging facilities; ε is scaling parameter.

(6) Consumer choice probability

Based on the multinomial Logit (MNL) model framework [12], the consumer choice probability is developed in this paper by incorporating all factors that affect consumers' vehicle purchase behavior described in previous sections. The purchase probability of PEV by the consumer is presented in (13):

$$P_{\mathrm{PEV}}=\frac{r\times \mathrm{e}^{U_{\mathrm{PEV}}}}{r\times \mathrm{e}^{U_{\mathrm{PEV}}}+\mathrm{e}^{U_{\mathrm{ICE}}}} \quad (13)$$

Where, U_{PEV} and U_{ICE} are the utility of purchasing PEV and ICE options, respectively.

C. Scale evolution modeling

From the micro-level perspective, the market evolution of PEVs is mainly determined by consumers purchasing decisions each year, and hence ABM is adopted to model individual consumer with different attributes and preferences over vehicle purchasing behavior. The flowchart of the market evolution model is depicted in Fig. 3.

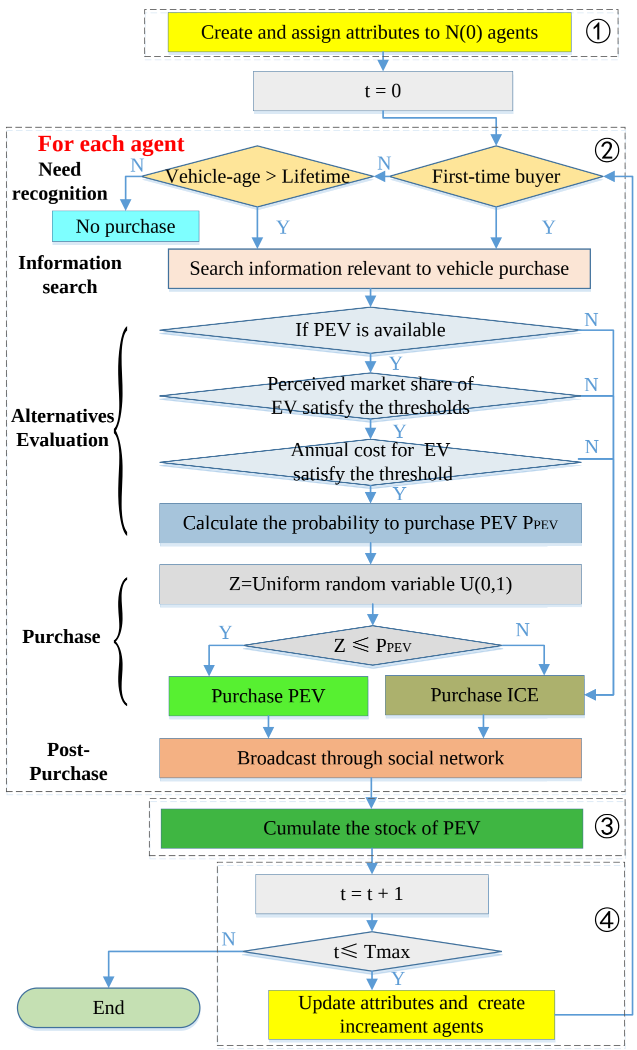


Fig. 3 Flowchart of the evolution model of PEVs

The simulation procedures are detailed as follows:

1) According to input datasets, generate the parameters of the market evolution model (e.g. consumer preference, innovation attitude, current vehicle condition and annual driving distance, etc.) and environmental parameters (e.g. technical development pattern, fuel price, subsidy, etc.). Program the electric vehicle evolution simulation systems, and create consumer agents of the first year.
2) For each consumer agent, perform vehicle purchasing decision making processes including need recognition, information search, alternatives evaluation, purchase and post-purchase based on the theory of consumer behavior. The first-time buyer needs to purchase a new car, and if the current age of the vehicle is greater than its lifetime, then the consumer decides to purchase a new vehicle. Then search all relevant information for vehicle purchase. If PEV is not available this year or the perceived market share and the annual cost of PEV cannot satisfy the threshold, then the consumer will buy a conventional car. Otherwise, the utility of each vehicle and consumer choice probability is calculated, and the purchase behavior performs accordingly.
3) Cumulate the stock of PEVs in this year.
4) If it is the target year, then the evolution simulation is terminated and output results, update attributes of each consumer agent, such as the vehicle age, and create the increment consumer agents. Then go back to step 2) for the next year.

IV. CHARGING BEHAVIOR MODEL

It is noted that home charging is regarded as the most economical and convenient way for private consumers to charge their PEVs, which is mainly considered in this paper.

A. Willingness to charge

The charging habits of electric vehicle users are different, which can be divided into two categories: " charge after the trip" and "charge when needed". Assuming that the charging behavior habits among users are independent from each other, then the charging behavior habit of an electric vehicle cluster approximately obeys the binomial distribution B(n, p), where p is the probability of generating charging intention at the end of travel, and n is the number of PEV users.

Therefore, the willingness to charge their vehicles during the charging demand calculation process is determined through the following two steps: 1) Set the distribution probability of the PEV user cluster p, where $p\in[0,1]$; 2) For each PEV user, generate a random number R subjective to U(0, 1), when $R\leq p$, the PEV user has the intention to charge after trip, namely W=1; when $R>p$, if the state of charge (SOC) of the PEV is lower than the threshold θ, the user produces the charging intention, that is W=1, otherwise, the user does not have the charge intention, namely W=0.

B. Charging strategies

Due to that the charging strategy will influence charging demand profile dramatically, different charging strategies are presented.

(1) Dual charging

In this strategy, the charging process of all PEVs starts with the rated charging power at the moment when arriving with charging intention till disconnected from the distribution network or the SOCs satisfy the expectations without any interruptions.

(2) Time-of-Use pricing

Considering the guidance of time-of-use (TOU) charging prices, PEV users will try to charge when the price is relatively low to improve economy. The objective is to make the following optimization decision:

$$\min \ C = \sum_{t=t_{arr}}^{t_{dep}} \Delta t \times P(t) \times \rho(t) \tag{14}$$

$$S_{exp} \le S(t_{dep}) \le 1 \tag{15}$$

$$P(t)=\{0, \overline{P}\} \tag{16}$$

Where, Δt is time interval, $P(t)$ is charging power at time t, $\rho(t)$ is charging price at time t, $\overline{P}$ is the rated charging power, t_{dep} is departure time, t_{arr} is arriving time, S_{exp} is the expectation SOC of PEV users.

(3) Distributed smart charging

A distributed charging management framework for the PEVs is developed to smooth load curves, which is shown in Fig. 4.

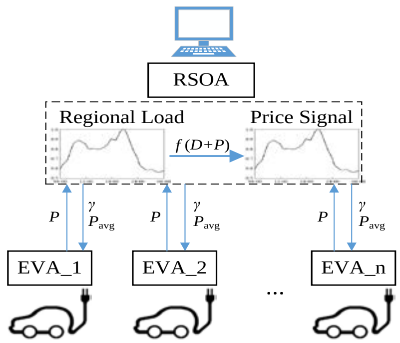


Fig. 4 Structure of the distributed charging strategy

Regional system operator agent (RSOA) will update the charging price signals during each round after receiving all of the charging schedules of electric vehicle agents (EVA). Then it will send it back to each EVA for updating their charging schedules again, till an equilibrium has been achieved. It is noted that the price signal is not the charge price for electricity bill settlement, but a virtual control signal associated with the regional load consisting of conventional load and charging demand. The price signal is formulated as:

$$\gamma(t) = k\left[D(t) + \sum_{i=1}^{N} P_i(t) \right] \Big/ P_{\max} \tag{17}$$

$$P_{\max} = \max(D(t) + \sum_{i=1}^{N} P_i(t)) \tag{18}$$

Where, $D(t)$ is the conventional load at time t, $P_i(t)$ is the charging schedule of EVA_i, N is the scale of PEVs, k is a positive parameter.

It can be seen that the price signal is influenced by charging behavior of all electric car users, indicating that PEV users compete for the limited low-price energy resources. Hence, the charging behavior of other users need to be considered in each round of bidding decisions of EVA. After receiving relevant information (price signal, the average value of the charging plans), EVA updates its charge plan through the following optimization model aiming at minimizing the charge cost and deviation from mass behavior [25]:

$$\min \ J_i = \sum_{t=0}^{T-1} \left\{ \gamma(t) P_i(t) + \delta (P_i(t) - P_{avg})^2 \right\} \tag{19}$$

$$P_{avg} = \frac{1}{N} \sum_{i=1}^{N} P_i(t) \tag{20}$$

$$S_{exp} \le S(t_{dep}) \le 1 \tag{21}$$

$$P_i(t) = 0 \quad t \notin [t_{arr}, t_{dep}) \tag{22}$$

$$0 \le P_i(t) \le \overline{P} \quad t \in [t_{arr}, t_{dep}) \tag{23}$$

C. Charging demand modeling

The flowchart of charging demand calculation under home charging scenarios is depicted in Fig. 5.

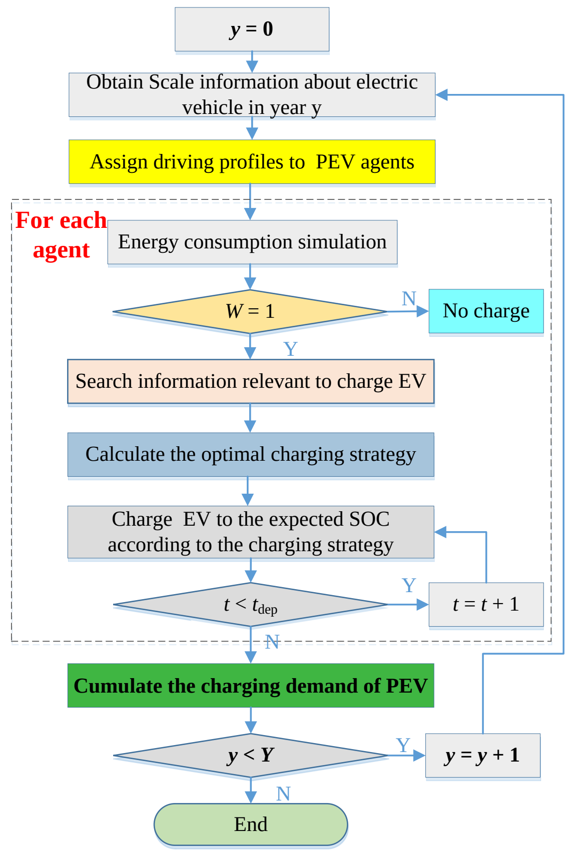


Fig.5 Flowchart of charging demand calculation

1) Obtain PEV scale information in the y-th year, generate and assign driving profiles to each PEV according to travel statistics, including arriving time, departure time and daily distance travelled [30].

2) For each PEV agent, perform the charging behavior.

Firstly, calculate SOC when arriving home:

$$S(t_{arr}) = S(t_{dep}) - \frac{m}{L} \tag{24}$$

Where, m is the daily traveling distance .

Then, if it has the intention to charge, search the relevant information and charge the PEV according to charging strategies with charging power $P(t)$, and the state transition equation of each PEV is:

$$S(t+1) = S(t) + \eta \frac{P(t)\Delta t}{B} \tag{25}$$

Where, η is the charging efficiency, B is the battery capacity.

3) Cumulate charging demand in the study area.

$$P_y(t) = \sum_{i=1}^{N_y} P_i(t) \tag{26}$$

4) If it is the target year, terminate and output the results otherwise continue to simulate for the next year.

V. CASE STUDY

A. Parameters setting

An urban area is taken as an example to verify the proposed model through simulating the evolution patterns of PEVs as well as the charging demand during 20 years. The effect of various impact factors are also analyzed. The basic parameters are set as follows according to regional statistical yearbook and other related statistical data: the number of households in this area is 87726, and there are 52635 vehicles consisting of 99% ICE and 1% PEV in the base year, the growth rate of vehicle scale is λ=0.15-0.012t till achieving saturated state. The annual depreciation rate of ICE and PEV are set as constants r_{dep}=20%, discount rate p=6%, annual vehicle kilometers traveled is subject to normal distribution N(12000, 3000^2), and the vehicle lifetime is set as 10 years. The percentage distribution of vehicle age is {0.2, 0.15, 0.13, 0.12, 0.1, 0.08, 0.07, 0.05, 0.05, 0.05} in the base year. The basic information of ICE and counterpart PEVs are shown in Tab. 1.

TAB. 1 BASIC INFORMATION OF VEHICLES

	ICE				PEV	
Displacement (L)	T_{use} (CNY/year)	P_{veh} (CNY)	r_e (L/100km)	Percentage (%)	L (100km)	B (kWh)
Below 1	180	4~6	5~7	3.07	1.2~1.5	10~16
1.0~1.6	360	6~10	6~10	20.81	1.5~2	16~30
1.6~2.0	420	10~15	7~12	37.43	2~2.5	30~35
2.0~2.5	720	15~40	8~15	26.97	2.5~3	35~45
2.5~3.0	1800	40~80	9~18	10.06	3~4	45~60
3.0~4.0	3000	80~200	12~20	1.66	4~6	60~100
Above 4.0	4500					

The consumer preferences are set based on the results of the user preference parameter identification in [12] and [31] through survey based methodologies. Due to the limitations of battery technologies, the retail prices of PEVs are about twice the price of a conventional car of the same class in the base year, but the price difference will gradually reduce with the breakthrough of technologies and scale effect. The electricity price is set as 0.8 Yuan/kWh, and gas price in base year is 6 Yuan/L. The purchase tax for conventional cars is 1/11.7 of the retail price, but the electric vehicles are exempt from purchase taxes. The subsidy for promoting PEVs is shown in Tab. 2.

TAB. 2 SUBSIDY FOR PROMOTING ELECTRIC PASSENGER CARS

Battery range R /km	100≤R＜150	150≤R＜250	R≥250
National subsidy (CNY)	25,000	45,000	55,000
Local subsidy (CNY)	25,000	45,000	55,000

The expectation SOC of the PEVs are set as 0.9, the charging efficiency is 0.9, and typical rated charging power $\overline{P}$ is set as {2.2kW, 3.6kW, 6.6kW, 8.8kW}. The conventional load curve of the studied area is depicted in Fig. 6, and the maximum load is 0.35GW with an annual growth rate 3%.

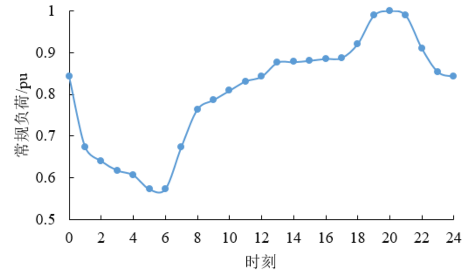


Fig. 6 Conventional load profile of residential area

B. PEVs scale evolution analysis

As the gasoline price, retail price as well as policy incentives are important exogenous baseline factors that construct the environment for consumers to make purchase decisions, three different scenarios are defined as follows:

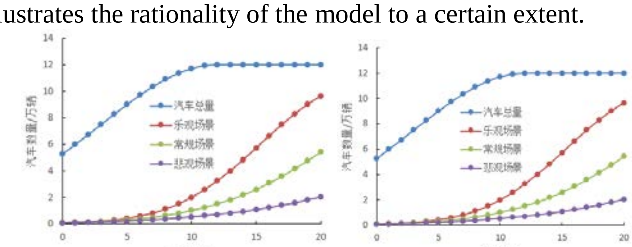
Optimistic scenario: the gasoline price increases with annual growth rate 6%, the retail price difference reduces 10% every year and the subsidy for PEVs decline 10% annually.

Medium scenario: the gasoline price increases with annual growth rate 3%, the retail price difference reduces 8% every year and the subsidy for PEVs decline 15% annually.

Pessimistic scenario: the gasoline price increases with annual growth rate 1%, the retail price difference reduces 5% every year and the subsidy for PEVs decline 20% annually.

(1) PEVs scale evolution patterns

The scale evolution patterns of PEV and ICE during 20 years under three different scenarios, as well as the total population of vehicles are shown in Fig. 7. Overall， it can be seen that the scale of PEV increases continuously over time with factors favoring PEV evolving and the consumers acceptance for PEV improving, while the population of ICE increases at first but declines gradually due to more and more consumers choosing PEV instead of ICE after a period of time. And the evolution pattern of PEV under optimistic scenario is a kind of S curve complying with the general rule of innovation diffusion, which illustrates the rationality of the model to a certain extent.



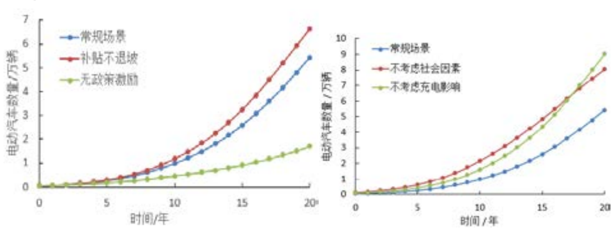
(a) Evolution pattern of PEV (b) Evolution pattern of ICE

Fig.7 Scale evolution of vehicles under different scenarios

Although the vehicles evolution trends in different scenarios consistent, but the specific shape does show a big difference. Specifically, under the optimistic scenario, the penetration of PEV increases slowly in the first 5 years due to technology immaturity, imperfect charging infrastructure deployment as well as low consumer recognition. With the improvement of these factors, the PEV scale steps into rapid development stage after 5th year, and the underline driving force can be explained as: the rising gasoline price, decreasing PEV price and the maturing technology make PEV competitive compared with ICE for consumers, and in turn the social utility of PEV increases with the growing number of PEV adopters, hence the growth rate of PEV adoption exaggerates further, which can be seen as a positive feedback system. Regarding ICE, the scale of ICE grows until the 9th year and shrinks thereafter under optimistic scenario, which will be exceed by the scale of PEVs around the 16th year. And the penetration of PEVs is almost 80.3% in the 20th year under this scenario. However, under medium scenario, the scale of PEV takes off after 7th year, and the population of ICE begin to shrink at 11th year, and 45.1% of the vehicles are PEV in the 20th year. Furthermore, the scale of PEVs increases rapidly after 10th year, and the penetration of PEVs is only 16.6% in 20th year.

(2) Influencing factors analysis

For analysis the impact of various factors on PEV diffusion pattern, different parameters are set accordingly, and the simulation results are shown in Fig. 8. It can be seen from Fig. 8 (a) that the scale of PEV grows relatively slow during 20 years without subsidy for PEV compared with medium scenario and constant subsidy. Therefore, the incentive policy is vital to cultivate the initial PEV market, which can bring more early adopters for PEV through compensating the higher price. However, the impact power of subsidy would reduce gradually, and the growth of PEV scale can be sustain itself when a certain number of PEV adopters exist. In addition, Fig. 8 (b) demonstrates the effect of range anxiety and social dynamics. It is obvious that the recharging effect is a great barrier for the development of PEV, and it is important to reasonably deploy charging facilities to alleviate this defection. Furthermore, by comparing the evolution pattern of PEV without considering social utility and the diffusion pattern under medium scenario, it shows that social utility would exacerbate market inertia, indicating that the impact of social factors cannot be ignored during innovation diffusion process.

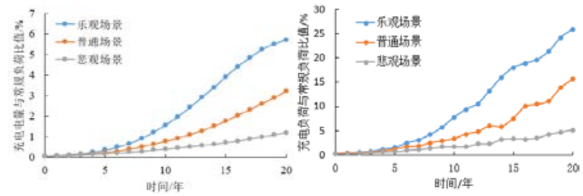


(a) Influence of policies (b) Influence of social and charging factors

Fig.8 Scale evolution of PEV with different parameters

C. *Charging demand analysis*

For evaluating the potential impacts on power systems due to PEVs integration from long-term, two indicators are presented, i.e. the ratio of daily electrical energy demand of PEV to conventional load (RED) and the ratio of maximum charging power with conventional load power (RCP). The simulation results of these two indicators during 20 years under different scenarios are illustrated in Fig. 9. It can be seen from fig. 9(a) that the evolution trends of RED are similar with the scale evolution patterns of PEV and the impacts of PEV integration from energy perspective are not that severe, as the RED is just 0.05% in the base year, and 5.7% in the 20th year even under optimistic scenario. However, the impacts of PEV from power perspective are much more obvious due to the overlapping effect between charging peak and conventional demand peak, and the values of RCP grow to 25.9%, 15.6% and 5.2% in 20th year from 2.9% in base year under optimistic, medium and pessimistic scenarios, respectively. Thus, with the development of PEVs, the charging demand becomes non-ignorable and will challenge the planning and operation of power system, and the charging service network and power distribution network need to be rationally planned and constructed to accommodate the evolution of PEVs



(a) Evolution patterns of RED (b) Evolution patterns of RCP

Fig.9 The potential impacts of PEVs integration under different scenarios

As stated before, the charging behavior habit is an important factor affecting the charging demand characteristics, so different distribution probabilities are chosen and the charging demand curves with p=0, p=0.5 and p=1.0 under optimistic scenario are shown in Fig. 10. It can be seen that the charging peak is delayed and reduced with the decrease of p, due to more "charge when needed" users would reduce the charging coincidence factor. In addition, it also shows that the charging peak occurs around 20:00 consistent with conventional load, which would amplify the negative impact. Hence, charging management strategies need to be deployed to friendly integrate a large population of PEVs into power system without violate the constraints.

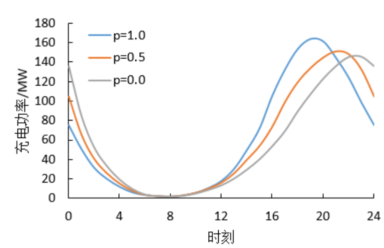


Fig.10 Charging demand under different behavior habits

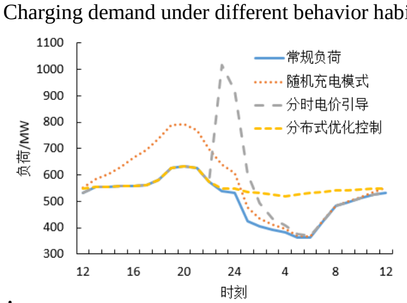


Fig.11 Charging demand of PEVs with different charging strategies

The charging demand of PEVs in 20th year with different charging strategies are shown in Fig. 11. As we can see that, the integration of charging demand will impact distribution system dramatically with dull charging and TOU pricing strategy, which will create new load peak, especially for the TOU pricing strategy, an sudden peak is observed due to users start to charge their PEV at the beginning of the valley price. However, the distributed charging strategy can accommodate PEVs friendly without any risk of violating the constraints of distribution system, and flatten the load profile to improve the operation efficiency of the distribution system.

VI. Conclusion

Considering the interactive relationships between PEVs scale and charging demand, an integrated dynamic framework is proposed in this paper to detect the possible evolution patterns of PEVs from a long-term perspective. Many factors affecting the evolution of PEVs, e.g. economy, social, environment and charging convenience, are incorporated into the vehicle choice model to emulate consumer vehicle purchase behavior. Furthermore, within the charging demand model, PEV users perform charging behavior according to different charging strategies, such as dull charging, TOU pricing guidance and distributed smart charging, and the effect of charging habit is also considered.

Case studies demonstrate the feasibility of the proposed methodology, and a few conclusion can be obtained: 1) The scale of PEVs grows slowly in the early stage, while with the improvement of relevant factors, the growth rate will accelerate and PEVs have a tendency to gradually replace ICEs; 2) The incentive policy for PEVs is vital to cultivate the initial market, but the driving power of subsidy would reduce gradually as the growth of PEV scale; 3) Social dynamics would exacerbate the market inertia, which cannot be ignored during innovation diffusion process; 4) The charging demand is highly dependent on the scale evolution of PEVs, and the specific shape of charging load is determined by users habits and charging strategies; 5) The impact of electric vehicles on the power grid is mainly reflected by charging power demand instead of electrical energy requirement; 6) Proper charging strategies can alleviate the adverse impact due to PEVs integration and improve the operation efficiency of power systems.

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