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RESEARCH ARTICLE

An Agent-Based Real-Time Game Model for Forecasting the Market Penetration of Vehicles in China

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ABSTRACT Internal combustion engine vehicles (ICEs), hybrid, plug-in hybrid and battery electric vehicles (HEVs, PHEVs, and BEVs) represent tradition, high technology, energy conservation and innovation respectively. The new energy vehicles (NEVs) include PHEVs and BEVs. This study innovatively proposes an agent-based real-time game model to simulate the market penetration of vehicles in China. The advantage of the model is in accord with the product diffusion theory and synchronous with the cognition of consumers. The purchase preference is described by a hierarchical variables structure, which forms a probit model with the approximately normal distribution based on the central limit theorem. The results show that when the individual purchase of ICEs will not bring any incentive for others to purchase ICEs, the market penetration of ICEs will decrease. The development of NEVs should focus on their own competitiveness, and the interaction between the proven technology of ICEs and the rapid development of NEVs is useful for NEVs. Restricted with the narrow price range, the market penetration of HEVs will keep steady. Finally, the high interaction frequency is good for NEVs, which indicates that WeMedias will play an important role.

INDEX TERMS Market penetration, real-time, agent-based model, probit model, payoff matrix.

I. INTRODUCTION

The automobile industry is one of the pillars of China's economy, and the sales volume of automobiles is 7.69 million from January to April in 2022. Among them, the sales of passenger cars and commercial vehicles are 6.51 million and 1.18 million respectively, so the development of passenger cars is the most concerned issue in people's life [1]. The sales are mainly distributed in four types of vehicles: internal combustion vehicles (ICEs), hybrid electric vehicles (HEVs), plug-in hybrid electric vehicles (PHEVs) and battery electric vehicles (BEVs). The power of ICEs and HEVs is only made of oil, and the oil consumption of HEVs is usually lower than that of ICEs. The power of PHEVs is made of oil or electricity, and the power of BEVs is only made of electricity.

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The Chinese government classifies PHEVs and BEVs into new energy vehicles (NEVs), and pursues many economic and policy incentives for the development of NEVs.

Although the market penetration (MP) rate of NEVs has exceeded 20% in some restriction purchase cities, the rapid growth still faces some challenges. First, HEVs have attracted many potential consumers, influenced by high oil prices and inadequate charging infrastructure. Tianjin and Guangzhou, two cities with a population of more than 13 million in China, have listed HEVs as fuel efficient vehicles, and their license plate lottery ratio is higher than that of ICEs [1]. Second, the public charging price is three times the household charging price. Assuming the charging cost is 0.15 RMB per kWh, the average operating cost in summer is 0.3 RMB per kilometer, and in winter 0.6 RMB per kilometer [1]. Considering the charging time and queuing time, the operating cost of NEVs is much higher than the expectations. Third, since 2022, the price of BEVs has kept rising. The spread of COVID-19 and the shortage of chips rapidly pushed up the price of raw materials. For example, the price of lithium carbonate has been risen from 50000 RMB/ton in 2021 to 500000 RMB/ton in 2022 [2]. The liquidity and the residual price of second-hand BEVs are significantly lower than that of second-hand ICEs, so the excessive price of BEVs will inhibit the development of NEVs. Fourth, the market share and the number of ICEs is over 97% and 280 million respectively. ICE's technology, insurance, refueling and maintenance are more mature, so they are still the first choice for many potential consumers, especially in the cities with unrestricted purchase.

The research on MP in China should focus on the evolutionary dynamics among them, rather than only one type of vehicle [3]. Although the turn-based gameplay is more common in the current research from the perspective of research methods, the asynchronous gameplay should also be considered [4]. In addition, the two-dimension payoff matrix in previous studies can not reveal the interaction among multi types of consumers adequately, and thus a multi-dimension payoff matrix should be introduced [5]. This paper establishes an agent-based real-time game model to forecast the MP in China. First, a probit model with a three-level variable structure is innovatively proposed to simulate the purchase decision among the four types of vehicles based on the random utility theory and the central limit theorem [6]. The utility of vehicles follows normal distribution with different mean and variance, and the mean is calibrated to a two-figure. The lower level of the range within three standard deviations is still a positive number, so the probit model will not lead to perverse forecasts with the assumption of normal distributions. Second, referring to the product diffusion curve, this paper labels consumers as "seed" and "normal", which have different interaction frequencies and interaction states in the payoff matrix [7]. A normal consumer can be upgraded to a seed consumer through gaining experiences during the iteration process. This dynamic experience mechanism is more suitable for the evolution of consumers. Third, this model has sufficient scalability in the framework to predict the MP, analyze the nexus among different vehicles, and help policy-makers to improve strategies accordingly.

In theory, this paper proposes the real-time game for filling the gap in agent-based models, which has an important reference value for predicting the penetration rate of the automobile market. In practice, this paper also gives some valuable suggestions. For example, we should pay more attention on the development of WeMedias, and it is the best way for developing NEVs by exploring own battery advantages.

The rest of this paper is organized as follows. Section II presents the methodologies for forecasting the MP of vehicles and reviews the related research topics. Section III proposes the methodology, which includes the agent description, the probit model, the payoff matrix, and interaction rules. Section IV provides a detailed case study and the corresponding sensitivity analysis. The managerial and theoretical implications are obtained in Section V. Section VI summarizes the conclusions and limitations.

II. LITERATURE REVIEW

In this section, we present a brief review of the existing literature including two broad streams. The first stream is about various methodologies for forecasting the MP of vehicles. The second stream captures the research topic in the related literatures. In the subsequent subsections, we elaborate upon each of them.

A. METHODOLOGIES FOR FORECASTING THE MP OF VEHICLES

The methods generally fall into two categories: the bottom-up modeling and top-down modeling [8]. Bottom-up models aggregate heterogeneous characteristics of technological or socioeconomic activities [9]. Top-down models apply the macroeconomic theory, econometric and optimization techniques with historical data [10]. At the micro level, Al-Alawi et al. also review three major modeling methodologies for forecasting the MP of vehicles: agent-based models (ABMs), consumer choice models, and diffusion time series models [11]. In addition, some other methodologies are presented as follows.

1) THE COMBINATION OF DESK RESEARCH AND DATA ANALYSIS

The combination of desk research and data analysis is an effective way in consulting and marketing. Zhou et al. list the local incentive for the purchase of a new electric vehicle in China, and compare the sales and the share of NEVs between car and bus [12]. The results show that national and regional incentives can play an important role for pushing the NEVs market. By collecting sales, governmental subsidies, purchase incentives, and specifications of propulsion systems, Propfe et al. identify the possible market share of BEVs from 2010 to 2030, and show that the success of BEVs depends to a great extent on external conditions in Germany [13]. Krupa et al. gather the data from 1000 stated US residents for understanding the factors in the MP of PHEV, and find that financial and battery concerns remain major obstacles [14]. With the SWOT analysis for the road vehicle industry in the United Arab Emirates, Kiani and Ahmed uses population, growth rate and vehicles per person to forecast the MP [15].

The advantage of the combination of desk research and data analysis is that it can give an accurate forecast in the short term. The desk research can order the key index and lead the data analysis. Its disadvantage is that it relies on industry experiences and ignores the emergence from the micro level to the macro level.

2) THE OPTIMIZATION MODEL

The optimization model generally sets the MP as a decision variable or a scale parameter. For example, Palencia et al. use a bottom-up static linear programming optimization model for determining the optimum MP with the objective of maximizing the overall score of the new vehicle sales [16]. The two-steps model combines vehicle fleet stock turnover dynamics and new vehicle market composition analysis to assess the MP. Noori et al. establish a multi-objective optimization model to minimize the life cycle cost, the environment damage cost, and the water footprint life cycle cost [17]. The goal is to find the most appropriate combination of vehicles, and calculate the ideal MP in each U.S. region.

In addition to being a decision variable, it can also be regarded as a scale parameter in sensitivity analysis. For instance, Chen et al. minimize the social cost with the consideration of the MP of autonomous vehicles, and examine the evolution of MP with different unsafety factors [18]. Niroumand et al. develop a novel mixed-integer nonlinear program to control the trajectory of mixed connected-automated vehicles, and propose eight different MP rates for each demand level [19]. Yao et al. study the impact of mixed traffic in centralized control models and decentralized control models with the MP analysis [20].

The advantage of the optimization model is its scalability. It can describe the correlation of different types of vehicles in the constraints, and obtain the optimum MP simultaneously. The disadvantage of the optimization model is that the optimum value is static. For perceiving the change of MP, two-steps models, multi-objective models, bilevel models and sensitivity analysis are the common ways.

3) SUMMARY OF THESE METHODOLOGIES

Compared with various methodologies, the mechanism of ABM is more proper for the vast territories and rich population diversity in China. ABM is a bottom-up method with excellent flexibility, and it can simulate the interactions in the customized environment. ABM generally establishes an if-then rule, which describes the interactions process. Wolinetz et al. develop a Respondent-based Preference and Constraint model to forecast PHEVs market share, in which the consumer discrete choice is the core theory [21]. Silvia et al. give a specification of the agents' attributes, and use eight questions to establish the decision rules depicted by a complicated flowchart [22]. Existing researches enrich the theory of ABM, which involve multiple model variables, different agent types, changeable flow charts and mixed models [23].

They also give some proposals for the MP of NEVs in China. Huang et al. discuss that the combination of government subsidies and charging facility construction is the most effective strategy for BEVs [24]. Zhuge et al. suggest that the MP of BEVs will increase over the period, while the rate of PHEVs remains the same in China [25]. The result is useful for local authorities and manufacturers to invest in technologies and infrastructures of BEVs.

For describing the interactions better, the agent-based evolutionary game model is established to find an appropriate strategy for resolving arising conflicts [26]. The number of agents in the population needs to be determined in advance. These agents interact with a randomly chosen counterpart each time by a symmetric 2-player 2-strategy payoff matrix. The agents will revise their strategies with a certain probability, which can be chosen by the user. At last, a revision protocol specifies that how an agent updates the strategy by obtaining a greater payoff [27].

Policy simulation, traffic and technology diffusion are the mainstream fields of agent-based evolutionary game models around vehicle research. Shi et al. establish a payoff matrix for observing different strategies between an enterprise and its benchmarking enterprise, and simulate enterprises' reaction to multiple policy interventions aiming at promoting the diffusion of low-carbon technologies [28]. Zhou et al. establish a payoff matrix between enterprises and consumers [29]. The enterprises are divided into two groups: one producing BEVs and the other producing ICEs. The consumers are also divided into two groups: one buying BEVs and the other buying ICEs. Anantsuksomsri et al. integrate an ABM with GIS, and develop a theoretical framework to analyze traffic congestion, in which an agent can decide his driving behavior including following traffic regulations or violating traffic regulations [30]. Shi et al. show a payoff matrix of two kinds of enterprises under various policy interventions [31]. By using the data from BEVs, enterprises do not show a high degree of sensitivity to mild carbon taxation. Fan et al. denote the total profit of manufactures as the payoff in the game matrix, and divide the behaviors of manufacturers into selling BEVs and selling ICEs [32].

The advantage is that payoff matrix is an immediate, concise and effective way for delivering information. Scholars generally use networks, if-then rules and equations to define interactions among agents in previous studies. Considering the importance of sensitivity, ABM should push visualization in the interactions, which is a challenging concept in the field of human-computer interaction. Dimara et al. give a definition of this concept, i.e., the interplay between a person and a data interface involving a data-related intent [33]. The payoff matrix is a good alternative for the interactions in visualization, and it should play a greater role in the agent-based evolutionary game model.

The first disadvantage is that mutation increases its complexity. The probability of mutation specifies the boundary condition in revising the optimum strategy, and how to determine the value relies on an empirical test. Since a small difference can lead to a large unforeseen consequence, the effectiveness of emergence will reduce. The second disadvantage is that the prerequisite of mixed strategy Nash equilibrium is the complete information. For incomplete information, the agent updates its behavior after perceiving data, which belongs to the Bayesian equilibrium theory. In addition, there are always rational and irrational agents, and thus the equilibrium solution does not exist in every interaction.

In summary, existing studies do not adequately capture the character of the payoff matrix, and they also ignore some drawbacks in mutation, equilibrium solution, and choice models. In addition, many studies use the multinomial logit (MNL) choice model to simulate the agents' purchase behavior [34]. However, the assumption IIA in MNL, namely the independence from irrelevant alternatives property, is not applicable to the market analysis for the four types of vehicles, since they belong to mutually substitutable products. There is not a closed-form solution for a probit model, and thus we will give different normal distributions to the four types of vehicles for every agent and simulate the purchasing probability in this study.

B. THE RESEARCH TOPIC IN THE RELATED REFERENCES

It is a main research topic for reducing greenhouse gas emissions and promoting the development of NEVs [35]. However, there is still a dispute between sustainable resource and NEVs, a reduction in greenhouse gas emissions and an increase in the human toxicity level [36]. China has adopted the dynamic zero COVID-19 policy for 3 years, which is an effective way to prevent the rapid spread of the virus. On the other hand, China has a population of more than 1.4 billion, and the side effect is a sharp decline in employment, industry, electricity and Logistics indicators. As a pillar of the economy, the vehicle industry should work hard for the economic growth [37]. These researches generally put NEVs as major objective, and ICEs as subordinate objective, which put forward a series of suggestions for increasing the consumer adoption of NEVs [38].

However, the four types of vehicles have different potential markets, and thus the nexus among them is another meaningful topic [39]. The current range of BEVs can not meet a long journey, and the range anxiety is still a boring problem. HEVs and PHEVs have no need for big capacity battery, and they focus on the paralleling connection technology between engine and battery. In contrast, the research and development of BEVs will encounter more challenges, such as high density battery, low temperature performance and software stability. The ICEs represent tradition and stability, the HEVs represent high technology, the PHEVs represent energy conservation, and the BEVs represent innovation and future. The four types of vehicles satisfy more consumer motivations, and the importance of their MP is on an equality level.

This study constructs an agent-based real-time game model among normal agents and seed agents. They move randomly, level up by accumulating experience, and update their purchase utility asynchronously in a multi-dimension payoff matrix. Compared with the mutation in an evolutionary game model, the proposed real-time game mechanism is closer to the reality.

III. METHODOLOGY

A. MODEL OVERVIEW

Figure 1 provides an overview of how agents interact and how their behaviors are modeled. Every humanoid denotes an agent, and different color denotes different types of agents. The green floor denotes the interaction domain. Each agent has his own step frequency, so some agents will move and others will stay during each iteration. The asynchronization simulates a real-time interaction. Each agent has different utility distribution in four types of vehicles. Following a series of interaction behaviors, each agent can make a purchase decision based on the simulated maximum, by updating his normal distribution of the four types of vehicles. The overall MP is averaged by a certain amount of agents.

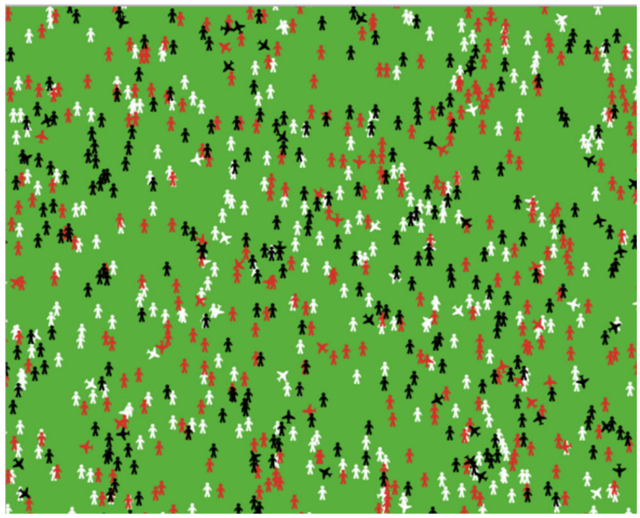

FIGURE 1. An overview of interaction environment.

B. REAL-TIME INTERACTION RULES

Considering the success of two real-time strategy games, i.e., Warcraft III and Diablo 2, an agent-based real-time game model is innovatively proposed [40]. Figure 2 shows the generalized flowchart of the agent-based real-time game model, which is programmed in the open-source software Netlogo [41]. Netlogo is a programmable modeling environment for simulating natural and social phenomena. Turtles and patches are two important concepts in Netlogo. The former denotes the mobile agents, whose behaviors can be defined under various conditions. The latter denotes the stationary grids, which can be defined as any shape.

The concept of the real-time game model comes from real-time strategy games, which have surpassed the popularity of turn-based strategy computer games [42]. The agent-based real-time game model allows all the agents to interact asynchronously with a payoff matrix.

The steps of the simulation cycle are described. First, the necessary parameters are initialized before simulation, and are explained in a yellow block. Second, there are two types of agents, who interact in a common region. The seed agents represent the innovative consumers, who have higher interaction frequency and more power in the payoff matrix than the normal agents. Third, all the agents can decide to move or stay by his own step frequency. When the decision is to move,

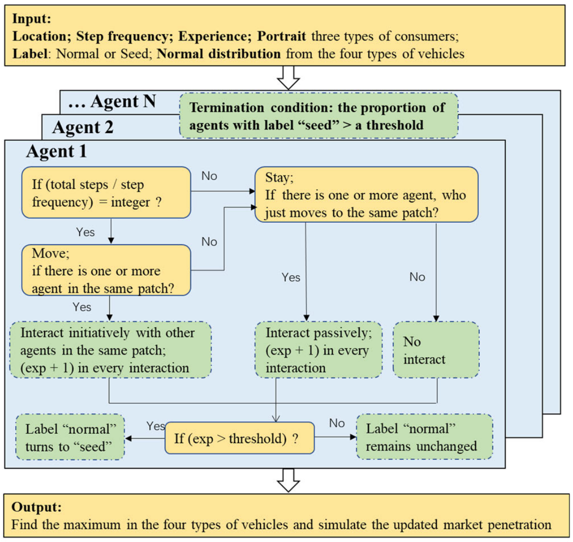

FIGURE 2. Flowchart of the agent-based real-time game model.

the agent can interact with other agents in the same patch. The interaction process can change the normal distribution of the four types of vehicles for each agent. When the decision is to stay, the agent can interact passively with another agent, who just moves to the same patch. Fourth, a normal agent can transform to a seed agent during the diffusion with the increasement of experience and interaction, as shown in Figure 3. Fifth, when the number of seed agents reaches a given threshold, the interaction will be terminated. The real-time interaction has three characters: asynchronous move, different interaction power and transformation by experience accumulation.

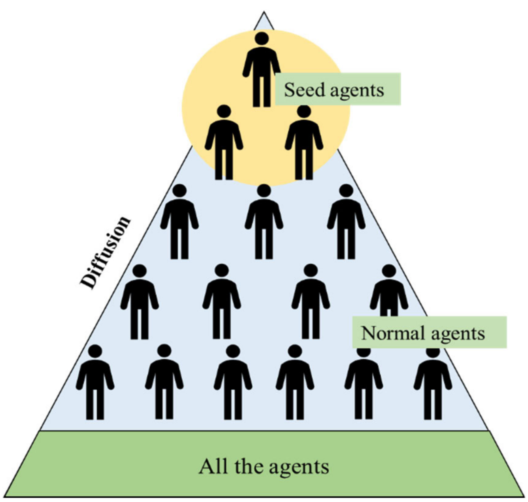

FIGURE 3. The diffusion from seed agents to normal agents.

C. MODEL DESCRIPTION

1) THE NUMBER OF AGENTS AND THE SIZE OF SIMULATION AREA

Chen et al. propose two indexes to balance the number of agents and the size of simulation area, i.e., the per interaction frequency and the interaction ratio [23]. When M agents stay on the same patch, the maximum interaction number is $M \times (M-1)$. Thus, the per interaction frequency equals the average theoretical maximum. The interaction ratio equals the ratio of the specific agents, which include all the agents but exclude those isolated agents on the respective patch. The number of agents should be enough, and Table 1 shows the simulation results. This study sets a base scenario, in which the number of turtles is 9000, and the number of patches is 2500.

TABLE 1. The simulation results of per interaction frequency and interaction ratio.

Number of turtles	Number of patches	Per interaction frequency	Interaction ratio
10000	10000	1.00	63.2%
10000	8100	1.23	70.9%
10000	6400	1.56	79.0%
10000	4900	2.04	87.0%
10000	3600	2.78	93.8%
10000	2500	4.00	98.2%
10000	1600	6.25	99.8%
9000	4900	1.84	84.1%
9000	3600	2.50	91.8%
9000	**2500**	**3.60**	**97.3%**
9000	1600	5.20	99.1%

2) THE BASIC ATTRIBUTES OF AGENTS

With the rapid and uneven development of vehicles in China, there are three types of agents in China's market, i.e., Rookie, Veteran, and New Generation [23]. The portrait and scope of interactions are shown in Figure 4. The blue arrow depicts the direction of interaction. The rookies can interact with all the agents. The veterans can only interact with themselves. The new generations can interact with veterans and themselves. Every type of agents is a mixture of seed agents and normal agents, whose location and initial experience are set to be a random position and 0 respectively. Label S and N denote seed agents and normal agents respectively. The number of rookies with S and N are denoted as A_{rs} and A_{sn}. The number of veterans with S and N are denoted as A_{vs} and A_{vn}. The number of new generations with S and N are denoted as A_{ngs} and A_{ngn}. The step frequency of seed agents and normal agents is denoted as SF_s and SF_n.

3) ESTABLISH A PROBIT MODEL

There are a lot of indexes in the purchase decision-making, and thus the key is how to establish a reasonable random utility model. It is effective to use a hierarchical structure to design the multivariable problem [43], and a three-level variable structure is constructed in this study, as shown in Table 2. Existing studies demonstrate that abundant variables

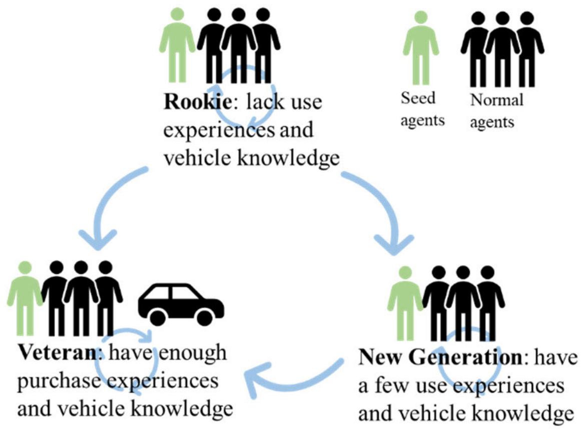

FIGURE 4. The portrait and interaction scope among the three types of agents.

will decrease the validity of emergence, and thus the second level variable is a necessary bridge between them. In reality, fourth level variables also exist. For example, the factors of the oil price include supply, demand, macroeconomic, international politics, gold market, shares market, speculation and psychology, etc. Assuming the oil price is the average of all the factors, its value approximately follows the normal distribution according to the central limit theorem.

TABLE 2. The structure of hierarchical variables.

First level variables	Purchase preference		
Second level variables	Purchase level	Use level	Product level
Third level variables	The price distribution of vehicle	The number of charging infrastructures	The residual price of a second-hand car
	The number of brands	The distribution of charging infrastructures	Battery warranty policy
	Purchase tax	The charging speed of charging infrastructure	NVH
	The subsidy in vehicle price	The price of oil	Innovation
	The license-plate lottery ratio	The price of charging	Range of NEV and PHEV
		Traffic restrict time and region	Vehicles ownership
		The traffic conditions	

For the probit model, this study adopts the following three reasonable assumptions. All the third level variables are at the same micro level, so they follow normal distributions with different mean and the same variance of 1. Based on the hierarchical structure, the assumption 2 and 3 assume a linear combination between different level variables.

Assumption 1: The third level variables follow normal distributions with different mean and the same variance of 1.

Assumption 2: The utility of the second level variables is a linear combination of the corresponding third level variables.

Assumption 3: The utility of purchase preference is a linear combination of the second level variables.

For each third level variable, this study distributes different mean to the four types of vehicles, as shown in Table 3. For example, the purchase tax is exempted for NEVs, but not for ICEs or HEVs, and thus the mean of NEVs is higher. With the huge number and high acceptance, the sale and price of a second-hand ICE are more stable, and thus the mean is set to be a higher value. Many cities have issued traffic restriction time and region for regulating ICEs, and thus the mean for ICEs is lower than other types of vehicles. The utility of purchase tax is distributed by four normal distributions, $N(1,1)$, $N(1,1)$, $N(4,1)$ and $N(4,1)$, where the sum of mean equals 10.

Other third level variables are analyzed by the same way, and the data is collected from the expert survey in China Automotive Technology & Research Center. Based on the assumption 2 and additivity of normal distribution, the normal distribution of second variables are calculated and bold in Table 3. For example, the utility of purchase level for ICEs follows $N(11,5)$, which obeys the sum $N(4,1)+N(4,1)+N(1,1)+N(1,1)+N(1,1)$.

Considering the different number of the third level variables, we nondimensionalize the mean and variance, where the non-dimension sum of mean equals 100. Based on the assumption 3 and additivity of normal distribution, the first level variable, purchase preference, follows a normal distribution, as shown in Table 4. For example, the utility of purchase preference for ICEs follows $N(83.31, 7.14^2)$, which obeys the sum $N(22,20)+N(17.14,14.29)+N(44.17,16.67)$. The probit model is fully elaborated. It is reasonable that the purchase preference follows a normal distribution.

The utility of purchase preference for the four types of vehicles are denoted as N_{ice}, N_{hev}, $N_{phev}$and N_{bev}, which generate four random values in each simulation. The maximum denotes the decision of the agent, which simulates the MP with one hundred thousand times. Obviously, the MP obtained by simulation is inconsistent with the real situation, and thus calibration will be discussed in the next subsection.

4) CALIBRATION AND VERIFICATION

The real MP data from 2018 to 2021 is listed in Table 5. Beijing, Guangzhou, Tianjin, Shenzhen and Shanghai are all restriction purchase cities with a population of over 15 million. In the nationwide region, the NEVs have a remarkable growth in 2021, where the proportion of BEVs and PHEVs is 11.8% and 2.1% respectively. Guangzhou and Tianjin increase the license-plate lottery of HEVs, and thus the proportion of HEVs is relatively higher, which are 9.0% and 6.2% respectively in 2021. Table 5 is derived by

TABLE 3. Normal distribution with different mean and the same variance of 1.

Purchase level	ICE	HEV	PHEV	BEV
The price distribution of vehicle	N(4,1)	N(2,1)	N(1,1)	N(3,1)
The number of brands	N(4,1)	N(2,1)	N(1,1)	N(3,1)
Purchase tax	N(1,1)	N(1,1)	N(4,1)	N(4,1)
The subsidy in vehicle price	N(1,1)	N(1,1)	N(4,1)	N(4,1)
The license-plate lottery ratio	N(1,1)	N(3,1)	N(3,1)	N(3,1)
Sum of purchase level	**N(11,5)**	**N(9,5)**	**N(13,5)**	**N(17,5)**
Use level	**ICE**	**HEV**	**PHEV**	**BEV**
The number of charging infrastructures	N(3,1)	N(3,1)	N(2,1)	N(2,1)
The distribution of charging infrastructures	N(2,1)	N(2,1)	N(3,1)	N(3,1)
The charging speed of charging infrastructure	N(3,1)	N(3,1)	N(2,1)	N(2,1)
The price of oil	N(1,1)	N(3,1)	N(3,1)	N(3,1)
The price of charging	N(1,1)	N(2,1)	N(3.5,1)	N(3.5,1)
Traffic restrict time and region	N(1,1)	N(1,1)	N(4,1)	N(4,1)
The traffic conditions	N(1,1)	N(2,1)	N(3.5,1)	N(3.5,1)
Sum of use level	**N(12,7)**	**N(16,7)**	**N(21,7)**	**N(21,7)**
Product level	**ICE**	**HEV**	**PHEV**	**BEV**
The residual price of a second-hand car	N(7,1)	N(1,1)	N(1,1)	N(1,1)
Battery warranty policy	N(5.5,1)	N(1.5,1)	N(1.5,1)	N(1.5,1)
NVH	N(2.5,1)	N(2.5,1)	N(2.5,1)	N(2.5,1)
Innovation	N(1,1)	N(2,1)	N(3,1)	N(4,1)
Range of NEV and PHEV	N(3.5,1)	N(3.5,1)	N(2,1)	N(1,1)
Vehicles ownership	N(7,1)	N(1,1)	N(1,1)	N(1,1)
Sum of product level	**N(26.5, 6)**	**N(11.5, 6)**	**N(11,6)**	**N(11,6)**

TABLE 4. The utility of variables by non-dimension.

Purchase level	ICE	HEV	PHEV	BEV
Normal distribution	N(11,5)	N(9,5)	N(13,5)	N(17,5)
Normal distribution by non-dimension	N(22,20)	N(18,20)	N(26,20)	M(34,20)
Use level	**ICE**	**HEV**	**PHEV**	**BEV**
Normal distribution	N(12,7)	N(16,7)	N(21,7)	N(21,7)
Normal distribution by non-dimension	N(17.14, 14.29)	N(22.86, 14.29)	N(30.00, 14.29)	N(30.00, 14.29)
Product level	**ICE**	**HEV**	**PHEV**	**BEV**
Normal distribution	N(26.5,6)	N(11.5,6)	N(11,6)	N(11,6)
Normal distribution by non-dimension	N(44.17, 16.67)	N(19.17, 6.67)	N(18.33, 16.67)	N(18.33, 16.67)
Purchase preference	**ICE**	**HEV**	**PHEV**	**BEV**
Normal distribution	$N(83.31, 7.14^2)$	$N(60.02, 7.14^2$	$N(74.33, 7.14^2)$	$N(82.33, 7.14^2)$
MP by simulation	**49.3%**	**0.1%**	**8.7%**	**41.8%**

the sales, which is from China Association of Automobile Manufacturers.

The normal distribution in Table 4 needs a calibration to conform with the real data. We fix the mean and standard deviation of PHEV, and multiply the coefficient and the normal distribution of ICEs, HEVs and BEVs. The updated purchase preference is listed in Table 6, and it can be seen that the simulated MP is close to the real data.

TABLE 5. The MP in China and some big cities.

Nationwide	ICE	HEV	PHEV	BEV	NEV
2018	94.7%	1.0%	1.0%	3.3%	4.3%
2019	94.3%	1.5%	0.9%	3.3%	4.3%
2020	92.0%	2.2%	0.9%	4.8%	5.8%
2021	83.1%	2.9%	2.1%	11.8%	13.9%
Beijing	**ICE**	**HEV**	**PHEV**	**BEV**	**NEV**
2018	81.8%	1.8%	0.3%	16.1%	16.4%
2019	82.6%	2.6%	0.4%	14.4%	14.8%
2020	78.0%	4.4%	0.3%	17.3%	17.6%
2021	71.2%	5.2%	1.0%	22.6%	23.6%
Guangzhou	**ICE**	**HEV**	**PHEV**	**BEV**	**NEV**
2018	85.9%	3.8%	4.9%	5.4%	10.3%
2019	79.7%	6.5%	3.4%	10.4%	13.8%
2020	79.2%	9.3%	1.5%	10.0%	11.5%
2021	68.0%	9.0%	3.2%	19.8%	22.9%
Tianjin	**ICE**	**HEV**	**PHEV**	**BEV**	**NEV**
2018	76.1%	4.6%	3.4%	15.9%	19.3%
2019	81.9%	5.4%	4.0%	8.8%	12.7%
2020	79.7%	6.2%	2.7%	11.5%	14.1%
2021	71.8%	6.2%	5.1%	16.9%	21.9%
Shenzhen	**ICE**	**HEV**	**PHEV**	**BEV**	**NEV**
2018	74.3%	1.8%	11.8%	12.0%	23.9%
2019	78.3%	2.0%	6.6%	13.1%	19.7%
2020	76.5%	2.7%	6.1%	14.7%	20.8%
2021	60.3%	3.3%	8.9%	27.5%	36.4%
Shanghai	**ICE**	**HEV**	**PHEV**	**BEV**	**NEV**
2018	87.0%	0.9%	8.2%	3.9%	12.1%
2019	88.8%	1.4%	5.8%	4.1%	9.9%
2020	77.7%	1.9%	7.6%	12.8%	20.4%
2021	62.8%	2.1%	10.5%	24.7%	35.2%

TABLE 6. The updated normal distribution by calibration.

Baseline	ICE	HEV	PHEV	BEV
Coefficient	1.06	1.24	1	0.98
Original normal distribution	$N(83.31, 7.14^2)$	$N(60.02, 7.14^2)$	$N(74.33, 7.14^2)$	$N(82.33, 7.14^2)$
Updated normal distribution	$N(88.31, 7.57^2)$	$N(74.43, 8.85^2)$	$N(74.33, 7.14^2)$	$N(80.69, 7.00^2)$
Simulation	**68.8%**	**7.4%**	**4.8%**	**19.0%**

D. PAYOFF MATRIX

We multiply two labels and four possible choices in vehicles, and obtain an 8×8 payoff matrix. It is an intractable problem for assigning 64 payoff values one by one, and thus we use if-then rules to divide the matrix into four regions. There are four colors: light green, dark green, light blue, and dark blue. The description of four if-then rules and the corresponding region color are shown in Table 7.

In the light green region, when the simulated choices are identical, the two agents will increase their own preference in some types of vehicles. In the dark green region, the simulated

TABLE 7. The description of if-then rules.

Number of if-then rule	Description of if-then rules	Color of region
1	The simulated choices between two agents are identical, and exclude the ICE	Light green
2	The simulated choices between two agents are identical, and only the ICE	Dark green
3	The simulated choices between two agents are inconsistent, and both exclude the ICE	Light blue
4	The simulated choices between two agents are inconsistent, and at least one of them is the ICE	Dark blue

choices are still identical. Considering the huge number of ICEs, the choice of ICE is unattractive for increasing preferences, and thus the payoff value is (0,0) between two seed agents. In the light blue region, when the simulated choices are inconsistent, the two agents will decrease the preference in their own vehicles. Similarly, the normal agents have a larger decrease. In the dark blue region, the inconsistent choices will bring change for normal agents, not seed agents.

Table 8 gives all the parameters in the payoff matrix, where they are all positive numbers. The parameter *st* denotes the benchmark value, and other parameters *d, d1, d2* and *i* denote the various product with different coefficient and *st*.

Seed agents have more power than normal agents in the interactions, and thus the inequality $i \geq st \geq d \geq 0$ holds in general. For example, one seed agent and one normal agent encounter with the same choice in HEVs, and thus the corresponding payoff value is *(d,i)*, which means that the normal agent will get more incentive in purchase preference. All the payoff values are verified by the experts from the automotive engineering research institute.

Each agent has an interaction vector $iv = (v_1, v_2, v_3, v_4)$, each component of which is a one-to-one match among ICEs, HEVs, PHEVs and BEVs sequentially. The *iv* is initialized as (0, 0, 0, 0), and will be continuously updated in each iteration based on the payoff value. For example, two normal agents encounter with the same choice in HEV, and the payoff value is *(st,st)*. The updated $iv' = (v'_1, v'_2, v'_3, v'_4)$ is denoted as (v_1, v_2+st, v_3, v_4). The agent will have a choice vector, which is denoted as $cv = (v'_1+N_{ice}, v'_2+N_{hev}, v'_3+N_{phev}, v'_4+N_{bev})$. Comparing all the components of *cv*, the maximum represents the current choice among the four types of vehicles.

IV. RESULTS

We list all the assumptions made during the model's construction and simulations. First, there are three types of agents, denoted as Rookie, Veteran, and New Generation. Second, the purchase preference can be described by a structure of hierarchical variables. Third, based on the central limit theorem, the additivity of normal distribution and linear combination of variables is used to establish a probit model.

There are some potential biases and uncertainties. First, it is assumed that each third level variable has its own fourth level variables, which are not displayed in the hierarchical structure. An example of oil price is given for validating the rationality. Second, the variance of all the third level variables equals 1. The purchase preference is given by different mean and variance, and thus the assumption is still feasible.

A. PARAMETER INITIALIZATION

Without interactions, the simulated MP is 68.8%, 7.4%, 4.8% and 19.0% for ICE, HEV, PHEV and BEV respectively. We initialize a baseline scenario, and all the parameters are shown in Table 9. When the two choices are both ICEs, the probability of the interaction is close to 50%, which is calculated by 68.8 X68.8%=47.3%. The payoff value *d1* is an important factor in the iterations.

The result of the baseline scenario is shown in Figure 5, where the MP of ICE is generally larger than others. For displaying the change better, we use the left axis to paint a scatter diagram of ICE, and the right axis to paint 3 smoothed line scatter diagrams. When the iteration terminates after 114 times, the MP is 64.3%, 8.3%, 6.4% and 21.0%. The MP of ICE decreases 4.5 percentage points, which means that a low *d1* can lead to a decline of ICE.

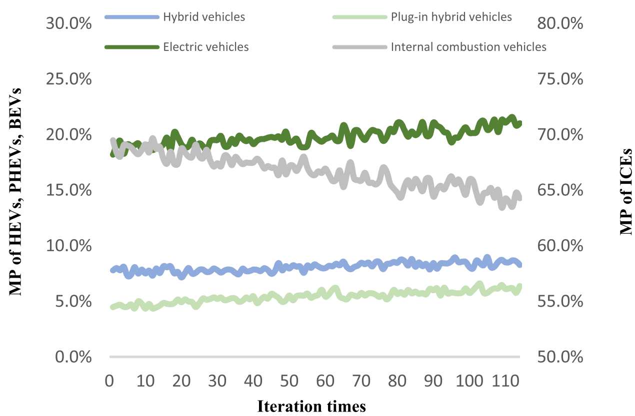

FIGURE 5. The MP under the baseline scenario.

B. COMPARISON WITH NO REAL-TIME INTERACTION RULES

The characteristics of no real-time interaction rules are as follows. First, all the agents move at the same step frequency. Second, the interaction scope is consistent. For example, all the agents can be set as normal rookies. Third, a normal agent can not transform to a seed agent by experience accumulation. Accordingly, the terminated condition is also changed, and thus the same interaction times are simulated. Compared with the initial value in Table 9, we set *Arn =9000* and *SFn=1*, and other numbers of agents equal 0. The results with scatter diagram are shown in Figure 6.

Figure 6 shows that the scatter diagram of MP in BEVs and ICEs has a larger increment and decrement, but their trends are identical. The scatter diagram of MP in HEVs and

TABLE 8. The payoff matrix.

		Ice	Hev	Phev	Bev	Ice	Hev	Phev	Bev
		S	S	S	S	N	N	N	N
Ice	S	*(0,0)*	*(0,0)*	*(0,0)*	*(0,0)*	*(0,d1)*	*(0,-d2)*	*(0,-d2)*	*(0,-d2)*
Hev	S	*(0,0)*	*(d,d)*	*(-d,-d)*	*(-d,-d)*	*(0,-d2)*	*(d,i)*	*(-d,-i)*	*(-d,-i)*
Phev	S	*(0,0)*	*(-d,-d)*	*(d,d)*	*(-d,-d)*	*(0,-d2)*	*(-d,-i)*	*(d,i)*	*(-d,-i)*
Bev	S	*(0,0)*	*(-d,-d)*	*(-d,-d)*	*(d,d)*	*(0,-d2)*	*(-d,-i)*	*(-d,-i)*	*(d,i)*
Ice	N	*(d1,0)*	*(-d2,0)*	*(-d2,0)*	*(-d2,0)*	*(d1,d1)*	*(-d2,-d2)*	*(-d2,-d2)*	*(-d2,-d2)*
Hev	N	*(-d2,0)*	*(i,d)*	*(-d,-i)*	*(-d,-i)*	*(-d2,-d2)*	*(st,st)*	*(-st,-st)*	*(-st,-st)*
Phev	N	*(-d2,0)*	*(-d,-i)*	*(i,d)*	*(-d,-i)*	*(-d2,-d2)*	*(-st,-st)*	*(st,st)*	*(-st,-st)*
Bev	N	*(-d2,0)*	*(-d,-i)*	*(-d,-i)*	*(i,d)*	*(-d2,-d2)*	*(-st,-st)*	*(-st,-st)*	*(st,st)*

TABLE 9. The initial value in the model.

Index	Description	Value
Number of patches	The patches form the simulated region, and multiple agents will interact in the same patch.	50x50
Number of agents	In enough number, the MP is simulated by average.	*Ars=300, Arn=2700, Avs=300, Avn=2700, Angs=300, Angn=2700*
Location	The initial location in the 50*50 parches.	The locations of 9000 agents are distributed randomly.
Step frequency	When the number of iterations is divided by step frequency, the agent will move.	*SFs=1*; *SFn* is a random integer in [2, 5].
Terminated condition	When the proportion of seed agents is over the threshold, the simulation is stopped.	The threshold is 0.5.
Experience threshold	When the accumulated experience is over the threshold, a normal agent will become a seed agent	The threshold is 200.
Move	The definition of a movement.	Turn right a random number in [0, 90']. Turn left a random number in [0, 90']. Forward 1.
Payoff value	Initialization of i, st, d, d1 and d2.	*st=0.3; d=st/2; d1=st/10; i=1.5xst; d2=st/2.*

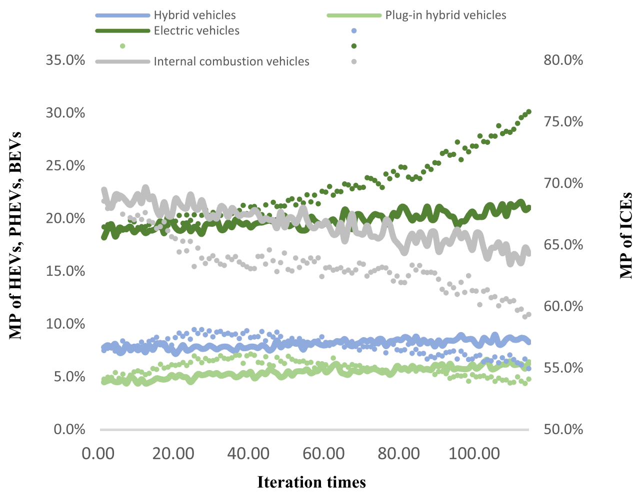

FIGURE 6. The comparison with no real-time interaction rules.

PHEVs first increase and then decrease, and the MP is 5.8% and 4.8% respectively. We generally use months or years as time units in the research on ABM, but the choice of unit is subjective. The disadvantage of the scatter diagram is that it lacks a clear terminated condition, and thus the reliability of MP is uncertain.

The advantage of real-time interaction models is closer to reality. The development of vehicles is synchronized with consumer cognition, so the ratio of seed consumers accords with the product diffusion theory. Iteration times rather than the time is used as the horizontal axis in the real-time interaction model.

C. SENSITIVITY ANALYSIS

1) THE IMPACT OF *ST*

The *st* represents the identity of normal agents in purchasing HEVs, PHEVs and BEVs, which is a standard value in the payoff matrix. The value of *st* represents the fluctuation during the interactions, which is related with other parameters. We set *st=0.1, 0.2, 0.4* respectively to compare with the baseline scenario, as shown in Figure 7. The increment of *d1* is 0.01, but the MP of ICEs decreases 1.2, 1.7 and 2.7 percentage points respectively, which means that the increment *d1=st/10* can not offset the decrement *-d2=-st/2*. Meanwhile, HEVs, PHEVs and BEVs all show varying degrees of increase, with 0.9, 1.4 and 3.3 percentage points respectively. Based on the current coefficients, the negative correlation holds between the *st* and the MP of ICEs.

2) THE IMPACT OF *D*

The *d* represents the identity of seed agents in purchasing HEVs, PHEVs and BEVs. The seed agent knows his own mind, and thus $st \geq d$ holds. We set *d=st/2*in the baseline scenario, and the sensitivity of *d* is shown in Figure 8. No matter how the *d*changes, the MP keeps steady. The situation

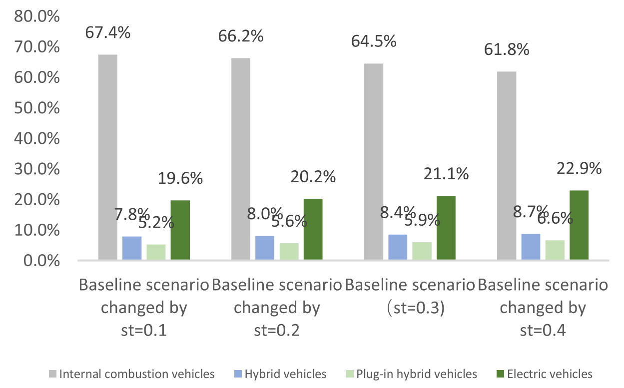

FIGURE 7. **The impact of *st* on the MP.**

means that it has a low impact on MP for increasing the identity of seed agents.

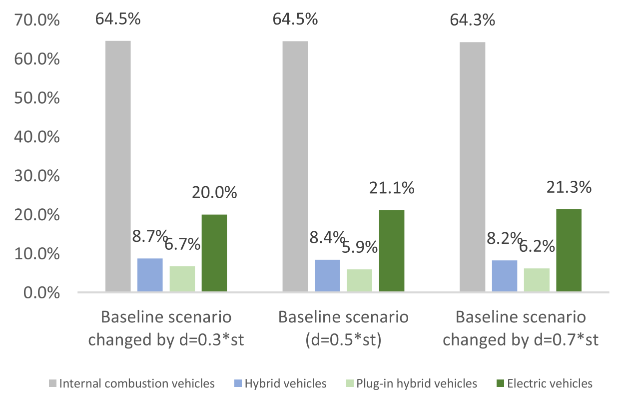

FIGURE 8. **The impact of *d* on the MP.**

3) THE IMPACT OF *D1*

The *d1* represents the identity in purchasing ICEs. A low identity will reduce the MP of ICEs, and thus we set $d1/st=0$, $d1/st=0.2$, $d1/st=0.3$ to compare with the baseline scenario, as shown in Figure 9. $d1=0$indicates that the identity in purchasing ICEs has disappeared. The dark green and dark blue regions demonstrate the inevitable decline in the MP of ICE, where there are no positive payoff values. The MP of ICE increases 21.1 percentage points from $d1=0.1*st$ to $d1=0.3*st$.The MP of ICE is 85.6%, which is close to the nationwide data in 2021. The ratio $d1/st=0.3$represents the scenario of cities without restriction purchase.

4) THE IMPACT OF *D2*

The *d2* represents the loss between two different purchase decisions. One is an ICE, and the other is one of HEV, PHEV or BEV. When two normal agents interact, both have a loss *d2* to update their interaction vector. When two seed agents interact, both have no loss to update. When a normal agent and a seed agent interact, the former has a loss *d2* and the latter has no loss. Decreasing the *d2* means that the purchase of ICEs will has a low impact on the other purchase of

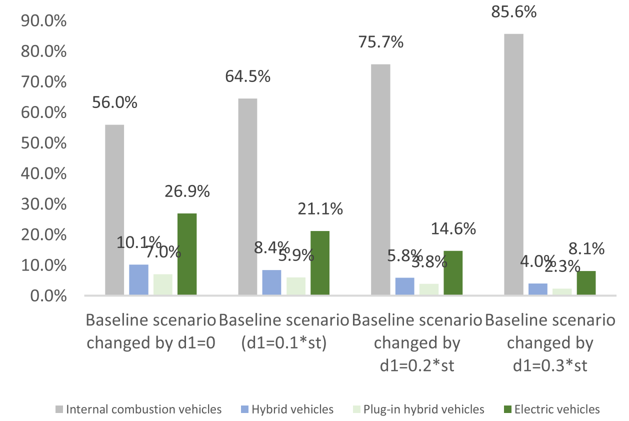

FIGURE 9. **The impact of *d1* on the MP.**

HEVs, PHEVs or BEVs, as shown in Figure 10. When $d2=0$ and $d2=0.25*st$ holds, the MP of ICEs increases by 6.1 and 15.5 percentage points, compared with 64.5%.

The negative correlation exists between the *d2* and the MP of ICEs. When $d1=0$and $d2=0$, all the payoff values related with ICEs are zero. The special situation means that the choice component in ICEs remain unchanged with N_{ice}, and the MP of ICEs still increases 1.7 percentage points. The result validates a conclusion that reducing the impact of ICEs cannot promote the development of NEVs and HEVs unilaterally.

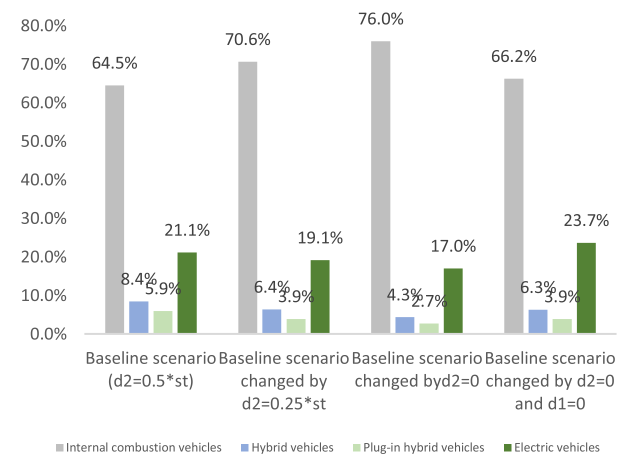

FIGURE 10. **The impact of *d2* on the MP.**

The development of NEVs should focus on their own competitiveness. The long history of ICEs has nurtured many vehicle cultures, including racing cars, classic cars, modified vehicles, etc. Even if the impact of ICEs is weakened, the rich culture and the consumption inertia will keep the growth of ICEs, as shown in Figure 10. NEVs have created many innovative vehicle scenarios with the unique electric system: remote control, autonomous driving, temporary energy center, etc. If the charging speed and charging convenience can be improved, the MP of NEVs can continue to increase.

V. DISCUSSION

A. THE IDENTITY OF ICES

Chengdu and Zhengzhou are cities without restriction purchase in China with a population of over 20 million and 12 million respectively, and the MP from 2018 to 2021 is shown in Table 10. Even in 2021, the MP of ICEs is still over 80%. The market share of ICEs is dominant in China, and thus the impact of ICEs is an important factor for MP. When two inconsistent purchases encounter, both will hesitate the former decision, especially in normal agents. Figure 10 represents a negative correlation between the impact of ICEs and the MP of ICEs, even if the identity of ICEs equals to 0.

TABLE 10. The MP in Chengdu and Zhengzhou from 2018 to 2021.

Chengdu	ICE	HEV	PHEV	BEV	NEV
2018	96.7%	0.8%	0.7%	1.8%	2.5%
2019	94.9%	1.0%	1.0%	3.1%	4.1%
2020	92.4%	1.4%	1.1%	5.1%	6.1%
2021	80.4%	1.9%	2.0%	15.6%	17.6%
Zhengzhou	**ICE**	**HEV**	**PHEV**	**BEV**	**NEV**
2018	92.2%	0.7%	0.4%	6.7%	7.1%
2019	94.9%	1.1%	0.7%	3.2%	3.9%
2020	91.8%	2.1%	1.0%	5.1%	6.1%
2021	81.0%	2.7%	2.6%	13.8%	16.4%

In the payoff matrix, the *d1* represents the identity of ICEs. When the purchase of ICEs will not bring any incentive for anther purchase of ICEs, the MP of ICEs will decrease obviously. Some best-selling vehicles from NEVs and HEVs attract many consumers. As a pioneering product, Tesla Model 3 attracts all the spotlight with the unique innovation and technology, which makes the purchase of traditional ICEs lose its charm and sells 0.5 million in 2021. Domestic brand BYD issues DM-I hybrid technology, which bring an amazing sales volume of 0.6 million in 2021. The second sales volume is 0.12 million from another domestic brand AION. As a HEV, the sales of the hybrid Corolla are 0.25 million in 2021.

Generally, the COVID brings a profound influence on the social economy and life in China, but the NEVs sales of Tesla and BYD achieve 0.9 million and 1.2 million from January to September in 2022. These best-selling vehicles from NEVs or HEVs will stimulate the purchase of ICE, which explains why the payoff value (*-d2, -d2*) happens between two normal agents. The proven technology in ICEs and the fast development in NEVs will increase the impact of ICEs and the reaction of NEVs, and thus the MP of ICEs will continue to decrease in the short term.

B. THE NUMBER AND INTERACTION FREQUENCY OF AGENTS

The role of a seed agent is a pioneer, who guides the product diffusion [44]. Figure 11 shows the updated MP when the ratio or the activity range of seed agents increases. The experience threshold represents the transformation condition from normal agents to seed agents. It is insensitive to the change of MP by adjusting the ratio of seed agents, but it is an effective way by increasing the interaction number. The iterations of four scenarios are 114, 88, 45 and 131 sequentially, and the corresponding MP is 64.5%, 65.2%, 66.7% and 62.7% in ICEs.

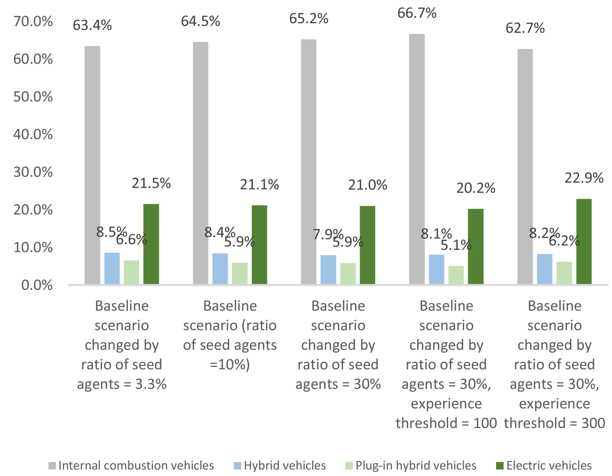

FIGURE 11. The MP with a change of ratio or experience threshold.

The change of the interaction frequency is more sensitive to the MP. First, the MP of HEVs deserves attention. When the ratio of seed agents increases from 10% to 30%, the MP of HEVs decreases 0.5 percentage points, and the MP of NEVs remain unchanged. Toyota and Honda contribute most sales of HEVs, the price range of which is between 160000 RMB and 250000 RMB. The few alternate brands and narrow price range form a particular segment population, who are insensitive to the change of number.

Second, the MP of HEVs will keep steady in the short term. From January 2022 to July 2022, the MP of HEVs is 9.9% between 160000 RMB and 250000 RMB, compared with 0.8% between 120000 RMB and 160000 RMB. HEVs loads a 1.8 kwh small battery, so the price is closed to the same type of ICEs theoretically. Dominated by Japanese enterprises, the higher price range will continue to exist in the short term. Although the domestic enterprise, Geely Auto, has developed Leishen Power as an intelligent hybrid system, the expansion of the price range needs more efforts from the domestic enterprises.

Third, the more the normal agents interact, the more the MP of NEVs will increase, which is shown in Figure 11. The boom of short videos brings high views in Bilibili App or Douyin App. The former achieves 17 billion views every day during 2021, and the latter achieves 6 billion active users every day. Some hot WeMedias own over ten million fans, and publish the introduction of new vehicle, performance test, second hand vehicle information, driving experience and so on, where a lot of potential consumers communicate. For example, in 2021, the event of runaway Tesla becomes a bomb news, which was commented and forwarded by a large number of WeMedias. The event triggered heated discussions among supporters, opponents and neutrals, and attracted many potential consumers to know about NEVs. Whether the event is premeditated or accidental, Model 3 is well-known. These typical circle marketing, event marketing or node marketing will accelerate the interaction frequency, and thus the MP of NEVs will increase.

C. LIMITATIONS

This research contributes an innovative methodology with practical reference value, there are also some limitations. The first limitation is on the three types of agents, who are in accord with the consumer portrait and have different interaction scope. The case ignores the difference in purchase utilities for every type of agents, which can be specified by interview or questionnaire. For example, the Rookies can have a higher mean in ICEs and a lower mean in NEVs than the New Generation. For each type of vehicle, there exists three different normal distribution for Rookie, Veteran, and New Generation. Multiple normal distributions increase the model's accuracy and complexity, and also bring a challenge in calibration. The second limitation is on the payoff value, which is given by empirical data. The initialization can be refined by survey in further research. For example, the power of seed agents can be amplified by adjusting values.

VI. CONCLUSION

In the past decades, China's domestic brands have been catching up with Honda, Benz, Toyota, etc., but there is still a gap, especially in the internal combustion engine and automatic transmission. The development of new technologies and new energies has broken the long-term leading position of ICEs and brought new opportunities for NEVs in China. Considering range anxiety and lifecycle cost, HEVs is a nice compromise option. The main findings and suggestions of this study are as follows. First, the MP of ICEs will decrease in the short term. The manufacturers can start a sale in ICEs for liquidating their inventory. The ICEs are still popular in many unrestricted traffic regions. Second, the development of NEVs should focus on their own competitiveness. The battery power provides a better condition for intelligence, which can cope with more usage scenarios. It is the key for developing NEVs by exploring more unique advantages. Third, the MP of HEVs will keep steady in the short term. Low oil consumption is an obvious advantage, and the price is a primary obstacle. If the price can be decreased below 100000 RMB, the MP may outbreak in China's market. Fourth, the MP of NEVs will continue to increase, and WeMedias can play an important role for the MP. In the recent information technology socialization time, traditional newspaper or TV have lost their roles in advertisement. We should make full use of new media such as WeChat, as well as new technologies such as Artificial Intelligence and Metaverse marketing to promote the development of cars.

This study has some innovations in the following aspects. First, in the real world, asynchronous and synchronous behaviors coexist, and thus the turn-based strategy is a specialization of real-time strategy. The model defines normal agents and seed agents to interact asynchronously, who have different interaction domains and interaction frequencies. Second, a hierarchical variable structure and a probit model are established to describe purchase preferences. The former solves the dilemma between abundant micro variables and macro emergence. The latter uses the hierarchical linear combination and the central limit theorem to construct the normal distribution in the four types of vehicles. Third, the information exchange is visualized through a payoff matrix, which extends the application of game theory in ABM. A two-dimension payoff matrix is usually used to obtain the equilibrium solution in previous researches. However, a multi-dimension payoff matrix is more suitable for showing the interactions between rational agents and irrational agents.

ABM is popular in economics and social sciences. There are some avenues for future research. First, the agent-based real-time game model can be applied for predicting a best-selling car, and help manufacturer make the life cycle management. Compared with using historical data, a real-time prediction model is valuable. Second, the proposed real-time model has a good flexibility and extensibility. For instance, network, geographic information system or consumer motivation can all be added to enhance the robustness of the real-time model.

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