Purchasing decisions on alternative fuel vehicles within an agent-based model *

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Abstract. We develop an empirically grounded agent-based model to explore the purchasing decisions of mutually interacting agents (consumers) between three types of alternative fuel vehicles. We calibrate the model with recently published empirical data on consumer preferences towards such vehicles. Furthermore, running the Monte Carlo simulations, we show possible scenarios for the development of the alternative fuel vehicle market depending on the marketing strategies employed.

Keywords: Agent-based model · Alternative fuel vehicle · Diffusion.

1 Introduction

According to experts, the achievement of the goals of sustainable transport requires an increase in the share of vehicles powered by alternative fuels (AFV) in road traffic [7,2]. Among these cars, battery electric vehicles (BEVs), plug-in electric vehicles (PHEVs), and hybrid electric vehicles (HEVs) are mainly included. Although the market share of AFV is constantly increasing worldwide, its smooth diffusion encounters a number of barriers including lack of sufficient charging infrastructure, high prices, and safety issues [13].

There are a number of studies on the technical, economic, social, and psychological factors that influence the choice of vehicle type when deciding to purchase it. The authors use various stated preferences methods to analyze what factors determine the decision to buy a certain type of a vehicle [6,1]. Apart from that, a large number of simulating and modeling studies, making usage of agent-based modeling (ABM), have been recently published [11,4,3]. ABM allows us, among others, to investigate how the individual decisions of the agents (i.e., households, consumers, etc.) and their social interactions lead to effects on the macroscopic level (e.g., market penetration of a given good). Based on [10,11,8,9], we propose

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an empirically grounded agent-based model with explicitly introduced interactions with local and global neighborhoods. Our proposed approach allows the model to be easily developed in the future, for example, taking into account space heterogeneity, individual consumer preferences, or interactions in online social networks. However, here, we focus on the zero-level approach, in which the environment is represented by a regular grid, and the agents are homogeneous in terms of preferences. This allows us to determine what is the importance of external factors such as global marketing or different government policies. What is even more important, it allows other researchers to replicate the results, which in our opinion is necessary for reliable model verification.

2 The model

We consider a square $L \times L$ lattice with periodic boundary conditions. The linear size of the system $L = 100$ is taken in most of our simulations. Each node is occupied by exactly one agent, and thus the total number of agents in the system equals $N = L^2$. Each agent has exactly four neighbors due to the network structure, and it can own exactly one car.

Initially, the agents do not have cars. We use a random sequential updating scheme, which mimics continuous time. This means that in an elementary update, only one agent is selected randomly from all N agents, and a single Monte Carlo step consists of N elementary updates (note that not necessarily all agents are updated in a single time step). The selected agent buys one car picked from the alternative fuel vehicle choice set. Motivated by the empirical studies [5], in our simulations this set includes in total 75 cars, 25 of each type (HEV, PHEV, and BEV). All cars are characterized by 5 attributes that are 5-level discrete variables. Car profiles are taken from the conjoint analysis: Tables 13, 16, and 17 in [5]. The vehicle attributes impact the overall utility that comes from purchasing a given car. The total utility of car $j \in \{1, 2, ..., 75\}$ is the sum of partial utilities associated with the attributes of this car:

$$U_j = \sum_{n=1}^{5} PU_{j,n}, \tag{1}$$

where $PU_{j,n}$ is the partial utility of the n-th attribute of car j. These utilities were estimated also through the conjoint analysis of consumers' preferences: Table 14 in [5]. To distinguish between different types of cars, we introduce a function:

$$f(j) = \begin{cases} \text{HEV} & \text{if the } j\text{-th car is HEV,} \\ \text{PHEV} & \text{if the } j\text{-th car is PHEV,} \\ \text{BEV} & \text{if the } j\text{-th car is BEV.} \end{cases} \tag{2}$$

Following [11,9], we assume that the consumer decision-making process depends not only on the total utility of a vehicle, but also on additional external factors that account for marketing, social influence, and the availability of

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recharging facilities. Thus, the probability that agent $i \in \{1, 2, ..., N\}$ buys car j is expressed by the following multinomial logit model:

$$P_{i,j} = \frac{W_{i,f(j)} \cdot RFE_{f(j)} \cdot \exp(U_j)}{\sum_{j=1}^{75} W_{i,f(j)} \cdot RFE_{f(j)} \cdot \exp(U_j)}, \tag{3}$$

where $W_{i,f(j)}$ is the willingness of agent i to buy a car of a given type, which captures the impact of marketing and social influence, whereas $RFE_{f(j)}$ is the refueling effect, which reflects the availability of recharging facilities for a given car type. The refueling effect accounts for agents' concerns related with low ranges of some AFVs, such as PHEVs and BEVs. We include this effect in a functional form that has already appeared in previous studies [10,11,9]:

$$RFE_{f(j)} = \begin{cases} 1 & \text{if the } j\text{-th car is HEV,} \\ 1 - DPe^{-\alpha_{\text{PHEV}} N_{\text{PHEV}}/N} & \text{if the } j\text{-th car is PHEV,} \\ 1 - DPe^{-\alpha_{\text{BEV}} N_{\text{BEV}}/N} & \text{if the } j\text{-th car is BEV,} \end{cases} \tag{4}$$

where DP is a driving pattern characterized by the society, N_{PHEV} and N_{BEV} are the numbers of agents that have already adopted PHEVs and BEVs, respectively, whereas α_{PHEV} and α_{BEV} are scaling parameters used to calibrate the model.

The novelty of our model is the formula describing the willingness of agent i to buy a car of type $f(j)$:

$$W_{i,f(j)} = \underbrace{h_{f(j)}}_{\text{marketing}} + \underbrace{p_l k_{i,f(j)}/k}_{\text{local influence}} + \underbrace{p_g N_{f(j)}/N}_{\text{global influence}} + \underbrace{1}_{\text{independence}}, \tag{5}$$

where $h_{f(j)}$ reflects the effectiveness of marketing for vehicles of a given type, p_l is the strength of local social influence, p_g is the strength of global social influence, $k_{i,f(j)}$ is the number of neighbors of agent i that already possess vehicles of a given type, $k = 4$ is the total number of neighbors of an agent, and $N_{f(j)}$ is the total number of agents in the system that have vehicles of a given type. The first term of formula (5) captures not only the influence of advertisements and promotions, but also the effectiveness of various policies, benefits, and advantages related to AFVs, such as subsidies, tax releases, or free parking spaces. We assume that all vehicles with the same engine type are described by the same value of parameter $h_{f(j)}$, and thus it takes only three values: h_{HEV}, h_{PHEV}, and h_{BEV}.

Regarding social influence, we distinguish between local and global one, just like in [8]. The local influence (word-of-mouth), the second term of Eq. (5), is proportional to the fraction of neighbors with cars of the same type as the considered car. Similarly, the global influence, the third term of Eq. (5), is proportional to the fraction of all agents in the system having such cars.

A pseudo-code to simulate our model is as follows:

0. Set parameters of the model: L, DP, α_{PHEV}, α_{BEV}, h_{HEV}, h_{PHEV}, h_{BEV}, p_l, and p_g as well as the time horizon of the simulation, T. Initialize the system. Set time $t = 0$.

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1. Count the number of agents in the system that have cars of each type, i.e., N_{HEV}, N_{PHEV}, and N_{BEV}.
2. Calculate the refueling effect from Eq. (4) for PHEVs and BEVs, i.e., RFE_{PHEV}, and RFE_{BEV}.
3. Draw number i from discrete uniform distribution $U\{1, N\}$. Agent i is selected to buy a car.
4. Count the number of neighbors of agent i that have cars of each type, i.e., $k_{i,\mathrm{HEV}}$, $k_{i,\mathrm{PHEV}}$, and $k_{i,\mathrm{BEV}}$.
5. Calculate the willingness of agent i to buy a car of each type from Eq. (5), i.e., $W_{i,\mathrm{HEV}}$, $W_{i,\mathrm{PHEV}}$, and $W_{i,\mathrm{BEV}}$.
6. For each $j \in \{1, 2, ..., 75\}$, calculate the probability that agent i buys car j, i.e., $P_{i,j}$ from Eq. (3).
7. Draw number u from continuous uniform distribution $U[0, 1]$.
8. Find index m such that $\sum_{j=1}^{m-1} P_{i,j} \leq u < \sum_{j=1}^{m} P_{i,j}$. Agent i buys car m.
9. Update time $t \to t + 1/N$. If $t < T$, go to point 1.

3 Results

To calibrate the model, we first run simulations without any marketing and social influence ($h_{\mathrm{HEV}} = 0$, $h_{\mathrm{PHEV}} = 0$, $h_{\mathrm{BEV}} = 0$, $p_l = 0$, and $p_g = 0$), and tune the values of α_{PHEV} and α_{BEV} so that the stationary adoption levels of HEVs, PHEVs, and BEVs correspond to those estimated based on the survey conducted in [5]. We focus on the stationary state of the system, since it is difficult to establish a general relationship between the Monte Carlo steps and the real time. In the survey, 48.8% of the respondents declared that they would buy HEV, 32% PHEV and 19.3% BEV. We obtain similar levels of adoption for $\alpha_{\mathrm{PHEV}} = 2.6$ and $\alpha_{\mathrm{BEV}} = 0.05$, see Fig. 1(a). Without having data for Poland, we set $DP = 0.49$, which approximates the aggregate driving pattern for Germany [10]. All the results that we present are averaged over 40 independent simulations.

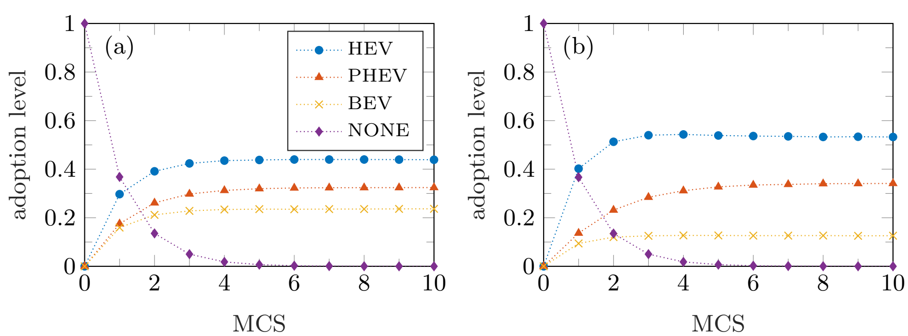

Fig. 1. Adoption levels of AFVs in a system without marketing ($h_{\mathrm{HEV}} = h_{\mathrm{PHEV}} = h_{\mathrm{BEV}} = 0$) and social influence ($p_l = p_g = 0$) as a function of time measured in Monte Carlo steps: (a) $DP = 0.49$ (driving pattern for Germany [10]) and (b) $DP = 0.78$ (driving pattern for Iceland [11]). NONE represents the fraction of agents without a car.

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After calibrating the model, we want to check how the driving pattern DP and different policies impact the behavior of the model. To verify the former, we simulate the system with the same values of parameters that were obtained within the calibration for $DP = 0.49$, but this time with $DP = 0.78$. This value characterizes countries with longer average daily driven distances, such as Iceland [11]. In Fig. 1(b) it is seen that increasing DP leads to a higher adoption level of HEVs at the expense of BEVs.

Next, we investigate how marketing campaigns targeting only one type of AFVs impact their stationary adoption levels. Figures 2-4 present the results for the systems where only HEVs, PHEVs, and BEVs are advertised, respectively. Under stronger social influence, marketing targeted at HEVs leads to their higher adoption level. The opposite happens in the case of PHEVs and BEVs. However, for HEVs, stronger social influence causes smaller gains in the adoption level that result from the increase of the advertising strength, see Fig 2. This diminishing effectiveness of marketing is related to the high initial adoption of HEVs. In contrast, we can achieve a considerable increase of PHEV adoption for a low intensity of advertisements when the social influence is strong enough, see Fig. 3(c).

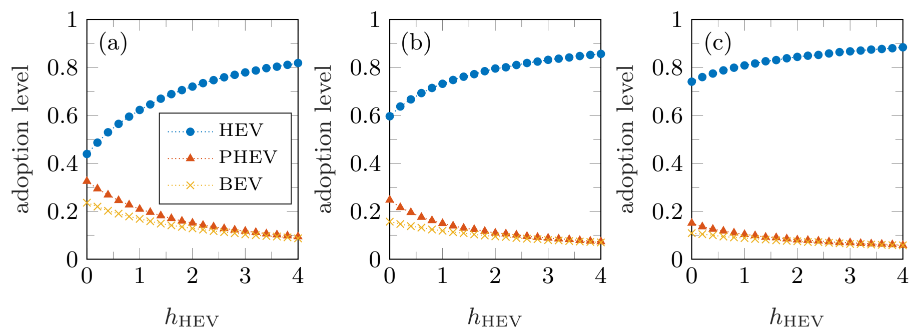

Fig. 2. Impact of campaigns promoting only HEVs ($h_{\mathrm{PHEV}} = h_{\mathrm{BEV}} = 0$) on the systems with different strengths of social influence: (a) $p_l = p_g = 0$, (b) $p_l = p_g = 2$, and (c) $p_l = p_g = 4$.

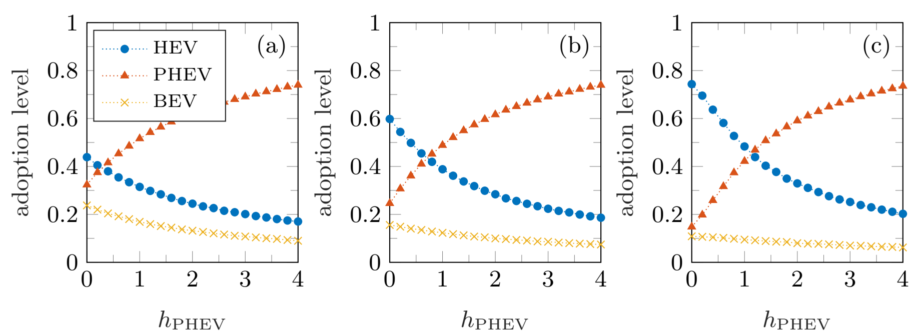

Fig. 3. Impact of campaigns promoting only PHEVs ($h_{\mathrm{HEV}} = h_{\mathrm{BEV}} = 0$) on the systems with different strengths of social influence: (a) $p_l = p_g = 0$, (b) $p_l = p_g = 2$, and (c) $p_l = p_g = 4$.

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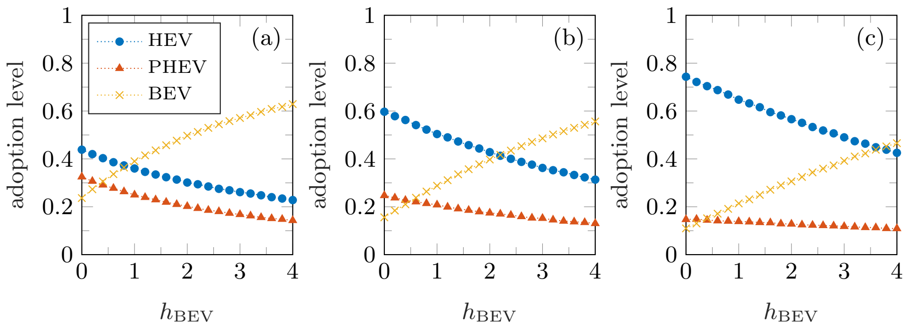

Fig. 4. Impact of campaigns promoting only BEVs ($h_{\mathrm{HEV}} = h_{\mathrm{PHEV}} = 0$) on the systems with different strengths of social influence: (a) $p_l = p_g = 0$, (b) $p_l = p_g = 2$, and (c) $p_l = p_g = 4$.

4 Discussion

Within our simple ABM, we were able to obtain results similar to those in [5] in terms of consumer choices between three types of alternative fuel vehicles: HEV, PHEV, and BEV. The calibration of the model allowed us not only to reflect the current sentiments on the market but also to show that the local and global impact is not always conducive to the spread of new solutions. That is why advertising is needed, whose strength must depend on the strength of social interaction to be effective. The results have revealed that the largest market share is gained by the vehicle type that is sufficiently advertised. This observation shows how important marketing strategies and government policies are in promoting a given type of vehicle.

We have also observed that social influence can either strengthen the effect of advertising (for HEVs) or reduce it (for PHEVs and BEVs). This may be related to the greater popularity of HEVs among drivers and thus the frequency of information and opinions provided on this subject. However, PHEVs and BEVs are still less popular, mainly due to their high price and limited network of charging stations, and thus the local and global influence may have a negative effect on diffusion.

Our model also allows us to observe the impact of the value of the driving pattern, DP, on the level of adoption and diffusion of vehicles. Comparison of results for medium and high values of DP indicates that BEV adoption is higher in countries more densely populated where the average distances covered are shorter and the charging station network is denser. Being aware of the weaknesses of our model (including homogeneous agents, simple network topology, lack of negative marketing, etc.), we believe that the model can be easily developed further to capture more realistic assumptions [12]. The available survey data [5] also restricted our model setup. First, we could not take into account other common means of transport, such as internal combustion engine vehicles, fuel cell electric vehicles, or public transportation. Second, not knowing how respondents had been impacted by marketing and social influence, we performed a model

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calibration without these factors. Taking these aspects into account would result in a more realistic setup; however, this requires more tailored empirical data, which we are missing.

References

1. Byun, H., Shin, J., Lee, C.Y.: Using a discrete choice experiment to predict the penetration possibility of environmentally friendly vehicles. Energy **144**, 312–321 (2018). https://doi.org/https://doi.org/10.1016/j.energy.2017.12.035
2. Chang, D.S., Chen, S.H., Hsu, C.W., Hu, A.H., Tzeng, G.H.: Evaluation framework for alternative fuel vehicles: Sustainable development perspective. Sustainability **7**(9), 11570–11594 (2015). https://doi.org/10.3390/su70911570
3. Huang, X., Lin, Y., Zhou, F., Lim, M.K., Chen, S.: Agent-based modelling for market acceptance of electric vehicles: Evidence from China. Sustainable Production and Consumption **28**, 206–217 (2021). https://doi.org/https://doi.org/10.1016/j.spc.2021.04.007
4. Kangur, A., Jager, W., Verbrugge, R., Bockarjova, M.: An agent-based model for diffusion of electric vehicles. Journal of Environmental Psychology **52**, 166–182 (2017). https://doi.org/https://doi.org/10.1016/j.jenvp.2017.01.002
5. Kowalska-Pyzalska, A., Michalski, R., Kott, M., Skowrońska-Szmer, A., Kott, J.: Consumer preferences towards alternative fuel vehicles. results from the conjoint analysis. Renewable and Sustainable Energy Reviews **155**, 111776 (2022). https://doi.org/https://doi.org/10.1016/j.rser.2021.111776
6. Lin, B., Wu, W.: Why people want to buy electric vehicle: An empirical study in first-tier cities of China. Energy Policy **112**, 233–241 (2018). https://doi.org/https://doi.org/10.1016/j.enpol.2017.10.026
7. Mazza, S., Aiello, D., Macario, A., De Luca, P.: Vehicular emission: Estimate of air pollutants to guide local political choices. A case study. Environments **7**(5) (2020). https://doi.org/10.3390/environments7050037
8. McCoy, D., Lyons, S.: Consumer preferences and the influence of networks in electric vehicle diffusion: An agent-based microsimulation in Ireland. Energy Research & Social Science **3**, 89–101 (2014). https://doi.org/https://doi.org/10.1016/j.erss.2014.07.008
9. Noori, M., Tatari, O.: Development of an agent-based model for regional market penetration projections of electric vehicles in the United States. Energy **96**, 215–230 (2016). https://doi.org/https://doi.org/10.1016/j.energy.2015.12.018
10. Schwoon, M.: Simulating the adoption of fuel cell vehicles. Journal of Evolutionary Economics **16**(4), 435–472 (2006). https://doi.org/10.1007/s00191-006-0026-4
11. Shafiei, E., Thorkelsson, H., Ásgeirsson, E.I., Davidsdottir, B., Raberto, M., Stefansson, H.: An agent-based modeling approach to predict the evolution of market share of electric vehicles: A case study from Iceland. Technological Forecasting and Social Change **79**(9), 1638–1653 (2012). https://doi.org/https://doi.org/10.1016/j.techfore.2012.05.011
12. Sobkowicz, P.: Modelling opinion formation with physics tools: Call for closer link with reality. Journal of Artificial Societies and Social Simulation **12**(1), 11 (2009), https://www.jasss.org/12/1/11.html
13. Wang, F.P., Yu, J.L., Yang, P., Miao, L.X., Ye, B.: Analysis of the barriers to widespread adoption of electric vehicles in Shenzhen China. Sustainability **9**(4) (2017). https://doi.org/10.3390/su9040522

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