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Agent-based model for electric vehicle adoption in Brussels

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Executive Summary

The paper aims at studying the relationship between the roll out of the charging infrastructure and the electric vehicle adoption in Brussels. This is modeled using an agent based model approach that integrates consumer agents and a charge point operator, enabling to observe the evolution of the infrastructure and adoption until 2030. This approach will facilitate future research on infrastructure policies and compare their efficiency.

1 Introduction

Climate change is often cited as being one of the biggest challenges of the 21st century. Greenhouse gas emissions, and carbon dioxide CO_2 especially, are one of the causes of climate change. Therefore, the European Union set carbon reduction targets for 2050. In order to achieve these targets, road transportation should heavily reduce its emissions, since it is responsible for about 20% of the European greenhouse gas emissions [1] and that personal transport by car is responsible for 12% of the European CO_2 emissions [2]. Shifting to a fleet of electric vehicles (EVs) could reduce the amount of emissions in Europe. The *Clean Power for Transport* directive adopted in 2014 by the European Parliament - currently in the process of being updated - aims at facilitating the uptake of such alternative technology. However, the adoption of electric vehicles is still not taking up in all European member states. In Brussels, the capital region of Belgium, the number of public charging facilities is still low with 149 charging points [3], even if the market share of electric vehicles has reached 2% of the new purchased vehicles in 2017 (1.645 EVs sold on a total of 75.368 cars)[4]. Public charging stations are even more needed since a big increase in numbers of EVs sold has been observed in Belgium in 2018 [5] with an annual growth of 41,1% for battery electric vehicles (BEVs), of 39% for gasoline hybrid EVs and of 9,8% for diesel hybrid EVs. This accounts for a total of 9.244 BEVs, 81.107 gasoline hybrid EVs and 5.905 diesel hybrid EVs. An influential factor for EV adoption is the availability of charging infrastructure [6, 7]. In Norway, access to charging infrastructure showed to be the incentive with the highest predictive power of BEVs sales on regional level, whereas financial incentives were more effective on municipal level [8]. Further, the installation of charging infrastructure is according to [9] a stronger predictor of EV adoption than financial incentives. Even awareness of the existence of charging stations has a positive impact on the EV uptake. People that noticed charging infrastructure are more likely to have interest in EVs than people that never noticed its existence [10]. Therefore, implementing a comprehensive charging infrastructure network would help improving the EV adoption in Brussels. This research aims at investigating the relationship between the increase of number of charging stations and the EV adoption in Brussels. This is accomplished by developing an agent based model (ABM) that simulates the interactions between the use and increase of the public charging infrastructure network and the EV uptake. In this paper, a proof of concept is presented analysing a small subset of the agent's population.
Next section reviews the literature on ABM simulations focusing on EV adoption. Section 3 details the ABM. The agents' initialization and routines, as well as the discrete choice model that is the basis of the vehicle choice, are described in this section. Section 4 reports the results of the proof of concept ABM. Finally, section 5 concludes this paper and presents the next development and research tracks.

2 Literature review

According to Bonabeau [11] an ABM system is *"system modeled as a collection of autonomous decision-making entities called agents"*, where *"each agent individually assesses its situation and makes decisions on the basis of a set of rules"*. In other words, an ABM is a complex multi-agent system where agents are individual entities that possess a state, attributes and a set of actions. The agent interacts with its environment or with other agents given its predefined set of actions. These interactions are only dictated by the agent's actual state and attributes. Therefore, the investigated complex system emerges from these local uncoordinated interactions and is not determined by a centralized decision system.
Table 1 shows a short review of the literature on ABM that simulate EV adoption. Although the scope and the time frame of the selected studies differ, four distinct kinds of agents were identified. All studies implemented a consumer agent. That agent is central to the studies and is the agent that takes the decision of shifting from conventional vehicles to EVs. Almost all studies implement a government agent or scenario that aims at stimulating EV adoption. Some studies also implemented more specific agents such as the car manufacturer, the vehicle [12, 13] or charge point operator (CPO) agent [14, 15]. The car manufacturer and vehicle agents decide what the specifications of the vehicles sold are, based on a metric (for example profit) [12]. The CPO agent determines where new charging stations should be installed during the simulation. This decision could be based on the use of the charging infrastructure at a certain point in time during the simulation and/or on the infrastructure's disposition [15].
Two different approaches were identified as decision function for the consumer agent who needs to choose the best alternative between different vehicles. Some studies opt for desirability functions, whereas most prefer to rely on discrete choice models. Discrete choice models [16, 17] estimate choices between two or more alternatives. Every alternative is defined as a combination of attributes. The consumer agent will choose the alternative with the highest utility. Desirability functions are mathematical expressions that combine attributes affecting the desirability of the alternatives. Examples of desirability functions are a cost-benefit analysis [18] or a minimization of the costs related to the purchase of a new vehicle [14]. In addition to the decision function, some studies implement a social mechanism that influences the choice between the alternatives. Examples are a network of social contacts [18, 14] and word-of-mouth communication between the agents [12, 19, 13].
The literature discusses mostly the adoption of electric vehicles without taking the impact of the charging infrastructure into account, or the growth of charging infrastructure without taking the EV adoption into account. In this paper, the relationship between these two components and how they influence each other are investigated using a discrete choice model and social interactions. Only one study to our knowledge analyzed the same relationship [15], but has different characteristics and context than this paper:

- the use of desirability functions instead of a discrete choice model.
- the charging stations are located in zones instead of using a GIS based-system with exact coordinates.
- it is a country-wide study, whereas this paper has an urban city context, with few places to charge at homes.

Table 1: Literature review of electric vehicle adoption ABM

Journal article	Consumer agent	Government agent/scenarios	Car manufacturer/ vehicle agent	CPO agent	Desirability function	Discrete choice model	Social influence
Zhang et al., 2011 [12]	X	X	X			X	X
Noori et al., 2016 [13]	X	X	X			X	X
Sweda & Klabjan, 2014 [14]	X			X	X		X
Gnann, 2015 [15]	X	X		X	X		
Eppstein et al., 2011 [18]	X	X			X		X
Querini & Benetto, 2014 [19]	X	X				X	X
Mueller & de Paan, 2009 [20]	X	X				X	
Shafiei et al., 2012 [21]	X	X				X	
Hoekstra & Hovegeen, 2017 [22]	X	X		X	X		X
Vermeulen et al., 2018 [23]	X				X		

3 Methodology

This section discusses the development of an ABM model in *MATSim* [24]. The scope of the model is the capital region of Belgium, Brussels until 2030. As described in section 2, the basic agent in EV adoption literature is the consumer agent. This agent is also the main agent of this paper and is modeled as a Brussels household. Each consumer agent has a vehicle assigned to it. During the simulation, each consumer agent has the choice to change its vehicle. The decision of which vehicle the agent buys next is based on a discrete choice model. The decision is based on the vehicle's attributes such as driving range, purchase cost, refueling time or density of charging/refueling stations. Finally, the CPO manages the charging infrastructure and extends the existing infrastructure with new charging stations based on the locations where charging event most frequently occur and where the EV demand is predicted to be higher.

3.1 Initialization of the agent and model data

This section describes the initialization of the model with the agents and the data. Two types of agents are used in the model, namely, agents owning internal combustion engine vehicles (ICE) and agents owning plug-in electric vehicles (PEV).

3.1.1 Data

MATSim uses a street network file to simulate the city traffic. This file was obtained from OpenStreetMaps [25] and prepared using JOSM [26]. Socio-demographic information about the neighbourhoods such as number of households was gathered on the BISA website [27]. Currently simulations are run with neighbourhood populations of 1% of the households, resulting in a population size of 5351 agents. In the proof of concept simulation discussed in section 4, the total agent population is equal to 483 agents. Each agent is initialized with a residence and a working place. The coordinates of those kind of locations were obtained from UrbIS [28]. The movement flows between the different neighbourhoods were used for initializing the traffic flow in the street network. This dataset was obtained through Brussel Mobiliteit [29]. The charging locations were obtained during a field study conducted in 2015. This list of charging infrastructure can be found on the website of Open Data Brussels and is still the last official updated list for charging infrastructure in Brussels [3]. This list consists of 67 charging locations with 149 charging points. Finally, agents were assigned PEV vehicles proportionally to the number of EVs present in their neighbourhoods in 2015.

3.1.2 Agent's daily plan pattern

Three different types of agents are created during the initialization phase. These three types are based on charging patterns identified in [30].

Resident 1: is an agent publicly charging overnight nearby its residence. It starts the charging activity after arriving home around 18 'o clock and stops charging the day after around 8 'o clock when leaving for work.

Resident 2: is also an agent that publicly charges overnight near its residence, but starts its job several hours later and arrives later in the evening. It starts the charging activity around 20 'o clock and stops charging the day after around 10 'o clock.

Visitor: is an agent publicly charging during the day nearby its working place. It arrives at its working location around 9 'o clock and start the charging activity. When leaving in the afternoon, around 17 'o clock, it stops the charging activity.

The population exists of 80% of resident 1 type agents, 15% of resident 2 type agents and 5% of visitor type agents.
Since the *MATSim* framework works with daily plans, each agent is initialized with standard daily plans that consist of activities and trips from one activity to another. The *resident 1* and *resident 2* agents are initialized with three plans, namely a normal plan that consist of a *home-work-home* tripchain, a start charging plan that consists of a *home-work-startCharge-home* trip chain and a end charge plan that consists of a *home-endCharge-work-home* plan. The *visitor* agents consist of two plans, the normal plan as *resident 1* and *resident 2* agents and a visitor plan that consists of a *home-startCharge-work-endCharge-home* tripchain.

3.1.3 Agent's attributes

The attributes of an agent are specific to the owned vehicle. An agent owning an ICE has two attributes: an ICE vehicle and the vehicle's ownership duration. The duration is initialized with a mean of 9 years(Belgian average [4]) and a standard deviation of 3 years. An agent owning a PEV has 5 attributes: a PEV vehicle, the vehicle's ownership duration, the capacity of the battery, the current state of charge and the energy consumption rate of the electric motor. The ownership duration of a PEV owner is initialized with a mean of 4 years and a standard deviation of 1 year. The reasoning behind the lower average is that electric vehicles uptake is starting now. The battery capacity is equal to 40 kWh at the start of the simulation and evolves up to 60 kWh in 2020 and later. The energy consumption rate per kilometer equal to 0,16 kWh/km.

3.2 Discrete choice function

Simulating the adoption of PEVs is achieved by using a discrete choice function. To estimate the utilities of the discrete choice function, a choice based conjoint analysis has been conducted for Brussels consumers. The survey consisted of a series of 10 experiments where the respondent had to chose between 3 alternatives described by the attributes referenced in table 2. The resulting utilities per attribute are denoted in the table as well as their values for both ICEs and PEVs from 2018 until 2025 and later. The PEV values are mainly based on a battery electric vehicle's values, where the ICE values are more based on those of diesel vehicles since Belgium has a large share of these vehicles in its fleet. The cost values of PEV vehicles decrease over time while they increase for the ICE and the range and refueling time attributes' values increase for PEVs denoting a technological increase for this type of vehicles.

Table 2: Values of discrete choice attributes from 2018 to 2030 for ICEs and PEVs

Attributes	Utilities	2018		2020		2025	
		ICE	PEV	ICE	PEV	ICE	PEV
Purchase cost (€)	-4.15e-06	20000	30000	22500	25000	30000	22500
Yearly cost (€)	-2.15e-05	2000	1000	3000	1000	5000	1000
Driving cost (€/100km)	-0.015	8	4	8	4	10	4
Range (km)	0.000112	800	240	800	400	800	600
Refueling stations (%)	0.0884	100%	ratio	100%	ratio	100%	ratio
Refueling time (min)	-4.25e-05	5	480	5	240	5	240
Ecoscore (0 to 100)	-0.000137	60	80	60	80	60	80
Acceleration (sec to 100 km)	0.0146	12	6	12	6	12	6
Brand & image (1 to 5)	-0.0112	3	3	3	3	3	3

Purchase cost: comprises the purchase price vehicle, the VAT and the registration tax.

Yearly cost: comprises insurance, maintenance and road taxes.

Driving cost: comprises fuel costs (ICE) and electricity costs (PEV).

Range: denotes the amount of km the vehicle can reach on a full tank/battery.

Refueling stations: denotes the ratio between actual coverage and optimal coverage. The ratio for PEV charging stations is not fixed, since the model adds new charging infrastructure depending on the PEV adoption rate. Therefore, this value is update every time new infrastructure is added at new locations.

Refueling time: denotes the time in minutes needed to refuel/recharge the vehicle.

Ecoscore: is a metric that rates how environmentally friendly a vehicle is. The higher the score, the more environmental friendly.

Acceleration: denotes the time it takes for a vehicle to reach 100km/hour.

Brand & image: is the visual aspect and perception of the brand and quality of the vehicle.

Currently, all agents share the same discrete choice function. In the future, each agent will have an individualized discrete choice function combined with its socio-demographic data. Also, the choice of vehicles is still very limited. Only two different vehicles are modelled, namely, ICE and PEV. This will be more elaborated in the future with different vehicle segments and more specific vehicle technologies.

3.3 An agent's routine

In the next sections, two behaviors of the agents are described, namely, how an agent chooses its new vehicle and how an agent with a PEV does decide to charge its vehicle.

3.3.1 Vehicle choice routine

Every month, each agent has the opportunity to change its vehicle. This probability of changing from vehicle is calculated based on the cumulative probability distribution of the ownership attribute. This means the longer a vehicle is owned by the agent, the more probable it will change its vehicle.
A summed utility value, denoting the preference of the agents for the vehicle, will be obtained by summing the product of the utilities with the values of the attributes, for a specific year, for a specific type of vehicle. These utilities and attribute values are referenced in table 2. The agent will choose the vehicle that has the highest summed utility value of the two vehicle types.
A next development step will be to add social influence to the model to simulate i.e. word-of-mouth, social networks, ...

3.3.2 Charging routine

Agents owning a PEV regularly need to recharge their vehicle. Charging events occur when an agent has a state of charge below 20%. The agent will decide to change its behavior for the coming day and will choose a plan that includes the start of a charging event (the start charging plan for *resident 1* and *resident 2* and the visitor plan for the *visitor* agents). After the charging event occurred the next day, the agent decides again to change plans to a plan including the end of his charging event, except if it was a *visitor* agent since the end charging event happens during the same day.
In case all the charging points of the agent's preferred charging location are occupied by other agents, the agent will report the charging to another day and change its preferred charging location to the nearest other charging location. This procedure is applied until the agent can charge its PEV.

3.4 A charge point operator's routine

The role of the CPO is to manage the Brussels' charging infrastructure. In our model, it only has to decide where to place new infrastructure. In some models, removal of infrastructure does also happen. This behavior is not implemented in this model.
Every month, the CPO assess the coverage of the charging infrastructure. If a charging location denoted saturation (meaning one or more agents could not charge at this location during previous month), then a new charging location in a radius of 350 meters is identified. The candidate locations for the new charging station are building blocks. Each building block has a predefined demand score that is based on the income, housing surface and household size in the neighbourhood [31]. The block with the highest demand score is identified as the location where the new charging station will be added. If no charging location is found (in the case there are already charging stations at the blocks in the radius), than the radius is extended by 100 meters until a new location is found or a threshold of 1 kilometer is reached. Extra charging points are added to the existing location, if there is still no new location identified.

4 Results

The results from the proof of concept simulation are discussed in this section. The proof of concept consisted of a small population of agents (483 agents) simulated during 50 iterations. Each year consisted of four days (iterations). The agents assess their vehicle choice every two days, as do the CPO with respect to the state of the charging infrastructure. Since the simulation is sped up, an agent charges almost every day (depending on the type of agent). The structure of the results is as follows. Firstly, the PEV uptake is discussed. Secondly, the charging events are detailed. Finally, the extension of the charging infrastructure is examined.

4.1 PEV uptake

Figure 1 shows the adoption rate of PEVs. There is a clear shift towards PEVs starting from 2025. Up until then, PEVs are never chosen as preferred alternative. This results from the discrete choice function used to make the decision. Because one global function is used, there is no versatility in behavior and all agents maximize the same utilities. Since, ICEs are financially more interesting (lower purchase cost) than PEVs up until 2025 and that the technological characteristics such as the range and the number refueling stations are not near the values for ICEs, agents never choose the PEV option and even trade their vehicle in for ICEs. Once the year 2025 is reached, the reverse happens and all the agents start trading their ICE in for a PEV. This reveals that the ABM in combination with the current discrete choice function favors the purchase price, since no infrastructure will be installed until 2025 when the purchase price for PEVs is lower than for ICEs. In an next development step, scenario's with proactive charging infrastructure installation will be tested for assessing the impact of the charging infrastructure coverage on the PEV adoption rate.

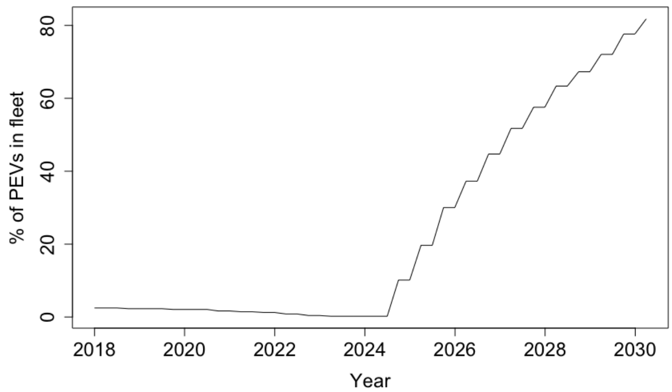


Figure 1: Evolution of the percentage PEVs in the agents' vehicle fleet

4.2 Charging events and infrastructure

The charging events match the evolution of the PEV fleet quite well, as plotted in figure 2. It increases as the PEV share increases. The reason behind the small delay in with respect to the PEV uptake is because of the small iteration count. In a larger example, this would not be noticed as hard as in theses examples.

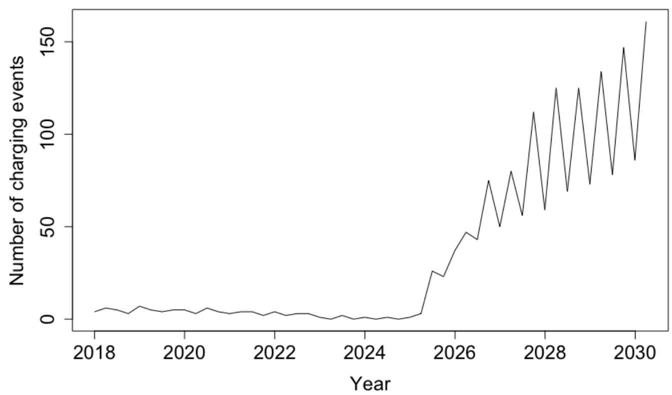
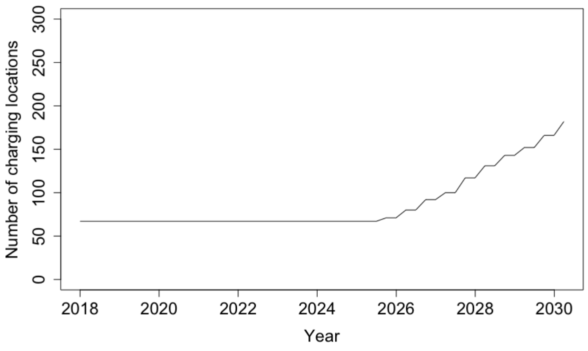
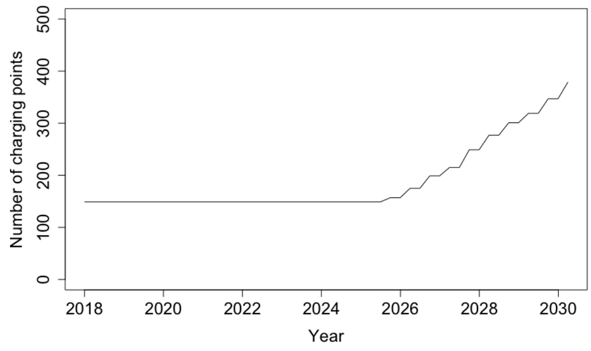


Figure 2: Evolution of the number of charging sessions

As the number of charging events start to increase, charging infrastructure gets installed by the CPO. Figure 3a shows the evolution of the number of locations where infrastructure is installed in Brussels. The process is a bit delayed since there is already sufficient charging infrastructure in 2025 when PEVs start to take up and the CPO is only going to install new locations once saturation occurs at some charging points. Currently, there is not much distinction between figures 3a and 3b, this is because of the small population size. When a larger population size will be used, some locations will need to have an increased number of charging points and figure 3b will know a steeper increase at some point in time.



(a) Evolution of the number of charging locations



(b) Evolution of the number of charging points

5 Conclusion

In this paper an ABM is presented that aims at simulating the EV adoption, charging infrastructure use and growth for the case study of Brussels until 2030. ABM are multi-agent systems that typically show a macro-behavior that is hard to explain but that emerges from predefined, simple, individual interactions of the agents with their environment and other agents. This method has often been used in the literature and is very suitable to such kind of complex problems. The defined model comprises three types of agents that simulate the adoption of EVs. The vehicle choice is based on a discrete choice function that is the same for all agents. The CPO adds infrastructure when there is too much charging demand and identifies new locations based on a predefined EV demand score in the neighbourhood of charging infrastructure that experienced saturation. The proof of concept results revealed that the uptake would not take place before the purchase price of the PEVs would be lower than for an ICE, even with lesser infrastructure coverage. Scenario's where CPO's act proactively will be applied in the future to investigate if a sufficient coverage incentivises the agents to adopt PEV even with a higher cost.
A limitation of the study is the number of different agents. Currently, only a proof of concept is simulated. Simulations with a large population size will be more representative of the speed of adoption past 2025. Another limitation is related to the discrete choice function. This function is shared amongst all agents. In the future there could be different discrete choice functions for different type of agents (i.e. based on socio-demographic information).
Future research tracks are the application of different government policies or changing the sensitivity of system parameters, such as the projected purchase price of EVs in the future, enabling to study their effect on the PEV adoption rate and the evolution of the charging network in Brussels. A final research track could be the integration of new charging- or vehicle technologies for studying the impact of alternative charging behaviors.

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