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Exploring EV adoption using an agent-based modeling approach

Master Thesis

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Exploring EV adoption using an agent-based modeling approach

C. Dai

Abstract— This paper describes a model that is used to predict the electric vehicle(EV) adoption in Dutch neighborhoods from 2016 to 2035. The agent-based modeling is used to simulate the car market. The car market is composed of different agents: consumers, a car manufacturer, a car dealer and cars. The cars that are sold can be EVs or cars with an internal combustion engine (ICE). The EVs and the ICE cars are manufactured by the car manufacturer, after which the dealer sells them to consumers. The consumers make buying decisions based on their preferences, their personal trip patterns and the total cost of ownership (TCO) of vehicles. Preference sets and trip patterns of consumers are heterogeneous resulting in different types of cars sold. Through simulating the car market in a neighborhood this way, the sales volume of EVs and ICEs in the coming years can be calculated while taking individual differences into account. We find a best guess scenario is developed for a neighborhood in the Hague in which EV sales reach 40% in 2025 and 90% in 2035.

Index Terms— Transportation, Electric vehicles, Consumer behavior, Cost benefit analysis, Agent-based modeling.

I. INTRODUCTION

Pollution and increasing energy consumption caused by transportation have been deeply discussed in recent years [1] [2] [3] [4]. In order to solve these problems, car manufacturers have been investigating the feasibility of the EV [5] [6]. Although the EV is more environmental friendly and fuel economical, it still has drawbacks of high purchase price and low driving range [7]. Currently, in order to accelerate the transition process from conventional to electric cars, the Dutch government uses monetary incentives such as tax reduction [8]. Non-monetary factors also influence people's buying behaviors. Based on research by Egbue [9], factors like gender, age and education all influence attitudes toward the EV. Apart from these factors, according to the research of Jakobsson(2016) [10], the electric vehicle may be significantly suitable for the households that already have one car. In addition to that, the research of Will(2016) [11] mentions that the grid stability and the sustainable energy resource of the EV are critical for the acceptance of electric vehicles.

Roosen(2015) [12] compares previous research regarding the evaluation of the EV. He found that most of these research ignored non-monetary factors. The research of Al-Alawi(2013) [13] estimates the composition of the cost of the plug-in hybrid electric vehicle. The cost is composed of the retail price, the maintenance cost, the insurance. Etc. The non-monetary cost is not included in the composition. The research of Wu(2015) [14]

compares the TCO of the electric vehicle and the conventional vehicle. However, the TCO is only composed of the capital cost and the operation cost. Non-monetary costs such as environmental cost and range anxiety are excluded.

This paper explores factors impacting EV adoption through simulating the car market. The simulation of the car market is based on comparing the TCO of the EV and ICE car. The TCO in this research is composed of both monetary factors and non-monetary factors. The research can help the government to adjust the incentives and take further effective measures to promote EVs' adoption.

II. METHODOLOGY

A. Background

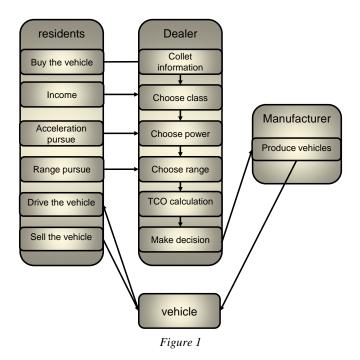
The research is investigated through modeling the passenger car market in one of the Dutch neighborhoods. This market model is a sub-model of a joint model called the Agent-based Buying Charging Driving (ABCD) model, which additionally models charging and driving behavior of EVs in the neighborhood.

B. Modeling method

In this section, the modeling method will be discussed. The top-down approach and bottom-up approach are compared first. We choose the bottom-up approach instead of top-down approach. Then the statistical model and analytical model are explained and the analytical model is determined as the modeling method. In the end, the reason why agent-based modeling method rather than equation-based modeling method is used in this project is interpreted.

Classical economists assume that consumers are largely homogenous and all behave in the same(rational) way. This allows them to describe customer behavior using a few top-down equations[15]. However, in reality consumers are irrational and heterogeneous. The bottom-up approach in this model acknowledges that all consumers are different[16]. These consumers' behaviors can better resemble the car market in reality.

Another differentiation between modeling methods is statistical versus analytical. Both the statistical modeling approach and the analytical modeling approach can be used to



resemble the real market. Using the statistical modeling approach [17], a large amount of real market data is used to train models. The statistical model can often accurately resemble the real market as long as this data is reliable. Although the statistical modeling approach often accurately resembles the real market, it is hard for modelers to fully understand and explain the inner working of these models. Compared to the statistical modeling approach, the analytical modeling approach may not resemble the real market as accurately as the statistical one, but it can help us deeply understand the real market. It is also easier for modelers to explain these models. Another reason of using analytical model is that there is not enough market information data of EV. We can only deduce the EV market through observing the conventional car market. As a result, the analytical modeling approach is used in our model to investigate the transition from ICE car market to EV market.

As it has been mentioned above, the bottom-up analysis approach and the analytical modeling approach where selected for this research. The modeling method best suited is the agent-based modeling[18] [19] [20]. This method uses simulated entities to resemble the reality[21]. The agents in the model represent the entities in real market. The agents may have different attributes, which can simulates consumers' heterogeneity. In addition to that, as the agents' behaviors are similar to the consumers' behaviors in reality, it is easier for us to use analysis approach to investigate the real market. Another advantage of using agent-based modeling method is that complex mathematical equations can be avoided in the model because the simulated market is represented by agents' behaviors and interactions.

C. Problem definition

Roosen[12] has reviewed previous research regarding to the comparative analysis between ICE and EV from 1997 to 2013. Based on Roosen's research, we find that if we need to compare

the value of EV and ICE car, we should first consider: evaluation method assumptions(vehicle life, discount rate, electricity mix, charging behavior, monetary cost of externalities, evolutions in assumptions), private costs(vehicle purchase cost, battery purchase cost, fuel/electricity cost, cost of private charging infrastructure, insurance cost, residual value, governmental measures), and external cost(vehicle exhaust pollution, fuel production pollution, electricity production pollution, noise pollution). In addition to Roosen's research, the choice-based conjoint analysis of Lebeau[22] further mentioned that the factors like the driving range, refuel/charging availability along the road, refuel/charging time, maximum speed and the brand/image/design/quality may also influence the consumer's choice between the ICE car and EV.

In our model, the car manufacturer constrains the cars included in the choice base class, acceleration, and range. The dealer makes decisions for consumers between ICE cars and EVs through comparing their TCO. Among the factors mentioned above, we simulated and analyzed three critical interdependent factors, namely the class, power, and range, that may influence the EV adoption in the Netherlands. As the passenger car market is investigated in this research, our model adopts the narrowest segmentation used by the commission of the European communities [23]. Based on this segmentation, we classified the mini car and the small can as the A-class car, the medium car and the large car as the C-class, and the executive car and the luxury car as the E-class car in our model. The class is the first critical factor because normally the selection of car class already contains the selection of power and range. An example is that the average power of A-class ICE cars is normally lower than that of C-class ICE cars. As a consequence, we have to select the class before we select the power and driving range. In addition to the class, the car power is critical because the cost of manufacturing a motor and an engine that have same power is quite different [24]. This difference may influence the TCO of the ICE car and EV. In the end, the driving range is a critical factor because short range is an obvious drawback of EVs compared to ICE cars currently [25] [26].

D. Car manufacturer's constrain process

As is the case in reality, our model also has residents, cars, a manufacturer, and a dealer. Residents go to the dealer to buy a car. An important aspect is that both the manufacturer and the dealer affect consumers choices of the car. E.g. the manufacturer determines what cars the consumer can choose from and the dealer uses his knowledge to influence the choice of the consumer. In order to make the buying module in our model comply with the real word, we are going to model the influences from both the manufacturer and the dealer.

Car manufacturers produce vehicles and sell them to car dealers. The car manufacturers make choices based on customer preferences, available technology, raw components supply, target market, financial ability et cetera. This data is hard to be obtained but we can look at the result: the existing vehicle models in the car market. The car market is oligarchic where all companies operate under similar rules regarding e.g. pricing.

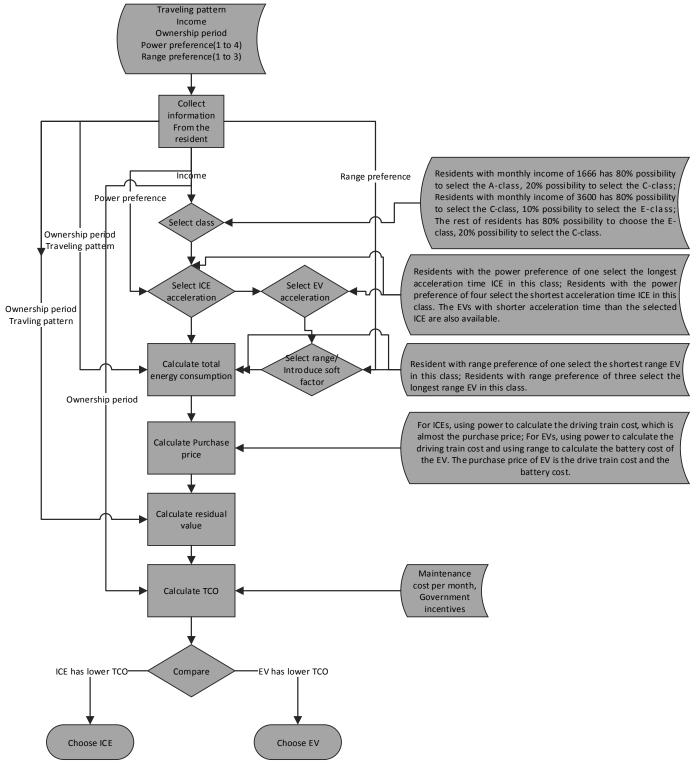


Figure 2

This equality combined with competition, ensures that the observed models and their prices are reliable input for our model, even though we don't have the information that the manufacturers use internally.

In the ABCD model, the car manufacturer first produces a limited number of vehicle types and we base those on our observation of the current market (and the models already in the pipeline). The amount produced is based on a very simple

estimate of the demand for cars caused by the residents in our model. In future years, the car manufacturer will adjust its car types and productivity based on the output from the model itself in previous years.

Thus the car manufacturer agent acts as a constraint that eliminates some car types that are available in theory but that are apparently unacceptable in the observed market. E.g. because they are demanded in lower numbers (that would make

the cars too expensive to produce) or because customers have hidden desires (e.g. in terms of "freedom" leading to large batteries) that are not accounted for in our model. Therefore, although some of the residents may not achieve their maximal utility in our model (they are less than completely satisfied), we have made sure that all of the types of traded vehicles actually exist in the market. Apart from eliminating unrealistic result, limiting available car types also saves computation time.

The consumer is resident of a neighborhood in the ABCD model. The residents own and drive their vehicles to travel. Each resident is given the attributes of car purchasing date and car using years randomly to determine the end use date. When the simulation date in the model equals the end use date, the residents will go to the dealer to purchase a new vehicle.

E. Dealer's selection process

In this section, two ways of selecting optimal are compared. The first way uses the difference between consumer utility(how much they are willing to pay) and car cost to find the maximal benefit for the consumer, which is based on the consumer theory. The second way uses a pre-determined way to select the optimal car in three steps.

Economists use utility of a consumer to represent how much (s)he is willing to pay for the vehicle. Factors we have chosen to represent this are: desired class, desired acceleration, desired range and other financial demands. All these utilities are cumulated to find the total utility for the consumer. The vehicle cost curves include the cost of class, the cost of dynamic(acceleration), the cost of driving range(for EV), other fiscal cost, et cetera. All of these are cumulated the total cost of ownership of the vehicle. The optimal vehicle for a certain consumer can be found once the benefit, which is the difference between the utility and the cost, achieves its maximal value. An alternative approach is that the dealer can comply with the predetermined rules to choose a vehicle for the resident. The choosing process is separated into three steps, namely the class selection, the power selection, and the range selection(only for EV). The dealer select the car class based on the income of the resident. As the E-class cars are the most expensive while the A-class cars are the cheapest on market. We assume that high income people are more willing to buy an expensive car and low income people are more willing to buy a cheap car. After that, the dealer can select the car power based on the resident's acceleration desire. However, only limited power choices are available because the car class has been determined. Then, the dealer determines the range for EV based on the resident's range anxiety. After the car class, power and range are determined, the ICEs and EVs that satisfy the residents demand are found by the dealer. The dealer can calculate the TCO of all these cars. In the end, the dealer will make the car with the lowest TCO as the resident's optimal potential car. We choose to use the pre-determined rules to select the optimal instead of using utility theory because quantify soft factors is hard to validate and not in coherent with the agent-based modeling approach.

III. MODEL ASSUMPTIONS

This Chapter explains assumptions of the model. The assumptions contain agents' definition, attributes and interaction. How to model the agents of resident, the car, the car manufacturer, and the dealer to resemble the real car market by making logical assumptions are explained in the paragraphs below.

In the ABCD model, the car manufacturer agent first manufactures ICE cars with three classes, namely A-class, C-class and E-class. In each of the ICE car classes, four kinds of acceleration time(0 to 100 km/h) can be chosen. ICE cars with the same class share the same weight. We can roughly calculate the car power from car weight and car acceleration time using the vehicle dynamic equations [27]. Based on conventional car market information [28] the purchase price of an ICE car with a specific power can be determined.

$$Price_{A-class} = 66.364 \times Power + 10847 [Euros] \quad (1)$$

$$Price_{C-class} = 130.65 \times Power + 15830 [Euros]$$
 (2)

$$Price_{E-class} = 257.68 \times Power + 18831 [Euros]$$
 (3)

In addition, the monthly maintenance cost of ICE cars during ownership period is also determined by the car manufacturer [29]. All of these values will be given to ICEs as inherent attributes when ICE cars are manufactured. Similar to ICE cars, EVs with the same class also share the same weight(excluding the battery). As the battery's weight will influence EVs' total weight, we need to determine EV's battery capacity first. Each class of EVs has three choices of battery capacity and three choices of acceleration time. The battery manufacturer calculates the pack weight for these batteries. Then the total weight of EVs can be determined. After the total weight and acceleration time are determined, we can use the vehicle dynamic equations to calculate the power of EVs. In the end, we can determine the drive train cost and maintenance cost through observing the market [28].

$$Price_{A-class} = 55.446 \times Power + 10847 [Euros] \tag{4}$$

$$Price_{C-class} = 55.446 \times Power + 25259 [Euros]$$
 (5)

$$Price_{E-class} = 55.446 \times Power + 36895 [Euros]$$
 (6)

The drive train cost of ICE cars and EVs are assumed to be constant in the coming years. The purchase price of the ICE is assumed to equal to the drive train cost while the purchase price of the EV is assumed to equal to the drivetrain cost and the battery cost. All of these ICE cars and EVs will be added to the inventory of the car manufacturer.

From model's starting date, the car manufacturer agent will manufacture the same amount of cars every year. These cars have the same characteristics as those have been manufactured before. On the other hand, as the battery price will decrease, the purchase price of EVs will also decrease. All of these cars will also be added to the inventory.

The residents that live in the neighborhood are given a monthly income number using a normal distribution that is based on average Dutch household income. The dealer will select the car class based on the resident's income. As in reality residents may not just select the class just based on their income, residents in our model only have 80% possibilities to follow the dealer's advice. Then, each of residents' car acceleration desire is ranked as an integer from one to four. The

consumer with the acceleration desire of one should select the car with the longest acceleration time in this class while those with the acceleration pursue of four should select the car with the lowest acceleration time. Similar to the acceleration pursue, the range anxiety of the resident is also ranked as an integer from one to three. The resident with the range anxiety of one should select the EV with the lowest range in this class while the residents with the range anxiety of three should select the EV with the longest range. As in reality, consumers may not only based on their range anxiety to select the range of the EV, in our model, the consumer only have 80% possibilities to follow the dealer's advice.

In our model, each resident owns an ICE car in the beginning. The resident will sell his car if his car ownership period has ended. Then the resident will go to the dealer for a new one. The dealer will first collect related information from the resident. This information involves monthly income, acceleration desire, range anxiety and car ownership period. After the class is selected, the dealer will select the ICE car's acceleration time. This ICE car with satisfied acceleration time is the first car that may be suitable for the resident. In addition to this ICE car, EVs with the same class and lower acceleration time can be made as alternative choices. Among the EVs with satisfied acceleration time, the dealer is going to select the EVs with proper driving range based on the consumer's range anxiety. Then the dealer will calculate the TCO for all suitable ICE cars and EVs. The TCO in our model is defined as the amount a consumer needs to pay every month during the car ownership period. The TCO calculation considers the purchase price, the energy cost, the maintenance cost, and the residual value. The dealer can get the information of purchase price and maintenance cost of cars from the car manufacturer. The energy costs of cars for each resident are calculated from the resident's driving patterns and cars' energy consumption per kilo meter. In the initialization of the model, 30 distances are generated for each resident as his monthly driving pattern. These driving patterns are generated based on Dutch drivers driving distances distribution.[27] The dealer can also get the fuel consumption per 100 kilo meters of ICE cars from the car manufacturer. Then the energy cost of ICEs can be determined. As for EVs, the energy cost is also affected by their driving range. So the dealer should know how far EVs will drive. The dealer can know EV's range and electric energy consumption from the car manufacturer. For each resident, the dealer will compare his single distance against the range of every EVs. If the distance is longer than the range, the driver will need to fast charge his car. The dealer can calculate how much energy is needed from the distance, range and the electric energy consumption. The other distances are achieved by slow charging energy. The residual value of each ICE is calculated from its purchase price P[Euro], driving distances d[km] and ownership period y[years] using equation(7)[29] [30].

$$Rv_{ICE} = ((y+1)^{-0.4y} + d \times 10^{-6}) \times P$$
 (7)

$$Rv_{EV} = \alpha (y+1)^{-0.4y} + d \times 10^{-6} \times P$$
 (8)

As in early years, people are skeptical about the residual value of the EV, the depreciation of EV is more than the depreciation of the ICE cars. With the increasing of residents' knowledge towards the EV, the depreciation of EV will increase. In the later years, the depreciation of EV will be less than the

depreciation of the ICE cars because a resold EV normally has lower maintenance cost and energy cost than a resold ICE. As a consequence. We can use the equation (8) to calculate the residual value of the EV. The multiplier α is less than one before 2026 and larger than one after 2026 [30]. The energy cost, the maintenance cost and the residual value is calculated as the net present value in the year that the resident goes to the dealer. The difference between the total cost and the residual value is amortized over the car ownership period monthly, which is the TCO of the car. In the end, the dealer will make the car with the lowest TCO as the optimal car for the resident.

In our model, residents go to the dealer with the income of their households. The dealer will make the resident own the optimal car. Meanwhile the dealer will ask the car manufacturer to remove this car from its inventory and manufacture a car with the same characteristics.

IV. RESULT

A. Scenario I: Basic scenario

Residents population	500							
Income[Euros/mont	166	166 3600		70	700		050	1330
h] distribution	6	50	3000)		0	0
	56	279		12	22	24		19
Range anxiety	1		2	2		3		
distribution	17	177		147		177		
Acceleration time	1		2	2		3		4
preference	159		98	3		90		153
Slow charging price[Euros/kWh]	0.25							
EV productivity limitation	No							
Government incentives	No							

Table[1] Basic parameters

The starting date of the model is 2010. Five hundred residents are simulated who have car ownership periods of 10 years. The distribution of range anxiety can be seen in the table 1. The car manufacturer manufactures C-class EV, E-class-EV, A-class ICE car, C-class ICE car, and E-class ICE car. The car types parameters

Car type	Battery capacity [kWh]				celera 1001		time [s]
A-class ICE	0			12	9	7	6
C-class ICE	0			9	8	7	6
E-class ICE	0			8	7	6	5
C-class EV	25	30	35	7		6	5
E-class EV	90	100	110	5		4	3

Table[2] Car type parameters (I)

can be seen from the table 2. In 2017, the car manufacturer increases the capacity of the batteries of C-class EVs. The parameters can be seen from the table 3.

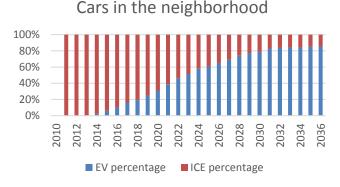


Figure 3

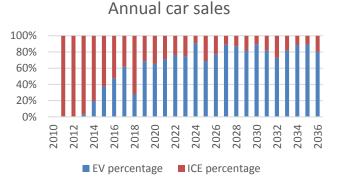
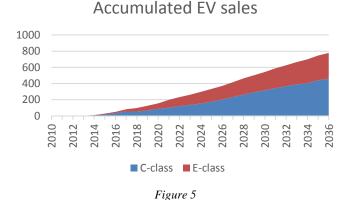


Figure 4



The cars in the neighborhood and the annual car sales from 2010 to 2035 are shown in figure 3 and figure 4, respectively. Residents only bought ICEs until 2013 because the TCO of ICEs were lower than the TCO of EVs. This may be caused by the high battery price[27]. With the decreasing of battery price, the adoption of EVs will achieve over 80% in 2035. In figure 4, there is an obvious decrease of EV annual sales in 2017. This is caused by the increase of C-class EVs purchase price. Although the battery price has decreased, the total cost of EV battery still increases because the car manufacturer increase the EV's battery capacity. The car manufacturer increases battery capacity to increase the range of their EVs. We can also see from the figure 4 that, in 2035, some residents will still buy ICEs. These residents want to buy an A-class car from the dealer but there is no A-class EV in our model. As a

EV adoption in the neighborhood

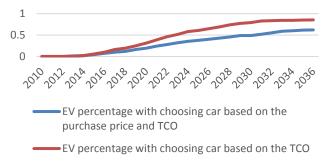


Figure 6

Annual EV sales percentage

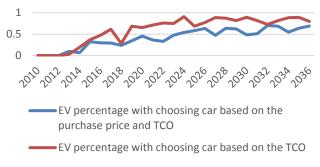


Figure 7

Accumulated EV sales

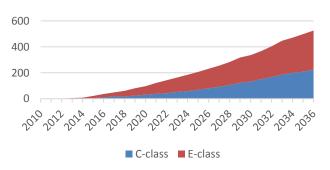


Figure 8

consequence, they can only buy A-class ICEs.

Figure 5 shows the EV market share of the C-class EV and E-class EV. More C-class EV than E-class EV are sold in the years between 2010 and 2035, which is in coherent with our input that most of the residents earn median monthly income and buy C-class cars.

B. Scenario II: Adding vehicle chosen based on just purchase price

The adoption of EVs in scenario 1 goes faster than what seems plausible. This is partly because the TCO's of the EVs in our model becomes lower than that of ICEs around 2018 for

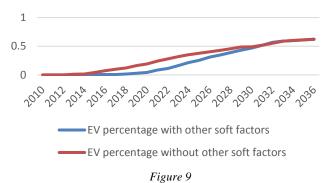
most consumers. In reality, some consumers may not select a car just based on a 10-year TCO but on shorter periods or just based on the purchase price. As a consequence, we make half of the residents in our model select a car based on TCO and half of the residents select a car based on the purchase price. The results can be seen from the figure 6, figure 7 and figure 8. If half of the residents select a car based on the purchase price, more E-class than C-class EVs are sold in the years between 2010 and 2035 because the C-class EV is much more expensive than C-class ICE car. As one of the essential advantage of EVs is low energy cost, less EVs are adopted if some consumers select a car just based on the purchase price.

C. Scenario III: Adding disposition towards EVs in early years

The EV adoption in the Netherlands until 2017 goes much slower than in the first two scenarios, which means there are some other factors influencing the adoption of the EV. Important factors could be soft factors like limited residents' knowledge of EVs, the limited choices of EVs in the market, disliking the hassle of charging, and more. To implement this in the model a percentage of the residents is given a disposition towards EVs. For example, in 2010 10% of the residents is willing to consider an EV, this percentage increases with the years, its values are shown in table 5.

The result after the disposition is implemented can be seen in figure 9, figure 10 and figure 11. Before 2017, very few EVs are sold because we assume 75% of the residents are not interested in EV. Even though for some of these residents, the TCO of the EV is lower than the ICE, they will still buy an ICE. After 2017, as more residents are interested in the EV, the annual EV sales start to increase obviously. In 2035, the adoption of EVs will achieve 60%, which is similar to the scenario 2. The share of C-class EVs and E-class EVs are almost the same, which means more E-class EVs should be sold if residents are interested in the EV. It shows that E-class EV are more attractive in early years.

EV adoption in the neighborhood



Annual EV sales percentage

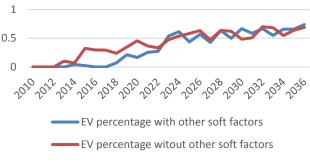


Figure 10

Accumulated EV sales

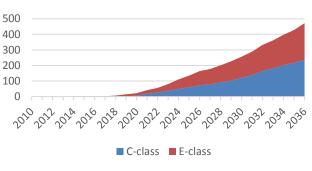


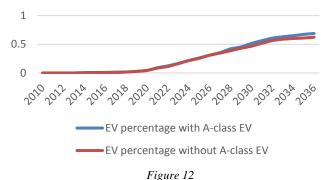
Figure 11

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EV adoption in the neighborhood



Annual EV sales percentage

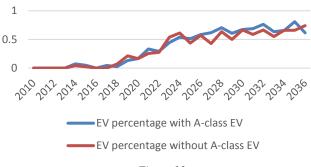


Figure 13

Accumulated EV sales

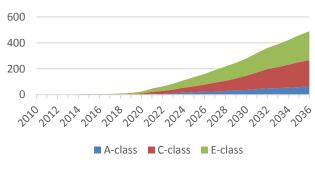


Figure 14

E. Scenario V: Change EV drive train cost

In the scenarios before, we assume that the drive train cost of EVs are constant from 2010 to 2035. In reality, if more EVs are sold, the drive train cost of EVs should be lower according to economies of scale[31]. In this scenario, we make the drive train cost of EVs decreases 1% every year from 2010. The result can be seen from the figure 15, figure 16 and figure 17. We can see that, there is a distinct increase of EV sales and EV adoption from 2026. We can also see that in 2035, the EV adoption is still less than 100%, which means some EVs still has higher purchase price than the similar ICE cars.

EV adoption in the neighborhood

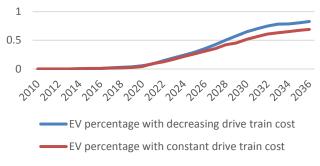


Figure 15

Annual EV sales percentage

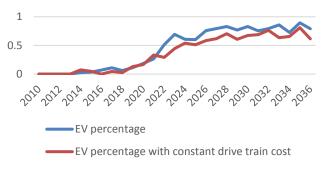


Figure 16

Accumulated EV sales

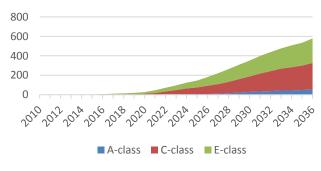
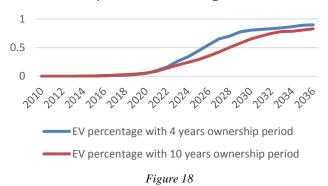


Figure 17

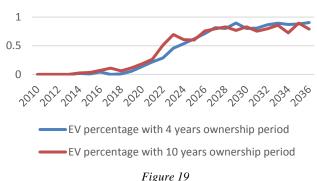
F. Scenario VI: Change car ownership period

As some of the consumers in reality will not keep their cars for ten years, we change the car ownership period to four years to investigate if the car ownership period will influence the EV adoption. The result can be seen from the figure 18, figure 19 and figure 20. In figure 19, we can see that in 2035 90% of the residents will still buy an EV, which means the EV still has lower TCO or purchase price if the car ownership is four years. Also, as the residents in the neighborhood keep their cars only for four years, more residents will replace their ICE car with an EV, which can be seen from the figure 18.

EV adoption in the neighborhood



Annual EV sales percentage



1 igure 1

Accumulated EV sales

Figure 20

G. Scenario VI: Change car ownership period

As some of the consumers in reality will not keep their cars for ten years, we change the car ownership period to four years to investigate if the car ownership period will influence the EV adoption. The result can be seen from the figure 18, figure 19 and figure 20. In figure 19, we can see that in 2035 90% of the residents will still buy an EV, which means the EV still has lower TCO or purchase price if the car ownership is four years. Also, as the residents in the neighborhood keep their cars only for four years, more residents will replace their ICE car with an EV, which can be seen from the figure 18.

EV adoption in the neighborhood

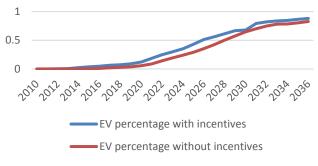


Figure 21

Annual EV sales percentage

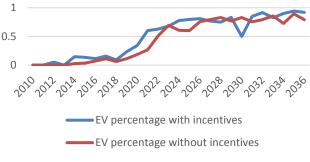


Figure 22

Accumulated EV sales

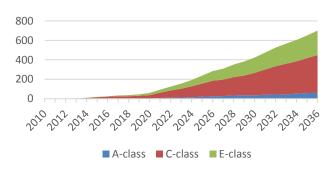


Figure 23

V. CONCLUSION AND DISCUSSION

In our research, we explore the EV adoption through simulating the car market. We resemble the car market by building an model using an agent-based approach. The consumers compare the EV and the ICE car, which has similar attributes, to consider if they buy an EV. If consumers only compare the TCO of the EV and the ICE car, most of the ICE cars in the neighborhood will be replaced by EVs. The EV adoption is rapid because the TCO of EVs will be lower than the TCO of ICE car. In addition, if we consider that some residents may compare the purchase price of the EV and ICE car, the EV adoption will be much slower. The C-class EV adoption is easier to be affected than E-class EV adoption if consumers only compare the purchase price of the EV and the

ICE car. We also simulate the EV adoption if A-class EVs are in the market. The introduction of A-class EV will slightly increase the EV adoption. We also notice that the high purchase price of A-class EV will delay the adoption of A-class EV in the neighborhood. In addition, we find that the decreasing EV drive train cost can increase the EV adoption. In the end, we investigate if the car ownership period and the government subsidies will influence the EV adoption. We find that ownership period will not affect the market share of EV and ICE cars but it will affect the EV adoption speed. The government subsidies can increase the total EV adoption.

In our model, we use a possibility disposition to represent some soft factors. These soft factors could be the residents' environmental attitude, residents' knowledge about the EV or the EV's popularity. These soft factors should be analyzed and implemented in further study.

APPENDIX

A. Abbreviations and Acronyms

ABCD: Agent-based Buying Charging Driving

• TCO: Total Cost of Ownership

• EV: electric vehicle

ICE: Internal Combustion Engine

B. Parameters

Car type	Battery capacity [kWh]			Acceleration time to 100km/h [s]			
A alasa ICE	[K W II]			12	0	7	[3]
A-class ICE	U			12	9	/	0
C-class ICE	0			9	8	7	6
E-class ICE	0			8	7	6	5
A-class EV	30	35	40	8	,	7	6
C-class EV	40	50	60	7	(6	5
E-class EV	90	100	110	5	4	4	3

Table[3] Car types parameters (II)

Income [Euro/month]	1666	3600	7000	10500	13300
Percentage [%]	11	55	25	6	3

Table[4] Income distribution

Year	Probability of considering EV
2010	10%
2011	11%
2012	12%
2013	13%
2014	14%
2015	15%
2016	20%
2017	25%
2018	35%
2019	45%
2020	60%
2021	75%

2022	90%
2023	95%
2024	95%
2025	98%
2026	98%
2027	99%
2028	100%
2029	100%
2030	100%

Table[5] Disposition

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