Modeling electric vehicle charging infrastructure deployment and usage with an agent-based approach

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By
Anand Vijayashankar
MSc Automotive Technology
Department of Mechanical Engineering
Research group: Control Systems Technology
Identity number: 0981246
Eindhoven University of Technology

Supervisor
prof. dr. ir. Maarten Steinbuch
Department of Mechanical Engineering
Eindhoven University of Technology

Project Initiator
drs. Auke Hoekstra
Senior Advisor Smart Mobility
Eindhoven University of Technology

Technische Universiteit Eindhoven University of Technology

Modeling electric vehicle charging infrastructure deployment and usage with an agent-based approach

Anand Vijayashankar
Department of Mechanical Engineering
Eindhoven University of Technology (TU/e), The Netherlands
a.vijayashankar@student.tue.nl

***Abstract* — This paper describes a model for electric vehicle (EV) charging infrastructure rollout (until 2035) and usage on the neighborhood scale. An agent-based approach is adopted to realistically model the complex interactions between the heterogeneous actors involved. EV buying behavior, driving patterns of residents (and commuters) and the charge point roll out policies determine the development of the charging network, both public and private. Moreover, the battery capacity of the EV, the distance to destinations and a charging strategy based on *SoC* (State of Charge) are used to model the usage of charge points (CPs) and thereby the impact on the electricity grid. Stringent rollout policies by the municipality result in 18 public CPs while relaxed rollout policies result in 70 public CPs in 2035. Two case studies using different neighborhoods are performed and the results suggest a public to private CP ratio of 0.22 for a residential neighborhood and 1.32 for a commercial neighborhood. The model does not consider realistic business cases for the CPO (Charge Point Operator), DC fast charging and developments in charging technology.**

I. Introduction

Over the past century, there has been a dramatic increase in the atmospheric CO_2 levels due to reliance on fossil fuels. This has increased the surface temperature of earth considerably leading to climate change. The transport sector covers about 23% of the emissions of which car passenger transport covers 11% [1]. There have been stringent limits placed on the tailpipe emissions of all vehicles and in spite of such efforts the transport sector is still one of the major contributors to GHG emissions. EVs have the potential to substantially decrease the GHG emissions [2].

Similar to Internal Combustion Engines (ICEs) having fuelling stations to refuel the car, EVs have charging stations that charge the vehicle. The network of such charging stations form the charging infrastructure. The presence of a good charging infrastructure aids the market penetration of EVs since consumers are going to buy electric vehicles if they are assured of a way of charging it. The charging infrastructure being a barrier to household adoption of EVs has been discussed in [3]. There are many stakeholders who are interested in the charging infrastructure. These stakeholders are hesitant to deploy charging stations without understanding the demand of electric vehicles and loads on the grid.

According to Bloomberg New Energy Finance (BNEF) [4], EVs are going to become as affordable as gasoline or diesel cars in the next six years. And when factors like the Total Cost of Ownership (TCO) comes to light [5], the EV market share is going to increase. This increase in market share of EVs will also increase the energy consumption. Since electricity is generated and supplied to consumers by the grid, the load on the grid will also increase. The forecast of increase in load impact on grid depends on other factors such as frequency and rate of charging, driving and charging patterns [6], size of the battery in the EV, EV adoption over the years (buying pattern of consumers) [7] [8] [9] [10], number of EVs at a specific location and number of charging points/stations. If the charging infrastructure of the future is known, it will help the stakeholders understand the load on the electricity grid better. This will lead to introduction of new policies to support development of EVs. The charging infrastructure of the future can be predicted by including development in the field of electric vehicles (battery prices, powertrain prices and TCO) and is co-determined by how consumers buy, charge and drive EVs.

To study the placement of CPs and loads on the electricity grid, there is a need for a model that represents the complex charging network. The existing research on modeling of charging infrastructure is discussed in section 2. These models do not take into account the spatial and temporal patterns. The charging infrastructure is in itself a complex network consisting of heterogeneous agents interacting between each other and the decisions are more complicated than yes/no or true/false decisions. This leads to the research question:

How to develop a model to determine electric vehicle charging infrastructure in the Netherlands until 2035 while addressing:

- *The type, operation and location of CPs*
- *Different stakeholders, their behaviours and the interaction between them*
- *Preferences of EV drivers and households*
- *Developments in the field of electric vehicles*

The paper is presented as follows: section II describes the existing research in the charging domain and what the model will add to that. Section III talks about the methodology

behind the modeling technique used and the approach used to build the model. Section IV elaborates the implementation, technical details of the model and assumptions present in the model. Section V presents the results of the model based on various scenarios. Section VI and VII provide important conclusions and suggestions for future work, respectively.

II. Existing Models

This section deals with the already existing models about the charging network and the different modeling techniques currently used to model the charging infrastructure. Major research is carried out in the field of charging infrastructure that has helped investors understand the demand of EVs [11].

The optimal placement of charging points for instance, enables drivers to charge efficiently by minimising transport distance or by maximising energy used from a CP. A simulation-optimization model was developed in [12] to optimally locate EV chargers in central-Ohio region, maximising their use by privately owned EVs, also by considering level-one chargers. Genetic programming was used in [13] which presented a model for e-vehicles including range of vehicles and battery depletion where they move around on a real city map (the city map of Vienna). A genetic algorithm was also used to increase electric miles by public charging infrastructure deployment in [14]. A multi-objective optimization model was developed in [15] which maximizes the number of households reached and minimizes the transportation energy cost. The decisions were made by mixed integer linear/non-linear programming that used energy aware constraints. In [16], an extensive analysis of charge event data at charge points located throughout Ireland and Northern Ireland were conducted. The optimal charging infrastructure is chosen in terms of economic and practical effectiveness.

A few mathematical models were also developed. [17] uses a mixed integer programming method. The algorithm minimized EV users' station access costs while penalizing unmet demand in Seattle. For large-scale integration of EVs into the grid, [18] minimizes the total transportation distance using a modified Binary Particle Swarm Optimization (BPSO) based on Taboo Mechanism (TM). Modified primal-dual interior point algorithm (MPDIPA) is used to minimize total cost associated with charging stations in [19].

The charging infrastructure is influenced by a considerable number of stakeholders who have their own behaviours/actions and should be considered from an individualistic angle. These behaviours again depend on a lot of other factors and cannot be modelled using basic yes or no/ true or false decisions. These models are very useful in optimizing the current charging infrastructure and are not useful to model the future. Moreover, spatial and temporal patterns are not used in the models to determine charging behaviours. The buying decisions of consumers [7] [8] [9] [10], frequency of charging, location of charge points, development in EVs, policies regarding EVs and their charging etcetera (mentioned in Section I) are all important to model the charging infrastructure. This is complex and a bottom-up approach would be useful to add complexity starting from a basic model.

The above factors are incorporated using Agent-based modeling (ABM), a modeling technique where stakeholders, drivers, EVs and CPs are considered as agents. The working of ABM and the definition of an actor in the context of ABM is given in the next section. As described in [20], "The key distinguishing element, that sets agent-based models apart from other models, is a focus on modeling individuals who can make decisions". An agent-based model for the adoption of EVs is [21]. The consumer (household sizes, commuting distances etc.) and government agents are taken into account in this but does not take other agents such as the charge point manufacturer or charge point operator (refer section 3). In a similar study [22], a choice-based conjoint data of about 7000 respondents were used to model heterogeneity of consumer preferences. The car manufacturer was included as an agent in this model.

An ABM focused on the deployment of charging infrastructure is mentioned in [23]. It includes an EV adoption model and uses the driving patterns to develop an agent-based decision support system for the strategic placement of chargers. A vehicle is bought by an agent based on price, fuel cost, greenness, social influence, long distance penalty, and infrastructure penalty. The study mentioned in [24] calculates EV charging demand in a certain area taking social and economic variables into account.

These models use few of the stakeholders. They either model the buying and driving behaviours [7] or charging and buying behaviours [9] by using a single day travel data [8] or driving profiles based on previous year's data. Hence, the individuality that ABM provides is not present in the models described. The model described in this article takes into account all the stakeholders involved in charging (discussed in the section 3), the interactions of the buying, driving and charging modules to realistically build the visualisation of the complex phenomenon. Individual travel and charging profiles obtained from the simulation which is based on behaviours of various agents are used. This can give real life energy consumption data useful for determining real-time loads on the electricity grid.

The technological development of EVs, specifically the battery and drivetrain price developments leading to the TCO (Total Cost of Ownership) is considered as part of the buying behaviours apart from the range anxiety, luxury preference and income level. Moreover, the inter-dependability between buying and charging, where a consumer's buying decision is affected by the availability of charge points is also included. The following section talks about the validation of the use of ABM, the approach used to build the model based on ABM, the modeling language, the stakeholders (agents) involved and their basic behaviours.

III. Methodology

The charging infrastructure is influenced by a lot of agents interacting with each other and is a complex Socio-Technical System (STS) similar to the electricity infrastructure [25]. It can be modelled using a relatively new modeling technique called Agent-based Modeling [20]. The study in [26] also talks about car-based transportation and the adoption of alternative fuel vehicles as a socio-technical system.

A. Bottom-up approach and agent-based modeling

ABM can be particularly used for energy networks [25]. This method models agents and their behaviours from a bottom-up perspective. As described in [20], "In agent-based modeling, a model of an actor, or a group of actors (e.g. a company, a governmental institute, a community of citizens), is called an agent". Moreover, these agents can be heterogeneous and can interact both in time and space, with each agent retaining memory of previous interactions.

Each agent may have a different story, rules & preferences. Unique behaviour for each agent is the result, similar to the real world. The system behaviour is obtained from these micro-entities interacting with each other. The system does not need to be described in advance like with a top-down approach. However, the interactions and the agents involved should be provided as input. [27] stresses the value of bottom-up modeling and explains how design changes occur at a lower level and system level changes emerge from this [20].

B. Verification and validation of ABM

Validation is one of the major challenges that an agent-based modeller faces as described in [28]. [29] summarises four steps to validate an agent-based model: *grounding*, *calibration*, *verifying* and *harmonizing*, which integrates the verification and validation process.

This research project forms the Charging module of the Agent-based Buying, Charging and Driving (ABCD) model which predicts the rise of electric vehicles and charging infrastructure along with the impact of smart charging in the Netherlands. The aim of the charging module is to model the charging infrastructure rollout and usage in Dutch neighbourhoods. An overview of the charging module is shown in Fig. 1. The model was *grounded* in this research domain.

The model was *calibrated* to match the actual charging infrastructure. This involved adjusting the CP, municipality and CPO agents to observe charging behaviours close to the real world. Global parameters were also adjusted to match the neighbourhood and nation-wide market – for example, the percentage of residents with an EV at the start of the simulation was obtained from the percentage of EVs in the Dutch market [30]. The model *calibration* and *verification* were also done using expert insights and predictions. Charging domain experts [31] [32] [33] [34] [35] [36] and problem owners (The ABCD model group) were involved in meetings every week to discuss the behaviour of agents, the dynamics of the system and systematic reviewing of the assumptions and outcomes. This method of *validation* has face validity and is the most commonly used validation approach according to [25].

The model was *harmonized* through independent testing of the charging module and further testing with the other parts of the ABCD model. The basic actions of charging were tested separately at every step of the model development. Testing using single and multiple agents were carried to find out if the model translates theory into computation. Moreover, the agents were also tested with extreme input values to "break" the agent [25] and find out threshold values of input that could cause the agent to behave differently.

Since all the four steps were carried out, the usage of ABM is well justified. The bottom-up model that was developed is explained in detail in the upcoming sections.

C. Bottom-up model development

In the charging model, the usage of charge points depends on the presence of work or home chargers, number of EVs and travel patterns. These in turn are understood from the activities of residents who own an EV. Thus building an environment with people and electric vehicles would be an important step to learn more about charging.

1) The environment

The environment is the world where agents interact with each other based on their individual behaviours. In this model, geographical data from real neighbourhoods were used. The model can be applied to any neighbourhood within the Netherlands as mentioned earlier. Two representative neighbourhoods determined by [36] that contain a mix of offices, residential spaces, parking spots, visiting places,

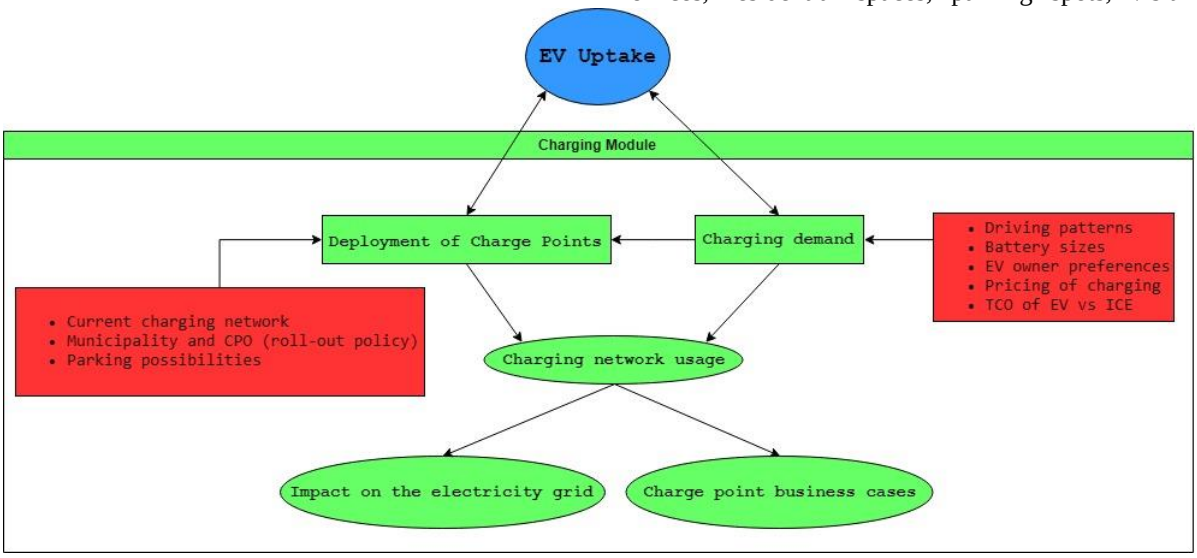

Fig. 1. Overview of the charging module

public and governmental buildings were used. This model can also be scaled to represent the whole of Holland. Two representative neighbourhoods, one in The Hague (Zeeheldenkwartier region) and the other in Arnhem (Alteveer region) are used. The Zeeheldenkwartier region is a neighbourhood in the centre of The Hague. It has predominantly smaller houses without private driveways and a few large houses for government officials. The Alteveer region is away from the centre of Arnhem and is a richer neighbourhood having larger houses and more private driveways than the Zeeheldenkwartier region.

GIS data of these neighbourhoods were used in the model. Exits - the points where people leave and enter the neighbourhood and roads - using which the residents and cars traverse through the neighbourhood were made in QGIS. These are also considered as agents in the model and were added to the neighbourhood to facilitate movement of people and cars. Next, the actors were added to the neighbourhood whose basic behaviours and interactions are discussed below.

2) Actors, basic behaviours and interactions

Once the environment was created, formulating the actors, their structures and behaviours is the next step. This is an essential step as mentioned in [25]. The agents relevant to the charging infrastructure are as follows (details on agents are discussed in the section IV):

- The resident: People living inside the neighbourhood. They have an EV or ICE at the initialisation. They own a house, have a work place and also go on trips.
- The commuter: People living outside but working inside the neighbourhood. Only commuters who own an EV are simulated since only their behaviour is interesting for the purpose of the model.
- The EV: Cars that move in and out of the neighbourhood and are of paramount importance to the charging infrastructure. Residents or commuters own EVs. The car manufacturer agent makes EVs – A, C and E class models and the dealer agent sells them. The driving patterns enable the EV to move around.
- Charge Point (CP): CP is responsible for charging an EV when it is connected to it. It charges at a specific rate that depends on the capabilities of the charger (AC single phase or AC three phase). It adds kWh to the battery at each time step and sends a signal once the EV is charged even though the EV remains connected after that until the driver comes to pick it up.
- Charge Point Manufacturer (CPM): The CPM develops charge points and determines the price of the charge point.
- Charge Point Operator (CPO): Charge point operator determines the selling price per kWh and makes money based on the amount of energy sold. CPO places a charge point once an EV is sold. It can be a public or private charger. It is also responsible for maintenance and repair of the CP.
- Municipality: The municipality agent is responsible for making the decision to place a CP when a resident requests for a public charger (before buying an EV) through the dealer. If the municipality's decision is negative, then the resident would not get a public charger and if positive, then the resident would get a public charger.
- Parking places/spaces: This agent divides and sorts the parking spaces.

Other agents are the buildings, roads, exits, car manufacturer and dealer. The consumer (household) and government agents have been looked into in [21], [10] and [7]. The municipality agent that is involved in the process of placing the CP was also taken into account. The CPO agent is used in [7] but it was a mere construction-destruction decision based on a certain formula. The rest of the model is explained in detail in section IV.

D. Software implementation

The current version of the model is implemented in GAMA, which was selected over other ABM platforms like NetLogo and Repast for its ease of use and open-source code. Moreover, it takes shapefiles containing GIS data to define the environment and also has intuitive agent-based language called GAML (GAma Modeling Language) which makes it coder-friendly [37]. It also has other useful agent-based capabilities, e.g. to *inspect* a single agent of the model to know what a specific agent is currently doing at any point during the simulation and how the attributes change during the simulation.

This project has multiple researchers working on other parts of the model and a version control system was much needed. For this, Git was chosen since it has local control over the repository (decentralised) which was needed for the researchers to work on their respective parts without disturbing the build of the master code. Naming convention is important in such situations and the naming convention in this model was followed such that it is readable like the *"home_CP"* species name for a home charger and not x, y or z to represent charger species which would lead to ambiguity.

Actions are sequence of statements that are executed only when called elsewhere and reflexes are sequence of statements that are executed at every time step. These can be defined in a species, model or experiment (used for running simulations and visualising). Actions, reflexes, species and variables were named such that all the collaborators jointly understand the model and no conflicts occur. The model files (which have an extension .gaml) are divided such that there are several files which have specific functions and not a single file containing several lines of code. GAMA handles these by the *import* function which lets to import all the files into a common build file which has the experiments related to the whole model. *ABCD_<name>.gaml* is the usual syntax of model files. The *name* is the part of the model the file is representing – e.g. *ABCD_charging.gaml* represents the charging module file which is imported into the *ABCD_build* file so that the charging part is present in the model. The next section deals with the technical aspects of the model on how the charging network is modelled in GAMA and also briefly on the buying and driving module. The interactions between these are also discussed based on the agent behaviours.

IV. Charging Model Development

This section deals with the technical aspects of the model on how agents are initialized and how they move around, how trip patterns are used, how the charging module works followed by what happens when agents buy/sell EVs. The charge point rollout methodology (disappointment point system), role of CPO, the municipality and the assumptions of each part of the model are also discussed.

The model aims to capture the buying, charging and driving activities of consumers who live inside the neighborhood. It also captures the driving and charging activities of commuters who come inside the neighborhood to work and go outside the neighborhood to their respective homes. This is important information for the CPs in the neighborhood since commuters contribute to the load on the grid during the day when residents of the neighborhood go outside the neighborhood for work/trips. As seen from Fig. 2, the neighborhood can be imported and displayed in 3D (wheat color – houses, grey – offices and light green – attractions) in GAMA.

Residents are assigned values for different attributes like the income, acceleration preference, range preference (level of range anxiety) and environmental attitude (attitude towards shift to EVs) [38]. Residents and commuters are assigned a work place. They are also assigned an activity and objective which records the activities they perform based on the objective e.g. the objective "working" means they have to leave to work and their activity would be "going to work". Residents have a living place inside the neighborhood which they own and a visiting place (for trips). The EVs that are created have a class, battery capacity, an SoC attribute (*kWh_in_battery*), fuel efficiency (km/kWh), an owner and parking attributes based on the availability of home parking. The simulation step is important for the charging and driving models to function properly. The step in this model is 15 minutes or 1 hour depending on the type of outcome required.

Assumptions:

- Residents and commuters own a single vehicle.
- The driving behavior of a household is represented by 1 resident.
- Residents can own an EV or ICE (Internal Combustion Engine). Each resident owns either an ICE or EV at the start of the simulation. Commuters owning an EV are only considered in the model.
- The residents who own an EV get a home charger if the agent has a private parking. If not, the agent requests a public charger close to the agent's living place.
- The car ownership for Zeeheldenkwartier region is 0.4 and 0.8 for Alteveer region from [39]. This means that there is a 40% (or 80%) chance that a household has a car for transportation.
- There is 20% chance that a household has a private driveway in Zeeheldenkwartier and 60% chance in the Alteveer region.
- The number of residents having an EV at the beginning is based on real-world market data - [30] [40].
- Two driver types – *working (commuting)* and *non-working* are implemented.
- Three classes of vehicles – A, C and E-class are considered to be available types of car for residents to choose from [5].

Fig. 2. Imported neighborhood (Alteveer) from the city of Arnhem on top of a google earth layer

A. *Driving pattern and trips*

Since we are considering real life situations, the time all of us leave for work or for a trip is not the same every day - the same is reflected in the model. At the start of every simulated day, the trips on that day are determined for each resident and commuter. The time someone leaves home for work is considered to be a random time between 06:00h to 10:00h. A resident has a probability of going on a day trip, evening trip and weekend trip. Agents depart when the simulation time of the day is the trip depart time and return when the time is the trip return time. Objective is set to "working" when the agent has to work, "resting" when he has to go home and "make a trip" when he is about to go on a trip. The current activity of the agent is also set accordingly. A snapshot during a random simulation day (evening) is shown in Appendix (A). The charge remaining in the EV is calculated using:

$$C_A = C - \left(\frac{x}{\eta}\right) \tag{1}$$

Where C_A = Charge remaining in the EV [kWh]
C = Battery capacity of the EV [kWh]
x = Distance of the last trip [km]
η = Energy efficiency of the EV [km/kWh]

Assumptions:

- The mersenne random number generator is used to generate random numbers [41].
- Trips that require the use of a car are only considered.
- Trips for commuters are not taken into consideration since that happens outside the neighborhood. Commuters always come with 100% charged EVs into the neighborhood.
- The time to leave for work is determined from [42] (when the step size is 15 minutes). The working time for commuters and residents is eight hours from the start of work.
- 50% chance for a resident who owns an EV has a work charger or a destination charger (for trips).

- The distances for work trips (both residents and commuters) and other trips (residents) are generated from OViN data [32].
- 10% chance that a resident goes for an evening trip, 20% chance that a *non-working* resident goes on a day trip and 40% chance that a resident goes on a weekend trip is assumed in the model. The departure and duration of various trips is given in Appendix (B) – Table III.

B. EVs and charging infrastructure

The charging in the model happens as follows:

- A person arrives either at home, work or visiting and makes a decision about charging.
- The person chooses a charge point if he/she wants to charge.
- The car goes to the CP and charges until it is full.
- The CP charges the EV at a certain charging speed (through an action).
- It stops charging when the car's battery is full but the car is still connected to the CP till the agent comes and picks up the car.

The model has a complex charging system which includes sockets for chargers. Sockets correlate to the number of cars that can charge simultaneously. The numbers of cars charging from a CP cannot be more than the number of sockets. The CPs also show the available number of sockets during the simulation i.e. if the number of sockets is initially 2 and then a car connects and starts charging, the number of available sockets is reduced to 1. If the number of available sockets is 0, then the attribute *accessible* (a Boolean) is set to false and the charger is no longer accessible for any other EV. The model also shows both visually and non-visually whether a charger is in-use or not, using an attribute *in_use* (a Boolean). When an EV is charging or parked the *in_use* is set to true. The CPs also record the cumulative energy supplied by them for which there is an attribute in each CP agent. The model also records the total energy supplied by all the public CPs in the neighbourhood. The CPs also have an attribute called *disapPoints* which is a part of the *Disappointment Points System* explained later.

Now, when an agent reaches the work place or home there is a search for a charge point if necessary. If the agent has a home or work charger, the EV gets charged always regardless of the SoC (State of Charge). But, when either of that does not exist, then the agent has to look for a public charger. This is when the sockets are useful to define real-world closeness. The agent checks the SoC of the EV and the distance to the closest public CP which is explained below and is called the *CSoC approach*.

Charging based on SoC of the EV (CSoC):

The agent checks the SoC of the EV and decides on the distance to look around for a public CP. If the agent finds a public CP in the specified radius which has a free socket (meaning it is accessible) then, the EV is connected to the CP and starts to charge. Table I summarises the SoC and distance to a public CP conditions that the agent uses. For commuters the first option (>=80%) does not exist and they do not charge if the charge is more than 80%. If there is no public charger available with these limits and specifications, then the agent does not charge the EV and parks the car at the respective parking place. The CPs are rated at 230 V x 16 A. The power output of the CPs is calculated as follows:

$$P = \frac{n \times V \times I}{1000} \tag{2}$$

Where P = Power supplied by the CP [kW]
n = Number of phases
V = Voltage rating of the CP [V]
I = Current rating of the CP [A]

TABLE I
CONDITIONS FOR POSITIVE CHARGING DECISION – *CSOC APPROACH*

State of Charge	Distance to a Public Charger (in meters)
>=80%	Less than or equal to 50 meters
<80% & >=60%	Less than or equal to 100 meters
<60% & >=40%	Less than or equal to 200 meters
<40% & >=20%	Less than or equal to 300 meters
<20%	Less than or equal to 500 meters

Assumptions:

- Home CPs and work CPs have a single socket and public CPs have 2 sockets.
- The year of placement of CPs initialised in the neighbourhood is assumed to be a random year between the 2010 and 2017. This does not apply to CPs that are placed later (for which the current year is the year of placement).
- DC fast charging is not considered in the model.
- Home CPs are AC single phase (3.7 kW power output - 230 V x 16 A) while work CP and public CP are AC 3 phase (11 kW power output - 230 V x 16 A).
- The speed of charging is solely based on the capabilities of the CP and not the EV.

C. Buying, selling EVs and placement of Charge Points

Residents in the neighbourhood are car owners. Every simulation month agents may decide to purchase a new vehicle if he/she does not own one. The resident also sells the vehicle when the ownership period is over. When the decision to purchase a new vehicle is made, a 'visit' to the car dealer provides the buyer with a list of currently available EV and ICE models with their respective battery size, power and class, all with a certain price tag. These available models and their prices develop over time. The dealer agent selects the right car based on the resident's income, range and acceleration preferences. More about the buying decisions are given in [38]. Before this, the resident asks the dealer whether he/she will get a public charger – this happens when the resident does not have a private parking at home.

The buying decisions are also affected by the availability of public/private charging. If the resident has a private driveway, he/she always buys a home charger given that he/she buys an EV. If the resident requests for a public charger (since he/she does not have private driveway), the dealer asks the CPO and municipality if they are ready to place a charger near the home

of the resident. Commuters are introduced at every month of the simulation. The ratio of the number of EVs in the neighbourhood to the number of residents which is called the EV ratio is used to introduce commuters. This is to make sure there is a like-like comparison of the number of residents with an EV and the number of commuters in the neighbourhood. Further, if a commuter's work place has a private parking possibility then there is 80% chance that there is a work charger installed. So, the model also includes the placement of work and home chargers. The charging module accounts for the selling of EVs also, i.e. residents already having a charger from the previous purchase of an EV, do not request for a new charger when they purchase their next EV. The rest of the section explains how the municipality decides whether to place a charge point or not.

1) *Disappointment Point System*

The disappointment point system adds *disapPoints* to the CP under certain conditions. When a resident or commuter is looking for a public charger, the charger that is *accessible* is chosen and the agent goes to that charger. If for some reason, the public charger that the resident/commuter goes to is not the same as the public charger closest to the living place/working place, then one disappointment point is added to the *disapPoints* attribute of the charger that is closest to the agent which means that the resident/commuter is not happy that the closest charger is not accessible when it is needed. Moreover, this disappointment point is added to the closest charger only if the distance the user has to go to find another charger is more than 100 meters since the user does not mind going 100 meters to find another charger. This way, given a neighbourhood, one can find out CPs which are not accessible often which is important for the municipality.

2) *Municipality agent*

The municipality has a certain radius of search up to which the chargers (within that radius) are checked for the *disapPoints*. This search radius defines the number of public CPs around the user that is checked. If all the chargers within that radius have enough *disapPoints*: defined by the *disapPoints_threshold* which is an attribute that defines the minimum number of *disapPoints* needed for that CP to be considered frequently-used; then the municipality sends a "yes" decision to place a public CP near the resident who requested for one. When the resident knows that the municipality is willing to place a CP, the chances of buying an EV is more than when a CP would not be placed. The decision from the municipality can also be a "yes" when there are no chargers in the search radius mentioned. The municipality decision making process is given in Fig. 3.

3) *CPO agent*

The CPO always makes sure there is a positive business case in the model and if the decision is "yes" from the municipality and the resident buys an EV, the CPO always places the CP. Predictions for the periodic costs (yearly costs) and the one-time fixed costs of CPs were taken from [43] and for a payback period of 10 years, the total price per CP per month that the CPO has to pay was found. A power law was fitted to the found estimates. The general form of a power law is:

$$f(x) = Kx^{\alpha} \tag{3}$$

where $x > 0$ and K, α are constants. As shown in Fig. 14 in Appendix (C), the power curve that was obtained is given by:

$$y = 108.38(1 + c - s)^{-0.256} \tag{4}$$

Where y = Price per CP per month [€/month]
c = Current year of simulation
s = Starting year (2013)
K = Price per CP per month in 2013 [€/month]
α = 0.256 (Learning index)

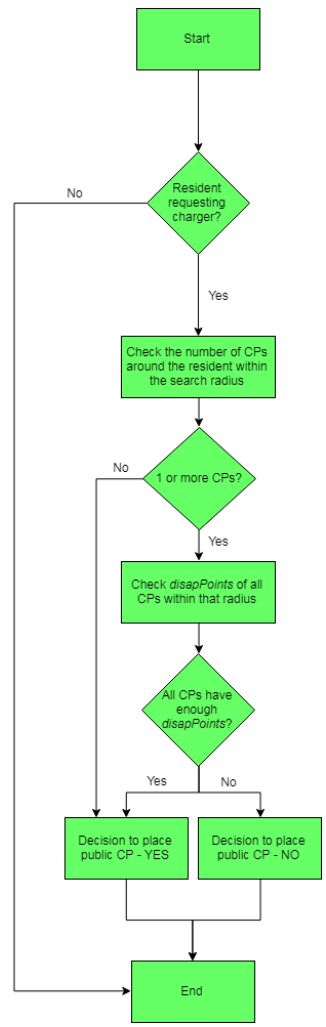

Fig. 3. Municipality decision making process

The slow charging cost calculated by the CPO is given by:

$$C_s = 1.15 \times \frac{[(E_{sold} \times C_{kWh}) + \sum_{i=1}^{n} y_i]}{E_{sold}} \tag{5}$$

Where C_s = Slow charging cost [€/month]
E_{sold} = Total energy delivered by the CPs [kWh],
C_{kWh} = Cost to deliver kWh by the CPO (11 cents/kWh)
$\sum_{i=1}^{n} y_i$ = The sum of the total cost per month of all the CPs in the neighbourhood [€/month]; n is the number of CPs

in the neighbourhood and y_i is the price per CP per month of the ith CP [€/month] (from eq. 4).

Assumptions:

- The radius of search for the municipality is set to 250m unless stated otherwise.
- The *disapPoints_threshold* is set to a value of 10 unless stated otherwise.
- The *disapPoints* are set to 0 for each CP every month after the buying decisions happen. Also, the cumulative energy supplied it reset every month since the calculations are made by the CPO on a monthly basis.
- There is a 70% chance that the resident is inclined to still buy an EV when the decision from municipality is a "no".
- A power law was assumed to find the fit between price per month per CP and years. The power law is based on the years and not the production number.
- Profit for the CPO is fixed at 15%.

To maintain a charging network that is accessible and to model a charging regime that is close to reality, different innovative approaches and systems like *CSoC* and *disappointment point system* were used in this model. These have a direct influence on the number of CPs placed and the impact on the grid. The next section presents the results obtained from the model under various scenarios that are interesting to the charging module.

V. Scenario Analysis and Validation

For the purpose of testing the model, single and multi-agent testing were done (as explained in section III). A single agent was explored using the *inspect* function of GAMA and determined whether it performs the required actions. For example, a resident has to go to office on weekdays and has to leave/return home by the time specified by the model. Extreme input values, interaction testing in a minimal model and sanity checks were done to check if a single agent functions as per the requirements. When the behavior of a single agent was verified, multi-agent testing was done. For this purpose monitors and charts were used to examine the statistics of the outputs. This section deals with some interesting scenarios and results obtained from the model. Parameters that influence the system behavior were changed to find the effect on the results.

The starting date of the simulations is taken to be 1st January 2017. The step size is either 15 minutes or 1 hour based on the scenario under consideration. To reduce computation time, the simulations were done for 200 residents and scaled up to represent an ownership of 0.4 and 0.8 in The Hague and Arnhem neighborhood respectively (as mentioned in section IV). Zeeheldenkwartier is used for simulations unless stated otherwise. For each scenario, the seed of the simulations were kept the same in order to analyze the influence of a certain parameter under the same conditions.

A. *Effect of search radius (municipality)*

Fig. 3 shows that the 'search radius' impacts the number of public charge points that are placed in the neighborhood. Fig. 4 explores this impact by showing the development of public CPs in the neighborhood with different search radii. The model is initialized with 3 public CPs. When the search radius is set to 100 meters, the number of public CPs the municipality has to check (when there is a request from the resident) for *disapPoints* is lower than with a search radius is set to 250 meters. 500 meter search radius spans almost 70% of the neighborhood (in this case) and it is a case where the municipality may end up checking all the public CPs for *disapPoints*. So, when there is a request for a public CP, a 100m search radius would result in lesser CPs checked for *disapPoints* and hence more probability of getting a public CP for the requested user. This results in more public CP in the neighborhood than with the search radius being 250m. Thus the *disappointment point system* impacts the placement of CP in the neighborhood.

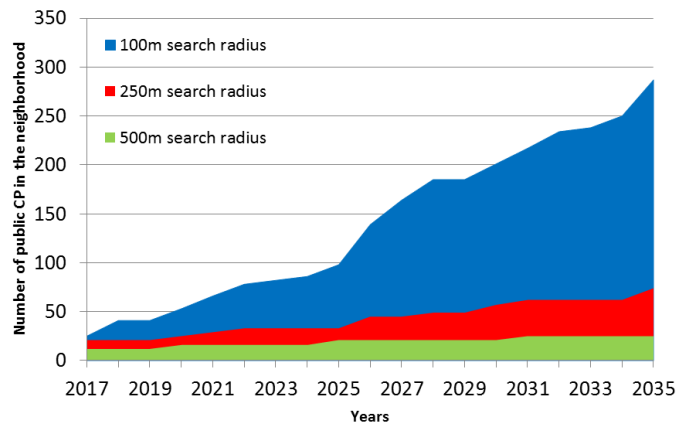

Fig. 4. Effect of search radius on number of public CPs placed

The increased charge point rollout between 2025 and 2028 is a result of increased EV sales, whose dynamics are attributed to the buying module (see Fig. 15 in Appendix (D)).

B. *Effect of battery size on number of CPs placed*

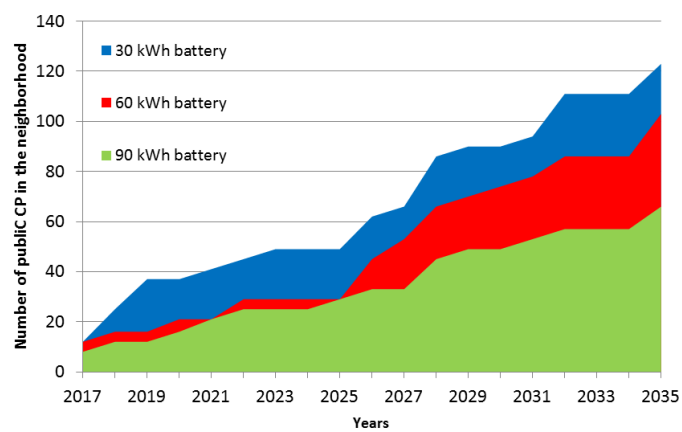

Fig. 5. Effect of battery size on number of public CPs placed

The effects of the *CSoC approach* are explored with scenarios keeping the battery sizes of the EVs in the neighborhood fixed at 30 kWh, 60 kWh or 90 kWh. 100m search radius is used. When every EV in the neighborhood is 30 kWh residents charge their EV more often because their battery provides less range compared to scenarios with higher battery capacities (see the explanation of the *CSoC approach* in Section IV). Charge points are used more often, theoretically leading to more *disapPoints*. Therefore, the number of public CPs placed

should be higher as shown in Fig. 5. On the other hand, when the EVs have a bigger battery size, then the users have enough charge to go back home from the destination without charging and hence the numbers of chargers placed is lesser (*disapPoints* are lower).

Note: these scenarios limit the EV buying options (one battery size per class), resulting in less EVs bought and less public CPs installed than in scenario A.

C. Effect of neighborhood type on number of charge points

As mentioned earlier, this model can be used for any neighborhood within the Netherlands since most of the inputs are calibrated for the Netherlands. Each neighborhood has different characteristics like the geographical location (i.e. urban, suburban, rural, etc.), density, road layout and connectivity; economic diversity and functionality (i.e. residential, commercial, retail, etc.). Table II in Appendix (A) provides more details on the neighborhoods used.

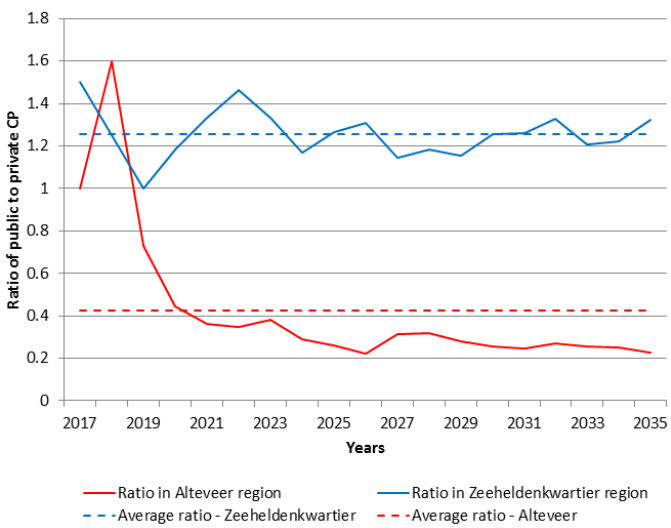

Fig. 6. Ratio of public to private CP in the two neighborhoods

Fig. 6. shows the ratio of public chargers to private chargers in the two neighborhoods considered. The model was initialized with 3 public CPs and 2 home CPs in both neighborhoods in order to have similar starting conditions. This caused the initial spike in the Alteveer neighborhood which has higher share of private driveways (and thus tends to get more private CPs more than public CPs). This is not the case with the Zeeheldenkwartier region where predominantly, houses do not have private driveways. Naturally, the public to private CP ratio is higher in Zeeheldenkwartier than Alteveer. The dotted lines represent the average ratio in both the neighborhoods.

Fig. 7 shows the number of work chargers placed in the neighborhood. For the Zeeheldenkwartier region, which has 204 offices, there are a lot more work chargers placed than the Alteveer region which has 4 offices.

D. CSoC and impact on the electricity grid

To study the impact on the electricity grid, the average electricity usage profile of a single household every 15 minutes was obtained from [44] and is given in Fig. 8. This was added with the load from EVs to give the total load on the electricity grid.

The simulations in this scenario were carried out with a step size of 15 minutes to accurately visualize the loads on the grid. 200 residents and 50 commuters were used and 40% of the residents were assumed to own EVs (Zeeheldenkwartier region) while all the commuters own EVs. The *CSoC approach* can impact loads on the grid as shown in Fig. 9. The simulation was run for two days. In the morning, residents travel outside the neighborhood to work and the load on the grid is due to the commuters. With the *CSoC approach*, commuters do not charge if they have more than 80% of charge remaining in their EVs which is why the peak loads are reduced during the day. In the evening, the residents only contribute to the loads and since all the residents are assumed to have a public or home CP at initialization, the loads on the grid are not affected by the *CSoC approach*.

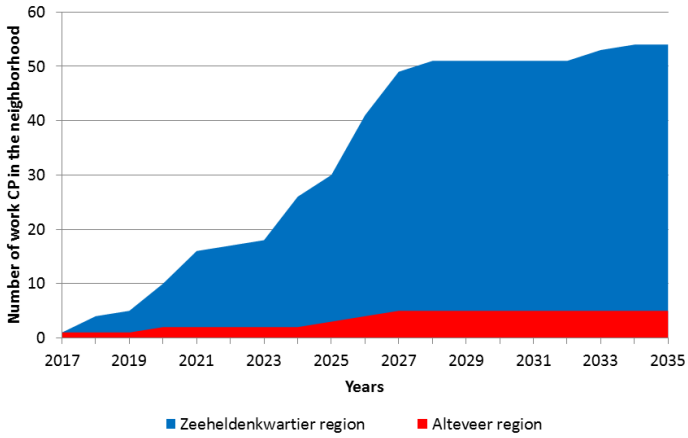

Fig. 7. Number of work chargers in the two neighborhoods

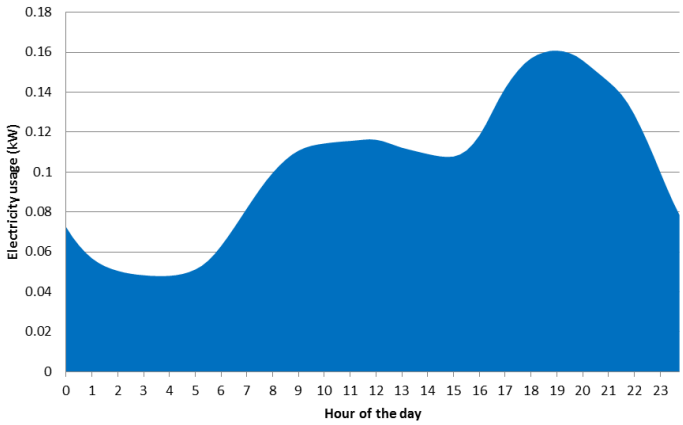

Fig. 8. Average electricity usage profile for a single household (every 15 minutes)

Fig. 10 shows the case when the availability of public CP is varied. The *CSoC approach* is used in this scenario. Residents who own an EV have 100% chance of getting a public CP in one case and 10% chance of getting a public CP in another case. If the resident has home parking, then he always gets a home CP. As seen in Fig. 10, the peak loads are lower when the number of public CPs are low. But, this might lead to a fact that the resident does not find a way to charge the EV even though the SoC of the EV is low.

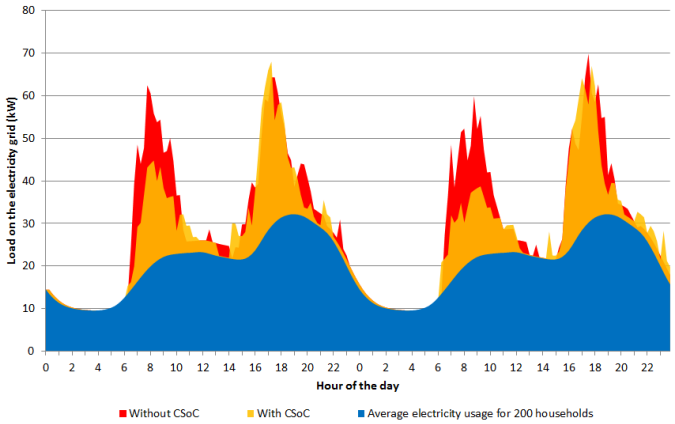

Fig. 9. Effect of *CSoC* on the electricity grid

Fig. 11 shows the case when the battery sizes of cars present in the neighborhood are 30 kWh and 90 kWh. The *CSoC approach* is used in this scenario. Residents have 100% chance of getting a public CP if they do not have home parking. Residents follow the same *CSoC approach* as commuters i.e. the first option in Table I is excluded for residents in this scenario. This means that both residents and commuters do not charge if the SoC is more than 80%. As seen from Fig. 11, using smaller batteries leads to more usage of charge points (refer scenario B) and hence larger loads on the grid.

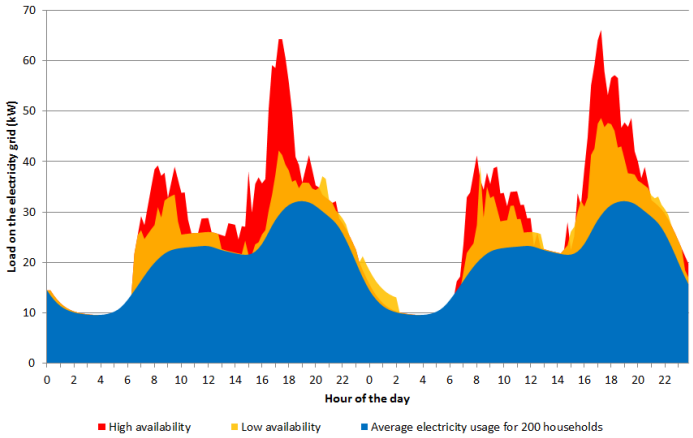

Fig. 10. Effect of the availability of public CPs on the electricity grid

VI. Conclusions

The agent-based model presented implements the *disappointment point system*, which is used by the municipality agent in the decision making process for the deployment of public CPs. Varying the search radius resulted in 70 public CPs (100 meter), 18 public CPs (250 meter) and 6 public CPs (500 meter). However, it was observed that the *disapPoints_threshold* did not affect the number of public charge points placed. This can be attributed to the refresh rate of the *disapPoints.* Also, it could be the fact that a few CPs get most of the *disapPoints* due to the *CSoC approach.* Therefore, when the municipality checks a specific radius, not all CPs have enough *disapPoints.*

Given a neighborhood with more private driveways, larger houses and lesser work places (Alteveer) it was observed that there were 27 public CPs, 119 home CPs and 5 work CPs placed in 2035. In Zeeheldenkwartier with comparatively lesser private driveways and more offices, it was observed that 70 public CPs, 53 home CPs and 54 work CPs were placed. This suggests that the model identifies and accommodates differences in neighborhoods such as population density, economic diversity and functionality to predict the charging infrastructure. Municipalities of specific neighborhoods can use this model to realistically determine the required public charging infrastructure and thereby the rollout policies needed. This allows municipalities and grid operators to be one step ahead and consider the shift to EVs a lesser threat to the grid.

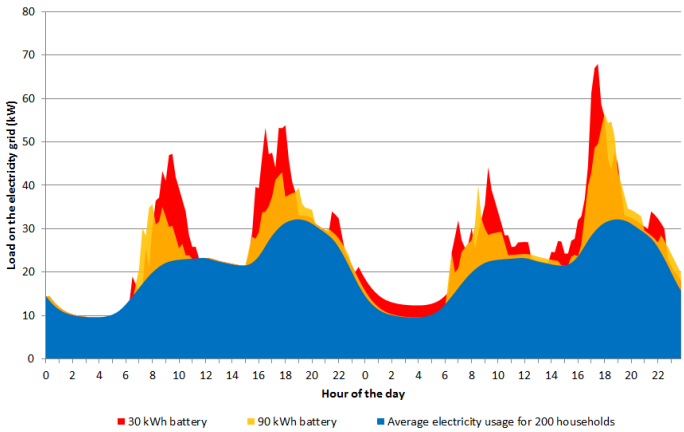

Fig. 11. Effect of battery size on the electricity grid

This model was also successfully used to determine the loads on the electricity grid based on the battery size of the EV, SoC (*CSoC approach*), distance to destination and existence of public charge points. The *CSoC approach* reduces peak loads in the morning from 60 kW to 45 kW (first simulation day). The case study on availability of public charging suggests a reduction in the peak loads (morning) from 64 kW to 42 kW when not every resident gets a public CP at initialization. This reduces the options available for EV drivers to charge. The model suggests that given a specific neighborhood, number of EVs and CPs, the loads can be reduced by users implementing the *CSoC approach*.

VII. Future Work

This model can be used to introduce smart charging strategies for efficient management of loads on the grid. Smart charging involves providing incentives such as cheaper electricity tariffs and faster rates of charging to users thereby allowing strategies like off-peak charging, valley-filling and peak shaving. Another interesting research avenue could be the use of the model for V2G (Vehicle-to-grid) capabilities where the EV provides power to the grid during peak hours and is re-charged during the night at cheaper rates.

The *disappointment point system* can be further developed to add *disapPoints* based on distances. Now, one *disapPoint* is added when the distance to the closest accessible charger is more than 100 meter. This can be improved by introducing *disappointment meter* which would just add the distance travelled to the public CP as *disapPoints*. Accurate modeling of the *disapPoints* is enabled through this but this would further complicate the decision making process of the municipality. The municipality agent places charge points based on the requests of users who have bought an EV only.

This can be improved by the municipality inspecting charge points regularly to find out which charge points have considerable amount of *disapPoints* and placing a charge point if a group of chargers at a certain area in the neighborhood have lots of *disapPoints*. This way the charging infrastructure is made more available for the EV drivers.

One limitation of the ABM developed in this paper is that the CPO agent always has a positive business case in contrary to the real world. The CPO looks at his business case and places a CP only in the event of a profitable venture. This was not introduced in the model. Also, the model does not include DC fast charging since a neighborhood level scale was considered and fast charging would be of more use when simulating larger areas (even the whole of Holland) and people go for longer trips and require highway charging. Developments in charging technology i.e. charging EVs based on the capabilities of both the EV and the CP, introduction of multiple sockets for work CP and more than 2 sockets for public CP in the coming years can be added to the model to further improve the predictions.

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APPENDIX

A. *The neighborhood in GAMA*

Fig. 12 shows the neighborhood of the Hague (Zeeheldenkwartier) during a random simulation day. Fig. 13 is the legend for understanding the neighborhood. Grey are houses, light blue is given to offices and orange to attractions. Light green is given to parking spaces. Green color represents offices or houses which have a private parking possibility. Table II provides details on the number of houses, offices and other buildings in the two neighborhoods.

TABLE II
NEIGHBORHOOD DETAILS

	Zeeheldenkwartier	Alteveer
Houses	2052	494
Offices	204	4
Exits	6	5
Attractions	73	3
Parking Places	574	99

B. *Departure and duration for trips*

Table III provides insight into the trip patterns of residents – the departure time and duration of the three kinds of trips used is given.

Fig. 12. Snapshot of a random simulation day evening in the Zeeheldenkwartier neighborhood

TABLE III
TRIP DURATION AND DEPARTURE TIMES

Type of trip	Time of Departure	Duration of trip
Evening	Between 19:00 and 21:00	Random of 3 hours
Day	09:00 (only for *non-working* drivers)	Random of 10 hours
Weekend	Between 00:00 to 13:00	Random of 24 hours

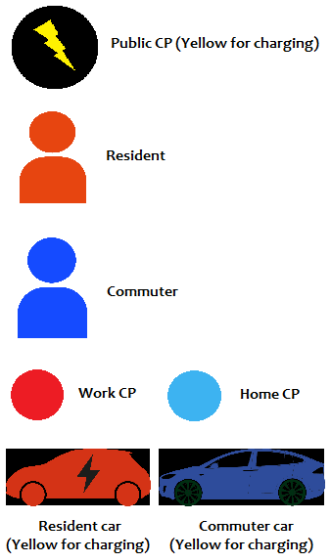

Fig. 13. Legend for the Zeeheldenkwartier neighborhood in GAMA

C. Power law for the CPO

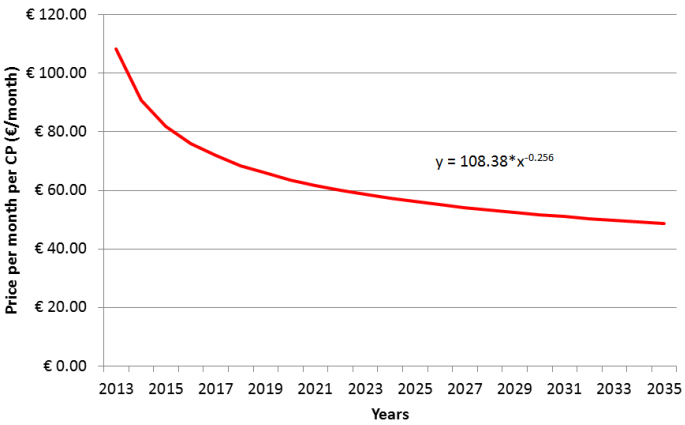

Fig. 14. CPO predictions of total price per CP per month

Fig. 14 shows the power law that is used to predict the price per CP per month that the CPO used to determine the slow charging cost of the neighborhood.

D. Cumulative EV sales based on search radius

Fig. 15 shows the cumulative EV sales in each year. It can be seen from Fig. 15 that the number of EVs sold increases considerably between 2025 and 2028 due to the ownership period of vehicles - which is a normal distribution having values of 9,10 and 11 years. This means that residents who own an ICE (or an EV) in 2017 tend to sell and buy another one, between 2025 and 2028 and in 2034 also.

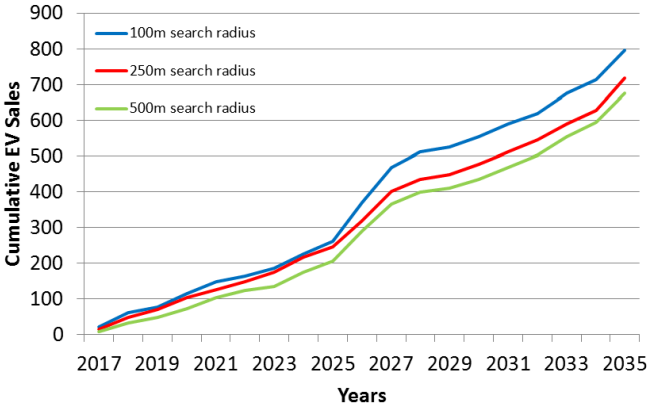

Fig. 15. Cumulative EV sales based on search radius of municipality