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Agent-based Model for the Adoption and Impact of Electric Vehicles in Real Neighbourhoods

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Abstract

This paper describes the methodology and first results of an agent-based model for the buying, charging and driving of electric vehicles (ABCD model). The model can be used to predict the adoption, use and impact (e.g. on CO2 output and the electricity grid) of the transition to electric vehicles. It uses an integral, multi-level agent-based approach grounded in transition management theory with representative Dutch neighbourhoods and brings together domain experts from a wide range of fields.

We present a variety of results that illustrate the capabilities of such a model and highlights a number of causalities. It should however be noted that these results are not yet generalized to the national level, that parameterization with domain experts is ongoing and that vehicle and battery supply are not yet included as a constraint. As such the results are preliminary and have limited generalization potential.

1 Introduction

Vehicles using electric drivetrains provide an alternative to internal combustion engines. That is important because internal combustion engines rely on either fossil fuels or biofuels and both have problematic characteristics.

Fossil fuels power the lions share of road transport but as the Intergovernmental Panel on Climate Change notes: burning fossil fuels is the main source of anthropogenic global warming which “will lead to high to very high risk of severe, widespread and irreversible impacts globally” and requires “an urgent and fundamental departure from business as usual” [1]. Since the transport sector is responsible for 23% of global energy-related green house gas emissions [2], we urgently need transportation that does not rely on fossil fuels.

Internal combustion engines can also run on biofuels. In an ideal world Europe could easily replace 0.5% of fossil fuels by biofuels and maybe even ten times more [3] but we have to acknowledge that biofuels are in global competition with nature and food for scarce topsoil and fresh water [4]. A passenger car uses about ten times as much energy as the average human and globally the energy supply from oil is about seven times the energy supplied to us as food [5]. Producing food is already causing worldwide depletion of aquifers [6], deforestation [7], [8] and severe soil erosion [9], [10] so multiplying agricultural output will not be easy. Biofuels are also linked to food crises [11]–[13] and taking indirect land use change into account negates most – if not all – of perceived carbon emission savings [14]–[17].

Through a process of elimination we can thus conclude that sustainable road transport implies using electric drivetrains, because they can use electricity. Solar and wind have the potential to supply abundant electricity [18] without competing for scarce water or fertile soil. Solar and wind are also becoming cheaper than fossil fuel and biofuel [19], [20]. For this reason, governments are stimulating the adoption of electric vehicles and indications are that falling battery prices [21], [22] will make them cost competitive within a few years [23].

The Netherlands is one of the countries where the adoption is especially fast [24]. However, the adoption rate and impact of EVs on the electricity grid and public space in the near future remain uncertain [25].

Suitable strategies for actors such as policy makers, charge point operators (CPOs) and distribution system operators (DSOs), are hard to lay out without qualitative and quantitative knowledge of the dynamics of EV penetrated neighbourhoods. This research addresses that issue by creating a model for the agent-based buying, charging and driving of EVs (ABCD model) in Dutch neighbourhoods by means of spatiotemporal simulations. The goal is to develop a realistic EV dynamics model able to load in Geographic Information System (GIS) data of any existing (Dutch) neighbourhood and apply advanced agent-based behaviour as observed by domain experts and as determined by surveys. The GIS data includes roads, buildings, parking places, the charging network and the electricity grid. The result is a multi-purpose model able to study the EV adoption in real cities and its relation to/impact on:

1) public space and policy making,
2) the local electricity grid balance,
3) technological developments such as smart charging, vehicle-to-grid, autonomous cars,
4) charge network supply and demand.

This paper first describes the approach and implementation. It then presents a model overview and model results. Finally, it offers conclusions and discussion.

2 A multi-level agent-based modelling approach

The ABCD model is a quantitative implementation of transition management theory [26]–[28]. It uses an adaption of the multi level perspective in transition management theory [29] (although it implements this perspective in ways not described in the literature). The ABCD model assumes many technological developments play out on a global level (e.g. plummeting battery prices). Policy incentives in the model work on the national or municipal level (e.g. EV buying incentives). These influences are then included in models of actual neighbourhoods that are considered to be representative. Inside these neighbourhoods, households decide to buy and use electric vehicles and different actors are responsible for the corresponding charging infrastructure.

This multi level perspective can not only be used to create a context for buying and charging decisions but also as a way to generalize findings. The results found in modelled neighbourhoods are projected unto other Dutch neighbourhoods with similar characteristics (although this feature is currently not yet implemented) and thus lead to a national prediction. In analogue fashion multiple representative countries could be modelled to predict global adoption.

The entire model uses an agent-based modelling approach. Agent-Based Modelling (ABM) is a relatively new modelling paradigm that uses small autonomous entities (called agents) that have a memory and make their own decisions. System behaviour emerges bottom-up through the behaviour and interaction of these agents [30]. Agents can be residents in a neighbourhood that contemplate buying an electric vehicle but also the electric vehicles themselves and buildings are agents. Basically, any entity that can have behaviour that is most easily modelled by assuming autonomy is a good candidate for an agent.

These agents closely correspond to real world entities. Thus empirical observations can be used for parameterization, verification and validation [31]. The system behaviour becomes an emergent property of micro-entity (agent) behaviour and interaction and can be modelled without describing the system in advance [32]. This makes ABM well suited for studying systems that are being transformed by radical innovation [33]. The energy transition – and specifically the adoption of EVs – is a prime example of this [34].

Another characteristic of ABMs is that agents can be highly heterogeneous and can interact in both time and space. Because each agent has a different environment and partly different (e.g. stochastic) behaviours, agents can lead unique lives, just like in the real world. This makes agent-based models suitable for studying complex socio-technical systems (STSs): systems in which social and technical elements interact [31].

As a side note we want to stress that ABM enables the inclusion of other modelling approaches. E.g. system dynamic stocks and flows can easily be represented by agents and equation based approaches can be expressed as agent behaviours. Thus ABM is well suited for a multi-paradigm approach. However, this is not true the other way round. System dynamic or equation based frameworks do not provide the possibility to incorporate autonomous agents.

3 Implementation

To predict the adoption and impact of EVs many aspects interact on different levels; sequential or partial models will not yield accurate results. The first level is the neighbourhood where residents purchase EVs when certain criteria are met and where they drive them around and charge them. Charging infrastructure present in the neighbourhood impact both buying and charging behaviour. Neighbourhoods also contain a road network, an electricity grid, households producing (though PV) and using energy and EVs that apply smart charging (or even V2G) to optimise the use of renewable energy while not overloading the grid. Several carefully selected representative Dutch neighbourhoods are used and municipal policies are active on this level. The second level is the national level. Here every neighbourhood is modelled as one agent that follows the simulation result of a representative neighbourhood that most closely resembles it. On this level national policies (e.g. income tax incentives) are active. The third level is global. Here technologies are developing. E.g. battery prices react to the economies of scale of increasing EV sales while PV and wind develop further.

The model is developed using the GAMA-platform: a modelling framework specifically designed for spatiotemporal agent-based simulations [35]. In order to capture and validate the appropriate behaviour the project includes not only model developers but also a team of domain experts. See figure 1.

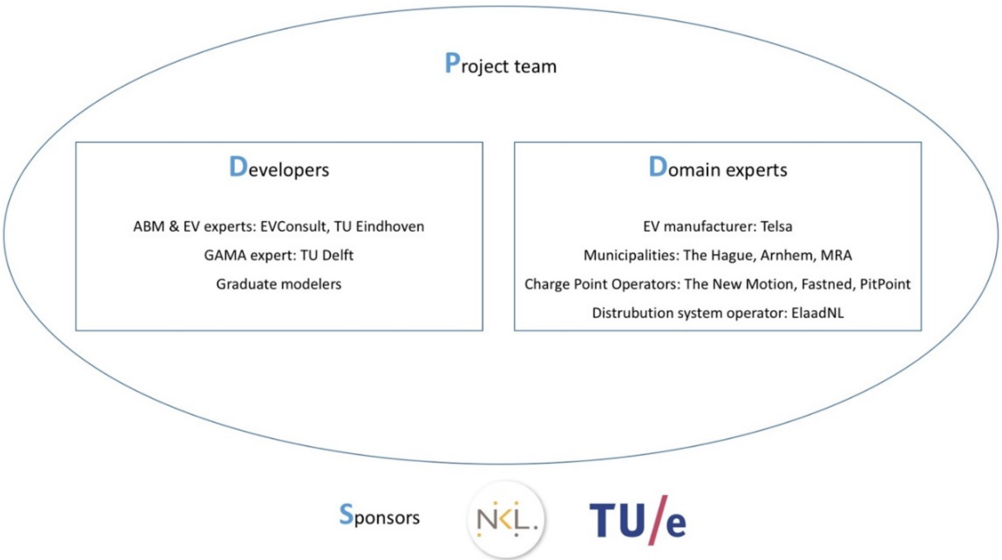

Figure 1 Project team for the ABCD model

4 Model overview

In this section we introduce the reader to the most important dynamics that are modelled on the local level. The model is developed in a flexible modular manner, meaning that, for example, driving behaviour and charge point roll out are programmed in different model files. A suitable feature for EV-stakeholders using the model, allowing them to change or elaborate specific dynamics without having to worry about understanding and corrupting the other modules. The basic structure of the modules is shown in figure x. The two main modules are 'Buying' and 'Charging' where EV uptake and the charging network plus usage are modelled. They interact with each other as well as with all the other modules. For example, buying of EVs is depended on the the charging price and current state of a variety of EV technologies. And whenever an EV is bought the owner will request a public or purchase a private charge point. The Charging and the Buying module are explained in more detail in the sections 4.2 and 4.2. The time step for the driving and charging dynamics can be set at either 1 minute or 15 minutes. The buying module additionally operates at time steps of 1 month.

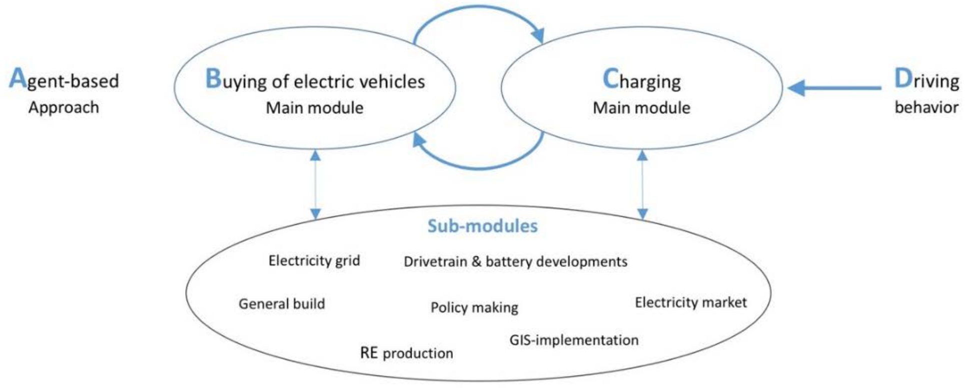

Figure 2: Overview of ABCD-model

4.1 Definition of the neighbourhood

A neighbourhood in the model consists of the following main elements:

- a road network
- buildings (houses, offices and attractions)
- the electricity grid
- charge points
- parking places

People (residents, visitors and commuters), each having unique driving needs and socio-demographics, and EVs interact with that environment. For example, by driving over the roads and charging at a specific charge point when a resident returns from work. The neighbourhood elements are imported as shapefiles provided by local municipalities (Figure 3). The socio-demographics of the residents are adjustable to define the neighbourhood as realistic as possible.

Figure 3: Imported neighbourhood from the city of Arnhem on top of a layer from Google earth.

4.2 Buying module

Residents in the neighbourhood are car owners. At each time step these agents may decide to purchase a new vehicle, this will depend on the degradation and lifetime of their vehicles as well as their personal preferences. When the decision to purchase a new vehicle is made, a 'visit' the car dealer agent provides the buyer with a list of currently available EV and ICEV 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 EV-buyer will make a cost-benefit analysis of the suitable choices taking, among other, its financial situation, fuel prices, trip patterns and charging availability into consideration. When EV uptake in the neighbourhood is considered to be representative for the EV uptake nation- or worldwide, it will in turn have its effect on the speed of EV development and mining of resources, i.e. the buying module also affect the module technology trends and EV prices. Figure 4 illustrates these dynamics.

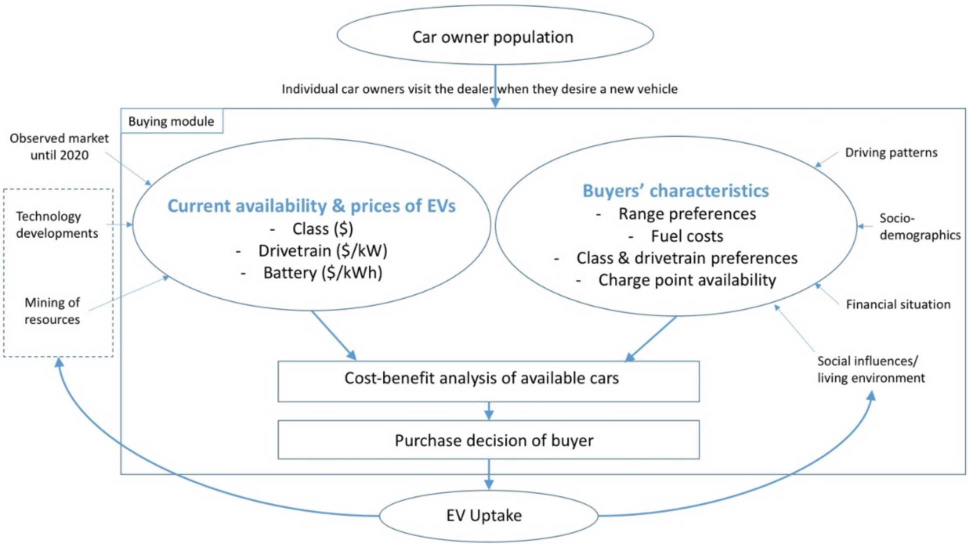

Figure 4: Dynamics of the Buying module

4.3 Charging module

The charging module treats the development and usage of the charging network as well as fast charging or destination charging outside the neighbourhood. EV owners with private parking possibilities purchase a private charge point, the others request a public charge point. The approval of a requested public charging point depends on the roll-out policy. If approved, a new public charge point will be created at one of the public parking places close to the requesting EV-owner. Attractions and offices with parking places (such as malls and sport locations) place chargers based on the share of EVs of their visitors. Public charge points can be used by residents, commuters and visitors. Non-public charge points are only used by EVs going to the destination to which that charge point is assigned.

When residents with an EV arrive at home they plug their EV into a charge point. The starting moment of the charging session depends on the EVs' current state-of-charge, the timing of its next trip, the smart-charging preferences and price incentives. Generally, the EVs charge at the maximum available charging speed until they are full. However, reducing the charging speed or vehicle-to-grid scenarios based on the energy market are easily integrated scenarios. The usage of the charging network allows for analyses of the grid impact and business cases for the charge points.

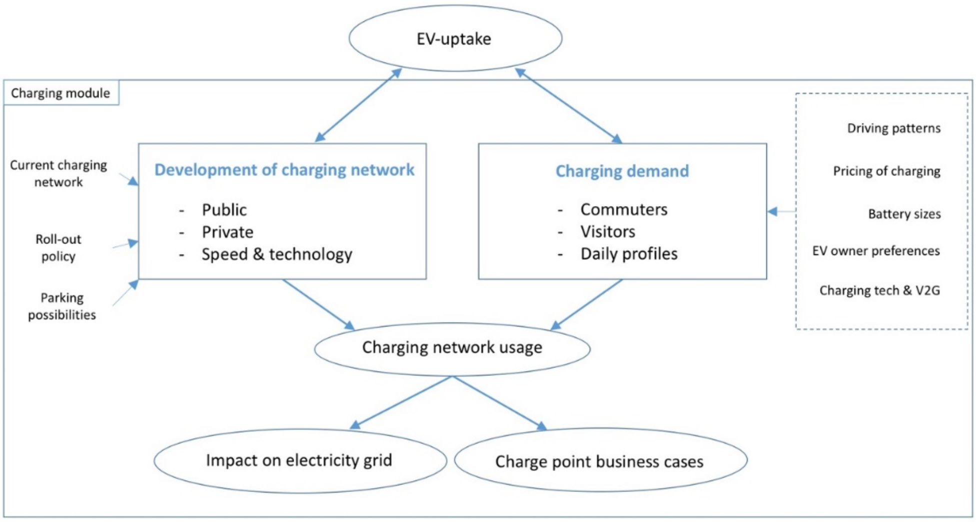

Figure 5: Dynamics of the Charging module

5 Preliminary Findings

The model is still in development (and will probably be for years to come) which means that some mechanics needed for realistic predictions are still missing and many variables are not yet exhaustively debated with domain experts Generalization and validation of neighbourhood results on a national level will only become possible after matching the representative neighbourhoods with all the other neighbourhoods that share their characteristics. Nevertheless, we can present some key mechanics and demonstrate the impact of certain variables.

5.1 EV adoption as a function of customer profile and cost of ownership

EV adoption is often modelled as a function of total cost of ownership (the cost per period of time) but this leaves out a plethora of conditions that exist in the real world. In the real world buying a car is: emotional; different for early adopters; different between classes; dependent on household size; dependent on income; and dependent on travel pattern. For electric vehicle factors like range anxiety and the situation with regard to charging infrastructure also comes into play. One-size-fits-all-models simply don’t cut it.

So far we have assumed that residents first decide for a certain class of car and that they then have different requirements regarding acceleration (some people like fast cars) and range (depending on their individual driving pattern). Figure 6 shows one result: the TCO of EVs in our population became positive compared to that of ICEs between 2014-2020. (Since the parametrization of our A-class cars turned out to be problematic the residents never chose A-class EVs which makes the scenarios lower but does not alter their trajectories.) Another scenario we ran assumed people sold the car after 4 years (with assumptions about resale value). This actually increased adoption because turnover was faster and second hand electric vehicles invariably had a lower TCO.

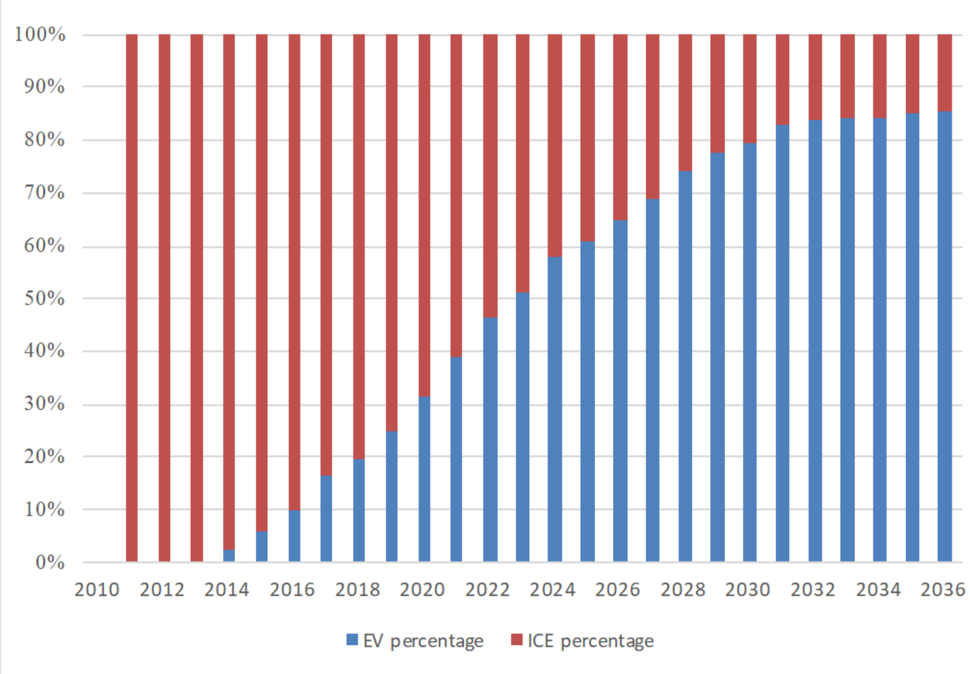

Figure 6: Buying behaviour based on a TCO of 10 years

Rationallity in buying decisions differs per person, the next graph shows two additional EV uptake curves which take that into account. One scenario shows the uptake when 50% of the people buy cars based on purchase prices instead on TCO. A third scenario adds a probability that car buyers don't even consider buying an EV. This probability can be seen as a merger between factors like the lack of knowledge of EVs or their positive TCOs, range anxiety, no charging availability. The probability starts at 90% in 2010 and gradually decreases to 10% in 2022 and 0% in 2028.

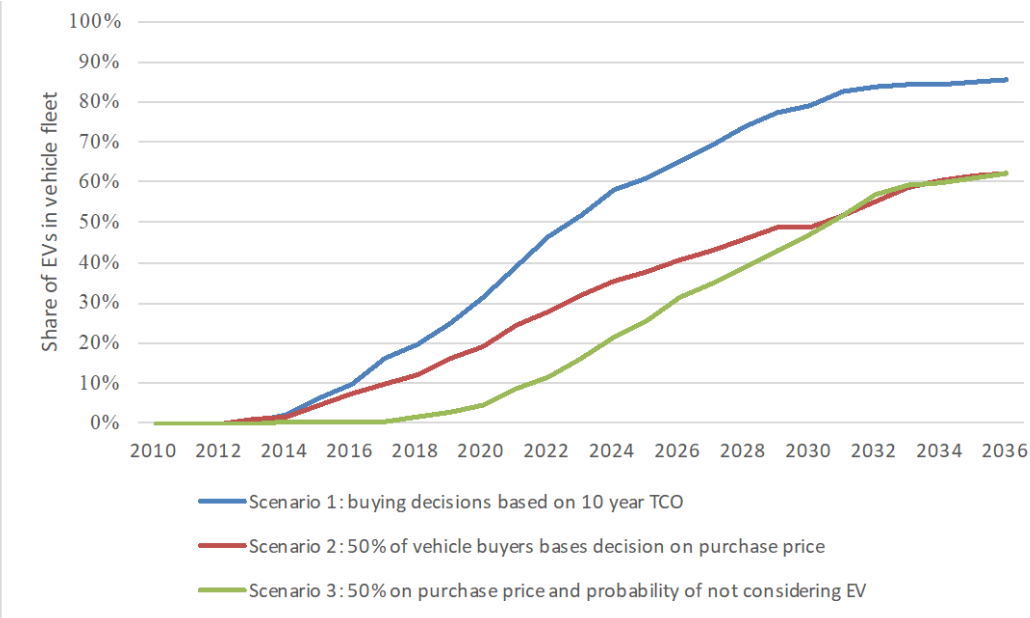

Figure 7: Effects of buying behaviour on EV uptake

Some other scenarios (figure 8) explore: decreasing drivetrain costs for EVs, car ownership periods of 4 years and a €5.000,- purchase grant for EVs (decreasing over time).

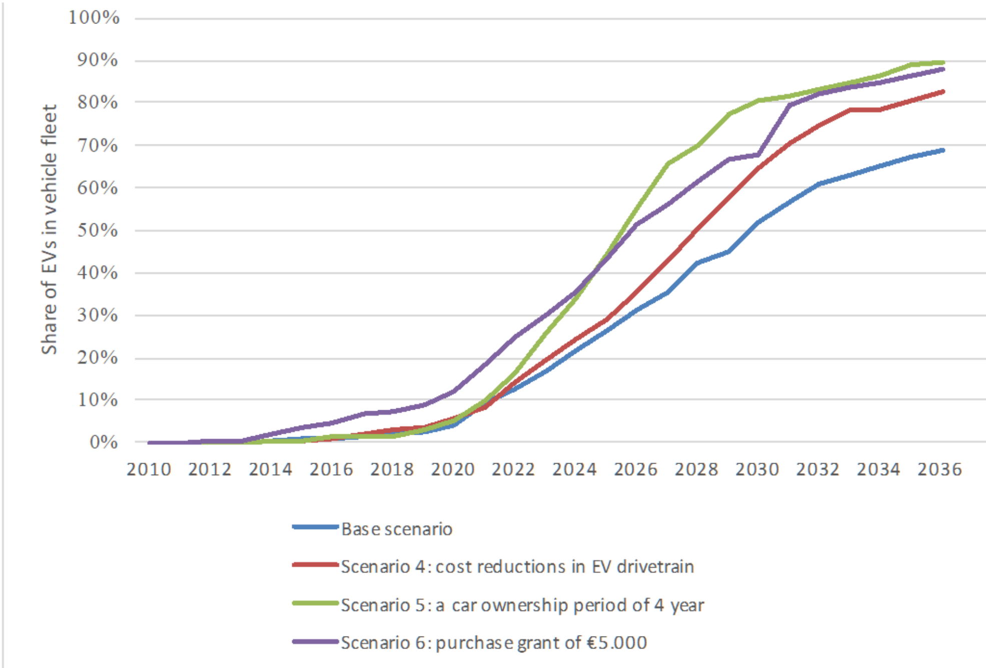

Figure 8: Explorative EV uptake scenarios

5.2 Charge points as a function of municipal policy and technological development

Charging infrastructure is often modelled as a ratio of EV sales but this can be highly misleading as our next results show. We concentrated on public charging infrastructure (which is the primary focus of government incentives and municipal policy) and used two novel mechanisms. First we introduced something we call 'disapPoints': every time an EV driver wanted to use a specific charger but that charger was occupied (meaning the EV driver was disappointed) the charger received an extra point. When chargers accrued too many disapPoints, more chargers could be placed in their vicinity. This matches behaviour we observed in municipalities. Then we introduced what we call a CSoC approach where charging is based on the state of charge (SoC). This means that EV drivers have a distaste for parking far away from their destination and feel less need to charge when their battery is fuller. This matched the behaviour we observed in our focus groups and surveys.

Having thus primed our model we asked ourselves: what happens when the municipality approves public charge points based on the criteria that there is no other charge point (with a limited number of disappoints) available in a given radius from the household? The result is presented in figure 9: increasing the radius greatly decreases the need for charge points. (Of course this means that people have to walk further to a charge point and this could lead to dissatisfied citizens and less EV sales.)

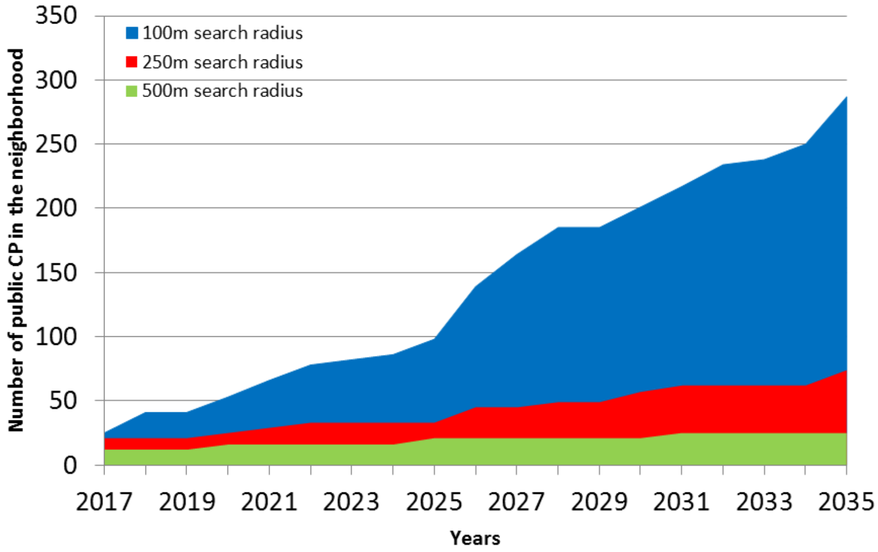

Figure 9 Effect of search radius criteria issued by municipalities on the number of public charge points

Another factor with a big impact on the number of charge points that appeared once we introduced the CSoC system was the size of the battery. With a bigger battery, EV driver more often decide not to bother with a charge point once it further away from their destination. They will simply charge tomorrow or the day after. This dynamic leads to a decrease in charge point use. On the other hand, it is a positive development for charge points operators because whenever the remaining charge points are used the amount of kWh charged per session is larger which increases the profit made on the charge point.

Other technological factors that could be taken into consideration are charging speed (where the lowest value of EV charging power and charge point power needs to be chosen), energy use, vehicle to grid (V2G) capabilities and smart charging capabilities.

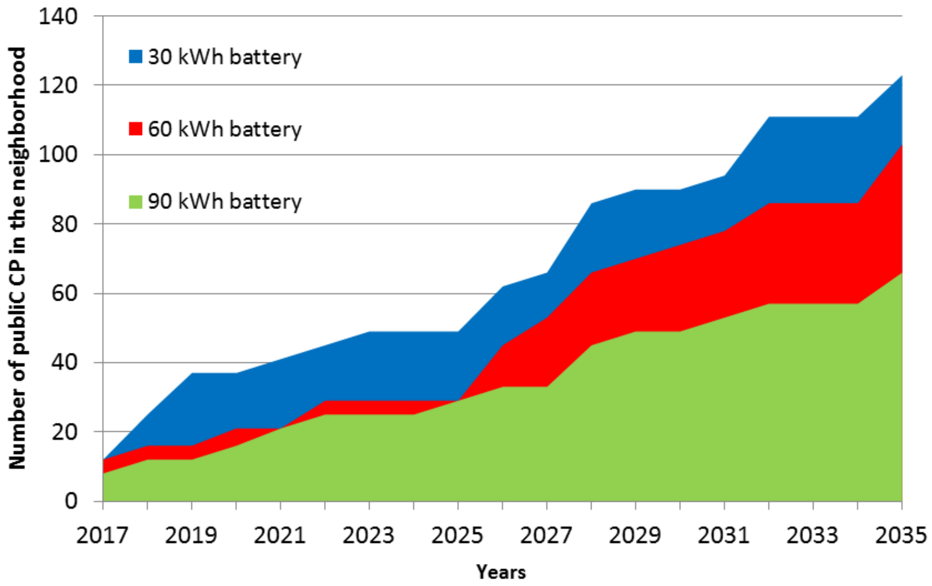

Figure 10 Effect of battery size on the number of public charge points

5.3 Charging as a function of neighbourhood characteristics

So far we've talked about the impact of TCO, customer preference, municipal policy and technology. But things can also be radically different between locations as a comparison of two Dutch neighbourhoods shows. The Alteveer region in the municipality of Arnhem is a relatively wealthy neighbourhood where many residents have private parking. There are also few offices, shops and other work locations. The Zeeheldenkwartier in the municipality of The Hague is a more typical neighbourhood in the centre of a city with a mix of homes and work locations and with fewer private parking places. The first result we could establish is that the ratio between public and private charge points would be radically different (figure 11).

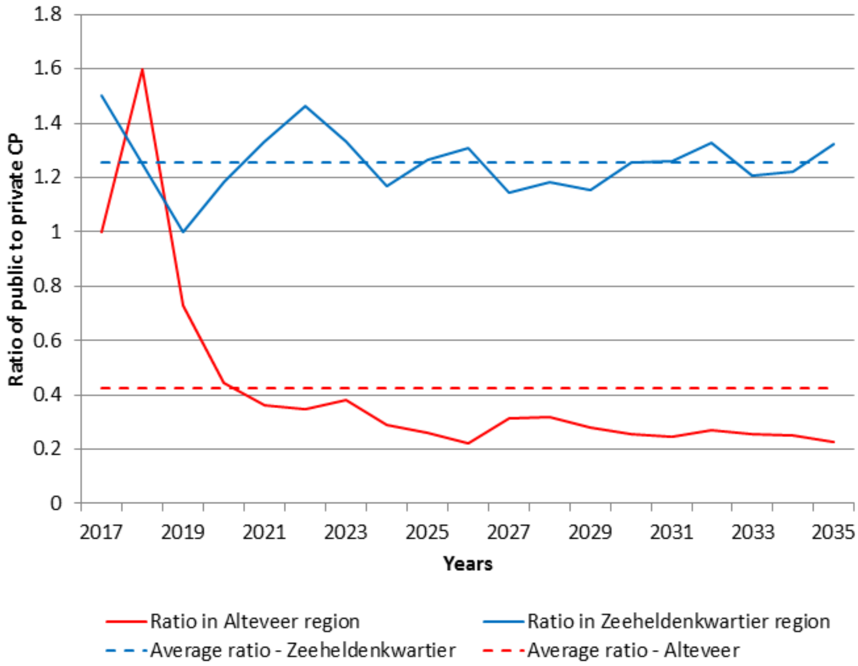

Figure 11 Ratio of public to private charge points in different neighbourhoods

The second result that we want to present is that the number of work chargers is radically different (figure 12).

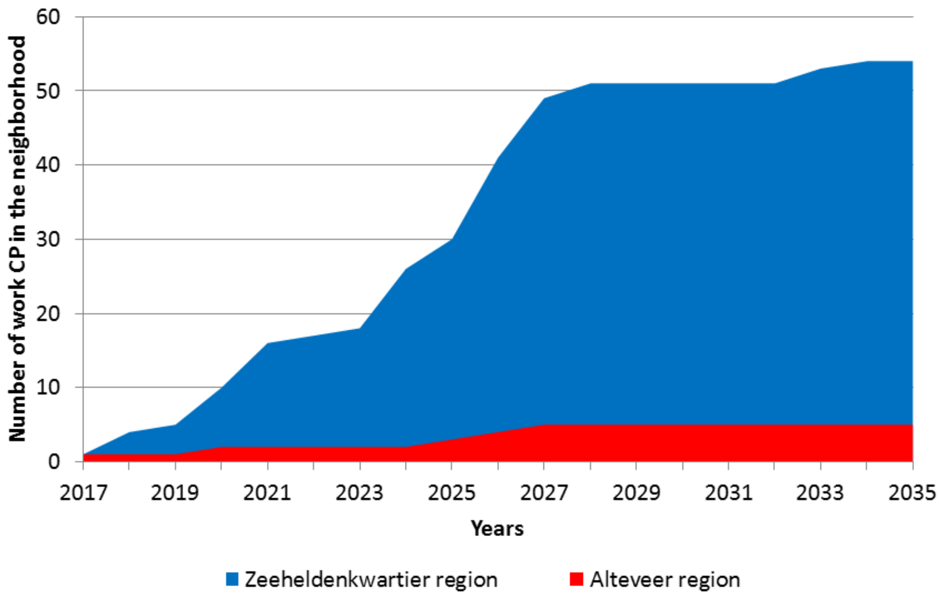

Figure 12 The number of work chargers in different neighborhoods

This illustrates that in order for a municipality to prepare itself for the rise of EVs it makes little sense to use average numbers. Rather it should tailor its approach based on the types of neighbourhoods involved.

5.4 Grid congestion as a function of EV adoption and battery size

Grid operators in the Netherlands take a pro-active stance regarding electric vehicles because of its potential impact on grid investments and grid security. They have created and championed open standards like OCPP (open charge point protocol) that accelerate innovation while avoiding the pitfalls of vendor lock-in and potentially unsecure proprietary protocols. They are now looking for ways to enable third parties called aggregators to facilitate smart charging. Smart charging means that the moment of charging can be dynamically chosen (if the consumer agrees) to minimize energy costs (which automatically means maximizing the use of renewables because they have the lowest variable costs) and avoid blackouts (or even minimize grid investments). In Lombok – a neighbourhood in the municipality of Utrecht – consumers are currently enjoying charge points that are much faster (at no extra costs) in return for lowering usage during times that network stability is threatened and they can even use bi-directional charging to optimise use of the neighbourhoods solar arrays [36].

Because every neighbourhood is different, municipalities are interested in using the ABCD model to predict where they should employ what strategy. An illustration of why that could be relevant is shown in figure 13. If 50 of 200 households would use electric vehicles for their commute this would lead to a significant load on the grid, that comes on top of their regular household use. We will refine this approach to incorporate all the factors mentioned before and then apply smart charging to calculate the cost this would save, especially in those neighbourhoods where grid congestion could be a problem.

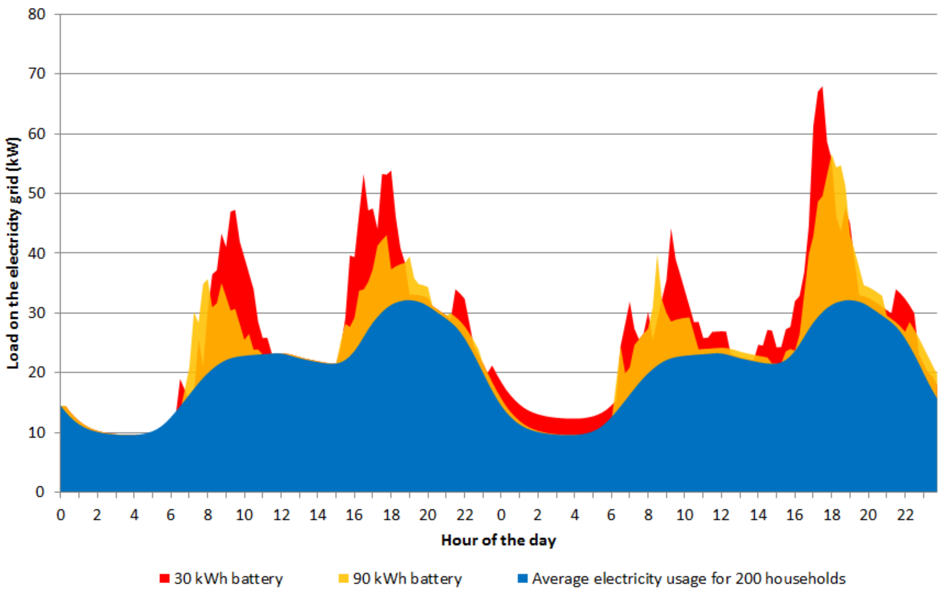

Figure 13: Two-weekday charging profile of 50 neighbourhood EVs with commuting owners

One of the advantages of agent-based modelling using GIS data is that multiple subsystems can be linked using their spatial coordinates. In this case we know the location of energy using appliances like buildings and parking places with charge points and we can connect that to the location of the electricity grid in order to be able to pinpoint exactly what grid elements might experience problems. Figure 14 illustrates this for the Alteveer region with the household and loads modelled on the top layer and the grid visualized on the lower layer.

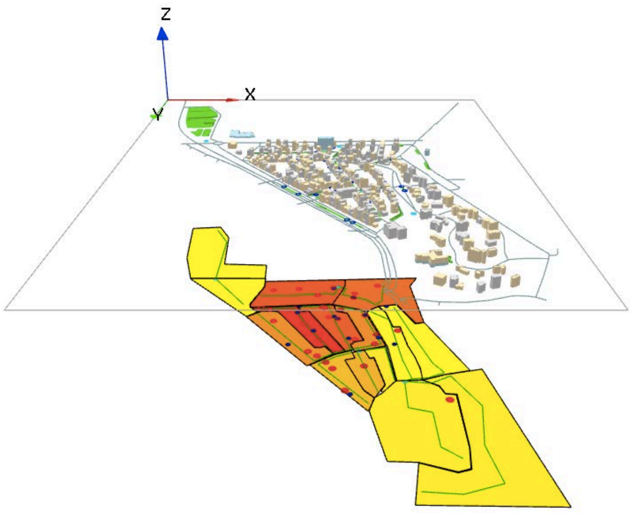

Figure 14: Electricity grid load visualisation. The lower layer depicts the grid with EVs (red when charging), power lines (green) and the grid load in the area they cover (coloured areas).

In an agent-based framework like the GAMA-platform, modellers can create and visualize as many layers as needed. Figure 15 illustrates this for the Zeeheldenkwartier neighbourhood. In this way it will even be possible to experiment with novel incentive schemes that ask charge points to monitor their local voltage and to cease charging (or even initiate V2G) when they see their local voltage dropping too far. The definition of “too far” would be determined based on their position in the electricity grid and an algorithm estimating the voltage at the end (lowest) and start (highest) of the grid element they belong to.

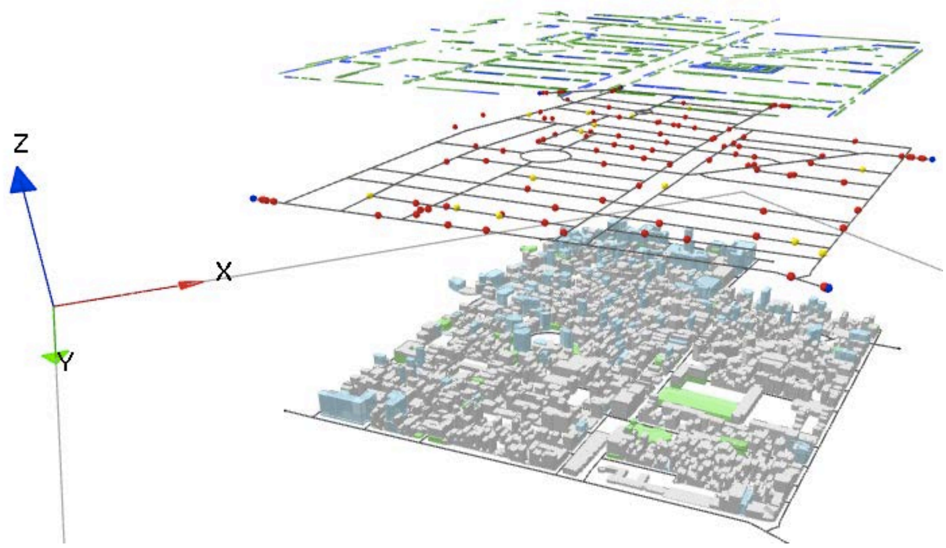

Figure 15:Example simulation of neighbourhood in the Hague. Bottom layer contains buildings, middle layer EVs on the road network (charging EVs are yellow) and top layer parking places (green if available)

6 Conclusion and discussion

A multi-purpose agent-based model, the ABCD-model, is developed to assist EV stakeholders in defining public policy and business strategies. The model is grounded in transition management theory and allows the development of scenarios for radical innovation in complex adaptive socio-technical systems using real world data.

The model enables users to study EV adoption and the impacts of it in realistic neighbourhoods based on socio-demographic and GIS data and to generalize the results to the rest of the country. Specific purposes are to analyse 1) the effectiveness of public policy, 2) the grid enhancement requirements, 3) smart charge and V2G opportunities, 4) the development of the charging network, and 5) the impact on air quality and the climate. A project team spanning the complete EV and electricity system domain allowed for a holistic system approach by identifying behaviour and market prospects in each relevant sector.

This paper showcases some preliminary results that illustrate how a model has to account for many factors such as: heterogeneous customers; individual total cost of ownership calculations; municipal policies; technological developments; neighbourhood type; grid situation; and smart charging regime.

We will develop this model further and hope this paper can inspire others to develop better models that can guide the transition to clean electric road transport.

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