Who must adapt? Modelling charging behaviour of individuals in a high EV future

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SHORT SUMMARY

With increasing usage of electric vehicles, an expansion of charging infrastructure is required. To investigate the individual's reliance on public infrastructure expansion, we modelled charging behaviour at home, at work and at public fast charging stations based on vehicular activity profiles from a desire-based transportation model. In a high electrification future scenario for the year 2045 most drivers can incorporate vehicle charging within their usual daily schedules as most charging events take place at the home location of the driver. Only 6.3% of vehicles are reliant on public fast charging infrastructure and therefore may require the driver to adapt their schedules. Our modelling results also show the spatial and temporal distribution of charging demand over the course of one week and pointing out the potential for smart charging strategies such as vehicle-to-grid charging or peak-shaving to reduce demand on the underlying grid infrastructure.

Keywords: Electric vehicles, charging infrastructure, agent-based modelling

1. INTRODUCTION

Mitigating the effects of ongoing climate change requires decarbonising the transportation sector. In case of individual motorized transportation, battery electric drive trains have outperformed their competitors and are expected to become the dominant technology in the future ***(Gnann et al. 2024)***. Increasing market penetration of electric vehicles requires new charging infrastructure to meet the energy demand. Charging infrastructure may come in a range of different forms, from 5 kW home charging to direct current fast charging with more than 150 kW. Therefore, a careful consideration of future charging behaviour is necessary to facilitate the expansion of not only the charging infrastructure, but the underlying electricity grid as well, considering the growing linkage between both, for example in form of vehicle to grid charging. This requires demand profiles with high temporal and spatial resolution, as increased electricity demand by charging may put additional stress on the grid ***(Plagowski et al. 2021)***. A viable method to produce such profiles is to build upon agent-based transportation models ***(Lin et al. 2019; Mallig et al. 2016)***, as their high level of detail also enables the consideration of the drivers behaviour ***(Patil, Kazemzadeh, and Bansal 2023).***

This paper investigates the question of whether drivers are required to change their daily schedules to be able to charge their vehicles. In a future with high market shares of electric vehicles, such deviations from habitual patterns may occur when infrastructure coverage is insufficient, infrastructure supply at peak hours is insufficient, or no infrastructure is available near the habitual daily activity patterns. We analyse this in a combined spatio-temporal-behavioural approach

based on highly detailed simulation of human activity and corresponding mobility, allowing to derive individual vehicle activity and parking profiles. We apply this model to the case of a mid-sized German town, Jülich, which exhibits demographic and infrastructural properties typical to most of Germany.

2. METHODOLOGY

Transport Modelling

Transport modelling follows a two-step process. In the first step, minutely resolved activity profiles of individual agents and their households are generated, including geographically explicit mobility profiles. For trips performed by car, one specific vehicle available in the household is assigned to the respective person and used for vehicle driving and parking profile generation. The agent's activity profiles are generated using the LoadProfileGenerator by Pflugradt et al. ***(Pflugradt et al. 2022)***, based on the desires of individual agents within the synthetic population. The tool models desires for each agent, the fulfilment of which decreases with time. Once the fulfilment has fallen below a certain threshold, the agent considers the desire for scheduling the next activity. If the agent performs an activity that satisfies the corresponding desire, the fulfilment value is reset. Locations where activities can be performed can be either within the agent's household or at a point of interest outside of the agent's home. For each activity that is performed outside the household, the agent has a set of possible destinations from which one is selected using a gravity model based on network distances.

As an input for the transport model, all travels are extracted from the activity profiles of the agents. These trips are then assigned to car-, cycling- and walking networks based on OpenStreetMap data and a public transit network generated form timetable data in GTFS format to calculate travel durations and -costs. Subsequent out-of-home trips are grouped together resulting in journeys. For each journey, one set of modes is selected from all consistent mode combinations by a discrete choice model, calibrated to travel time and cost. For each household the assigned vehicles are then distributed to journeys where the mode "car" was selected, considering possible usage conflicts due to simultaneous journeys. In cases where no car is available, another combination of modes is selected for the affected journey.

Modelling Electric Vehicle Charging

Data on the trips covered by the EV and the parking locations of said vehicle are extracted from the results of the transportation model described in the previous section. This results in an activity profile for each EV consisting of the driven trips with distance covered and the parking events with their duration. For each trip in the vehicular activity profiles, the energy required is then calculated from the distance covered and an assumed average fuel efficiency of 0.16 kWh/km.

Charging of an electric vehicle may take place at three location types with significantly different charging characteristics. Charging at home requires a private parking spot with a grid connection and is usually performed with a low charging power of 5 kW. Although slow, this method is attractive when available due to its comparatively cheap electricity prices. The second option is

charging at the workplace. Here charging is assumed to be at a higher power of 22 kW on average. Charging at work may also be beneficial due to potential subsidies by the employer. Thirdly, public charging stations can be installed at a wide range of parking spots and, are therefore accessible to especially those who cannot charge at home or at work. Public charging can come with an average charging power of 150 kW, to allow recharging within a short time span, for example while doing the groceries.

As a first step for modelling the charging behaviour, all options are identified where the vehicle can be charged when parked. This includes the access to a charging station of any type and requires a parking duration above 60 min when parked at home or work and 5 min when parked at a public fast charging station. Subsequently, the required energy to reach the next charging option is calculated by summing over the energy required for each trip in between. After these preparations, the real charging events are determined by a simple algorithm: For each vehicle an initial state of charge is assumed according to the parking position at the start of the week. Vehicles parked at home or at work with access to charging station are assumed to have a state of charge of between 60% and 100%, respectively, in accordance with the charging strategy, that will be explained below. For all other vehicles, the initial state of charge is randomly distributed between the value required to reach their next charging opportunity and 100%.

The algorithm then iteratively evaluates each possible charging opportunity. A charging event is initiated when one of the following conditions is met: The current state of charging is not sufficient to reach the next charging opportunity with a safety margin, or the current state of charge is below 60% and the vehicle is parked at a charging station at home or at work. The first condition for charging is self-explanatory. For the other conditions, it is assumed that the charging at home or work is always desirable and the user therefore starts charging early to allow for a higher flexibility. The energy charged within one event is limited by the remaining capacity of the battery and the duration of parking and the charging power. After each charging event, the state of charge is updated by adding the charged energy. Finaly, the Energy required to reach the next charging opportunity is subtracted and the process repeated for the next possible charging event.

Test Case Setup

We show the results of our charging behaviour model for the city of Jülich in the German federal state of North Rhine-Westphalia for a future scenario of the year 2045. Activity profiles for all 32,092 inhabitants of the municipality of Jülich are simulated. The projected development of a new commercial zone, as well as new single-family home areas, were included in the distribution of workplaces and dwelling places.

The scenario contains 14,070 individual cars assigned to the different households of which 94.6% are assumed to have a battery electric drive train, following Germany's national long-term scenarios ***(Gnann et al. 2024)***.

The national German mobility survey "Mobilität in Deutschland 2017"***(infas et al. 2018)*** shows, that in mid-sized cities such as Jülich 88.3% vehicles in single- and double family homes and 80.2% vehicles in multifamily homes have access to private parking. We assume that all private parking can be electrified and therefore the respective shares of vehicles have access to a home

charging station with a power of 5 kW. Finally, we assume that 40% of job sites provide charging opportunities with a power of 22 kW each.

3. RESULTS AND DISCUSSION

Parking Profiles of Electric Vehicles

Figure 1 shows at which locations the vehicles are parked over the course of a week. During the weekdays, a clear daily pattern can be recognised. At nighttime, almost all vehicles are parked at the home locations of the agents. In the morning this number decreases as the agents drive to work or to perform other activities. In the evening, this reverses although the process is spread out over a long period of time. On weekends, far less cars leave their parking spot at the agents' homes. Here practically no cars are parked at workplaces. Instead parking at locations of other activities doubles. In general, the cars are parked for the most time and only used for transportation purposes on average only for 2.76 h a week. In the full week not less than 8,000 vehicles are parked at any point in time at the agent's home locations. Only around 1,500 vehicles during the week and around 3,000 vehicles at the weekend are parked at locations other than the homes and workplaces of the agents. This shows, most vehicles are parked at locations with longer parking times. We therefore conclude that a significant share of the total EV fleet is available at any time for charging processes. Furthermore, the fact that the vehicles are parked at home and at work for most of the time where charging infrastructure is widely available shows that there is a significant base of vehicles that can participate in vehicle-to-grid operations at any time.

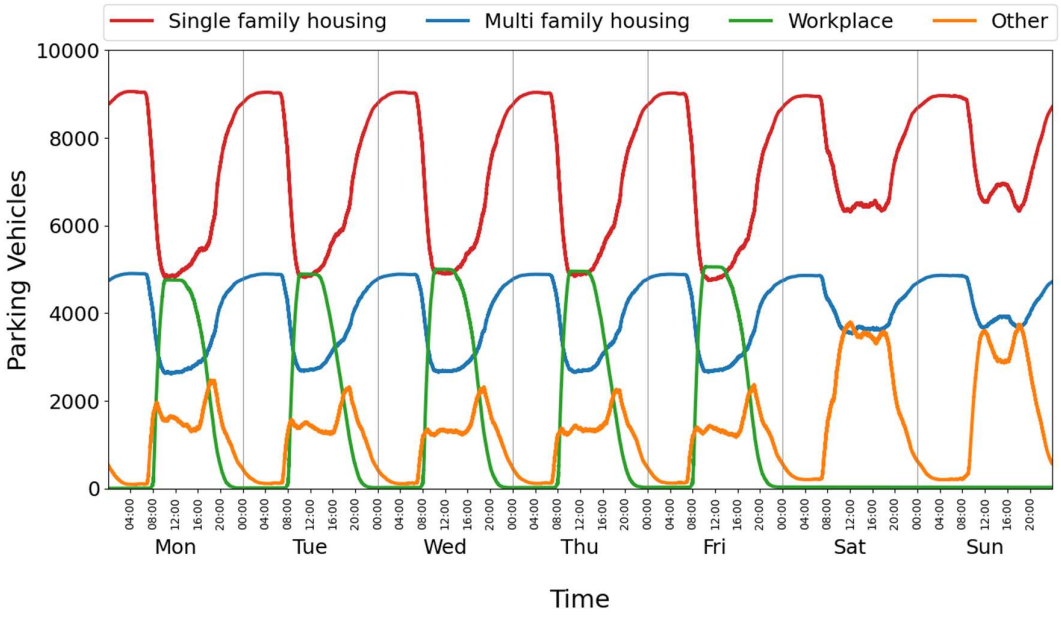


Figure 1: Parking locations of the electric vehicles for the city of Jülich, Germany over the course of a week.

Charging Power Demand

The combined power demand for all charging events is shown in Figure 2. The power demand spikes in the evening hours, when the vehicles return home and are recharged. Power demand then falls off over night as more EVs complete their charging. During the weekend, charging demand is slightly lower and the charging peak in the evening is far less pronounced, as the agents do not follow the strict schedule of a typical working day.
Charging at the workplace exhibits a sharp demand peak in the morning of weekday. This peak is caused by the agents arriving to work all at a similar time and wanting to charge their car immediately. Additional demand at other times, caused for example by workers deviating from the traditional working schedule is only very limited. Therefore, to operate charging- and grid infrastructure with a sensible level of utilization during the whole time, it may be necessary to avoid sharp peaks in charging demand as we see here. To achieve this, the charging demand needs to be distributed over time. Workplace charging is especially well suited for such charging management strategies as the vehicles usually are parked for the full working day with the end of work as a foreseeable departure time.
Charging demand is on a comparatively low level during the whole week. Some small demand peaks can be observed in the morning and evening hours, when agents perform most of their out of house activities besides work. No fast charging demand is present at night, as almost all vehicles are parked at their respective home locations. Overall, the total power demand for public fast charging fluctuates strongly during the whole time, caused by the short charging durations and high charging powers.

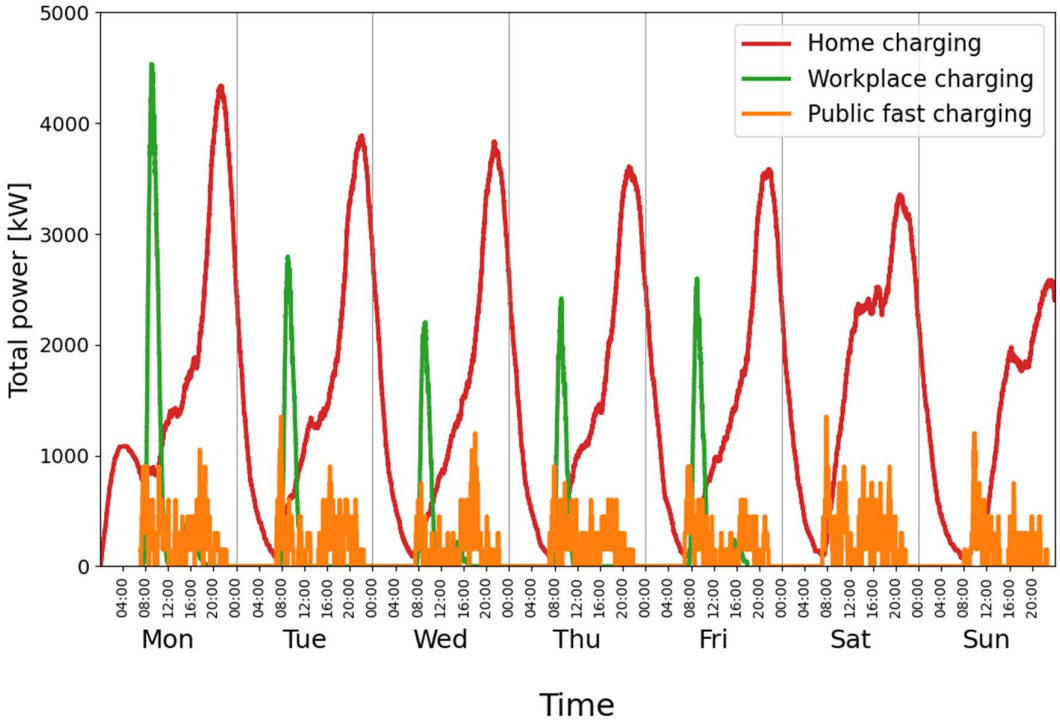


Figure 2: Weekly profile of the total power demand to charge electric vehicles, differentiated according to the charging locations.

Spatial Analysis of Charging Power

In Figure 3, the spatial distribution of the weekly energy demand is shown for the different types charging infrastructure. Over all cases, the city centre sees the strongest charging demand. Although the agents living in more suburban residential areas are likelier to have private parking and therefor access to a home charger, the population density in the city centre is so large that it overshadows this effect and therefore leads to a high charging demand here. As many points of interest are located in the city centre, that are visited by the agents as workplaces or to perform activities, a high charging demand is present here as well. As the time profiles for home and work charging complement each other, sharing charging infrastructure between work and home charging may be a possibility to reduce the required infrastructure expansion in such central locations. In case of workplace charging, a significant demand is also present in commercial areas in the outskirts of the city as many workplaces are located here.

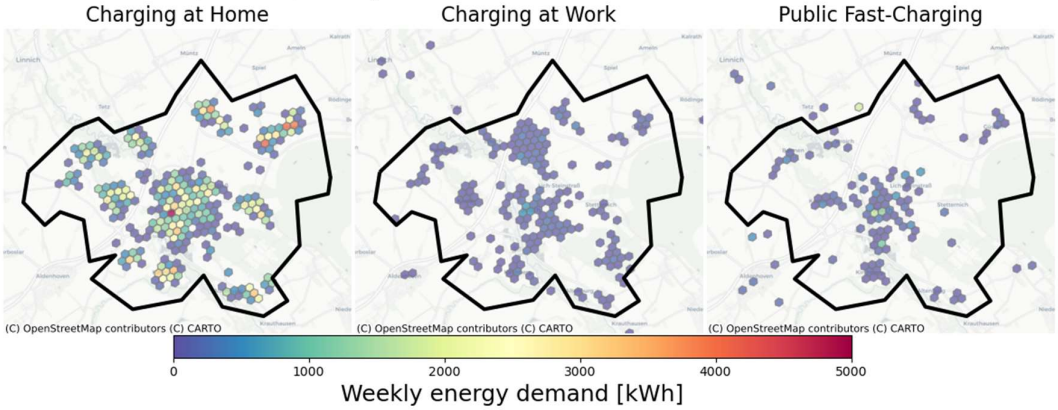


Figure 3: Spatial distribution of the weekly energy demand for charging electric vehicles in the city of Jülich, Germany shown for different charging technologies.

Implications on Behaviour of the Drivers

Within the scenario analysed above, 83.2% of vehicles can satisfy their energy demand for daily trips solely by charging at home. Further 4.1% of vehicles additionally charge at their workplace. With solely charging at work, another 5% of vehicles satisfy their energy demand. Therefore, given adequate expansion of charging infrastructure at home and at work, the largest part of charging demand can be fulfilled during the daily activities of the vehicle operators.

Only around 6.3% of vehicles require the use of public fast charging stations and therefore are at risk of needing to change their behaviour where sufficient access to public charging stations is not given. If this is not the case, the vehicle operators are restricted in their mobility behaviour. Possible consequences are for example detours to deliberately bring the vehicle to accessible charging infrastructure or even replanning their daily schedule, choosing other destinations or other transportation modes.

4. CONCLUSIONS

Our results show that only people without charging opportunities at home or work – those requiring public fast charging – will need to adapt their mobility behaviour in the future because of electric vehicle charging. This will effect 6.3% of the electric vehicle fleet. How much the vehicle operators have to deviate from their habitual driving patterns depends on the future availability of public fast charging infrastructure. This assumes that charging infrastructure at workplaces grows as expected, all private parking can be electrified and that corresponding grid infrastructure keeps pace.

For private charging infrastructure at home or at workplaces, we observe significant potential for peak shaving to reduce stress on the electrical grid. Scheduling or queuing charging events during peak hours has been discussed as potential solution many times before, yet those discussions often neglect the connection to mobility needs of individuals. Our modelling shows that cars are parked for most of the time, even with all needs being satisfied, and therefore available for demand response and vehicle-to-grid interactions.

Such analysis should further be conducted for broader case studies, especially rural regions, to determine the share of the population with insufficient access to charging. Effectively, this perspective becomes relevant as ease of use is important to widespread adoption of electric vehicles.

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