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Agent-based simulation to assess the impact of electric vehicles on power networks: Swindon Borough Case Study

Maria Silva Pedro[a]*, Jeffrey Hardy[b], Koen H. van Dam[c]

[a] *Energy Futures Lab, Imperial College London, London SW7 2AZ, UK*
[b] *Grantham Institute, Imperial College London, London SW7 2BU, UK*
[c] *Department of Chemical Engineering, Imperial College London, London SW7 2AZ, UK*

Abstract

Due to air quality concerns and stricter carbon targets, surface transport electrification is quickly spreading, posing questions on the impact it will have on national and local electrical networks. This paper proposes an agent-based model to assess the per-minute weekday and weekend impact of the uptake of Electric Vehicles (EVs) over the next decade on local electrical and charging infrastructures, aimed at local decision-makers and stakeholders for transport electrification forecasting purposes. This study compares two scenarios, the first assessing the case where no restrictions are imposed on the daily charging events, and the second scenario where the peak electrical demand period between 5pm and 8.30pm is constrained for charging. Swindon Borough is selected as case study since it has one of UK's highest EV adoption rates and has ambitious aims for decarbonisation. The results show that, over time, scenario two consistently lessened the constraints imposed on the grid by lowering the weekday and weekend peak loads up to 7% and 20%, respectively, and through lowering the usage rate of the charging infrastructure by around 12%. This scenario postponed the 5pm to 8.30pm EV charging demand to later hours, resulting in delayed load waves in residential areas that, over time, took values of higher proportion of the daily peak, forecasted to match it by 2036. However, controlling the EV demand through this strategy became less effective over time, and so, constraining charging between 7am and 2.30pm is suggested for further control. To conclude, this scenario can be portrayed in reality by adding flexibility to the grid, through the use of time-of-use tariffs (TOUTs), hence, if well implemented, postponing the upgrade of the grid and the charging infrastructure, presenting savings to the network operator, charging network stakeholders and EV users. The paper thus highlights the advantages of using a model of a heterogeneous population with fine spatial and temporal detail to provide decision-support to key stakeholders in planning energy transitions.

Keywords: Agent-based model; Electric-vehicle; Electricity networks; Synthetic Population;

* Corresponding author.
E-mail address: mariapedro1998@gmail.com

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1. Introduction

After the IPCC's Special Report on Global Warming of 1.5ºC warned about the necessity of limiting the global surface temperature to lower levels than 2ºC [2], the Committee of Climate Change advised the UK government in 2019 to commit to a Net Zero future by 2050 [3]. Analysis by the Committee of Climate Change shows that surface transport is the largest emitting sector, contributing to 23% of all green-house gas emissions, and mitigating measures are needed at national and local levels. Electrification of surface transport is an important mitigation strategy as it fuels the shift from fossil fuels to electricity, improving local air quality and reducing CO_2, in line with grid carbon intensity. However, this transition must be done cautiously as to not result in further constraints to the electrical network.

Agent-based modelling (ABM) has been applied to transport electrification, and according to Daina [4], most papers assessing EV patterns employ a simple activity-based approach referring to observed data from conventional vehicles' driving patterns and schedules [5,6], and fewer by conducting surveys specifically to newly electric vehicle users [7]. In order to provide more accurate and realistic EV driving patterns, our methodology describes agents' activity scheduling according to the largest review assessing EV charging behaviour in the UK [8], and characterizes agents based on spatially-explicit socio-demographic datasets.

Forecasting the requirement for charging infrastructure according to the demand in space and scale, incorporating future EV uptake as well as planned land-use changes and development, leads to a more accurate projection of the EV load profiles, which can be used to assess the impact on the distribution network and primary substations. Our agent-based model assesses the decade-long evolution of the impact of EV charging on the local electricity grid considering the EV and charging-point forecasts compliant with the Net Zero agenda created by Regen [9]. The paper firstly compares unconstrained and constrained EV charging scenarios, and provides insights on: the daily EV load profile per charging-point; the overall average usage rate of charging-ports per primary substation; and charging-event statistics regarding their duration and the type of area they are located on (residential, workplace, commercial). Secondly, it aims to provide a replicable methodology for future projects assessing the local impact of growing EV penetration. Swindon Borough (SB) is used as case study since it has seen one of UK's highest EV adoption rates and has ambitious aims to decarbonise council's own operations by 2030 and the whole Borough by 2050.

Nomenclature

ABM	Agent-based model	SB	Swindon Borough
EV	Electric Vehicle	SOC	State-of-Charge
MSOA	Middle Super Output Area	TOUT	Time of use Tariffs

2. Methodology

2.1. Model overview

The agent-based model developed here is mainly formed by 3 entities: agents, grid cells and the environment. An agent is commonly defined as an entity that behaves within a constrained environment and it shows a certain level of autonomy and flexibility. The grid cells are the territory where the agent activities take place leading to transport demand and movement across the network. Finally, the environment includes the remaining factors that are not intrinsic to the agent but influence the agent's behaviour in some way. All these are described in more detail below.

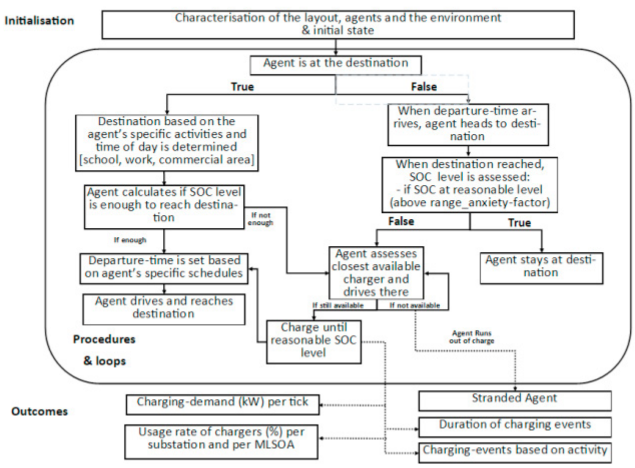

Fig. 1. Model overview

The software selected to develop the model was NetLogo [10]. This toolkit was chosen due to its ease of use, straightforward model creation and editing, ability to incorporate GIS data, and the availability of relevant example applications such as the model by Van Der Kam et al. [11]. Fig. 1 shows a simple visual representation of the initialisation, main model procedures and outcomes.

2.2. Environment

The model is defined by one-minute time-steps and the counter starts at 5am since, according to schedules from literature [8], this is the earliest people typically leave home. This time-step, or tick, was determined so that in each tick the agent could move the space equivalent to one grid cell, considering the average driving speed on A-roads in the Swindon area and the chosen size of grid cells. State variables describe the technical elements of the system and EV charging. The car model selected for the simulation was the Nissan Leaf with a 40kWh battery capacity since it was the fully-electric passenger car with the largest fleet size in 2019 [12]. The charging percentage, the state-of-charge (SOC), consumed when moving forward per tick was calculated as 0.3%, and the speeds at which Nissan Leaf charges with the different charger-types of 7kW (slow), 22kW (fast) and 50kW (rapid) [13] were 0. 2%, 0. 2% and 2%, respectively. This EV model is fitted with a 6.6 kW on-board charger which translates into equivalent charging speeds when connected to all chargers apart from rapids.

2.3. Grid Cells

The spatial representation of SB was converted to NetLogo from an exported Middle Super Output Area (MSOA) shapefile where each grid cell represents 751 m x 751 m creating a model landscape of 29,200 m x 37,666 m. The location and size of key areas were extracted from SB council's geo-spatial database (including future plans), and from the OpenStreetMap database. The main primary-substations in the borough were imported from online available shapefiles [14]. The main state variables defining the grid cells then are the name of the MSOA they belong to, the type of area they describe, such as workplace, commercial, school, car park and petrol station, the closest primary-substation that is assumed to feed the cell, and, finally, the type of chargers deployed in it, which can be destination (7kW), car park (22kW)and fuel station (50kW) chargers with associated charging rates.

2.4. Agents

The main agents in the model represent SB residents and their characteristics were described using proportions extracted from the latest Census statistics per MSOA. The forecasted population growth was taken from Population Estimates from the ONS datasets. The agent's state variables are defined in terms of their residence, employment status and location, responsibility for children, number of cars available per household (0, 1, 2), parking availability (off-street, on-street, inadequate on-street and no parking) and whether they drove to work. Another breed of agents represents the public charging-ports, which, following the Regen forecasts, were deployed per primary-substation and type of area available. The "Destination – 7kW" chargers deployed in commercial areas, the "Car Park – 22kW" chargers in car parks and "Fuel Station – 50kW" chargers in fuel stations.

The number of EV adopters per residency MSOA were extracted from the Regen forecasts also discretized per primary-substation. Following the assumption that key factors describing early EV-adopting agents are the availability of off-street parking and second car ownership [9], the EV fleet is created based on agents characteristics. The remaining non-adopters are neglected as their behaviour is outside of the scope of this study. This process generates a synthetic population closely matching the current and future SB's EV fleet size, that grows from around 1,000 agents in 2020 to 33,000 in 2030. Finally, the forecasted number of residential on-street and off-street chargers, and workplace chargers per primary-substation were assigned, respectively, to EV adopters with on-street parking availability, off-street parking availability and employed residents that drove to work.

2.5. Behaviour description

The activity scheduling is based on patterns observed on UK Power Network's Charger Use Study [8]. Agents' schedules vary between the combination of being employed or not and having children or not, and they follow their assigned schedules through the non-static variable *destination*. For example, on a weekday, some agents take their children to school, always the closest from their residence, then some go to work and pick up their children when returning home for work, while some go straight home. Moreover, agents that are not employed nor have children choose between going to a commercial area or remaining home on a weekday, which is a behaviour that all agents follow on a weekend. This way, the observed patterns were translated into decision-rules for the driver agents.

Moreover, each agent is given a *range_anxiety-factor*, which is a randomly generated variable between 15 and 30, describing the SOC at which the driver starts to look for a charger. Their charging requirements are then assessed before they depart for a *destination*, evaluating if there is enough charge for a round trip and whether there is an available charger at destination, and when they reach their destination, assessing if their SOC level is above their *range_anxiety-factor*. If required, the agent will plug in to the closest available charger. However, if an agent's EV battery runs out of charge due to lack of charger availability, the agent is defined as *stranded*.

2.6. Scenario creation

To evaluate the impact of possible interventions, two scenarios were created. In the first scenario no constraints were imposed on the charging infrastructure, but for the second all charging-ports connected to fully constrained and partially-constrained primary-substations (based on data from the local power network operator) were made unavailable during the highest peak demand period between 5pm and 8.30pm [1]. In this scenario, an exception is made for EVs with not enough charge to reach their destination. Hence, this scenario attempts to portray how charging during a more constrained period could be discouraged (e.g. with TOUTs), providing insights in the value of smart charging strategies as well as investments in the charging infrastructure.

3. Results and Analysis

The evolution over a decade is portrayed analysing the years 2020, 2025 and 2030. The following figures show the resulting EV load profiles and plotted analysis.

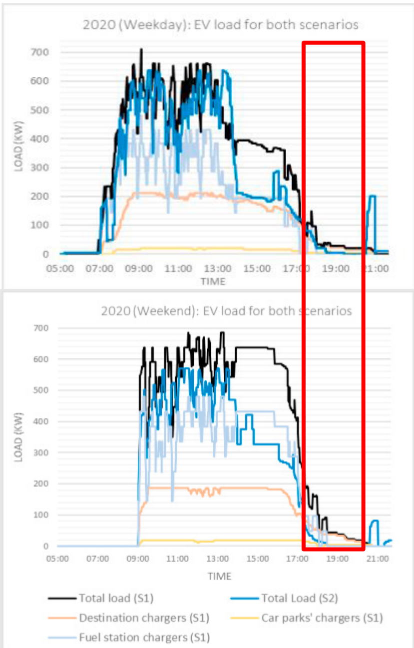

Fig. 2. 2020 picture: EV load profiles for both scenarios during a (a) weekday and (b) weekend

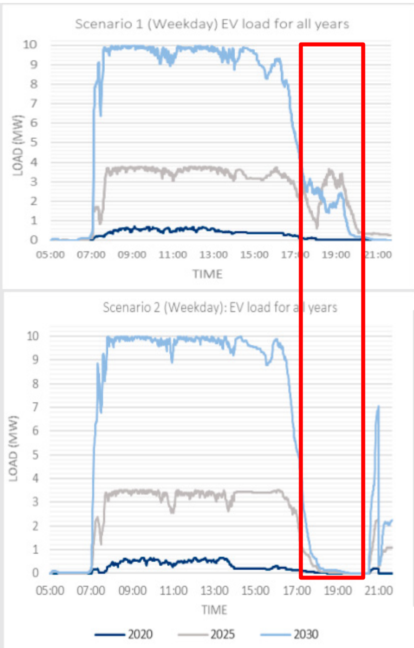

Fig. 3. EV load profiles during the weekday for (a) Scenario 1 and (b) Scenario 2

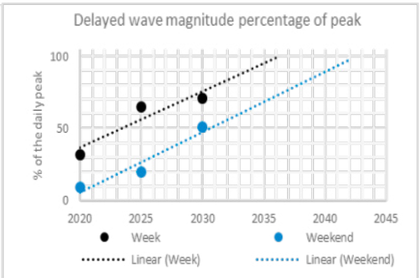

Fig. 5. Delayed wave magnitudes projection

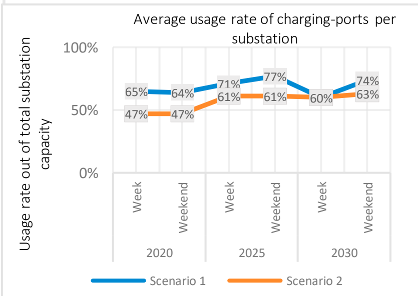

Fig. 4. Average daily usage rate of charging installed capacity per primary-substation

ıd by 7% on week days, and during the weekend by 20%. However, it can be seen from Fig. 2 and Fig. 3 that constraining the charging availability postponed demand for later hours, creating delayed waves that with time reach higher proportions of the peak magnitude, as observed in Fig. 5. Variability between years is caused by EV uptake, available charging infrastructure as well as stochasticity. Then, Fig. 4 shows that EV patterns in scenario 2 use the charging infrastructure less, on average a 12% decrease in utilisation.

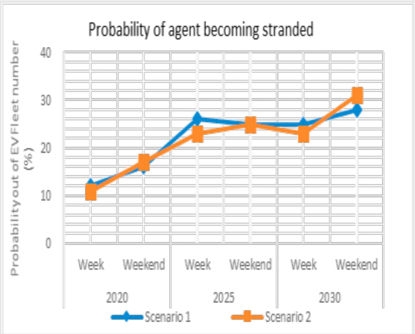

Fig. 6. Proportion of stranded EVs

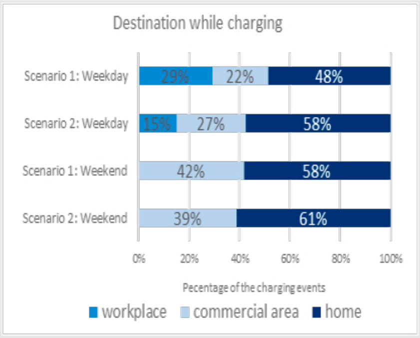

Fig. 7. Destination of agents while charging on the public charging infrastructure

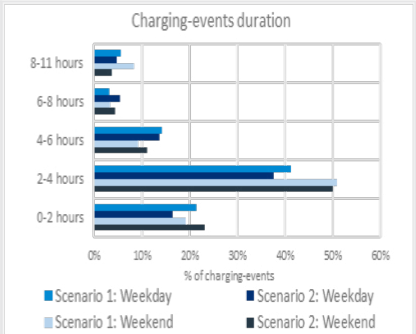

Fig. 8. Duration of charging-events

Fig. 6 indicates that constraining the charging availability does not contribute to a higher percentage of stranded EVs (i.e. vehicles that run out of charge due to not finding a charging port). The percentage of stranded agents then provides insights into whether or not the charging infrastructure is sufficient to meet expected demands from the EV fleet. Fig. 7 shows that in scenario 2 the demand of charging events near residential areas increased, especially during the week, due to charging being delayed during peak. According to Fig. 8, although duration of charging events is similar between the scenarios, a slight increase in the average duration is seen in scenario 2.

4. Discussion and conclusions

The simulation results have shown that constraining the charging availability between 5pm and 8.30 pm provides a reduction in the peak demand, average loads and usage rates of the charging infrastructure. If well implemented, EV demand can be controlled through TOUTs, where higher prices would incur during higher demand and lower supply periods, and vice-versa. Then, the benefits it can bring are observed from the Distribution Network Operator (DNO), the charging infrastructure stakeholders and the EV users' standpoints. This is because the electrical infrastructure is built to reliably cover the peak load, and so, by reducing its' magnitude, local grid upgrades can be delayed and overall lower investment is required, also supported by Strbac et al. [1]. However, by constraining a charging period, a high ramping on demand is introduced immediately after it, possibly causing an operational challenge to the grid. As the usage rates of the charging infrastructure decrease, the required installed capacity is lowered, reducing the investment required. However, by reducing the charging capacity installed, their location must be optimised to avoid that being a bottleneck in the decarbonisation of the transport sector. Finally, since EV charging profiles show lower average loads and peaks, EV users would depend on lower charge levels and so spend less on charging requirements.

Between the years analysed, the EV charging loads increase at a rate of two thirds of the increase in EV adopters and, over time, the delayed loads reach greater proportions of the peak magnitudes, matching it by 2036. Therefore, controlling the use of the grid should be done cautiously as to not create further grid constraints. Furthermore, by 2030, scenario 2 has a negligible impact in reducing peak loads, suggesting that additional high peaking periods should be assessed for control, such as between 7am and 2.30pm. This period was also corroborated by Strbac et al. [1] as reaching the highest EV load peaks in a commercial district area. The increase in the use of the public chargers near residential areas in scenario 2 suggests that the delayed load waves lead to the creation of overnight charging-events, and might have an impact on charging infrastructure roll-out decisions.

Between the model runs, there was variability associated with the number of EVs and charging ports deployed in comparison with the inputted Regen forecasts. This was primarily a result of the assumptions considered due to the lack of data availability, such as the real layout of the electrical network and the area delineation for charger deployment. The assumption considering the grid cells to be connected to the closest primary-substation led to some primary-substations being neglected. Delineating specific areas for the deployment of different charger types within a Borough-wide scope analysis, lowered the granular description of the land and available space, reducing the charger deployment compared to the forecasts.

To conclude, this paper proposed an agent-based modelling approach for the simulation of EV users traveling and charging patterns following two different scenarios within the next decade to support local and national carbon reduction strategies. The focus of the model is to assess and compare the difference between charging load profiles resulting from scenarios and to advise a local stakeholder on how to proceed with their EV strategy, including the impact on the grid and the need for charging infrastructure to promote uptake.

This approach can be a valuable tool for council decision-makers or other local stakeholders to simulate the feasibility and efficacy of proposed measures or strategies. Furthermore, by extending this study to a full-day analysis, including the night period, overnight charging-events could be assessed as an alternative to cover the bulk of charging requirements. Due to the high variability associated with the EV and charging-port deployment, this study can be used as a starting-point to assess specific high traffic zones, which can then be further analysed by narrowing the scope of the study to achieve more granular and consistent results. This can be employed to support local decisions not just at the network level, but for particular development locations in the city and for certain groups of users, leading to fine-tuned local sustainability plans.

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