Understanding the Complex Behaviours of Electric Vehicle Drivers with Agent-Based Models in Glasgow

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Abstract

With the new policy aimed at advancing the phase-out date for the sale of new petrol and diesel cars and vans to 2030, the electric vehicle (EV) market share is expected to rise significantly in the coming years. This necessitates a deeper understanding of the driving and charging behaviours of EV drivers to accurately estimate future charging demand distribution and benefit for future infrastructure development. Traditional data-based approaches are limited in illustrating the granular spatiotemporal dynamics of individuals. Recent studies that use conventional vehicle trajectory data also have the sampling bias problem, despite their analyses being conducted at a finer resolution. Moreover, studies that use simulation approaches are often either based on limited behaviour rules for EV drivers or implemented in an artificial grid environment, showing limitations in reflecting real-world situations. To address the challenges, this work introduces an agent-based model (ABM) with complex behaviour rules for EV drivers, taking into account the drivers' sensitivities to financial and time costs, as well as route deviation. By integrating the simulation model with the origin and destination information of drivers, this work can contribute to a better understanding of the behaviour patterns of EV drivers.

2012 ACM Subject Classification Computing methodologies → Modeling and simulation

Keywords and phrases Electric vehicles, agent-based modelling, charging demand, route choices

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Category Short Paper

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1 Introduction

The transition from petrol/diesel-based vehicles to alternative fuel vehicles can play an important role in reducing global greenhouse gas emissions and air pollution. The UK government has announced to bring forward the phase-out date for the sale of new petrol and diesel cars and vans to 2030, and to require all new cars and vans to be completely zero-emission at the tailpipe from 2035. The new policy targets necessitate a higher electric vehicle (EV) penetration rate and create opportunities in the market for electric vehicles. Therefore, it is essential to illustrate the behaviour patterns of EV drivers and provide a deeper understanding of the spatial distribution of their charging demand.

Data-driven approaches have been used to explore EV driver behaviour and charging demand in previous research, mostly relying on statistical methods to understand charging behaviours [7]. However, the use of socio-demographic statistics [5] and travel survey data [2],

Table 1 The attributes of hypothetical charging stations.

Station name	Charger name	Charge speed(kW)	Charge price (£/kWh)
Station 1	1A	6	0.3
Station 1	1B	2	0.1
Station 2	2	12	0.6

despite their rich attributes, can be limited in demonstrating the granular spatiotemporal dynamics of individuals and their decision-making processes. Alternatively, recent studies have used GPS data from conventional vehicles [9] or EV fleets like taxis [12] to understand EV behaviours. Although these datasets can demonstrate spatiotemporal trajectories of drivers in a finer resolution, their ability to represent all types of EVs – including private EVs, ride-hailing EVs, and other commercial EV fleets – can be questionable. As a result, these datasets could introduce sampling bias and lead to systematic errors in the conclusions.

More importantly, the utilisation of the datasets above cannot fully capture the various features of EV drivers' behaviours, including their sensitivities to charging costs and psychological preferences. Sensitivities to charging costs can affect a driver's behaviours in various ways, such as travel distance [13], the payment for charging [6], and the time spent waiting and charging [3, 14]. Meanwhile, the psychological factor refers to a driver's comfort level with a low State of Charge (SOC) [15]. Given the limited availability of EV trajectory data, integrating these complex EV driver behaviour rules with the origin and destination (OD) information of drivers through simulation methods can provide opportunities to explore detailed EV trajectories and a granular charging demand distribution.

Agent-based modelling (ABM) offers a simulation method to plan, design, and experiment with micro-agents in an artificial computational environment [11]. Compared to statistical methods, ABMs can represent a richer and more detailed set of individual agents [4] and enable interactions both between and within agent types [8]. Previous studies have applied ABM to simulate the behaviours of EV drivers. However, research gaps exist because they either captured limited behavioural rules of EV drivers [16], or were implemented in hypothetical grid environments rather than real-world road networks [1]. Consequently, this work aims to provide a deeper understanding of the driving and charging behaviours of EV drivers by creating an ABM with comprehensive behaviour rules and implementing the model in a real-world road network in Glasgow.

2 Data and methods

2.1 Data and study area

The geographical scale covers the area between Glasgow city centre and the West End in Glasgow. The study area is shown in Figure 2. As described in Table 1, two hypothetical charging stations are situated within the area. Station 1 is equipped with two chargers, while Station 2 has one charger. Each charging station operates at a hypothetical charging speed and charging price. The origins and destinations of EV drivers are stochastically selected from the 869 nodes on the road network using a simple random sampling method. Twenty-two cars are simulated in each iteration.

2.2 Model development

In the model, the SOC consumption rate is assumed to be constant, as operating conditions and environmental influences that can potentially affect the energy usage of vehicles are not considered. Furthermore, a driver is sensitive to a particular SOC threshold, meaning that when the SOC falls below this threshold, the driver recognizes that the battery has depleted to a level where recharging is necessary. The full battery capacity of the vehicles is assumed to be 100kWh [10]. The starting SOC value of each driver is set at 100%. The SOC threshold is randomly selected to be either 40% or 50%. This threshold ensures a considerable amount of charge remains in the battery, thus reducing the likelihood that the driver will be stranded without power for the simulation purposes. An ABM model is developed using the Mesa package in Python to integrate the complex behaviours of EV drivers. The model includes two types of agents: EV drivers and charging stations. The behavioural rules of the model are demonstrated in Figure 1.

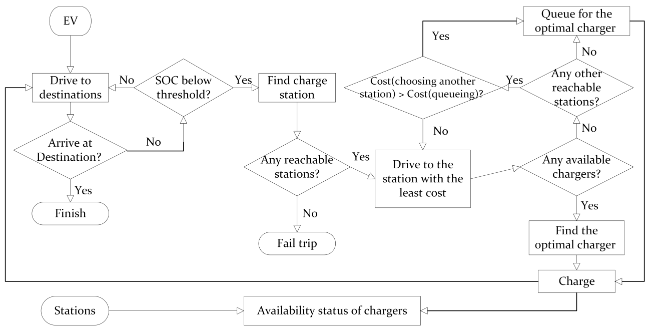


Figure 1 Behavioural rules of EV drivers and charging stations.

Drivers start their journeys from the origins and drive to the destinations following the Dijkstra's shortest path on the road network. A driver searches for an optimal charging station with least cost when the SOC falls below the SOC threshold. The cost of station p is denoted by equation 1. α represents a driver's sensitivity to charge payment. β, ϵ and δ represent the cost in GBP that a driver attributes to each additional unit of travel distance to find a charging station (GBP/km), each extra unit of time to spend while charging (GBP/minute), and each decrease in the degree of availability at a station (GBP/%), respectively. Since the drivers cannot predict the queueing time at the station before their arrival, we use *availability*, a value ranging from 0 to 1, to indicate the percentage of available chargers at the station. This provides an estimate of the likelihood of not encountering a queue upon arrival at the station.

$$Cost_{station\_p} = \alpha \times payment_p + \beta \times distance_p + \epsilon \times charge\_time_p + \delta \times availability_p \quad (1)$$

If a driver cannot find a station within reach based on the current SOC, the status of the EV driver changes to 'fail trip', and the driver will not be able to continue the journey. Otherwise, the driver will follow the shortest path to the optimal charging station. Upon arrival at the station, drivers are updated with the most current availability status of the chargers. If at least one charger is available, the driver will select the optimally available charger with the least cost. If all the chargers are occupied and another station is reachable given the current SOC status, the EV driver will compare the cost of queuing to the cost of finding another station, choosing the option with the lower cost. Otherwise, the driver will queue for the optimal charger before beginning to charge. The cost of charger q at the selected station is denoted by equation 2. It comprises the charge payment and the cost in GBP that a driver attributes to the time spent queueing and charging. It should be noted that the payment and charge time in equation (2) can be different from equation (1) due to the change of charging circumstances in the charging station when the drivers arrive.

$$Cost_{charger\_q} = \alpha \times payment_q + \epsilon \times charge\_time_q + \epsilon \times queue\_time_q \tag{2}$$

If the SOC drops below the threshold again, the driver will recharge. Upon reaching the destination, the driver evaluates the total cost incurred during the trip ($Total\_cost$), which is calculated in equation 4. It is composed of the deviation and the cost spent at all used chargers. *Deviation* is calculated in equation 3. It refers to the difference in distance between the planned route (the shortest path between the origin and destination) and the actual route taken by the driver. γ represents the cost in GBP that a driver attributes to each unit of deviation (GBP/km). i is the i-th decision made by the driver while j is the j-th charger used by the driver. m is the total number of decisions made by a driver and n is the total number of chargers used by a driver.

$$Deviation = \sum_{i=1}^{m-1} Distance_{i,i+1} - Distance_{plan} \tag{3}$$

$$Total\_cost = \gamma \times Deviation + \sum_{j=1}^{n} Cost_{charger\_j} \tag{4}$$

3 Results and discussion

3.1 Simulation Results

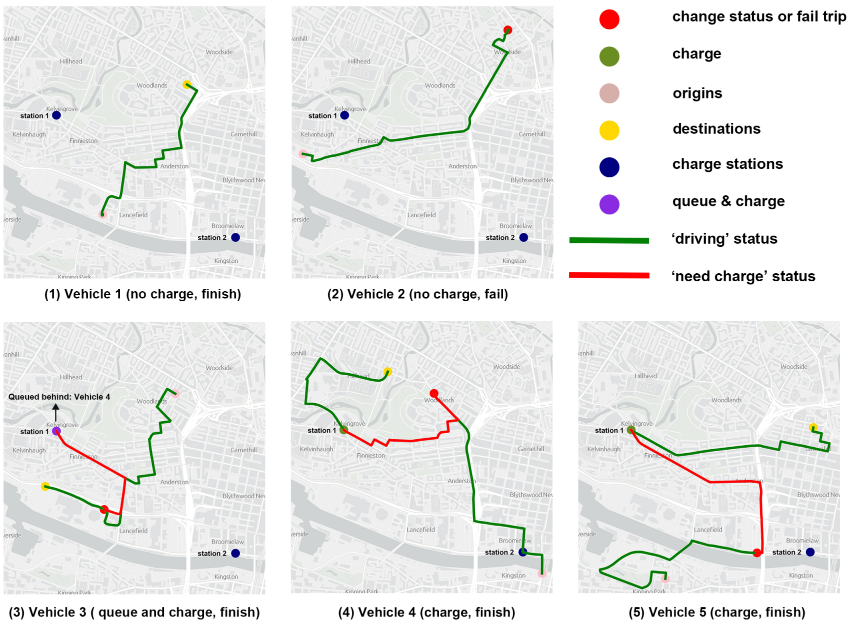


Figure 2 EV routes.

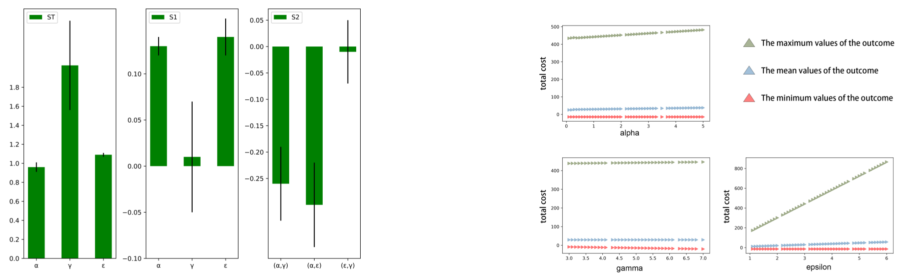
Table 2 Simulation results.

Vehicle ID	Final status	Deviation (km)	Cost(£)	Charge time (min)	Charger	Queue time (min)
1	finish	0	0	-	-	0
2	fail trip	0	0	-	-	0
3	finish	1.88	9.95	[51.43,150.94]	1B	41.48
4	finish	0.56	8.57	[8.57, 51.43]	1B	0
5	finish	0.24	28.7	[9.58, 25.54]	1A	0

Five samples of the simulation results are presented in Table 2. The visualised routes are shown in Figure 2. EV-2 fails to complete its journey because it cannot reach any of the charging stations with the remaining SOC. EV-3, EV-4, and EV-5 charged en route. EV-3 queued behind EV-4 for charger "1B", resulting in a wait time of 41.48 minutes.

3.2 Model calibration

As shown in Figure 3, the One Factor at a Time (OFAT) and Sobol' method-based sensitivity analyses were performed to determine the robustness of the results and guide further improvements of the model. The confidence interval was calculated at 95%. The results suggest the presence of higher-order interactions in the function, as the total-order indices are larger than the first-order indices for all parameters. Furthermore, the OFAT sensitivity analysis is conducted to explore the sensitivity of total cost to charge payments (α), to deviation (γ), and to charge and queue time (ϵ). The variations of α, γ, and ϵ can affect the total cost if a driver charges during the trip, but have no effect on the total cost if a driver does not charge (Total cost = 0).



(a) Sobol' Analysis. **(b)** OFAT Analysis.

Figure 3 Sensitivity analysis results.

4 Conclusion and future works

This work has developed an ABM that integrates the complex behaviours of EV drivers. The simulation results show that the drivers' sensitivity to deviation is the strongest determinant of the total cost. Additionally, the results of the sensitivity analysis show that the cost function needs to be further modified to include nonlinear terms and interaction terms between the variables.

The model presented is based on multiple assumptions and is limited in reflecting real-world situations. In future work, we plan to replace the hypothetical stations with real-world public charging stations, and substitute the randomly generated OD information with real-world trajectory data of vehicles. This will enable us to explore how driving patterns might change when a driver adopts an EV. Based on the trajectory data,we also aim to integrate the heterogeneous behavioural rules of different drivers into the model. Charging session data will also be used to validate the simulation results and ensure that the simulated driving and charging behaviours accurately represent real-world scenarios.

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