eCHARGE 4DRIVERS

D7.1

EV Charging Market Models

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Table 1: List of abbreviations and acronyms

Abbreviation	Meaning
API	Application Programming Interface
ABM	Agent Based Model
BDI	Belief Desire Intention
CSat	Customer Satisfaction
CP	Charge Point
CPID	Charge Point IDentifier
CS	Charge Station (made up of several charge points)
CPO	Charge Point Operator
eC4D	eCharge4Drivers
eMSP	eMobility Service Provider
EU	European Union
EV	Electric Vehicle
FIFO	First-In First-Out
OEM	Original Equipment Manufacturer
RA	Range Anxiety
SOC	State of Charge
UoS	University of Sussex

EXECUTIVE SUMMARY

EV charging market models have been developed to allow the results from eCharge4Drivers to be extrapolated to other regions and for future scenarios. This supports the planning of EV infrastructure and policies to see if they are suitable and support the formulation of appropriate strategies. The planning of infrastructure and policies brings a wide range of stakeholders together, eMSPs, CPOs, OEMs and, local and national authorities. A range of modelling approaches were reviewed before selecting an Agent Based Modelling approach, e.g. [1]. This report provides a unique approach to integrate the wide range of requirements in a single model that allows trade-offs between stakeholders.

A number of parametric studies have been carried out to use the model to evaluate the impact of several new policy or infrastructure decisions. Many of the results have confirmed intuitive responses, however the real use of the model is in considering complex multivariable interactions between pricing, user behaviour and policies. To this end, a number of more complex situations have been studied and the model has provided insight into the corresponding behaviours. The following observations were made:

- Range anxiety has been used as an interactive indicator of user behaviour, increasing when the EV has been stranded and reducing as confidence builds following successful trips. The range anxiety can then be used to affect two behaviours; the decision of when to look for a charge point and the price at which the driver will pay for electricity. This coupling of EV user 'state' and behaviour has been found to successfully replicate expected behaviours.
- In building the model, the topic of queuing behaviour was studied to address the situation when an EV arrives at a charge station and the charge points are occupied. The length of time in a queue was used to inform the EV driver satisfaction. In future work, additional factors for customer satisfaction may be added, e.g. whether a charge point is operational or the time to set up payment.
- At current ratios of numbers of EVs to EV charge points, the range anxiety can be managed. If, as the numbers of EVs increase to make up a significant percentage of the vehicle population, the number of charge points does not follow and the ratio of EVs to EV charge points increases, there will be increased range anxiety and reducing customer satisfaction that may have a negative impact on the take up of EVs.
- Market studies showed that price changes may have a temporary effect on charging behaviour, but they then settle back to previous levels – since the EVs still need to be charged.
- As expected, green minded EV drivers (those who select charge stations powered by renewable energy) ended up with increased range anxiety as they have access to less charge points and they are often more expensive.
- Pricing had more complex interactions as when the range anxiety increases, the model also increased the amount the EV driver was prepared to pay for electricity. The model showed that if high power charge points were introduced, they would benefit the smaller battery vehicles more than the large battery vehicles.
- Additional charge points were introduced to improve customer satisfaction. It took a number of iterations to deliver the expected results since the response of the model could be masked by other factors. For example, adding expensive charge points had limited effect because EV drivers were not prepared to pay the extra and hence did not use them as expected.
- Introducing legislation to encourage charge points to be released once the EV has charged can reduce range anxiety
- A number of booking systems were investigated and the response to the bookings were largely as expected, reducing range anxiety and improving customer satisfaction. It was also expected that as more people could book, the benefit would reduce, however within the parameters of the study this did not emerge.
- Home charging reduced the range anxiety. Extending this to consider the impact on different social demographics, it is likely that more affluent EV drivers will have less range anxiety than poorer EV drivers. This is more pronounced in cities where the journeys are short and being able to charge overnight can effectively remove range anxiety from the daily life.

1 INTRODUCTION

1.1 Project introduction

eCharge4Drivers is an H2020 project running from June 2020 to May 2024 and deployed by a consortium of 32 partners. Charging an electric vehicle (EV) is still not as convenient as refuelling a conventional vehicle, potentially posing a barrier to increase the market uptake of EVs. eCharge4Drivers works to substantially improve the EV charging experience within cities and for long trips. The project develops and demonstrates user-friendly charge stations and innovative charging solutions as well as smart charging services for the users. By capturing users' perceptions and expectations on the various charging options and their mobility and parking habits, eCharge4Drivers will organise demonstrations in 10 areas across Europe, including metropolitan areas and Trans-European Transport Network (TEN-T) corridors. Charge stations in these areas will offer user-friendly and convenient functionalities for EV drivers of passenger and light vehicles and motorcycles, such as direct payment methods and bigger, user-friendly displays. Using the knowledge generated, the project will also propose an EV Charging Location Planning Tool, fostering the broad implementation of charging infrastructure in Europe.

1.2 Purpose of the deliverable D7.1

The objective of the work carried out under Task 7.1 is to study user acceptance of EV charging using an EV charging market model. The model is used to provide additional learning from the approaches studied in eCharge4Drivers and to investigate the application of these approaches to other locations.

An agent-based modelling approach has been set up and calibrated to four demonstration areas, covering both city demonstrations and country or long-distance demonstrations. The calibrated models have been used to study future scenarios to identify recommendations to update the policies and/or infrastructure.

The objectives related to this deliverable have been largely achieved taking into account the evolution of the project and data availability.

Regarding data availability, this task is reliant on usage data from the demonstration areas. The usage data has been provided in the form of charge point session data from four demonstration sites that includes energy consumed, so this has been used as the principal parameter to validate the models. The battery swapping use case is significantly different to the EV driver model and has not been included in this task.

1.3 Intended audience

Deliverable D7.1 is public.

This deliverable presents information that is useful for different stakeholders in the e-mobility landscape. The description below is only a brief overview of the main stakeholders that might benefit from the content of this deliverable.

EV charging market models have been developed to allow the results from eCharge4Drivers to be extrapolated to other regions and for future scenarios. This supports the planning of EV infrastructure and policies to assess their impact on EV driver satisfaction and provides a tool to investigate the formulation of appropriate strategies. The planning of infrastructure and policies brings a wide range of stakeholders together; EV drivers, eMSPs, CPOs, OEMs and, local and national authorities. This deliverable provides a unique approach to integrate the wide range of requirements in a single model that allows tradeoffs between stakeholders.

1.4 Structure of the deliverable and its relation with other work packages/deliverables

This deliverable reports on one task: T7.1 EV charging market models, with sub-tasks summarised in Table 2. The models have been calibrated using data provided by demonstration sites (WP5) and findings from the demonstration sites (WP6.3).

Table 2: eCharge4Drivers D7.1 modelling sub-tasks

Modelling sub-tasks	Leader	Approach
Model Approach	UoS	Review modelling approaches, considering demonstration site use cases.
Application of modelling approach to EV charging	UoS	Configuration of model to specific features of EV charging infrastructure, for example booking services and queues at Charge Stations.
Calibration of models	UoS	Data collection and cleansing from a range of demonstration sites. Calibration of model parameters to achieve an acceptable correlation with the data from the demonstration sites.
Analysis of model responses	UoS	Analysis of a range of scenarios using the model to provide guidelines for future infrastructure and policies.

The deliverable D7.1 contributions from Task 7.1 have been linked to the impact areas in the overall eCharge4Drivers context in Table 3.

Table 3: eCharge4Drivers impact areas and specific contribution of Task 7.1 to each area

Impact area	Contribution from Task 7.1
Usage	Consider the impact of infrastructure and policy updates on the way users utilise the charging infrastructure and the related services to provide feedback on future scenarios (both changes to infrastructure and policy, and changes to EV populations)
Quality of Experience	Analyse the impact of the users' satisfaction with the charging experience – for example the availability of charge points, time for queuing and differences between social groups
Acceptance	Analyse acceptance through impact on user satisfaction and range anxiety to indicate how the infrastructure and policies received.
Environment & Society	Assess a range of policies to achieve improvements in sustainability and stimulate electric mobility across the society. For example by considering how to balance the availability of private charge points that favours affluent members of society with public charge points for the wider community.

2 BACKGROUND AND CONTEXT

2.1 User behaviour and the decarbonisation of transport

The Intergovernmental Panel on Climate Change (IPCC) has recently highlighted that “Having the right policies, infrastructure and technology in place to enable changes to our lifestyles and behaviour can result in a 40-70% reduction in greenhouse gas emissions by 2050. This offers significant untapped potential,” IPCC Working Group III Co-Chair Priyadarshi Shukla. “The evidence also shows that these lifestyle changes can improve our health and wellbeing.” The EU have published the their Sustainable and Smart mobility strategy that targets a 55% reduction in transport, [2], emissions by 2035 and carbon neutrality by 2050. This strategy is backed up with regulations to drive the uptake of zero emission transport, [3].

Sales of Electric Vehicles (EVs) are increasing rapidly with the share of EVs in total car sales rising from 1.9% in 2019 to 14.6% in 2023, [4]. However, EVs still only represent 1.7% of the total fleet on the road. The transition from combustion engine vehicles to EVs requires a significant change in behaviour that may lead to unforeseen consequences that may slow the adoption of EVs, especially when the number of EVs on the road becomes more significant. For example, if all the passenger cars were EVs, there would be approximately 50 times more EVs.

At the same time, the number of public charge points is increasing, from 2020 to 2024 they increased by over 5 times, [5]. Number of EVs to charge points is a useful metric to track the capacity which varies across Europe. The EU target of 10 EVs per charge point is only met in the Netherlands and Austria, while Norway has over 30 EVs per charge point.

EV user experience has been reviewed in [6] and covers topics such as range anxiety, changes to route planning, changes to driving style through to the introduction of regenerative braking. The use of policies to affect EV charge station efficiency is studied in [7] which showed that financial incentives for encouraging EV users to move their EV once it is charged may be effective in improving the efficiency of EV charge stations.

As the number of EVs increases, the charging experience is becoming more complex with new and interdependent behaviours emerging. For example, queuing at charge stations is an emerging problem because early adopters may have had more access to home charging and charge stations on routes have been largely underutilized so the probability of a queue forming was low. Other aspects to consider include the differences in situations between urban and rural users, people living in apartments versus family homes. There are few studies of these emerging charging experiences and this is the motivation for this report.

2.2 Requirement for user behaviour modelling

The eCharge4Drivers project is studying a range of user-friendly functionalities to reduce barriers and improve take up of EVs. These functionalities include; smart charging, tariff and incentives, plug n charge, booking service, route planner, enhanced information to driver, high power charge point, lamp post charge point, user friendly charge point, battery swapping and preventative diagnostics.

This report introduces a model of user behaviour to provide additional perspectives for a number of the use cases and functionalities. The additional perspectives include:

- The process of building and calibrating the model forces detailed analysis of the data and how EVs operate,
- Once built, the model can be used to assess impact on EV user behaviour and satisfaction by
    - applying a similar policy/infrastructure to different areas
    - varying the parameters of the policy/infrastructure
    - exploring new behaviours that emerge from the model
    - predicting the impact of future scenarios

2.3 Terminology

A brief note regarding the terminology used in this report. For the purposes of this report, a charge point is defined as a space where one vehicle can charge and charge station is a group of charge points.

3 EV CHARGING MARKET MODEL

3.1 Review of modelling approaches

The activities started with a review of market models, taking into account the project specific requirements, availability of data and desired outputs from the model. A key consideration is to ensure that the model can capture the actions that are being trialled at the demonstration sites and output the EV driver response.

This requires the model to be able to include:

- Data for specific charge points (e.g. price, power, location)
- Data for the EV population (e.g. vehicle types, battery sizes, numbers of EVs)
- Models of how the EV responds to different charge points (e.g. fast chargers require less time and are usually more expensive)
- Behavioural responses such as when and where the EV driver chooses to charge.

Many modelling approaches are based on predefined charging scenarios and the application of these to a charging infrastructure. For this project, we need to consider the interaction between charging behaviour and the detailed changes to the infrastructure. Modelling approaches that were considered include: Revenue Management, Random Utility Models, Logit Models and Agent Based Models. They are briefly reviewed below, leading to the conclusion that Agent Based Models are the only approach that meets the requirements of this project.

3.1.1 Revenue management

Revenue Management is an approach for optimising revenue in a dynamic market, it has its roots in the airline industry where there is a trade-off between increasing the price for tickets to increase revenue versus not selling enough seats on a plane, [8]. If the price is too high, not enough tickets are sold and the revenue is low whereas if the price is too low then all the seats may be sold but again the revenue is low. By introducing a dynamic pricing where the prices may be lower in advance then increase close to the flight and then fall just before the flight, the revenue can be increased. The process of setting prices can be posed as a control problem where the objective is to maximise revenue and the passengers can be modelled to give a predicted purchase profile.

The application of Revenue Management to the EV charging market was considered for this project because, like a flight, the charge stations have a fixed capacity and the charge point operators would like to maximise revenue from the charge points. However, there are a number of differences between these two scenarios:

- The charge point occupation is a continuous process rather than discrete. This means that the charge point can be used and then once the car has left, it can be used again. Whereas the flight is a discrete event with seats that need to be filled, once they are filled they cannot be filled again. The flight tickets are on sale for a limited timescale whereas the charge points are generating revenue continuously.
- The choice made by the EV driver is about when and where to charge the EV. The EV driver may vary their pricing sensitivity depending on several factors such as; battery charge levels, their personal risk assessment for running out of charge, planned journey, availablility of charge points.
- The demand for flights may be easier to predict based on historical data, whereas the EV charging demand may be more variable, at least while the the EV market is rapidly developing.
- This project is interested in how EV drivers modify their behaviour based on changes to infrastructure that lead to new scenarios that may not have been considered earlier. For example, queues at charge stations.

Whilst it may be possible to configure the Revenue Management approach to some aspects of EV charging, it was not selected for this project because of the challenges in modelling detailed changes to infrastructure and policy, combined with the interactions to the EV driver behaviour. This is especially problematic in large models, where the complexity and variability of the interactions between a large number of EV users and infrastructure settings would likely make the model currently intractable, however in the future, with access to more user data and data analytics this may be revisited.

3.1.2 Random Utility and Logit Models

The Random Utility Model is a framework where decision makers are assumed to choose a path that maximises their own utility from a set of mutually exclusive alternatives. In [9], this model is used to give the EV driver freedom to delay the charging at a charge point if they know that the electricity may be cheaper in the future. For the purposes of this study, this scenario is not relevant since currently, the price of electricity at the charge points only changes slowly and secondly, for this model, the EV driver is assumed to charge when they arrive at the charge point. However, this approach may have value for the Smart Charging demonstrations within eCharge4Drivers where the charging is delayed in exchange for a financial incentive.

A Logit model refers to a logistical regression model that estimates the probability of an event occurring based on a set of independent variables. So, for the case of EV charging, this could be used to model the probability of an EV charging based on battery state of charge (SOC).

These approaches can be used as part of a larger system model, but would not be sufficient on their own as they do not take the full system into account. In [9], they have been used to study individual EV driver situations rather than considering the wider EV ecosystem and interactions between EVs.

3.1.3 Agent based modelling

Agent based modelling (ABM) is an approach that simulates interactions between various ‘agents’, as well as their individual and collective behaviour within a specific environment. For example, in a traffic simulation, an agent may be a vehicle, with the environment defined by the roads. It is an established means to simulate and study the interactions of complex systems and has been applied to many situations, for example evacuation modelling, customer flow in supermarkets through to traffic simulations, [10], and EV charging, [1].

Considering agents in more detail, [11], an agent is identifiable, self-contained and discrete with a set of characteristics and rules that govern its behaviour. The details of the characteristics and rules for the EV charging market model are provided later in this section. The agent can interact with other agents in the environment and these agents can be the same type or different types of agents. Agents can learn over time to adapt their behaviours based on their experience within their environment. This allows new scenarios to emerge from updates to infrastructure and policies.

The use of the Belief-Desire-Intention (BDI) software model has been implemented in ABM as an extension to object-oriented programming, thus creating a simulation of autonomy within the “object” class and instance. This is termed an intelligent agent, which can act against environmental information, according to pre-defined behaviours defined as sub-classes within the agent class [12]. BDI agents in the context of traffic have been implemented throught the JACK framework, [13], within air traffic control and other defence settings. Other agent-based programming frameworks that have been used within the infrastructure (telecommunications) context include the Java Agent Develoment framework (JADE), originally developed by Telecom Italia S.p.A. [14].

An ABM is built from the bottom up, modelling the system at a microscopic level of detail to then allow the macroscopic behaviour to emerge. It is suitable for systems that have nonlinear individual behaviour (e.g. rule based logic or thresholds), behaviour that exhibits memory and adaption, as well as interactions that are heterogeneous (e.g. depend on the individual agent) [15]. The BDI framework that agents are build upon implements the autonomy of individuals within a population, but also allows for interaction between them, thus forming a complete system with potential emergent behaviours that are not necessarily obvious from its constituent parts.

This makes ABM suitable for the detailed study of changes to the EV charging infrastructure and policies, such as how the number of charge points or pricing strategy may influence EV user satisfaction. By modelling individual EV users, the ABM can also study the impact of increasing numbers of EVs on EV user behaviour and satisfaction.

This work implements the agents in Python, using the MESA framework, [16], which offers unique advantages in terms of the ubiquity of the Python language and associated data analysis tools. With MESA, researchers and developers can easily create, analyze, and visualize agent-based models to gain insights into various real-world phenomena, such as traffic flow, market dynamics, and social behavior. At its core, MESA provides a flexible framework for agent definition, behavior specification, and modeling the environment in which they operate. Users can create custom agent classes with tailored attributes and behaviour rules, allowing for the representation of diverse agent types with unique characteristics and decision-making processes. Additionally, Mesa offers built-in modules for defining spatial grids and networks, facilitating the simulation of agent interactions in spatially structured environments.

One of MESA's key strengths lies in its simplicity and ease of use. Its intuitive application programming interface (API) and extensive documentation make it accessible to users of all skill levels, from novice modelers to experienced researchers. Furthermore, MESA's modular design encourages code reuse and experimentation, enabling users to quickly prototype and iterate on their models. With its rich set of features and active community support, MESA has emerged as a go-to tool for ABM practitioners seeking to explore and understand complex systems in different domains.

For the reasons described above, an Agent Based Model within the MESA framework was chosen as the most suitable modelling platform to study EV user behaviour and satisfaction.

Balancing the advantages of using Agent Based Models, there are two key challenges that need to be considered: the definition of the agent characteristics/rules and the computational demands (memory and processor performance). These are related since increasing the detail of the rules and characteristics can increase the computational demands. The approach adopted in this project has been to simplify the rules as far as possible whilst retaining a representative behaviour for the EVs and charge stations. The computing memory was also a function of the extent of the agent logging. During the model configuration a detailed log was generated. When extending to larger populations, MESA allows the logging to be reduced to the outputs of interest.

3.2 Application of Agent Based Modelling to EV markets

This section explains how Agent Based Modelling has been applied to capturing behaviours within the EV charging market. The model considers the interactions between the EVs and the Charge Points. The guiding principle for building the model is to aim for simplicity whilst retaining the operating characteristics of the charging ecosystem.

This model sets out to simulate the behaviour of EV drivers as they charge their EVs. The model is built up from three agent types to allow the various interactions to be simulated; an EV agent, a Charge Station (CS) agent and a Location agent, Figure 1. The model is initialized and the agents carry out their actions as time progresses, using a discrete timestep.

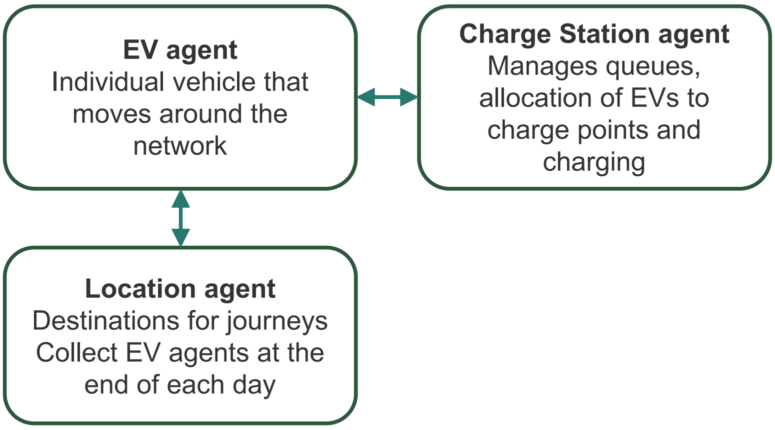

Figure 1: Overview of initial agents in the EV agent based model

3.3 Model structure

The model uses a staged random scheduler for agent activation. This means that agents are selected at random to run their 'step' functions, stage-by-stage, once, every timestep. Each agent's 'step' functions are discussed later in this section.

The model environment is a grid of cells, associated with longitude and latitude coordinates. Each cell can contain any number of agents at any time step. During a run, the model agents exist at various locations on the grid using positional coordinates. The EV agents are mobile and move during the simulation, while other agents (Charge Stations and Location agents) are fixed in space.

The interactions of the individual types of agents are shown in Figure 2

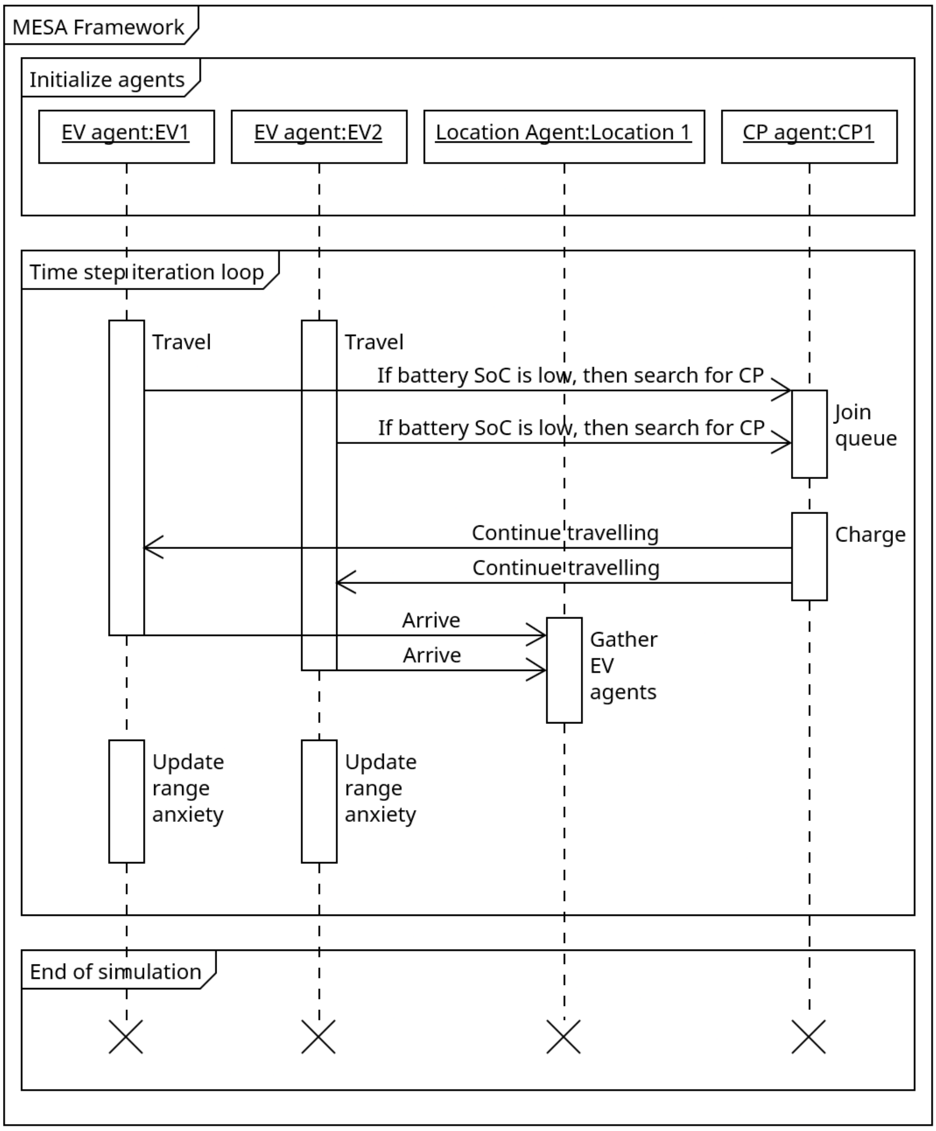

Figure 2: Overview of agent interaction in the EV agent based model

3.3.1 EV agent 'step' functions

EV definition: The EV agent models both the EV and driver. The initial parameters of the agent are generated using a Monte Carlo method from a distribution of typical EV characteristics. Each EV has its own characteristics such as battery size, average speed and electrical energy consumption that are generated. The agent has additional parameters associated with the driver, for example the maximum price they would be prepared to pay for electricity, an initial 'range anxiety' and 'customer satisfaction', the destination location, journey start time for each day and probability of having home charging available. Additional features could be added in future, such as charging at work, however an agent based model requires a simplified set of rules to allow scaling to large numbers of agents.

EV move: The EV agent moves between locations, using energy as it moves, depleting the battery. The EV agent has a state machine, Figure 3, that manages this behaviour, from 'idle' to 'travel' for example. As the battery state of charge (SOC) reduces below a threshold, the EV moves to state 'travel low' where it is looking for a suitable place to charge the battery. The EV can now look for a nearby charge station.

EV charge: On arrival at a charge station, the EV checks if there are available charge points. If there are no charge points, it joins the charge station queue, otherwise it starts to charge. The charge rate is calculated from the maximum of the EV charge acceptance and the charge point power rating. The EV is charged to 80% SOC and then leaves the charge station to complete its journey.

EV queue: The EV joins the queue at the charge station which follows a 'first in first out' procedure. This provides a link between EV agent and charge station agent.

Exceptions: The model requires a number of exception procedures to ensure that EVs are able to continue with the simulation and do not get stuck or stranded. This involves a recovery action that takes the EV to the destination and charges the battery back to 100% SOC. Exceptions include; recovery if battery SOC is zero, recovery if the EV is in the queue at the charge station at the end of the day.

EV driver response: The EV driver response is modelled with two parameters; range anxiety (RA), and customer satisfaction (CSat).

RA is a parameter that varies from 0 to 1, with 0 being no anxiety and 1 being very anxious. RA is also a parameter that affects the behaviour of the EV driver by changing the battery SOC threshold at which the driver starts looking for a charge point (i.e. the transition to 'travel low'). A more anxious driver will have a higher SOC threshold and will therefore start to look for a charge station earlier than a less anxious driver. The RA is updated every day, decreasing by an amount if successfully arriving at the destination or increasing by a different amount if the EV is stranded.

CSat is a parameter that varies from 0 to 1, with 0 being dissatisfied and 1 being satisfied. CSat does not affect the behaviour of the model. The CSat parameter is updated every day, increasing if the queue time was below a threshold and decreasing if the queue time is above a threshold.

The use of two parameters is based on the customer satisfaction models that consider minimum service requirements and value enhancing service requirements, [17]. In this model the RA is used to reflect minimum service requirements related to getting stranded. Whilst CSat reflects the value enhancing requirements by considering the time spent in queues.

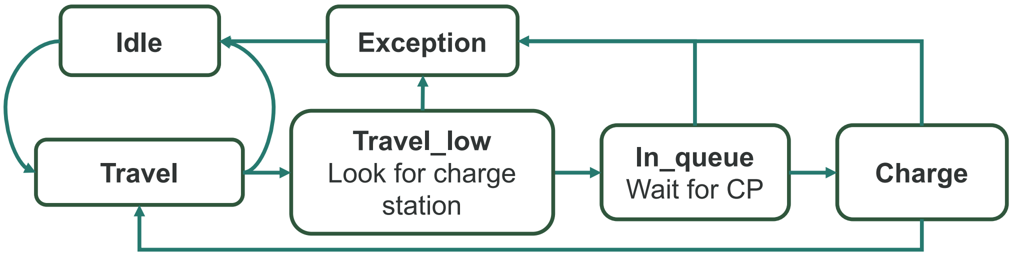

Figure 3: Overview of the EV state machine

3.3.2 Charge Station Agent

CS definition: The CS agent includes a model of the queue and the occupancy of the CS. The input information includes the location of the charge station, the number of charge points together with a set of information associated with each charge point (e.g. charge power, price of electricity and so on).

CS queue: The CS queue is managed on a first in, first out basis.

3.3.3 Location Agent

Location definition: The location agent is defined by its location, as a source or destination for the EVs. It is only used to track the EVs and records the EVs present at each time step.

3.3.4 Model space

In this work, real-world case studies were used to calibrate the model, to ensure its accuracy and fitness for the desired purpose. These are derived from the trial locations of eCharge4Drivers. The environment which the model agents are situated in and interact within, for each case, is defined as a grid of cells with dimensions as described in Table 4. More details on the calibration and the specifics for each case study are provided in Section 0. Converting between geographic coordinates (latitude and longitude) and model coordinates (x, y) is a commonplace task in spatial analysis, particularly when addressing grids sizes. This process involves scaling the latitude and longitude coordinates to fit within the dimensions of a grid specified by the modeller. The range of the latitude and longitude values within a specified bounding box are determined first and then scaled to the grid dimensions.

Table 4: Model space dimensions

Model	Grid width	Grid height	Latitude range	Longitude range
Austria	800	500	46.3° – 49.4°	8.0° – 17.82°
Barcelona	800	500	41.3° – 41.5°	2.05° – 2.3°
Grenoble	800	500	45° – 45.3°	5.64° – 5.85°
Turkey	2200	2200	35.81° – 43.4°	19.9° – 44.57°

3.3.5 Model timescale

The models are temporally flexible and can be run at variable resolutions. The model adjusts EV functions relating to inter-location movement and charging relative to the selected time resolution to achieve equivalent behaviour across timescales. The model was run primarily at a 15-minute resolution. The selected time resolution corresponds to an individual unit of time is referred to as a tick and can be thought of as the smallest discrete unit of time within the model.

Building on this framework, the activities of the model agents as regards time are further structured in terms of hours and days and various agent activites are performed on a tick-by-tick, hourly or daily basis as appropriate. The overall model time horizon is flexible and has been adjusted to match the measured data when calibrating the models.

3.4 Details of agent behaviours

3.4.1 Electric vehicle movement

Due to the spatial nature of the system being simulated, almost all agents in the model, including the EV agents have a position attribute stored as a pair of x and y coordinates. Each location and charge station agent also has a position attribute.

The EV agents in this model undertake a trip every day. This trip may be an *inter-location* trip e.g from Location A to Location C or a *local* trip within a location. The destination is selected at random according to the overall vehicle flows in the model. EV agents on a local trip do not physically move from grid cell to grid cell, while those on inter-location trips do. The distance for the local trip is selected from a list of typical trips at the start of the day, for example going to work, going to the shops. The agents moving between locations move across the grid space in a straight line in small discrete steps between origin and destination location grid cells while on a trip between origin and destination locations. This action is defined in the model as ‘move’.

Furthermore, ‘move’ as well as other important mechanisms of EV movement are covered and represented as ‘travel’. This agent action/behaviour involves increasing the agent’s odometer attribute by the distance margin, decreasing the remaining battery capacity by the ‘consumption rate’, the amount of energy consumed by the EV agent to perform the movement action. This 'consumption rate' is itself dependent on other agent attributes and is discussed later in this section. There variant of travel used by EV agents on local trips does not include 'move'.

The energy consumption rate is modelled as a linear function dependent on the EV agent's speed. The agent speed is a heterogenous, randomly assigned value drawn between certain upper and lower bounds for each agent, according to the model configuration. It is a permanent variable, and the EV maintains this speed throughout the duration of the model run, except when the agent is undertaking a local trip, where the speed is halved.

The EV agent behaviour can be tracked for each individual EV. Figure 4 shows the detailed results for three EVs. The graphs are intended to illustrate the overall behaviour rather than specific results. For example, the range of SOC during the simulation, the evolution of RA and Customer Satisfaction, the states being dominated by 'idle' and 'travel' with intermittent charging and the range of routes that cover all the locations.

The results for each EV are different because they have different parameters (battery size, location and so on) and they have different journeys.

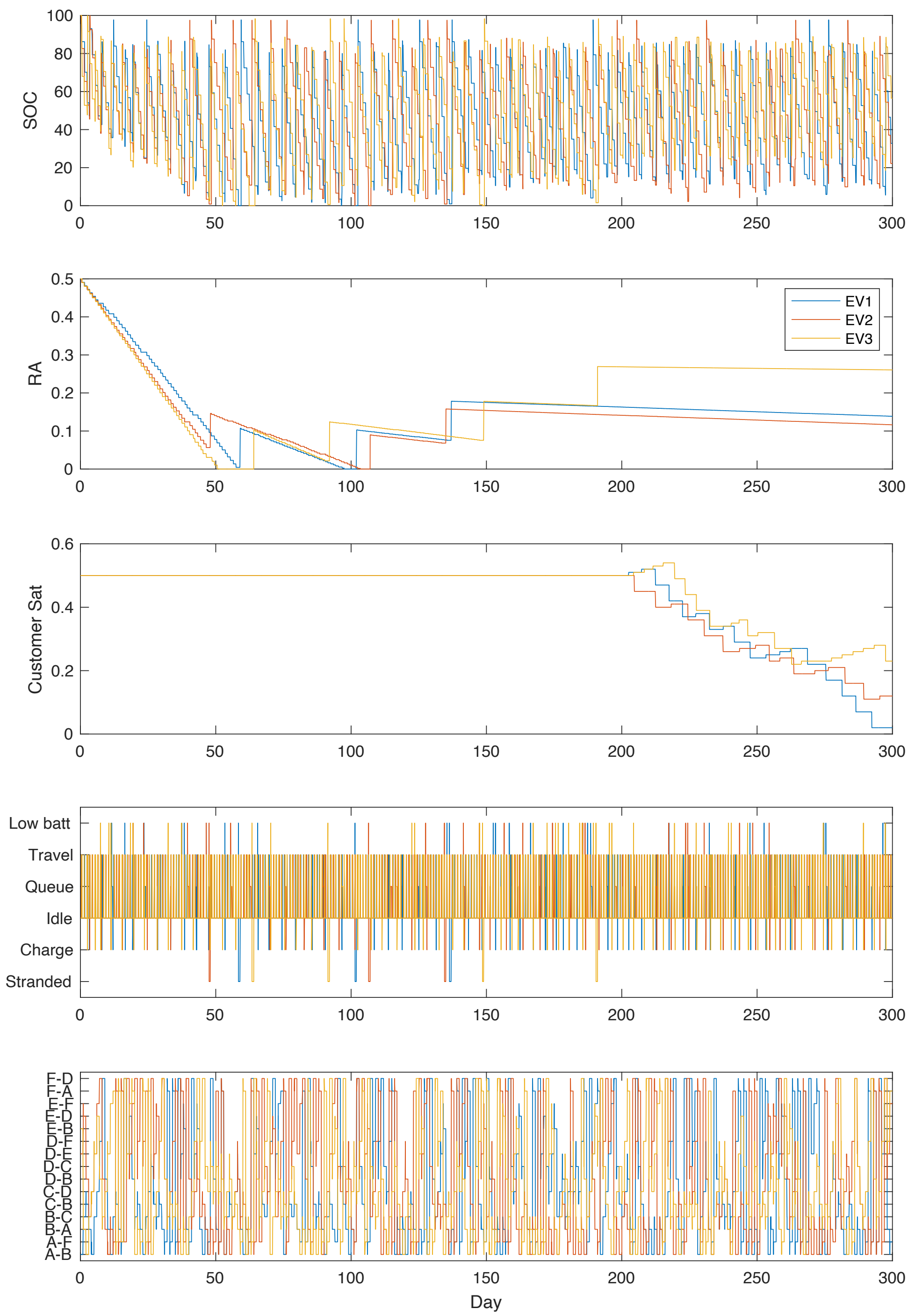

Figure 4: Detailed results for three EVs.

3.4.2 Charge station modelling, including queues

Charge stations are modelled as static agents in the model. Charge station agents can have multiple charge points as well as a queue for EVs which interact with the charge station agents. The queue is modelled as a first-in, first-out (FIFO) queue. Some of these charge station agents are situated at the 'Locations' and some are 'Route' charge stations – usually highway stations in positions which lie in between any two locations.

One of the inputs to the model is a file which lists all the characteristics of the charge stations present in a locale including the charge point power rating, and other characteristics such as “greenness” of energy source, post charge delay (a time delay between finishing charging and vacating the charge point) and energy provider label. Another input into the model is a list of charge stations and their locations, expressed in coordinates in model space.

In addition to modelling queues, the queue can be used to approximate alternative behaviour of EV drivers. For example, in a city, if a charge station is full then the EV driver would be likely to try looking for another charge station. In the model, the charge points can be grouped together in a virtual charge station to allow the EV driver to access additional charge points in the vicinity. If all are still full, then the driver enters the queue.

Figure 5 provides a zoom into the operating mode plot to provide more details of the queuing behaviour where the queues occur prior to charge events.

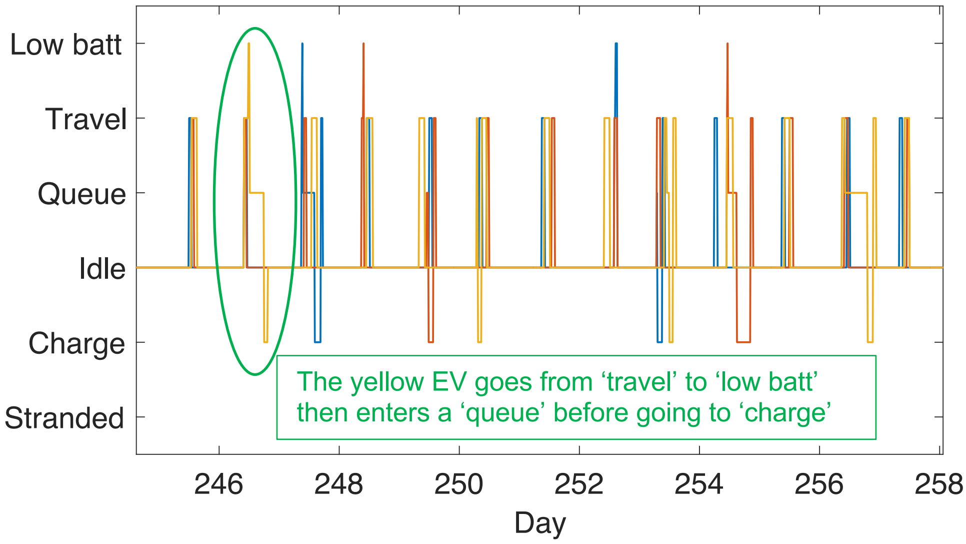

Figure 5: Zoom into operating modes to show queuing prior to a charge event.

3.4.3 User behaviour modelling

Two user behaviors are represented in this model. The first behaviour, range anxiety (RA) is a value which represents the EV driver’s perception of their vehicle’s battery’s State Of Charge (SOC) and defines when the EV will start to attempt to charge. It is modified by certain events within the model which lead to an increase or decrease in this value. These events include the EV running out of battery and getting stranded, forcing the EV driver to rely on an emergency services intervention for rescue and transportation to its destination. Other events which impact the RA include being stuck in a queue at the end of the day, that increases RA, and successful completion of a journey that reduces RA.

This RA value drives and modifies the EV driver’s behaviour in two ways:

1) by impacting the threshold value which triggers the EV driver’s transition into a ‘travel_low’ state. A high RA means the EV driver transitions to ‘travel_low’ state at a higher state of charge, a low RA means the EV driver waits for longer before going into the ‘travel_low’ state and

2) by changing the price at which the EV driver is prepared to pay to charge. As the RA increases, the EV driver is prepared to pay more to charge the vehicle. This is implemented as a lookup table of correction versus RA that can be calibrated.

The second behaviour, customer satisfaction, measures the EV driver's satisfaction with the charging experience. It is influenced primarily by the amount of time an EV spends in queues, relative to set benchmarks. If an EV spends less than 30 minutes in a queue, customer satisfaction increases, however, if an EV spends more than 90 minutes in a queue, its customer satisfaction decreases. The margins for increasing and decreasing customer satisfaction are flexible and are set in the model's configuration file as part of the model calibration. If the EV is in a queue at the end of the day then it is an exception and the EV is moved to the destination and the customer satisfaction is reduced. Again, the agent based modelling approach requires simplified rules to be applied, so whlist more complex situations can be envisaged, this approach has been selected as a compromise to deliver realistic behaviour whilst maintaining a simple rule structure.

It is important to note that the customer satisfaction does not impact the EV behaviour, so updates are inactive at initialisation and remain disabled until some time has passed in the model – currently set to 100 days. In other words, it is a time lagged/ time delayed value which does not change until a set number of days into the simulation run. This allows the model's system RA level behaviour to settle, as evidenced by a stable average RA for EV agents in the system.

These two behaviours are ultimately functionally linked. The EV agent's range anxiety affects the frequency of charging events, which can affect the number of EVs in charging queues and ultimately, the time spent by the EV agents in those queues.

3.4.4 Booking Systems

A simplified booking system has been implemented in the model to simulate the impact of a booking system, with bookings only being scheduled on a day-by-day basis rather than multiple days in advance.

An inherent limitation of any booking system is its dependency on the availability of the reserved charge point and of the parking space it is installed at. In some demonstration areas, the effectiveness of a booking system was compromised when the designated parking space was occupied by unauthorized vehicles. In absence the means to enforce sanctions, e.g. remove such vehicles, the reservation system failed to provide access for EVs that have booked a charging point. This is a critical barrier towards implementing a booking service. In the agent based model, this is simulated by forcing unbooked vehicles at charge points to vacate the charge point and rejoin the queue if a booked vehicle arrives.

There are three actions required to implement the booking system:

- Decide if EV wants to book,
- Book CP,
- Manage charge point and EVs to make sure EV uses booked slot and manage other EVs to make sure they do not take the slot.

The decision to book is based on the SOC. If the SOC goes below the SOC threshold for the current journey and the EV has booking enabled, then then the booking procedure will start.

The booking procedure looks at all charge points on route and picks free one for the timeslot when the EV will reach the charge point. This requires the model to estimate time of arrival. If no free ones, return a failed booking.

Once the travel starts for the day, the EV with a booking starts the journey and when it arrives at the booked charge point, it can bypass the queue and go directly to the reserved charge point. If another EV is charging there, it would have been removed from the charge point and re-joined the queue at the charge station.

The booking process is managed by an additional agent, the booking agent that manages the booking schedule for the day.

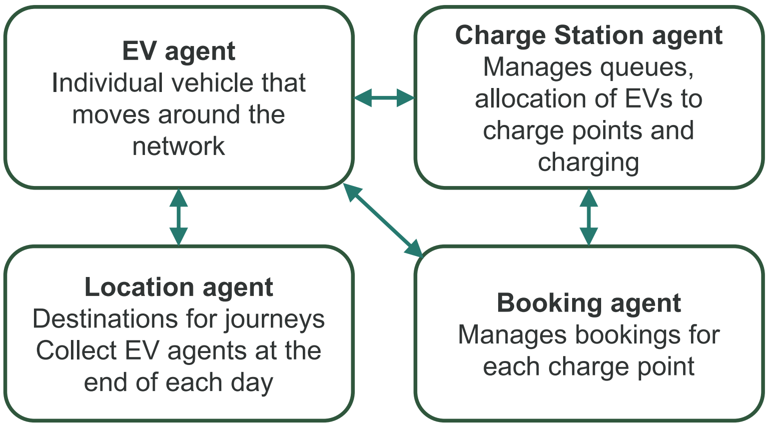

Figure 6: Addition of Booking Agent

4 MODEL CALIBRATION

Model calibration is a process where model parameters are set up to reflect available measured data. The calibration of an Agent Based Model is often challenging as there are usually boundaries between the area of interest and the rest of the world. For example, an ABM of traffic in a city needs the traffic flows in and out of the city.

A second challenge is when the model is used to assess the impact of a change, for example an increase in the number of charge points. In this case, it would be helpful to be able to compare the measured and predicted behaviours before and after the increase in charge points.

The datasets used for parameterizing the models in this study came from a variety of sources and structures. Broadly speaking, the model is calibrated with two input data sets; the physical definition of the charge points and charge point usage over a period of time. This leaves a large number of parameters that have to be estimated or derived with some assumptions.

- Number of EVs at each location and their typical route preferences
- The flows of EVs into and out of the region
- Pricing at CPs
- Pricing preferences
- Charging behaviours (charge at home versus slow charger versus fast charger)
- Region variations of the above parameters

The different demonstration areas can be roughly grouped into two; those at a country level and those at an urban or city level. This results in a variation of spatial scales involved in each of the locales modelled in this study. For example, Turkey is modelled at the country level and the locations considered in that context are individual cities. Somewhat differently, Barcelona is modelled at the city level and composed of several district-level locations. This is to reflect the purpose of each study; for a country simulation the travel between cities is the main focus, for a city simulation, the travel between districts in the city is of interest.

The calibration is complicated further by uncertainty in the measured data sets. The charge point data typically consists of charging events (start time, end time, energy delivered) but is missing EV related information such as where the EV has travelled from/to, where the EV is based and pricing information. The calibration process therefore needs to assume parameters associated with travel planning and pricing for example.

4.1 Charge point location data

The charge point data used in this study includes key information about the location of the charge point, the rated power output, the current type (AC/DC) and in some of the collected datasets, the charge point operator. The detailed pre-processing of the data is summarised in Annex 9.1Charge point location data.

4.1.1 Turkey (country)

The model has been configured with the DC charge point data for Turkey to allow the study to focus on high power charging, Figure 7. The measured data included over 120,000 charge sessions. The data was cleansed to consider complete charging records and charge points, resulting in 211 charge stations with 266 charge points across the following 16 key locations Ankara, Bursa, Kocaeli, Istanbul, Balikesir, Antalya, Aydin, Manisa, Izmir, Batumi, Artvin, Kayseri, Mersin, Diyarbakir, Kirklareli and Edirne. Locations with lower population counts and lie in-between the main locations included locations/cities such as: Bilecik, Isparta, Afyonkarahisar, Trabzon, Samsun, Corum, Eskesihir, Sakarya, Yalova, Bolu, Konya, Askaray, Mugla, Aydin, Denizli, Usak, Adana, Malatya, and Gaziantep. Charge points associated with these locations were converted to Highway Charge stations between locations and labelled accordingly.

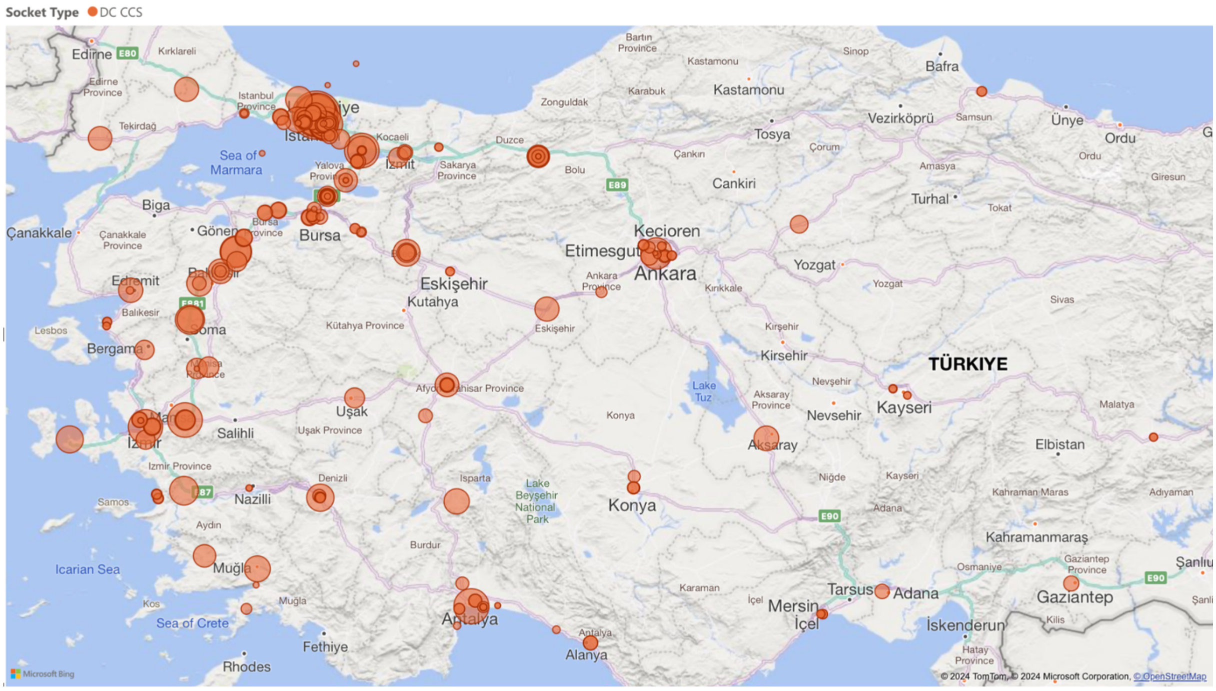

Figure 7: DC Charge point locations in Turkey, with bubble size proportional to sum of energy delivered.

4.1.2 Austria (country)

The charge point data for the Austria model was based on DC charge points to focus on high power charging. The measured data was provided for over 180,000 charging sessions over 3 months in 2023. The charge points were grouped according to post code, and there were 186 charge points in the model.

4.1.3 Barcelona (city)

The charge point data for Barcelona consisted of 79 charge point locations once the data had been cleansed, with over 50,000 charge sessions. This dataset was then manually inspected and labelled. Each charge point was assigned one of the ten district names for the district it belonged to. Each charge point was also given a unique model-compliant name dependent on this district name.

4.1.4 Grenoble (city)

The Grenoble charge station dataset inlcuded charge point information for 30 charge stations including 93 charge points across 20 districts in the city and over 12,000 charge sessions. Following preprocessing, the charge points in the dataset were assigned coordinates in model space, ensuring that all the charge point latitude and longitude information fall within the defined bounds of the study locale. Afterwards, the dataset was augmented with other charge point characteristics the route name, Chargepoint ID (CPID) and default values for pricing, “greenness”, booking, provider, resulting in ‘Input chargestation dataset 2’ for the locale.

4.2 EV populations and Vehicle Flows

The number of EVs at each location is needed to calibrate the model to a measured data set. A starting point for assigning the number of EVs to a location could be based on the population at that location. This is likely to be a reasonable approach for models of a country where the locations are cities. However, there may be other influences such as relative affluence in different cities since EVs are still a luxury item and / or purchased by early adopters who have a 'green' outlook.

An alternative approach is to consider the number of EVs per charge point. This ratio can be quite stable and since the number of charge points is known, it can be used to estimate the number of EVs.

However, the calibration of these parameters is not straightforward and is complicated by several factors, including:

- In the country level models, the ABM is being used to study the use of the high power chargers so the EV population should reflect the EVs that use the high power chargers. This population will vary from city to city as different cities have different charge point infrastructure strategies.
- Within the regions being studied, there are competing charge point operators (CPO). The charge point data is typically from one CPO, missing the charge events from other CPOs. This may have a larger impact across cities where different CPOs may dominate.
- The unknown number of visitors from outside the region that can increase the utilisation of the charge points, but do not remain in the region overnight.
- The number of EVs charging on street may be a function of where the EVs are located during the day, rather than their original location (ie. If they charge at work or when shopping).
- The range of use cases including destination charging and fast charging.

To set the number of EVs at each location for the purposes of the ABM calibration the following approaches were taken with the objective of achieving a reasonable match to the total energy supplied at each location, bearing in mind that the purpose of the ABM is to simulate vehicles periodically requiring charging and interacting with charge points.

- For the country models
    - Compare models with a) approximate populations in each location and b) populations based on numbers of charge points and select the most promising
    - Refine the model for those cities that differ from the measured charge point data (for reasons listed above)

- For the city models use an EV distribution that reflects the energy delivered in different districts

A related parameter that also needs to be defined for the ABM is the vehicle flow between each location. The approach taken here was to start with the traffic flow data from eCharge4Drivers deliverable D1.2 [18] where the EV traffic flows in the demonstration areas were summarised. An example is presented in Figure 8, taken from Figure 374 in [18].

Figure 8: Inter city EV traffic flows in Istanbul and Western Turkey demonstration area

Where this data was not available, for example, in Barcelona, traffic flows were approximated based on the commentary within [18]. For example, taking 'Sarria, Les Corts, Sants-Montjuic have high activity. Ciutat has more commercial activity. Horta Guinardo, Nou Barris and Sant Andreu are lower residential.' The traffic flows were configured with more travel to Ciutat from Sarria, Les Corts and Sants-Montjuic.

Note, the number of EVs is indicative and is also related to the EV population being studied. For example, in the country models, the number of EVs is based on the number of EVs that use fast chargers and carry out inter city travel. Whereas in the city models, the number of EVs is based on the number of EVs that use public charge points.

4.2.1 Turkey (country)

The model of the charge points in Turkey has been configured as follows:

- Use the distribution of charge points to initialise the numbers of EVs (based on current distribution of charge points)
- Estimate inter city EV traffic flows from Figure 8.
- Calibrate the charge point pricing in Ankara since the amount of energy delivered was less than expected for the number of charge points. This could be because of competition from other CPOs making the ZES charge points relatively expensive.
- Increase the number of EVs per charge point in Istanbul since it is likely that there are more EVs in the largest city that do not have access to charge points at home.
- Update the range of travel times that were too short. This was limiting the total amount of energy that could be provided as the charge points were under-utilised.
- Calibrate the total number of EVs to achieve a reasonable correlation.

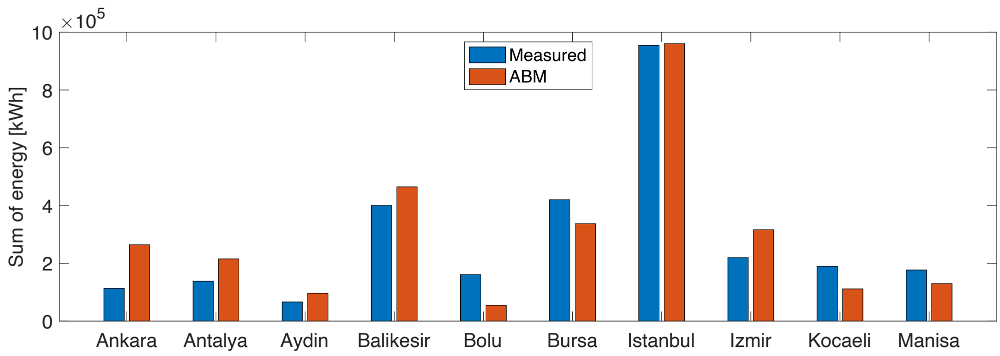

Figure 9: Sum of DC charge point energy charged at different locations in Turkey over 1 year.

Discussing the differences between the ABM and the measured data:

- In Ankara the model still predicts a higher amount of charging, may be due to competition from other CPOs.
- Bolu and Balikesir also have lower amounts of charging. In these cases, the locations are on routes between larger cities. To get more accurate estimates, more accurate traffic data would be required.

4.2.2 Austria (country)

The model of the charge points in Austria has been configured as follows:

- Use the distribution of charge points to initialise the numbers of EVs (based on current distribution of charge points)
- Estimate the inter-city EV traffic flows from [18]
- Calibrate the total number of EVs to achieve a reasonable correlation.

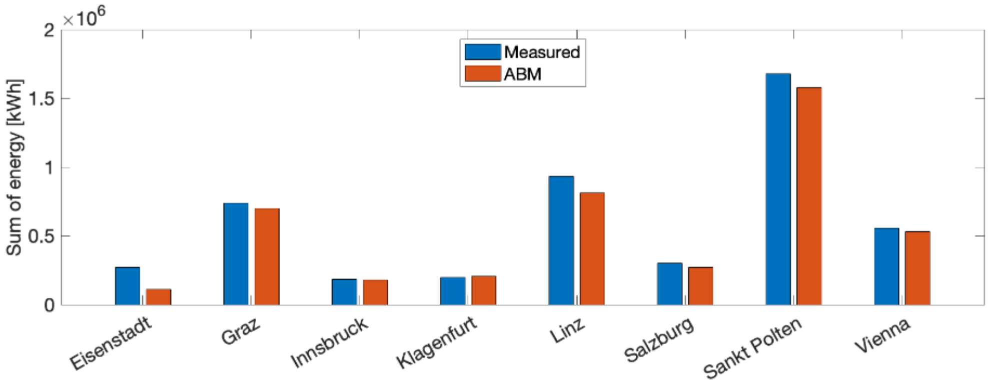

Figure 10: Sum of DC charge point energy charged at different locations in Austria over 3 months.

Discussing the differences between the ABM and the measured data:

- The largest percentage discrepancy is for Eisenstadt, which may be due to the classification of the locations. The region has the lowest actual population and also the lowest number of DC charge points. The measured value may be high because of traffic flows coming from outside Austria.
- Sankt Polten has the largest absolute difference, which may also be due to traffic flows coming from outside Austria.
- These highlight some of the challenges in calibrating ABMs.

4.2.3 Barcelona (city)

The Barcelona model was calibrated as follows:

- The EV traffic flows were based on the commentary from [18].
- The EV populations in Barcelona were based on the energy delivered in each district.
- Calibration of total number of EVs to achieve a reasonable correlation.

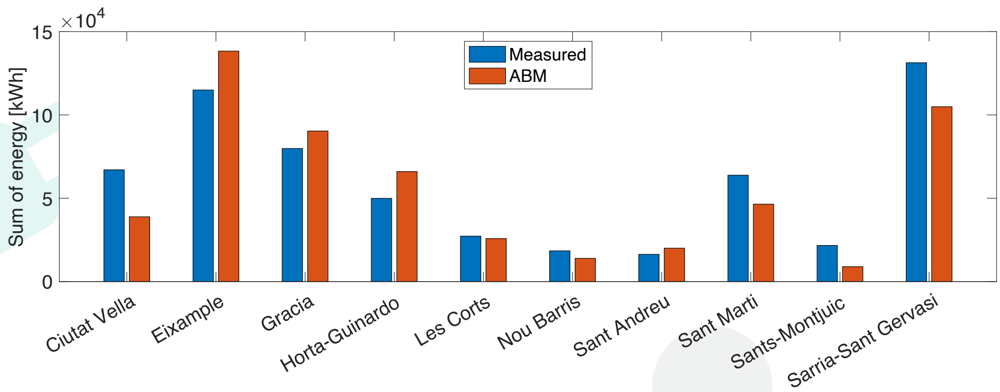

Figure 11: Sum of charge point energy charged at different locations in Barcelona over 1 year.

The total energy flows compare well with measured energy of 591MWh and simulated energy from ABM of 530 MWh. The individual distributions are shown in Figure 11. This shows a reasonable correlation between across the city, with an over prediction in Eixample and an under prediction in Ciutat.

4.2.4 Grenoble (city)

The Grenoble model was calibrated as follows:

- The EV traffic flows were based on the commentary from [18].
- The EV populations in Grenoble were based on the energy delivered in each district.
- Calibration of total number of EVs to achieve a reasonable correlation, however it is noted that since the distribution is dominated by one district, the calibration is difficult at the other locations.

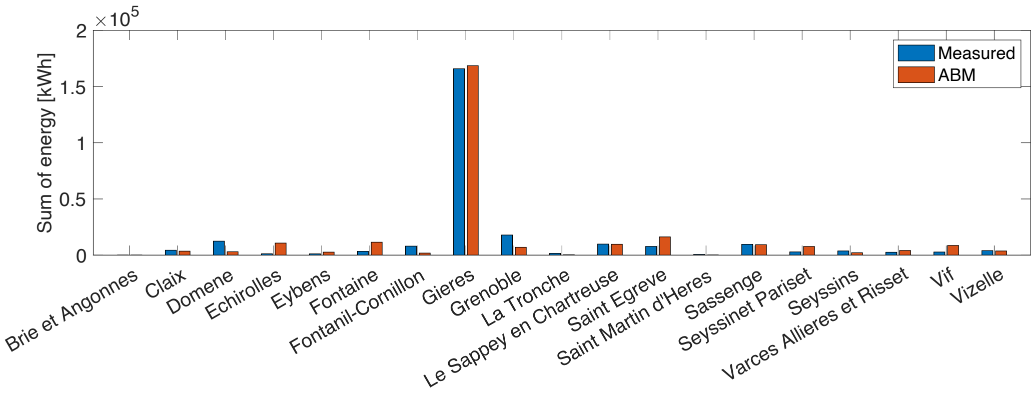

Figure 12: Sum of charge point energy charged at different locations in Grenoble over 1 year.

The charging profile in Grenoble was dominated by the central Grenoble district. This reflects the charge point infrastructure currently in place in Grenoble. As the EV market evolves in the coming years, it will be important to understand the balance between private and public charge points as EVs spread into less affluent districts.

4.3 Post demonstration data

The impact of changes after the demonstration actions was used to calibrate the impact of changes within the demonstration areas. Two features have been considered in this section, the impact of booking systems and the impact of pricing strategies.

4.3.1 Impact of booking in Turkey

A booking system was introduced across the network in Turkey in June 2022. In the first 3 months the number of reservations increased, but then fell back, as shown in Figure 13. This figure also shows the charge events over the same period, showing that the peak in August 2022 was not a function of increased charging events. The figure is showing the percentage of the total events for each month to allow comparison between the two variables since there were approximately 25 times more charging events than reservations.

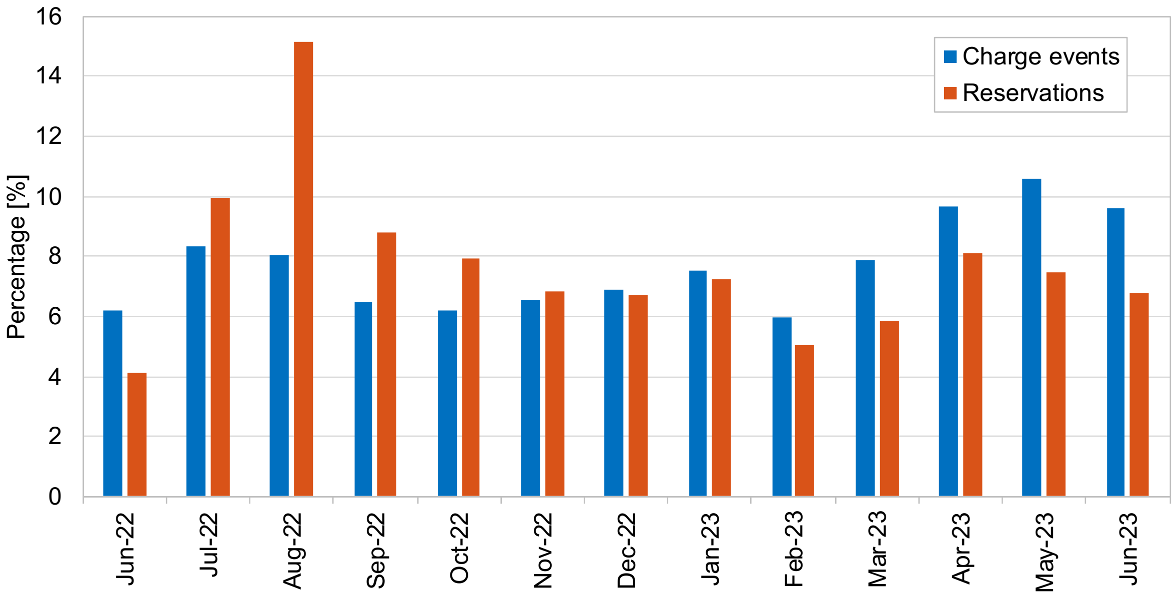

Figure 13: Charge events and reservations in the Turkey demonstration area.

These results were used to refine and develop the booking model. An ABM is based on simple rules to generate emergent behaviour, however it was found that the booking model soon became complex and challenging to implement to allow it to cover all the eventualities encountered by the EV agents.

The first step in calibrating the model was to focus on on just the booking system. The EVs were configured with no price preference, no green energy preference and with large batteries to avoid behaviour driven by pricing, green energy selection or battery size.

Some general comments about calibrating the model:

- For long inter city journeys, as found in Turkey, the ABM booking system allows booking of one charge but the journey often needs more than one charge. As a consequence, the difference between vehicles with bookings and non-booking vehicles on these journeys was reduced.
- At lower numbers of EVs, there is sufficient capacity since the EVs are not queuing excessively - shown by the customer satisfaction being around 0.5. In these cases, the booking system is not going to have a major impact.
- As the number of EVs increase, the impact of the booking system increases and there is a benefit for the EVs with bookings.
- As a consequence, the changes in range anxiety were quite small so the study focussed on the overall trends.

In Figure 14, the range anxiety has been plotted for those vehicles that book and those that do not book. Considering the situation with 500 EVs, it was found that the vehicles with bookings generally had a lower range anxiety than those with no booking.

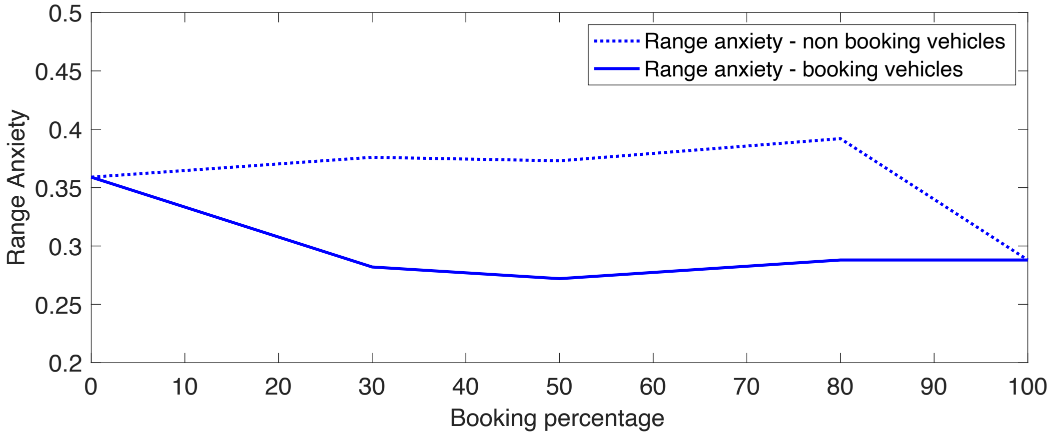

Figure 14: Impact on range anxiety with variation of the percentage of vehicles booking charge sessions.

Qualitatively, this may also be what is seen in Figure 13, where the number of reservations increases but then falls back as users calibrate to the availability of bookable charge points.

Additional analysis of the population in Figure 15 shows how the booking system has moved approximately 20% of the population with a range anxiety from 0.3 to 0.6 to around 0.1 to 0.2. The booking system is reducing the number of EVs that would be affected by range anxiety by approximately 20%.

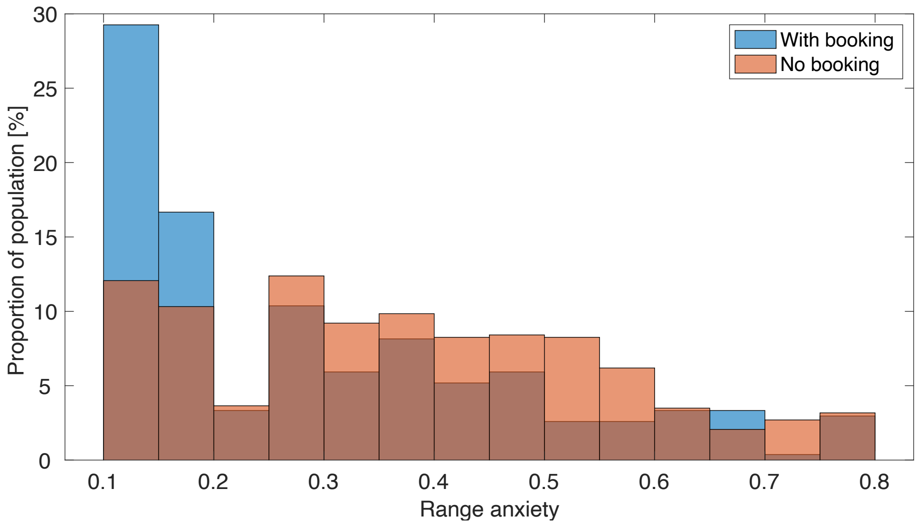

Figure 15: Impact of booking on Range Anxiety: Turkey with 900 EV

4.3.2 Impact of Pricing in Barcelona

The impact of pricing has been compared to the experience in Barcelona where the charge points were initially free. When a charge was introduced, the usage dropped but soon recovered back to similar levels.

In the agent-based model, this has been studied by starting with free charge points and a user preference for free charge points. The user preference is the price they are prepared to pay for charging and has been calibrated according to Figure 16. This can be interpreted as follows, for a range anxiety of 0 to 0.5, the correction to the price preference is zero. As the range anxiety increases above 0.5, the price correction rises, increasing the price the EV is prepared to pay for the electricity.

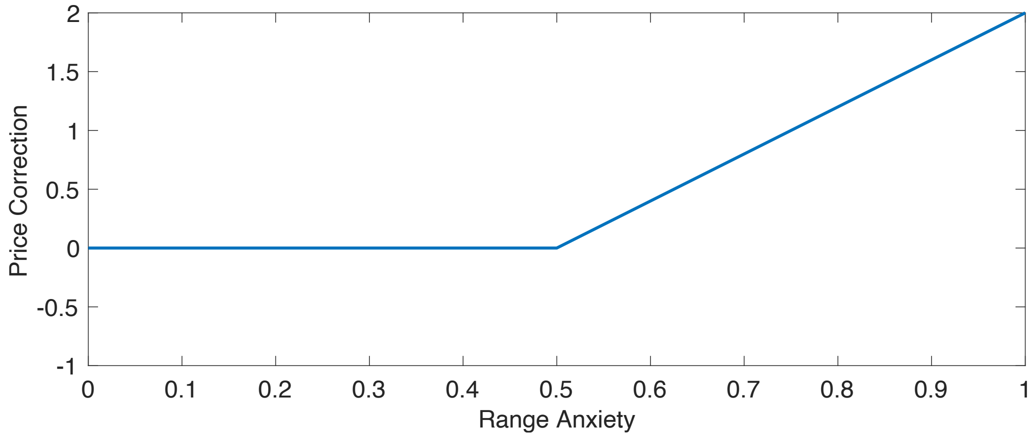

Figure 16: Price Correction Calibration

Three scenarios were run with the model:

1) Free electricity and users expecting free electricity
2) Market pricing applied but users expecting free electricity
3) Market pricing applied with users expecting market pricing

The RA profiles for each scenario are presented in Figure 17 to Figure 19.

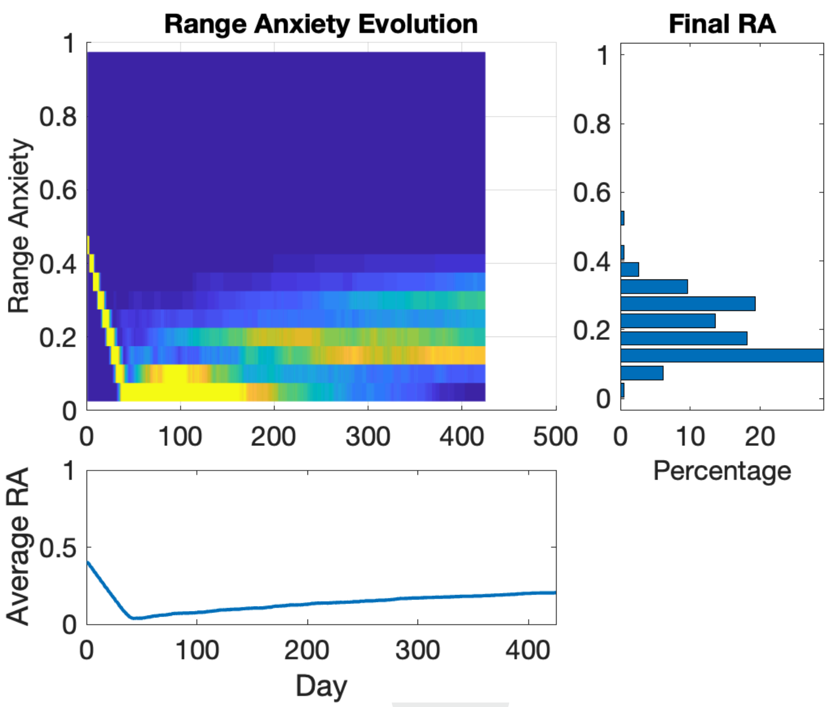

Figure 17: Scenario 1: Free electricity and users expecting free electricity.

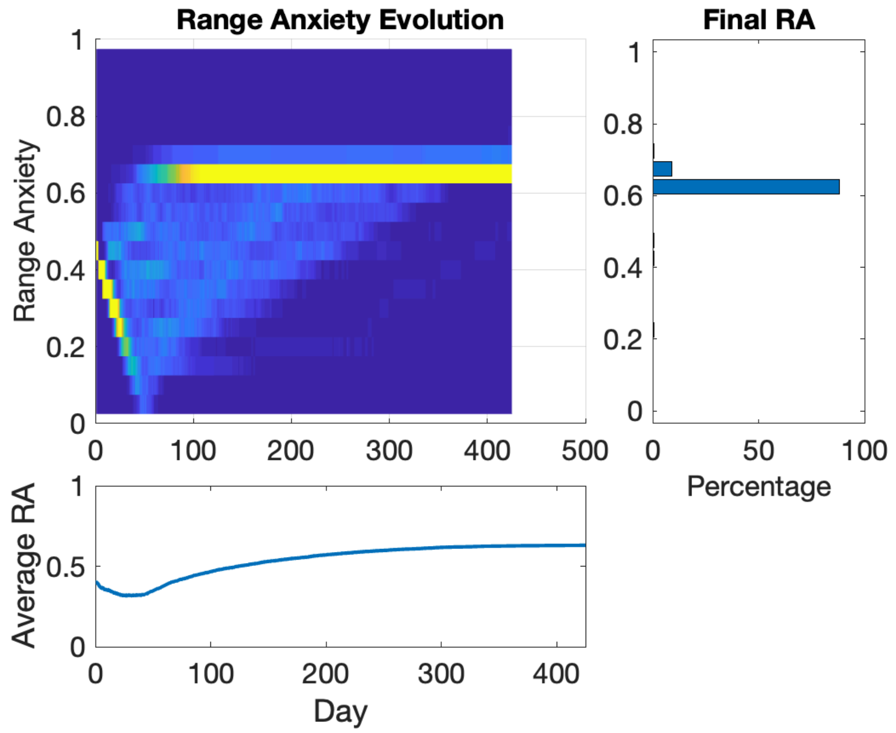

Figure 18: Scenario 2: Market pricing applied but users expecting free electricity

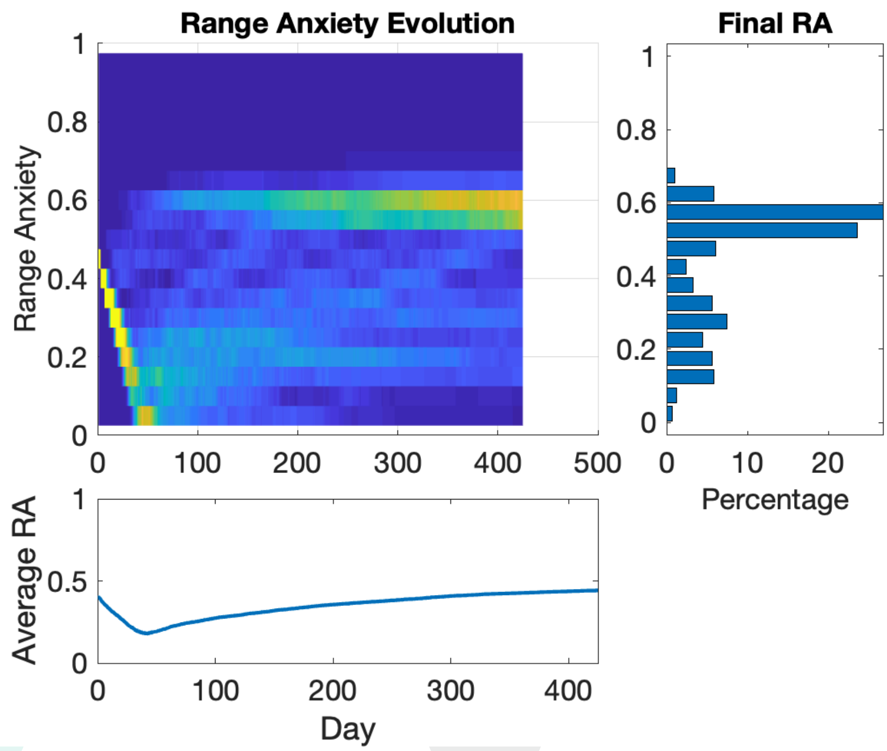

Figure 19: Scenario 3: Market pricing applied with users expecting market pricing

The final RA for each of these scenarios was calculated, as shown in Table 5, and followed a similar trend to the heuristic experience from the actual implementation in Barcelona.

Table 5: Range Anxiety versus Pricing Policy in Barcelona

Scenario	Average Range Anxiety	Discussion
1) Free electricity and users expecting free electricity	0.20	Model not affected by pricing, so RA is as low as possible whilst reflecting the number of EVs.
2) Market pricing applied but users expecting free electricity	0.63	All EVs need to increase their price expectation from 0. This means that the RA should rise above 0.5 according to the characteristic in Figure 16.
3) Market pricing applied with users expecting market pricing	0.44	There is now a range of user expectations so some will need to increase their price expectation, leading to some EVs having a RA above 0.5. The increase is less than required for Scenario 2 so the resulting RA is less. In addition, there are also some EV drivers that could afford to charge, leading to the distribution in Figure 19

5 MODEL ANALYSIS

The resulting ABM model has become relatively complex and as part of the calibration process a number of outputs from the simulations have been reviewed to ensure the models made sense. For these parameters, there is no measured data available to compare with.

5.1 EV movements

Over the simulation period, it is important to ensure that the vehicles remain distributed in a roughly constant ratio. This means that one location should not accumulate all the EVs, since they are free to drive between all the locations. There is a degree of noise as the movements are randomly selected using probabilities associated with the observed traffic flow patterns. This has been checked for each location with the results from Barcelona presented in Figure 20.

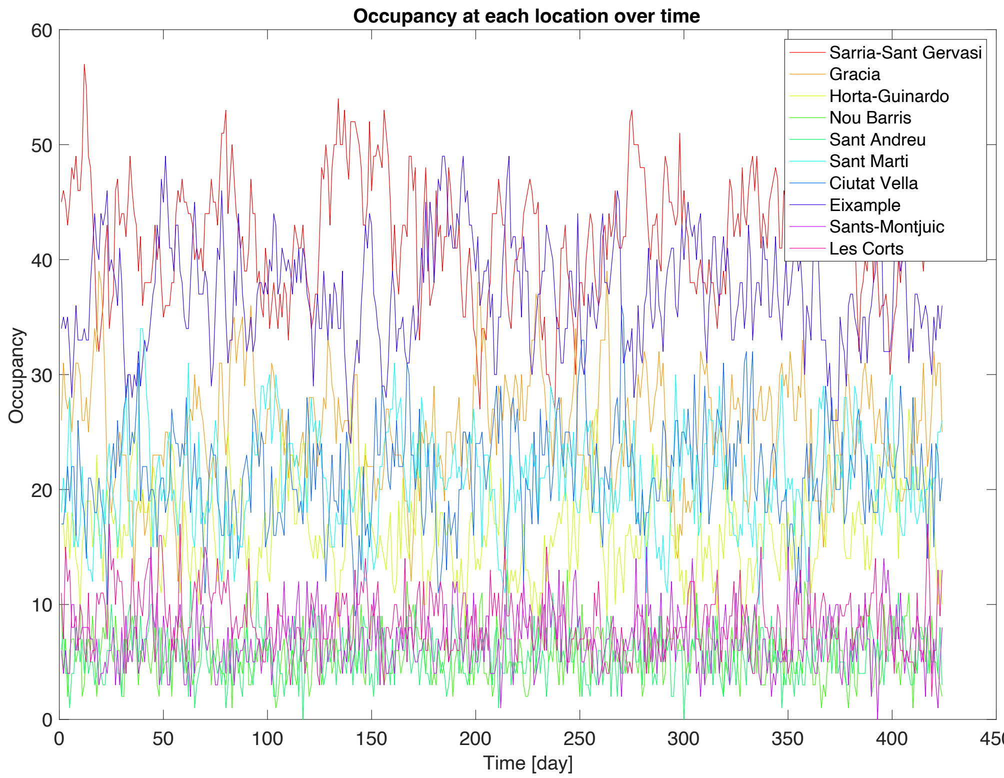

Figure 20: Occupancy of EVs in each district of Barcelona

5.2 Numbers of stranded vehicles

During the settling phase of the model, as the range anxiety of each vehicle settles down, the number of vehicles that get stranded should reduce to a low number. This is because in reality, the number of stranded vehicles with an empty battery is not high since the inconvenience of these events is very high and after a couple of events, EV drivers will take action to avoid reoccurance.

In this section we have included the number of stranded vehicles for Barcelona, Figure 21. This figure shows the expected behaviour with no vehicles stranded at the start when the batteries are full, as the vehicle start getting low on battery and with the initial range anxiety of 0.5, several get stranded. They then learn and the number getting stranded falls as the range anxiety settles.

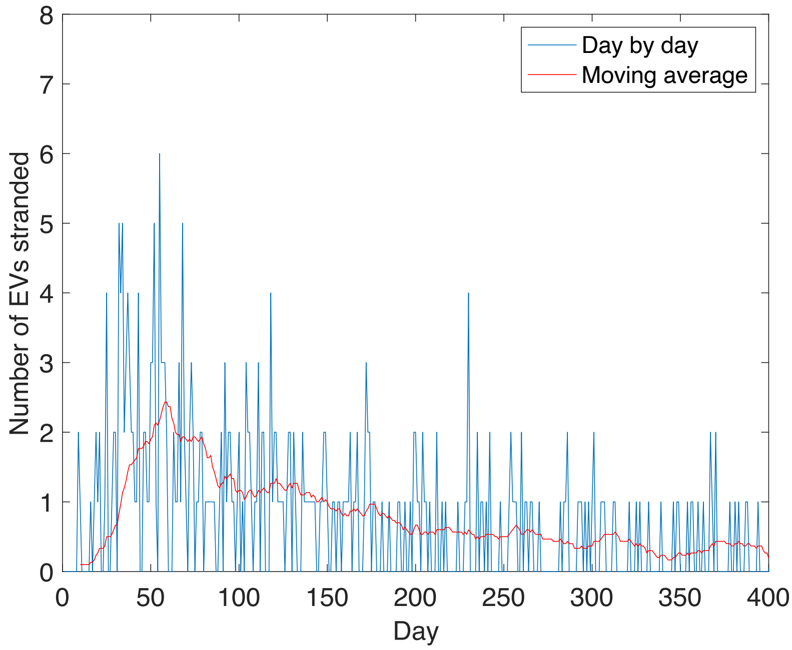

Figure 21: Number of EVs stranded in Barcelona Simulation

5.3 Queue distributions

One of the features of the ABM is that it has a queuing behaviour included to manage the situation when there are too many EVs for the available charge points. There is no data to compare these results to since queues are not recorded at charge points.

The models are analysed to present the predicted queuing behaviour, as shown in the Figures in the following sections. The data is the normalised sum of queuing times at each charge station, with the size of the bubble giving an indication of the relative probability of queuing predicted at each charge station. Normalised to the maximum sum of queuing times. The colours refer to the different districts within each model. Note: for the country models, the highway charge points have been loosely grouped with districts for presentation purposes only.

The queue distributions are related to the numbers of EVs trying to charge. The EVs in the model either carry out local trips or travel to different locations. In general, there are more EVs carrying out local trips than intercity trips, which results in the highway charge points being less likely to have a queue forming.

5.3.1 Turkey

The queue distribution in Turkey shows a high probability of queues in Balikesir that has a high level of traffic passing through that could increase the loading on the charge points. Manisa, Izmir and Istanbul have some queues forming that could present an issue if the numbers of EVs increase in these areas.

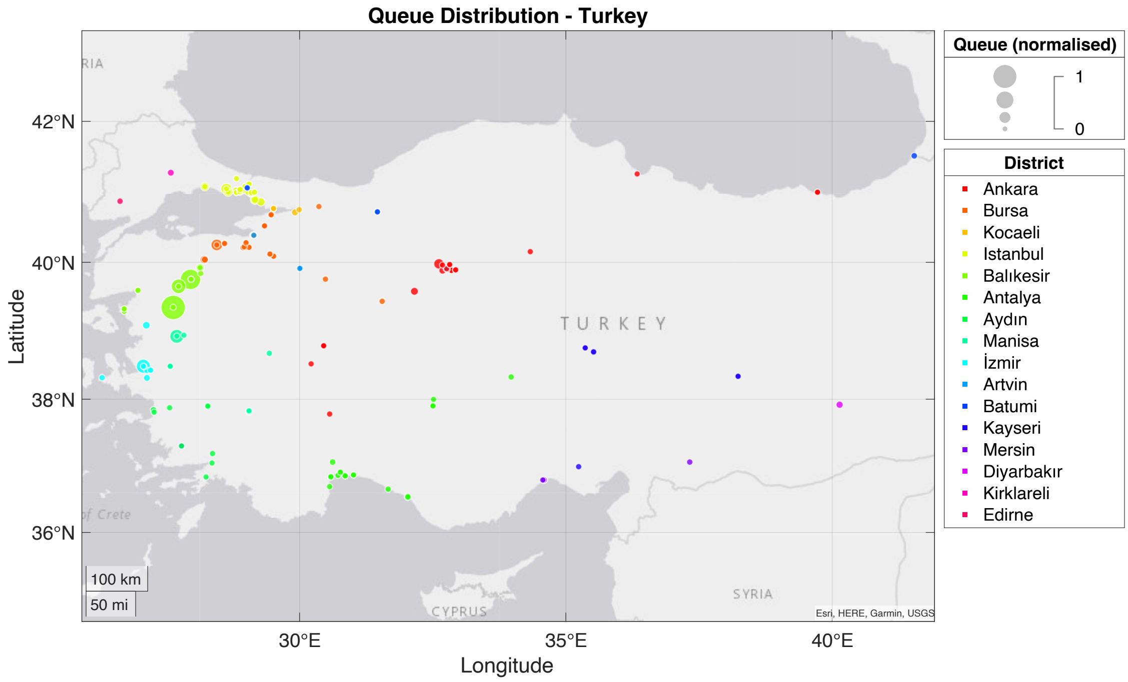

Figure 22: Initial queue behaviour in Turkey. The size of the bubble giving an indication of the relative probability of queuing predicted at each charge station, the colours refer to the different districts within each model

5.3.2 Austria

The queue distribution for Austria, Figure 23, shows a more uniform distribution across the different regions. The queues do not appear to be related to the absolute population – ie. The most populous regions have similar levels of queues to sparsely populated regions. This is not a surprise since the model is based on a constant ratio of number of EVs to numbers of charge points.

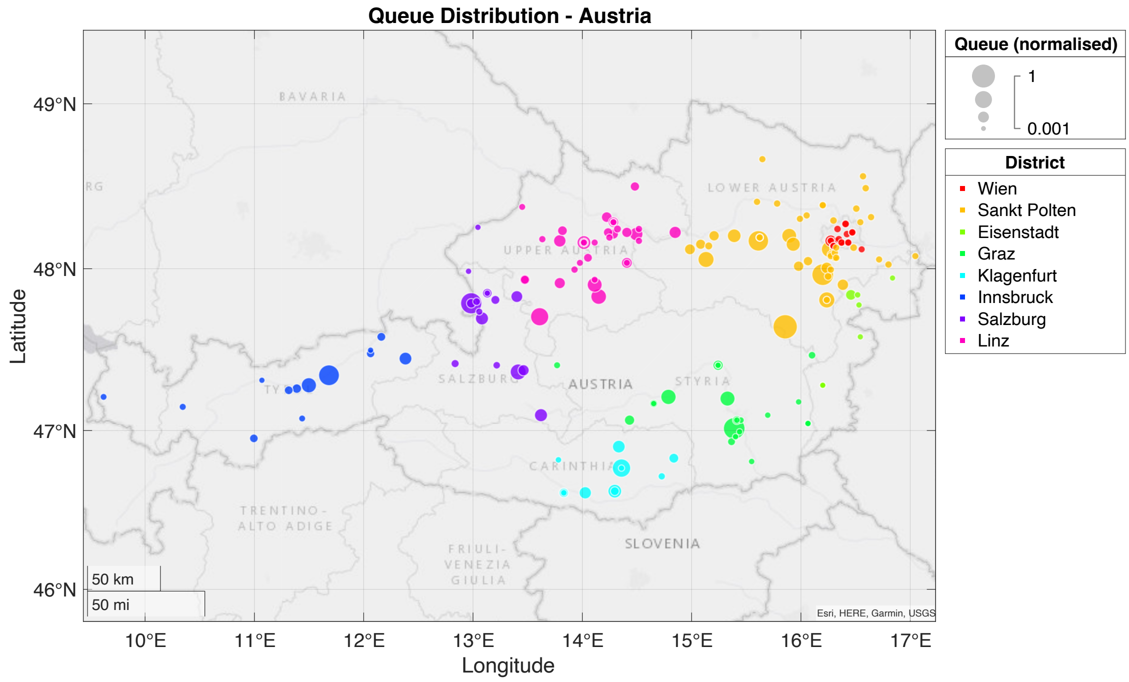

Figure 23: Initial queue behaviour in Austria.

5.3.3 Barcelona

Figure 24 shows the initial queue behaviour in Barcelona. There is a higher probability of queues in the Eixample and Sarria-Sant Gervasi districts.

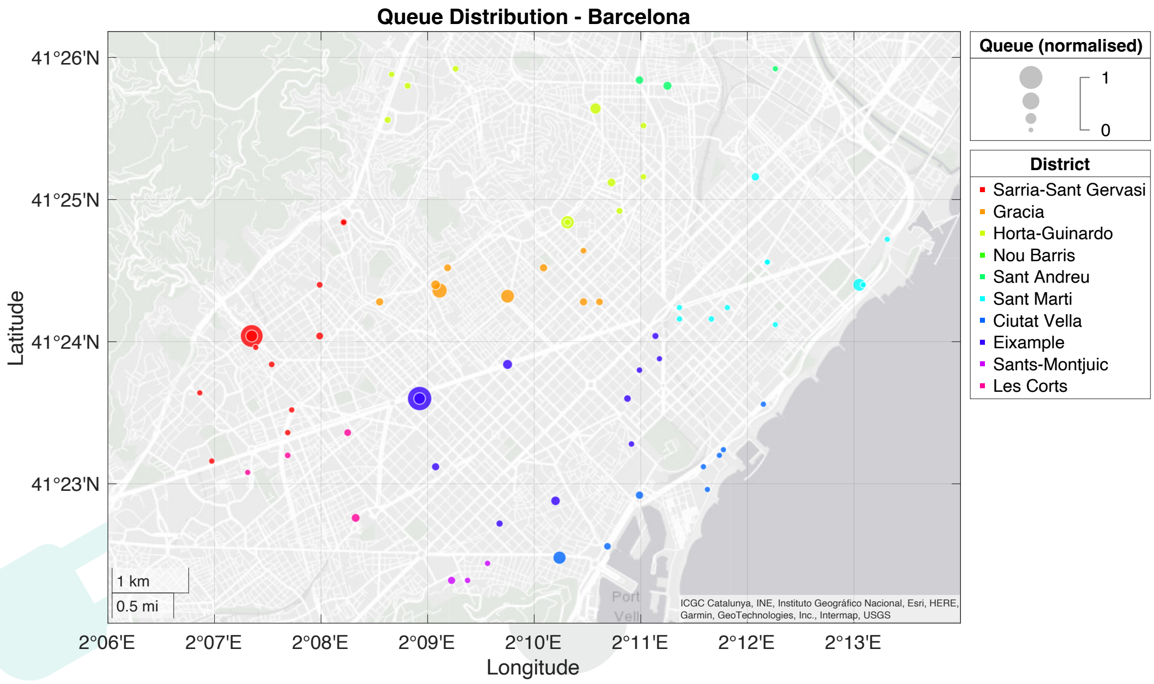

Figure 24: Initial queue behaviour in Barcelona.

5.3.4 Grenoble

Figure 25 shows the initial queue behaviour in Grenoble. As expected from the EV populations, the highest probability of queues is in central Grenoble.

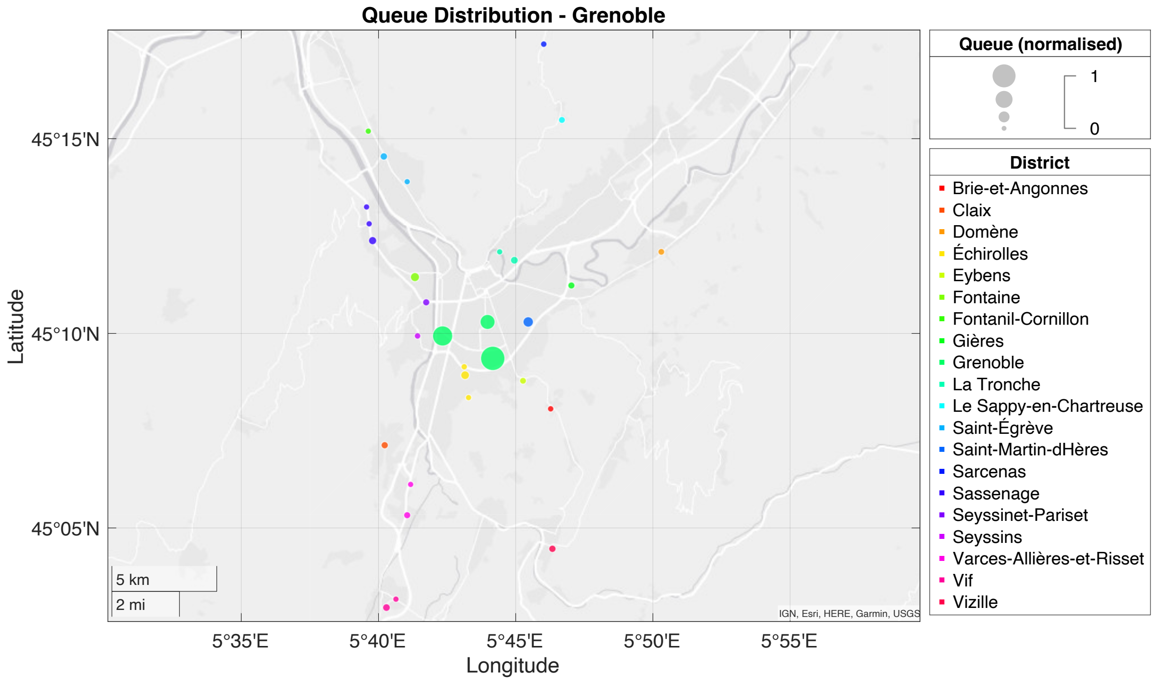

Figure 25: Initial queue behaviour in Grenoble.

5.3.5 Queue Discussion

The investigation into queues is a theoretical study since the number of queues is not measured. However, carrying out this analysis drives additional analysis into how queues and queue behaviour may emerge in the future.

There are already discussions online and between industry bodies, for example some CPOs include advice related to charge point 'etiquette' and touch on aspects such as 'only fill up the battery with sufficient charge for your journey' to avoid drivers blocking charge points whilst filling up to 100% SOC. This is especially important when the last 20% charge is at a lower charging rate.

Comparing the locations, we see that the country models have a broader distribution of queues, with larger queues on the highways whilst the city models tend to have the queues concentrated on a couple of charge stations. This may be partially due to the longer journeys carried out in the country models where charging is carried out en-route at charge stations with limited numbers of charge points compared to the cities that have a higher density of charge points.

6 EV MARKET STUDIES

6.1 Number of EVs

The number of EVs present in the simulation directly impacts the dynamics of charge station occupation and queueing behaviour. The more EVs there are in the simulation, the larger the queues formed at charge stations. However, this direct impact is qualified by factors such as the number of charge stations and the number of charge points at the charge stations, the power rating of the charge points as well as the current range anxiety of the EVs in the simulation.

The model was run several times, with different numbers of EVs, ranging from 100 to 2000, and the impact of this EV count on the observed range anxiety and customer satisfaction metrics for each EV at the end of the model run was analysed.

6.1.1 Austria

The average range anxiety and customer satisfaction for all EVs at the end of each 190-day run is shown below in Figure 26. Range anxiety ranges from 0 to the enforced maximum of 0.8. As the number of EVs increases, the average range anxiety across model runs is generally just below the maximum value. This value does not vary significantly as the number of EVs increases.

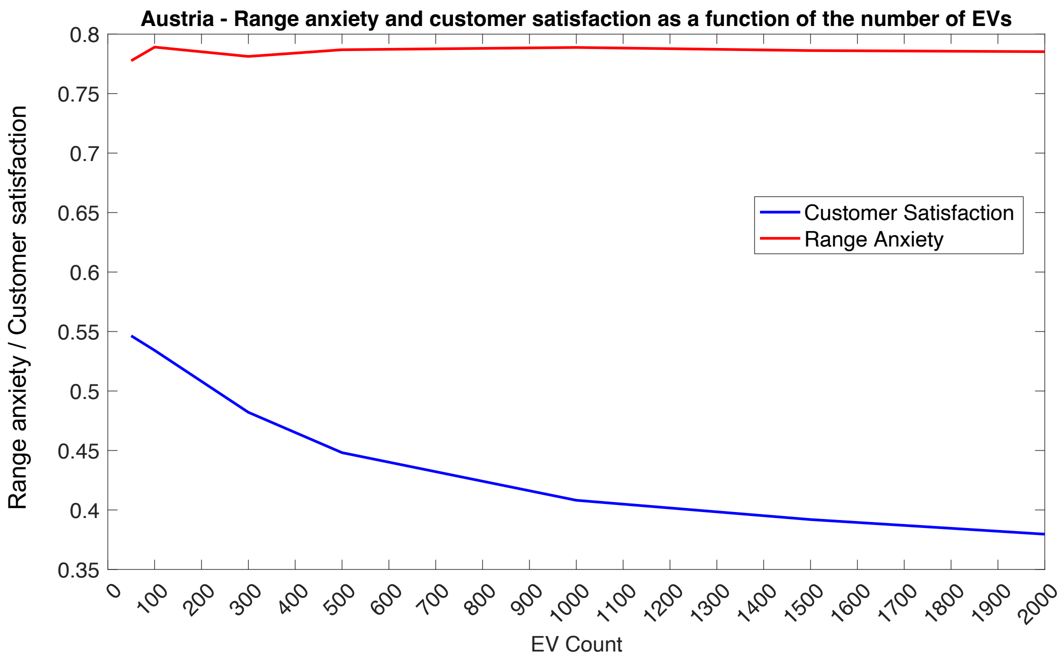

Figure 26: Average range anxiety and customer satisfaction as a function of the number of EVs (Austria)

The average customer satisfaction on the other hand shows a clear downward trend as the number of EV increases, with sizable reductions present for every increase in EV count.

6.1.2 Barcelona

The average range anxiety and customer satisfaction for all EVs at the end of each 425-day run is shown below in Figure 27. As for Austria, the customer satisfaction reduces with increasing number of EVs. The range anxiety also increases with number of EVs.

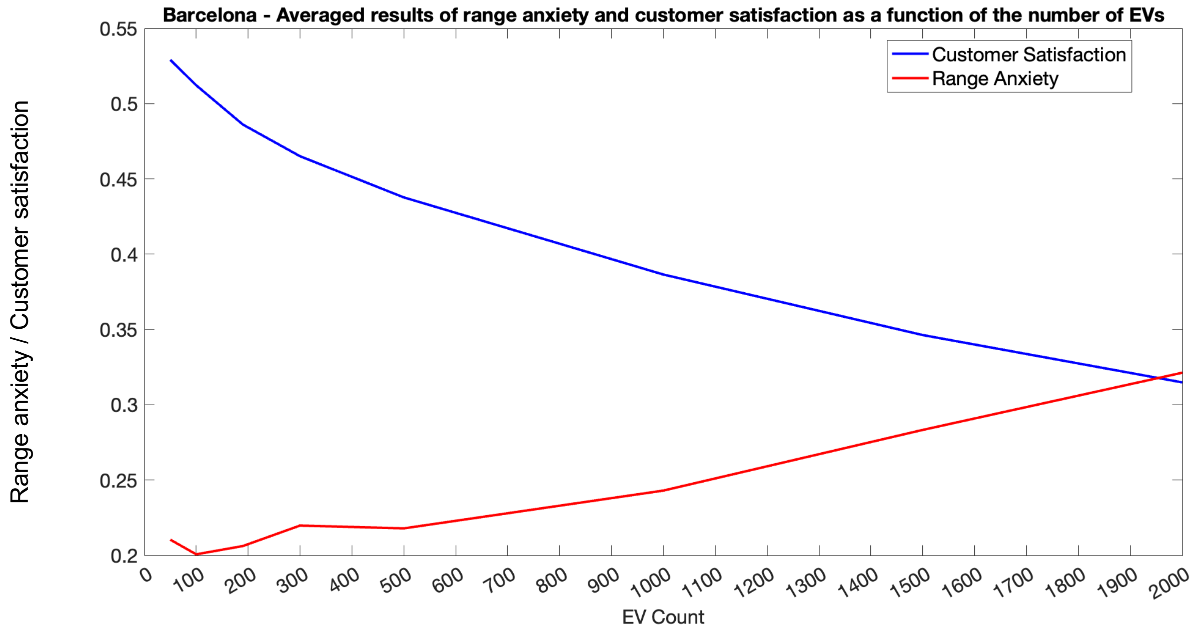

Figure 27: Average range anxiety and customer satisfaction as a function of the number of EVs (Barcelona)

6.1.3 Discussion

The results for Austria have a high range anxiety, this is related to the model configuration where there are longer journeys than Barcelona so are more likely to need charging on their journeys. The range anxiety for Austria is not strongly affected by number of EVs as it is already high. For Barcelona, the range anxiety rises as there are more EVs using the charge stations and increasing the probability of the charge point being unavailable.

The customer satisfaction decreases for both cases, suggesting there is more likelihood of longer queues at charge points as the number of EVs increases.

6.2 EV parameters including battery size

The model can be configured with a range of battery sizes. For example, the model has been configured with two distributions of battery size corresponding to 'standard' and 'long range' batteries, with mean battery sizes of 40kWh and 70kWh respectively. Figure 28 shows that the range anxiety of the EVs with smaller batteries is higher than the larger batteries.

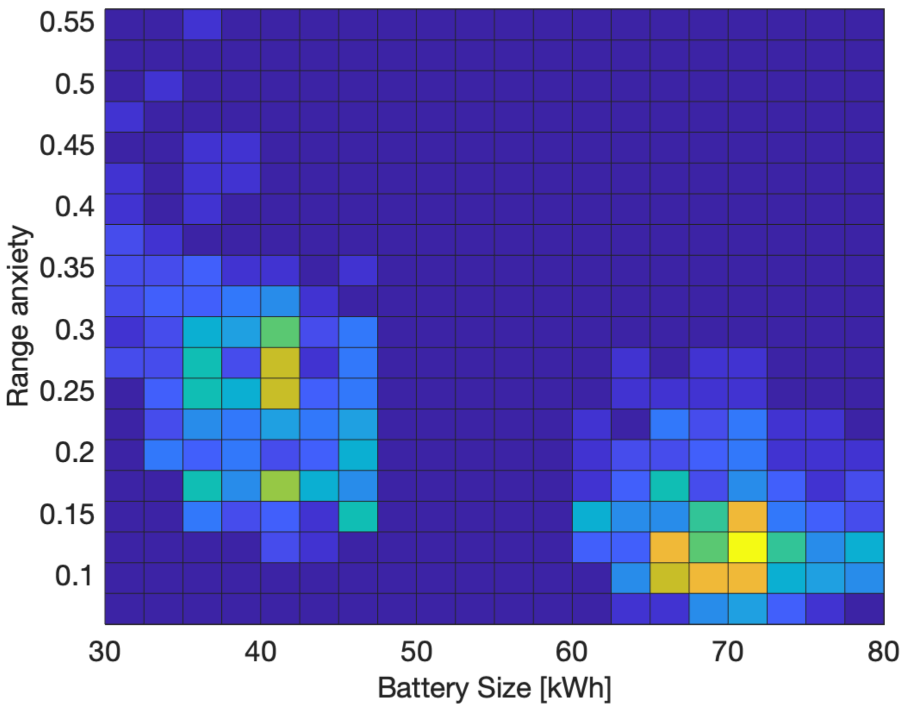

Figure 28: Impact of battery size on range anxiety

6.3 Pricing study

This study considers the complex interactions between pricing and EV driver behaviour. In particular, it considers how increasing range anxiety can make the driver pay more for the electricity ie. when worry of running out of charge outweighs the cost of the electricity.

The model was run in Barcelona, and additional 120 high power charge points were added to the model. These high-power charge points were more expensive so only EV drivers who were prepared to pay more could use them. In the model, the range anxiety increases the price the EV driver is prepared to pay for electricity.

The model has the two distributions of battery size, centred around 45 and 80 kWh. The larger battery has a lower range anxiety, as discussed in Section 0, and this leads to a lower price threshold. The smaller battery has a higher range anxiety and has a higher price threshold. This means that when high-power chargers are added to the network, they benefit the smaller battery vehicles more than the larger battery vehicles. This can be seen in Figure 29 where the smaller battery range anxiety increases and the customer satisfaction reduces while for the larger battery, the changes are minimal.

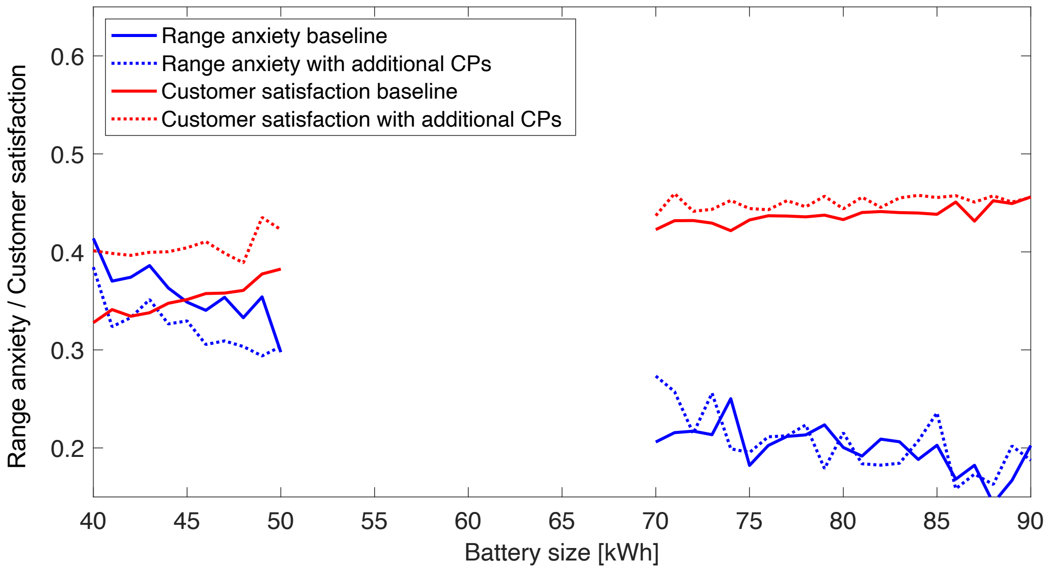

Figure 29: Range anxiety and customer satisfaction for additional high power charge points (Barcelona)

6.4 Booking systems

In addition to the study in Section 4.3.1, the booking system has been used to study how the booking system interacts with other features of the model. For example, by varying the number of EVs to assess how the booking system operates as the population of EVs increases. The results for Turkey are presented in Figure 30 and show that the range anxiety is lower for vehicles that book. For these results, the average customer satisfaction was found to be approximately constant at 0.5.

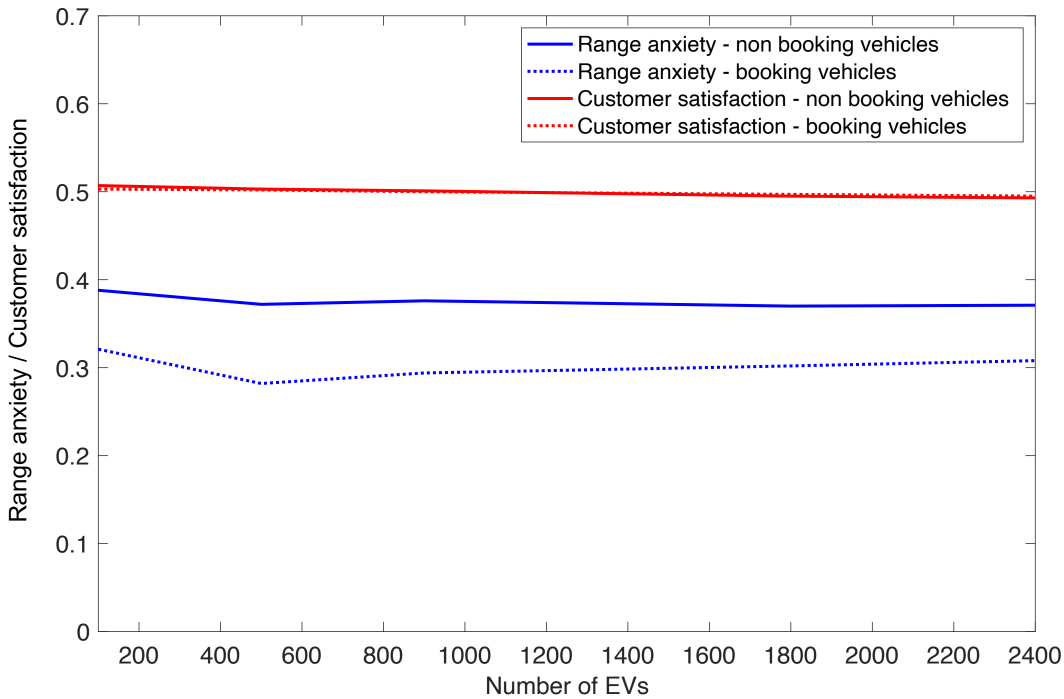

Figure 30: Range anxiety and customer satisfaction when varying the number of EVs with 30% booking probability (Turkey)

The booking system was implemented in Barcelona and the number of EVs was varied with 30% booking probability, Figure 31.

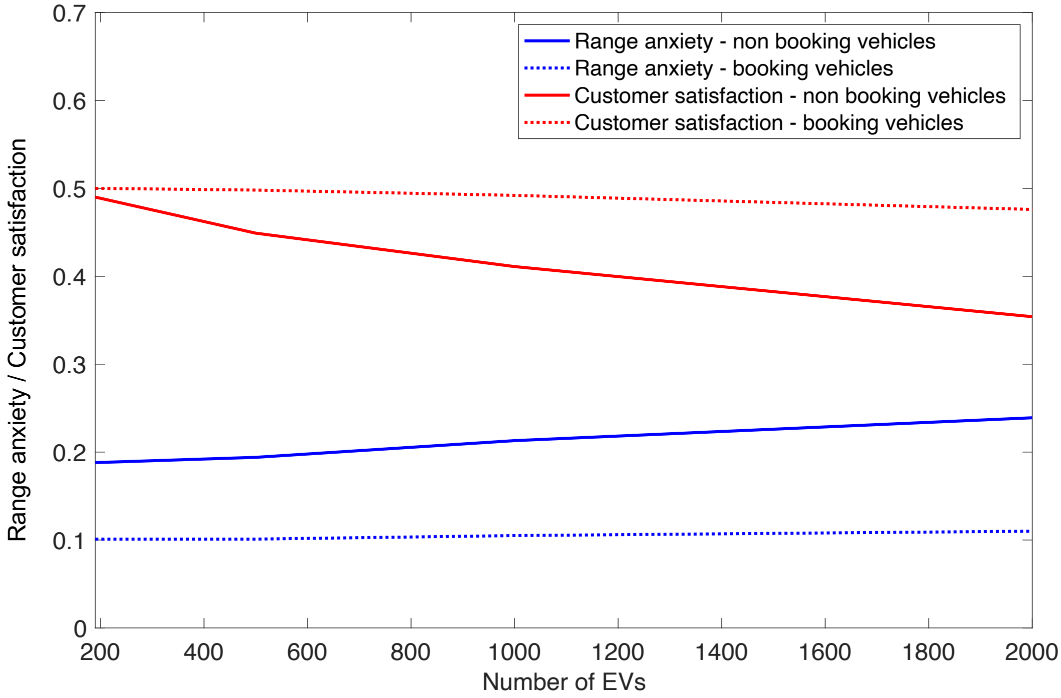

Figure 31: Range anxiety and customer satisfaction when varying the number of EVs with 30% booking probability (Barcelona)

There is a similar reduction in range anxiety with the introduction of the booking system, however the overall range anxiety is lower in Barcelona and there is a trend of reducing customer satisfaction amongst the EVs that do not book.

These results may be due to the following observations:

- Increased distances between locations in Turkey that causes more range anxiety
- Lower number of charge points in Barcelona that restricts access to charge points at lower numbers of EVs

Leading to the conclusion that the booking system effectively reduces range anxiety and also maintains customer satisfaction

6.5 Number of EV charge points

The number of charge points at a charge station is an intrinsic limitation to the amount of charging possible at a charge station. Queues form at a charge station when demand for available charge points outstrips the availability of unoccupied or suitable charge points. It should be highlighted, that once an EV has tried unsuccessfully to charge at least once it evaluates the prices of all CPs at the charge station and if the lowest priced CP is still above the EV's preferred price, it leaves the charge station. This behaviour ensures that EVs do not wait pointlessly in queues. The resulting queues recorded can therefore be considered legitimate queues and this flow of action, as reasonable queueing behaviour.

6.5.1 Charge station queue analysis

The number of EVs in queues at each timestep is one of the outputs from the model. By summing the count of EVs in the queue at each charge point over the whole simulation time, it is possible to see the charge stations where there are significant queues over the course of the model run. To improve the EV driver experience at charge stations, the size and spatial distribution of queues were analyzed, using output from the model's charge station agents.

The models were run in Austria with 1000 EVs and in Barcelona with 190 EVs for 190 and 425 days respectively. The queue data at each timestep was grouped and summed for each CS, resulting in a clear indication of which charge stations had the largest queues. Once these CSs were identified, additional charge points were added to those CSs.

6.5.2 Additional Charge points - Austria

In Austria, after the queue analysis was conducted, as can be seen in Figure 32, charge station B-B_5 stood out with the largest queue count. This CS was fitted with 25 additional CPs while the CSs with the next four highest queue count were augmented with five additional CPs. In total, 45 additional charge points were added across the charge stations.

This change in charge point configuration was moderately effective in reducing the sizes of the queues at all the targeted CSs. The overall queue sizes reduced significantly and the change improved ease of charging for the simulated EVs as shown in Figure 33 as represented by queue sums and EV experience metrics deployed in the model. The queue heatmaps in Figure 34 and Figure 35 show the spatial distribution of the queues across the Austria model before and after adding the additional charge points. Due to the small number of charge points affected, these plots are very similar with minor updates to the Sankt Pollen region.

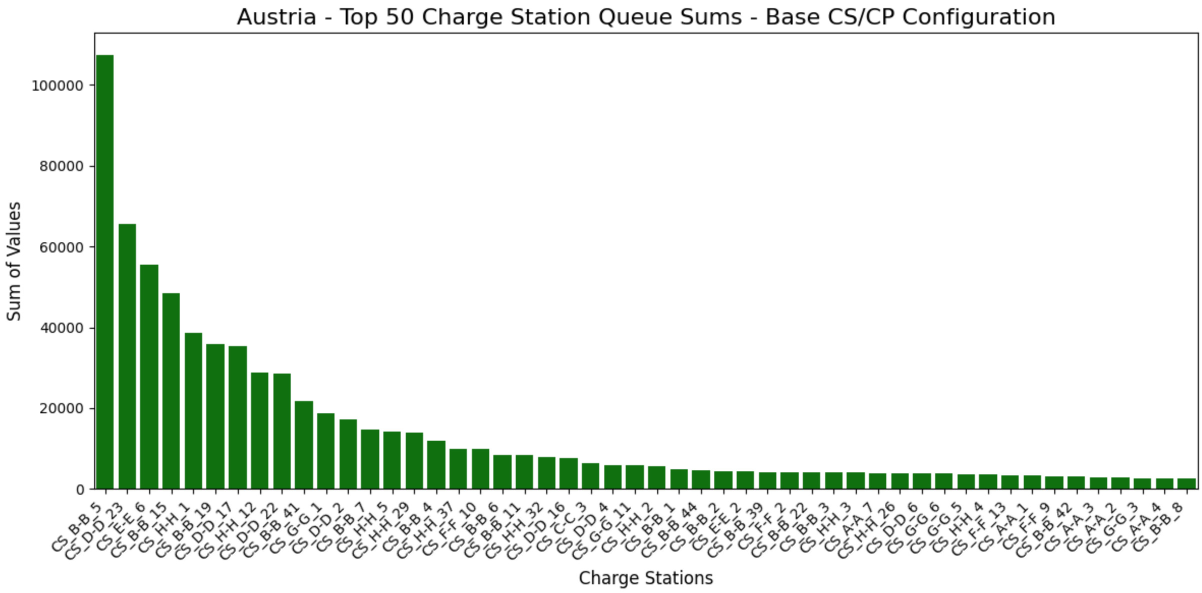

Figure 32: Austria - Top queue lengths at charge stations before the addition of additional charge points.

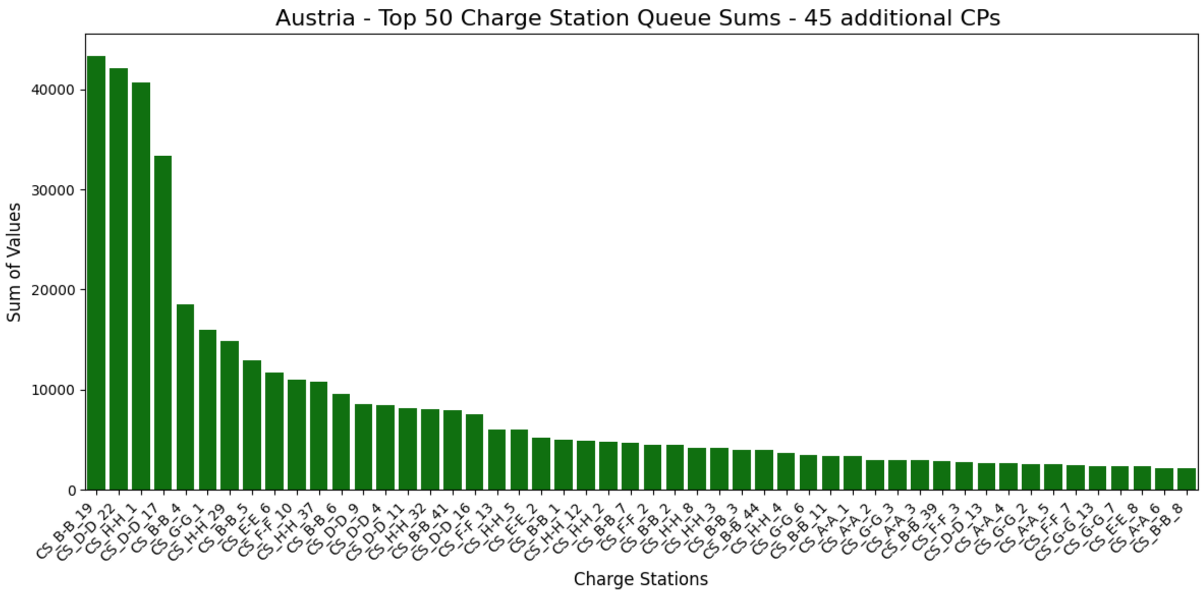

Figure 33: Austria - Top queue lengths at charge stations after the addition of additional charge points.

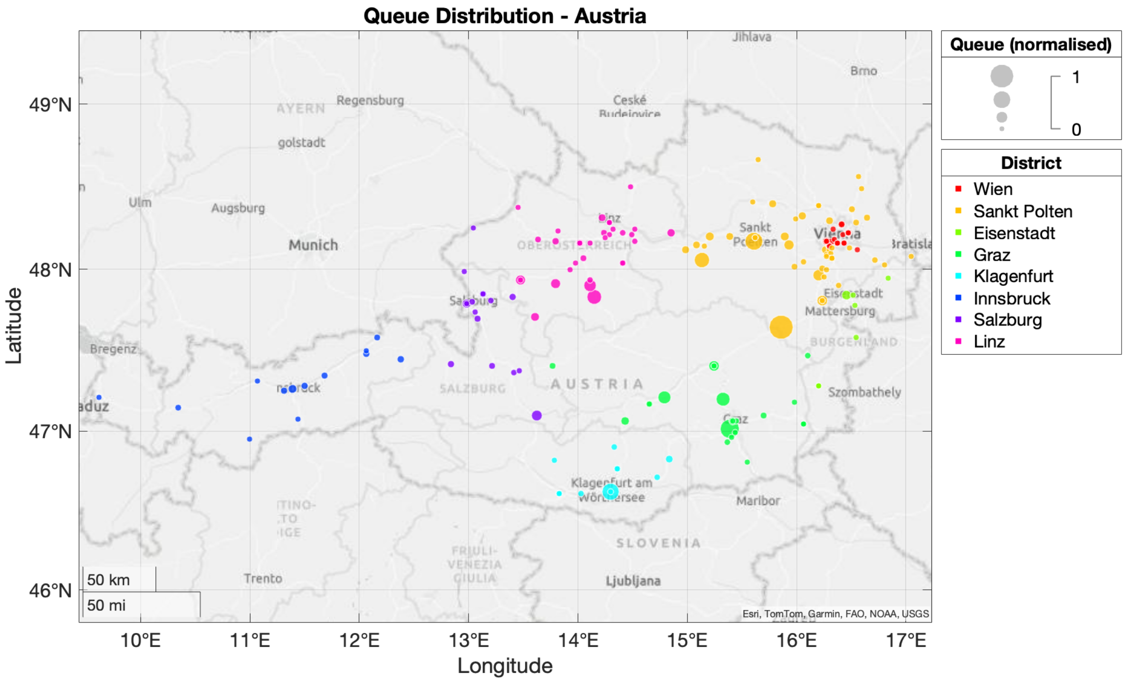

Figure 34: Austria – Initial charge station queue distribution.

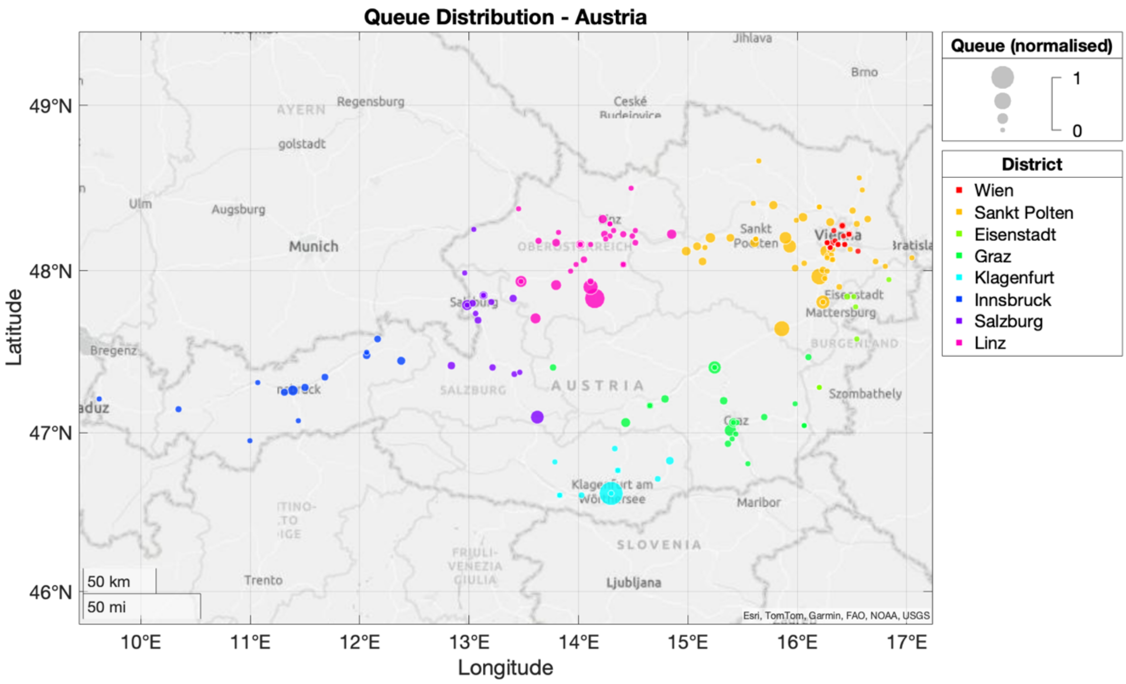

Figure 35: Austria - Impact of additional charge points at charge stations on average EV range anxiety and customer satisfaction.

6.5.3 Additional Chargepoints - Barcelona

Given the limited effectiveness of applying additional CP strategy in Austria, a different approach was taken in Barcelona. The charge station queue analysis results are presented in Figure 36 and the stations with very large queues were identified. Following this, the three CSs with the largest queues from each location were selected as peak points. Also, the top 50 stations in terms of queue length were also considered peak points and selected for additional charge points. Any overlap between these two sets of charge stations was disregarded and there was no repetition. This approach ensured that the CSs associated with the largest queues were included, and that all the districts in Barcelona would be impacted by this change. As a result of these changes, as seen in Figure 37, the size of the largest queues at all CSs were reduced by at least 50%.

After the additional charge points were added in Barcelona, the queues at the targeted charge stations reduced by a significant margin, but the queues at other charge stations increased in some districts. Figure 38 and Figure 39 show the queue heatmaps in Barcelona before and after the addition of supplementary chargepoints. Visually, reductions of queues in Ciutat Vella, Gracia, Nou Barris, Horta-Guinardo and Sarria-Sant Gervasi are observable.

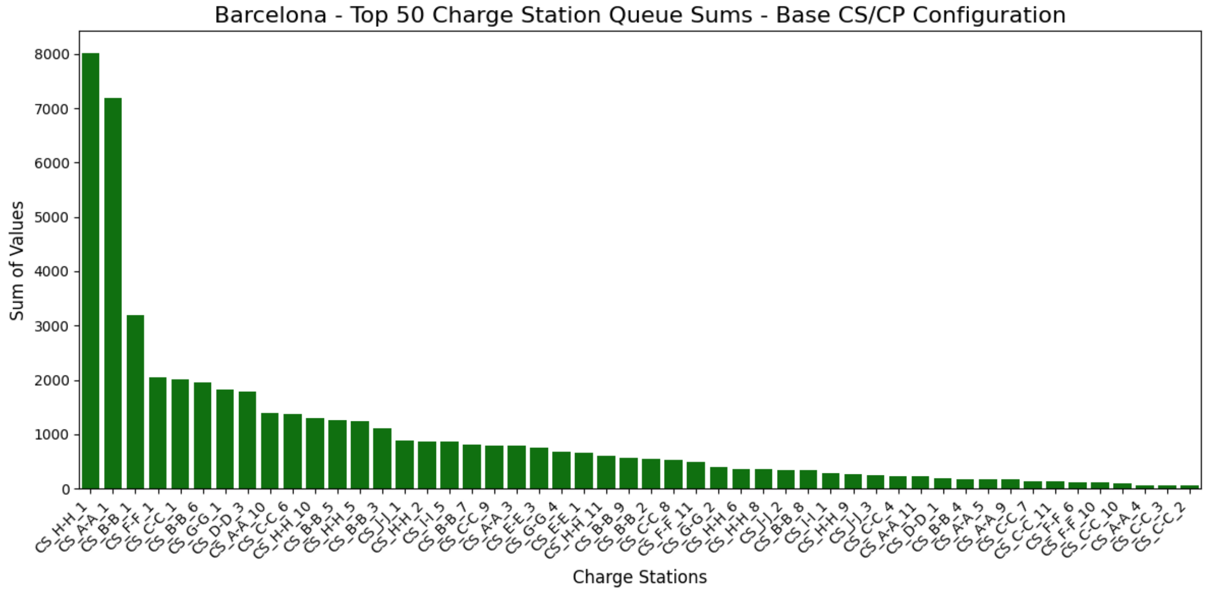

Figure 36: Barcelona – Top queue lengths at charge stations before the addition of additional charge points.

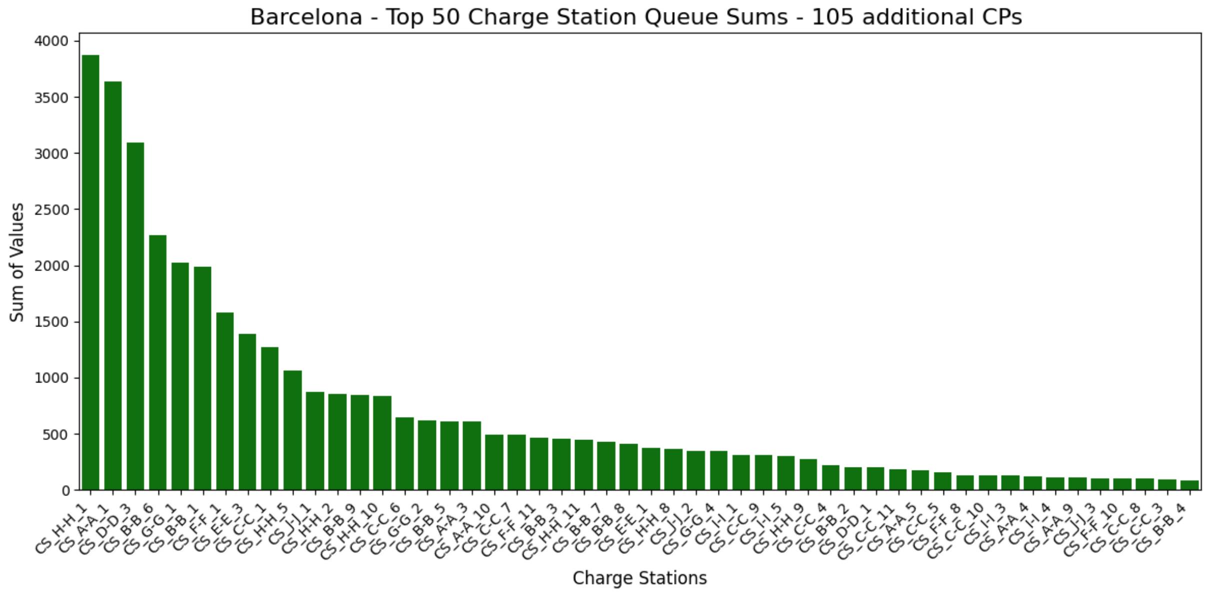

Figure 37: Barcelona – Top queue lengths at charge stations after the addition of additional charge points.

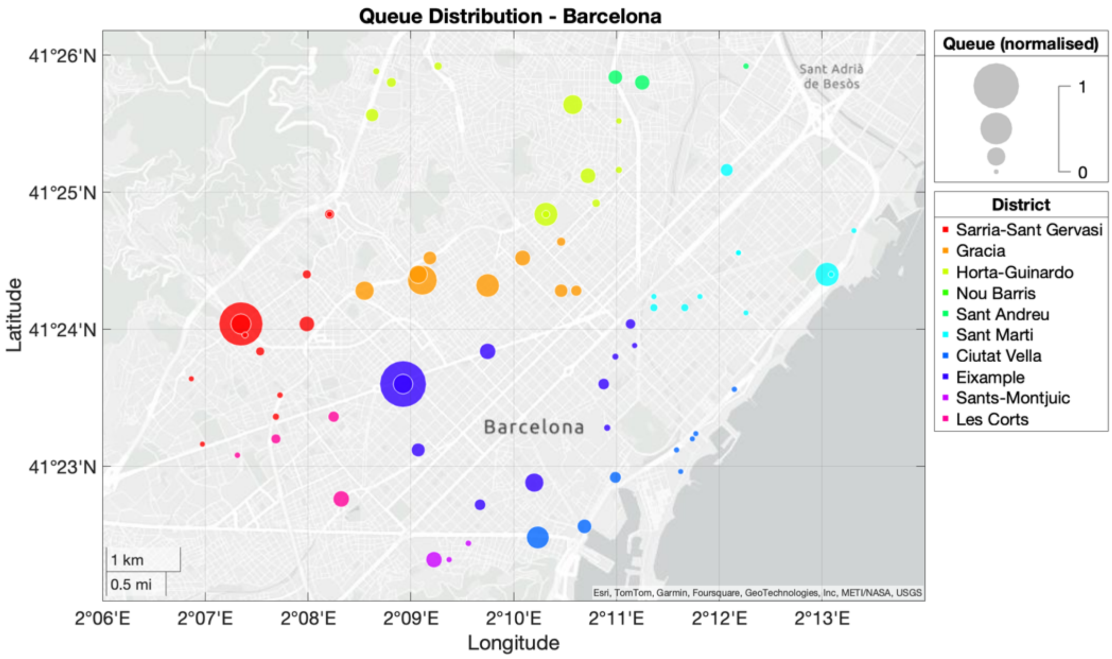

Figure 38: Initial charge station queue distribution in Barcelona.

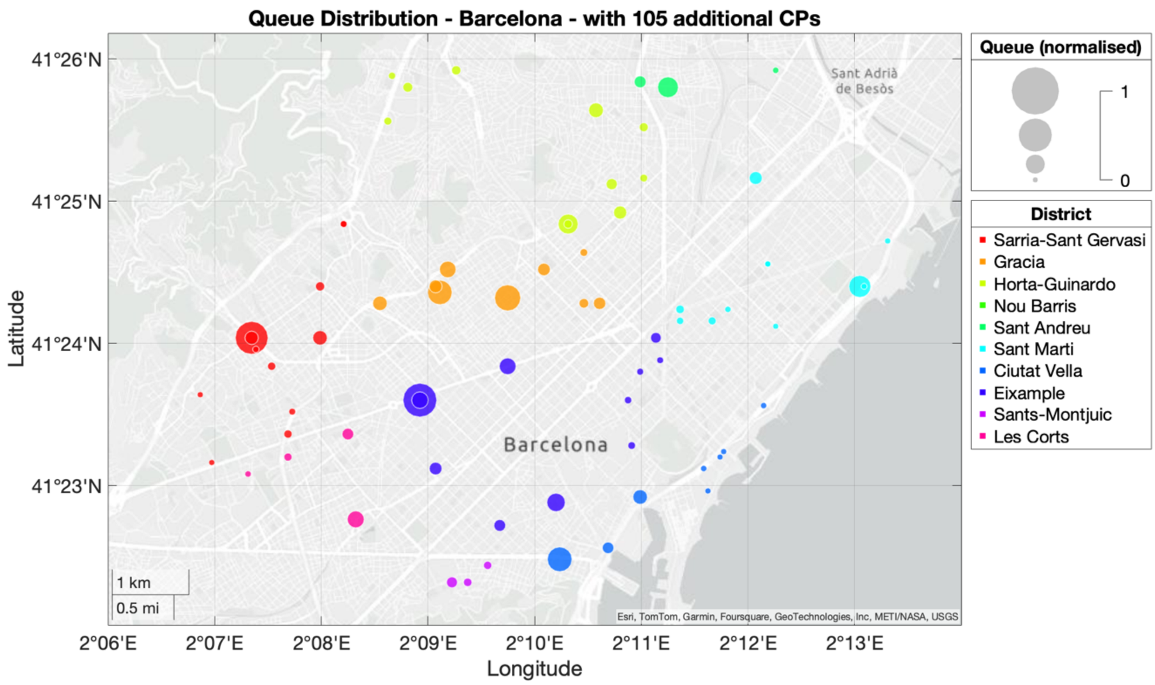

Figure 39: Charge station queue distribution after addition of additional charge points in Barcelona.

6.5.4 Impact of additional charge points on range anxiety and customer satisfaction

The results from the studies of extra CPs give interesting results. Barcelona is a city-scale model with shorter inter-location and local trip distances, when compared to a country locale such as Austria.

Two important conclusions can be drawn. First, adding CPs using a limited selection criterion of the CSs associated with the largest queues (to five in the Austria case) is not enough to substantially reduce queues and thus, impact CS positively. This shortcoming is possibly compounded further by the longer trip distances discussed above. When more additional CPs are added, the impact on both RA and CSat is more significant. This suggests that a wide-sweeping approach to CP addition is far more effective than a more limited intervention, for improving the EV driver experience.

Second, the pricing of the additional CSs is very important and is responsible for many of the specific responses to the efficacy of these interventions. The ways in which the CP pricing affects model dynamics has been discussed in Section 6.3. If the additional CPs are priced out of the reach of the drivers, the underlying queue situation is not properly addressed, and the EV drivers have will need to change their behaviour and sensitivity to pricing to take advantage of more charge points.

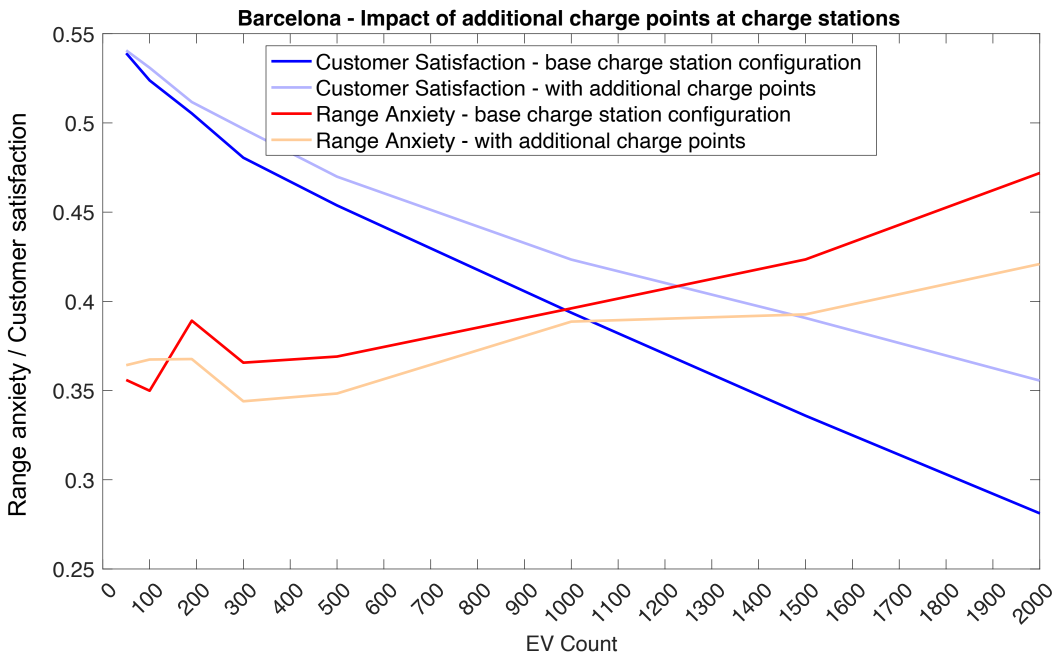

Figure 40: Impact of additional charge points at charge stations on average EV range anxiety and customer satisfaction (Barcelona)

In the Austrian locations, with the exception of Vienna and Eisenstadt, the pricing of the CPs is significantly high. The pricing is especially high in Innnsbruck and Salzburg. This pricing structure effectively nullifies the impact of increased CP choice.

The interaction between the EV's preferred price and the pricing of energy at the CPs, is a core linkage of interaction dynamics. Even though the EVs adapt over the course of the simulation run by becoming increasingly tolerant of higher prices over time, if the gap between an EV's evolving preferred price and the CP price is too large, relative to the rate at which the EV's become more tolerant, the absolute increment in the number of CPs has little impact on the success of the queue reduction effort.

As regards charge point pricing, the results from Austria show that while the range anxiety remains characteristically high, the reduction of average customer satisfaction beyond the baseline is possible as the number of EV increases. There are initially improvements in average customer satisfaction due to the additional charge points, but by the 700 EV mark, these are nullified. As the number of EVs continues to increase, the improvement to average customer satisfaction is overwhelmed by the EV charging demand on the charge points due to the higher EV count, leading to a lower average customer satisfaction.

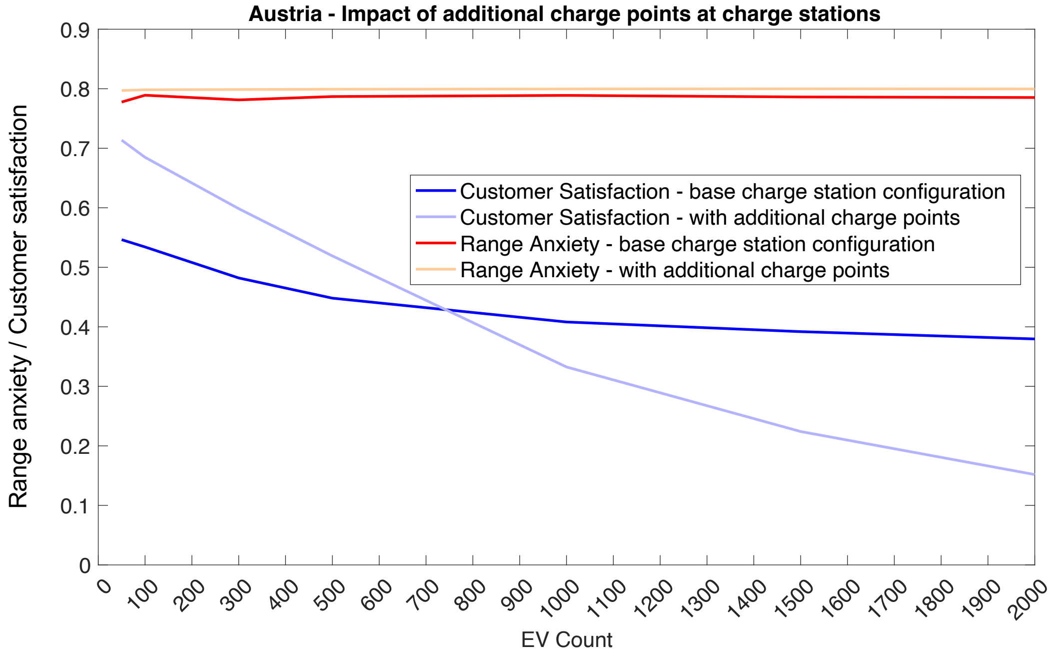

Figure 41: Impact of additional charge points at charge stations on average EV range anxiety and customer satisfaction (Austria)

6.6 Market study of green energy providers for charge points

In the model, the supplier of the electricity for each charge point can be defined. The EVs respond to this by having a preference for a given supplier that is defined by a probability distribution. For example, 20% of EVs may prefer to use supplier A, 40% of EVs may prefer to use supplier B and 40% of EVs may have no preference.

The model has been configured with a green energy provider and used to carry out the following studies in Barcelona.

6.6.1 What happens when the percentage of EVs that prefer green energy changes?

Over time, it is likely that the percentage of EV drivers that prefer green energy will increase as they become more concerned about climate change, [19]. This can be simulated in the model by varying the initial distribution of drivers. This simulation is based on having three green charge points per charge station. The resulting average range anxiety and customer satisfaction of the green EVs and the whole fleet are shown in Figure 42.

The range anxiety for the green drivers is significantly higher than those who are not selective. As the percentage of green drivers increases, the range anxiety of the whole fleet increases steadily, reflecting the increased number of green drivers.

In addition, the customer satisfaction for these runs was constant, suggesting that with three charge points, there is still sufficient capacity to avoid excessive queues.

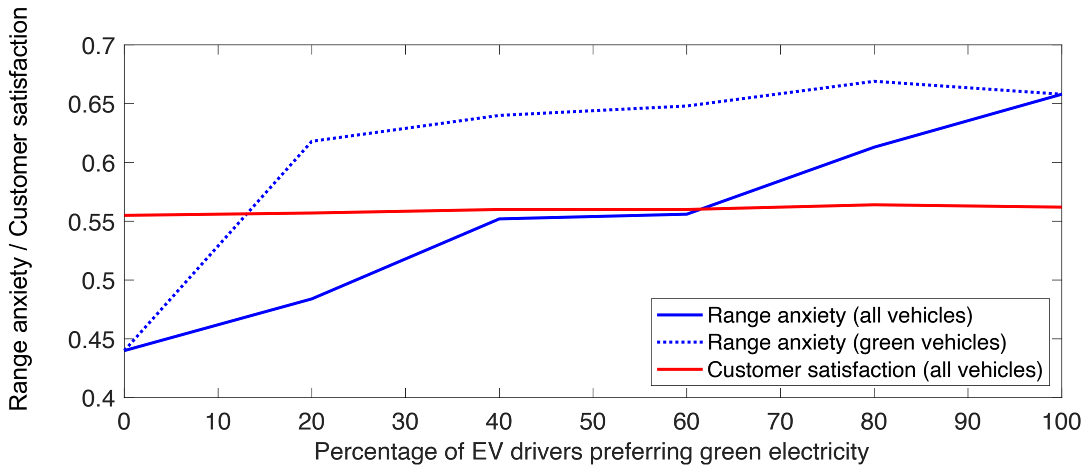

Figure 42: Impact of preferring green electricity on range anxiety and customer satisfaction.

6.6.2 What happens when the number of green charge points changes?

In parallel with the percentage of EV drivers that prefer green energy increasing, the number of green charge points may also increase. This can be simulated in the model by varying the energy provider of individual charge points, for a percentage of green drivers set at 20%. The resulting average range anxiety and customer satisfaction of the green EVs and the whole fleet are shown in Figure 43. The range anxiety for the green drivers is significantly higher than those who are not selective. As the number of green charge points increases, the range anxiety of the green drivers reduces rapidly, suggesting there was a 'bottle neck' in supply of the green energy that was causing high levels of anxiety.

In addition, the customer satisfaction for these runs was constant, suggesting that with only 20% of the fleet being green drivers, there is still sufficient capacity to avoid excessive queues.

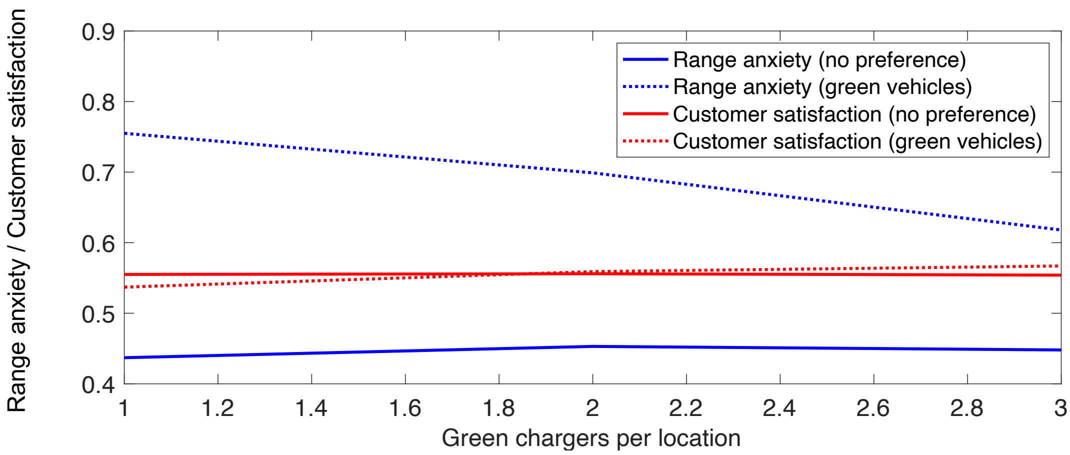

Figure 43: Impact of number of green charge points on range anxiety and customer satisfaction.

If the percentage of green drivers is increased to 80%, with only one green charger per location, the fleet range anxiety increases from 0.44 to 0.67, whilst the customer satisfaction still remains at around 0.55. At this level of range anxiety, the driver will only use a small amount of the battery before re-charging so this increases the number of charge events, which are shorter than if the battery is allowed to discharge fully. The customer satisfaction metric increases for each successful charging event and decreases if the EV is stuck in a queue. In this simulation, the increased number of successful charging events may balance any additional queuing, resulting in a roughly constant customer satisfaction.

6.6.3 What happens when the price of green electricity increases?

Increasing the price of green electricity increases the range anxiety across the whole fleet and in particular for the EVs that prefer green electricity. This is because the whole fleet can use the green charge points so any increase in price will raise their range anxiety as well as the green drivers, see Section 6.3. The EVs that prefer green electricity will only be able to access the more expensive electricity and hence their range anxiety will be more than the rest of the fleet, Table 6.

Table 6: Impact of increased price for green electricity

Simulation conditions	Range Anxiety of EVs who prefer green electricity	Range anxiety of rest of fleet
Original pricing	0.61	0.45
Increased price for green electricity by 50%	0.71	0.54

6.7 Legal enforcement

Most of the areas covered in this study do not have existing local regulations to ensure that EVs do not block the charge points once they have finished charging. A notable exception to this is perhaps Barcelona, which has put in place local regulations which result in the towing of EVs which remain at charge stations beyond active charging time windows. Taken with the sizable likelihood that charge stations are sited near recreation centres which incentivise prolonged stays for EV drivers, offering additional value for time spent at charge stations, it becomes important to examine the impact of extended stays of EVs at charge stations on charge point availability to the general public. This EV driver delay dynamic was explored within the model to characterize and quantify its impact on the EV driver metrics used in the study, as it mirrors real world-driver experience.

This behaviour was represented in the model using the ‘Post charge delay’ (PCD) - a charge station input parameter which stipulates the amount of time an EV waits at the charge point after a charge session, rendering that charge point unavailable to other queued up EVs at the charge station. This parameter is tuneable, and this study explores the impact of an additional hour of wait time at the charge station, after the completion of a charge session by an EV. The results are varied as in the comparison between Austria and Barcelona.

6.7.1 Austria results

In Austria, the results show that this additional delay at the charge station reduces customer satisfaction as EVs spend more time waiting unnecessarily in queues. This negative effect on customer satisfaction appears to worsen as the number of EVs in the simulation increases. Conversely, RA remains high across simulations and appears mostly insensitive to the total count of EVs present in the simulation. This reflects the challenge of successfully completing comparatively (relative to a city-scale model) longer trips between locations in a country-scale model.

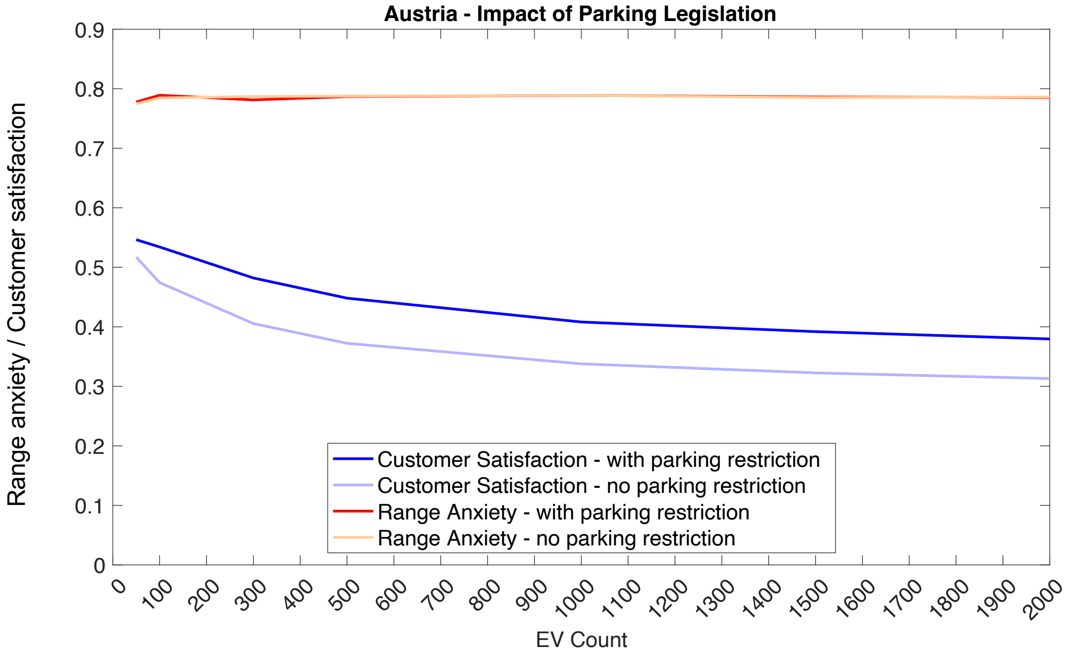

Figure 44: Austria - Impact of parking legislation on range anxiety and customer satisfaction.

6.7.2 Barcelona results

In Figure 45 below, the impact of parking legislation on average range anxiety and customer satisfaction for EVs in Barcelona can be seen. Range anxiety generally increases with increasing EV numbers while customer satisfaction appears to be inversely related to the number of EVs – a result consistent with outcomes from other modelled locations such as Austria.

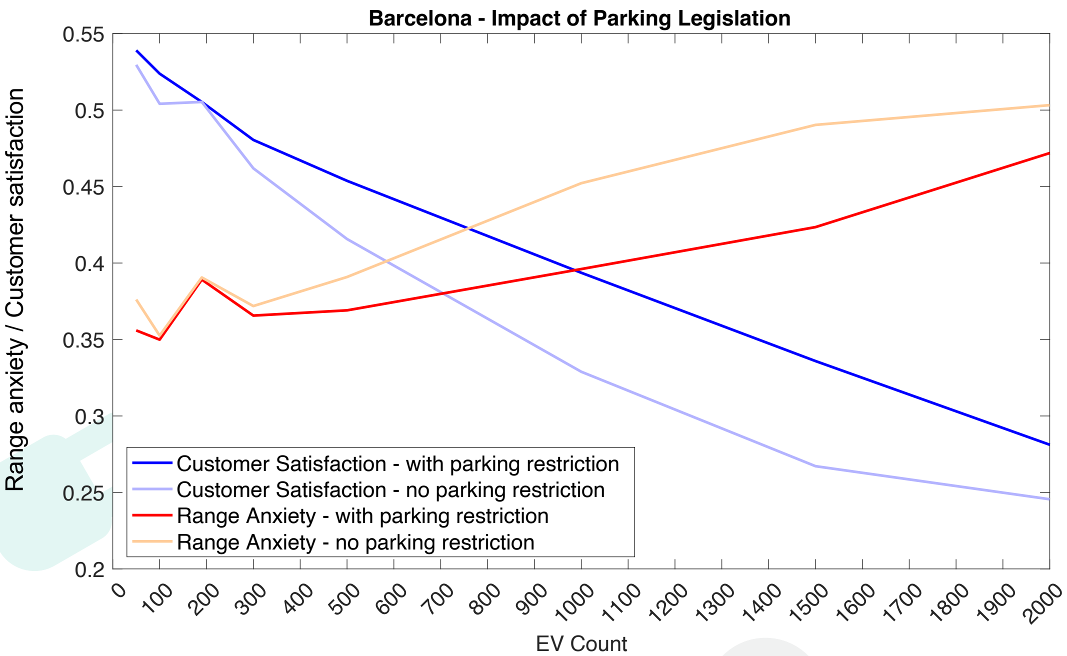

Figure 45: Impact of Parking Legislation without charge point pricing influence (Barcelona)

Figure 46 shows the influence of the charge point pricing schema on the model target indices. When the price of electricity is not a factor, the impact of the parking legislation results in lower range anxiety across EV counts. Customer satisfaction retains its downward-sloping trend as EV count increases, but the differential between average customer satisfaction in the base scenario and the parking restriction scenario is significantly reduced.

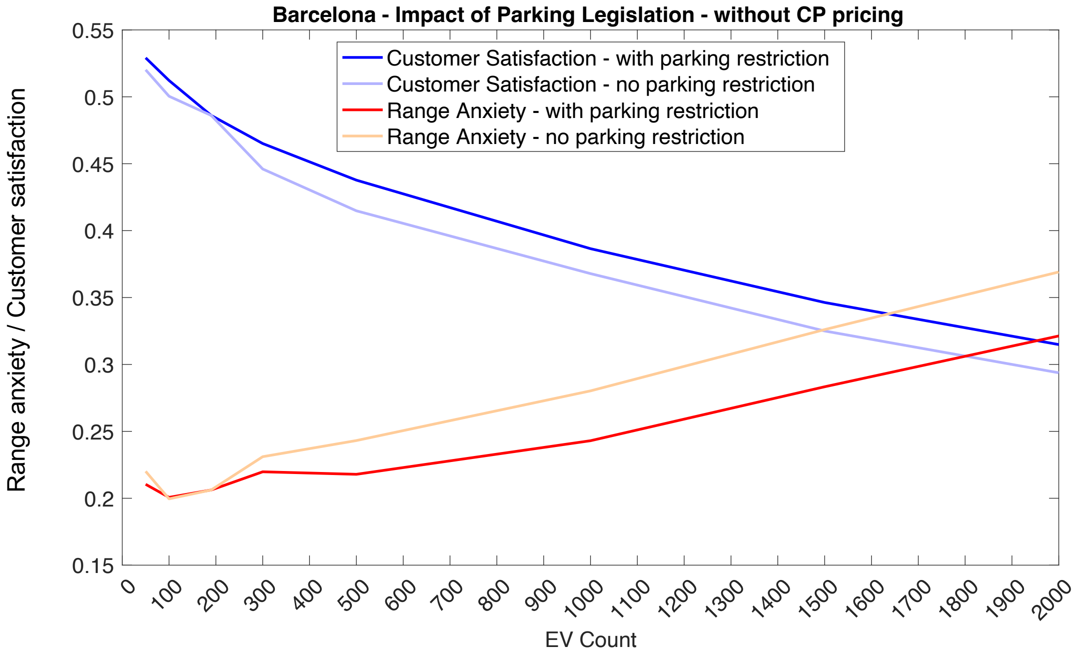

Figure 46: Impact of Parking Legislation - without CP pricing (Barcelona)

6.8 EV adoption versus social demographic

The availability of home charging in many locations naturally favours a higher income demographic. Exceptions being in more rural or lower populated regions or where policies have led to significant EV chargers in communal garages.

The model has been used to study how the availability of home charging impacts EV driver range anxiety and, as expected, found that drivers with home charging had a lower range anxiety than those without. This result could be used to set a target for range anxiety for the general population for new policies or updates to infrastructure.

The model was assessed in both Barcelona and Turkey. In Barcelona, all the vehicles that charged at home tended to the minimum range anxiety. This was because the daily journeys within the city were less than the range of the battery. With home charging, the battery is charged up every night and can therefore easily complete the daily travel without getting a low battery resulting in the minimum range anxiety.

In Turkey, the vehicles that charged at home had a lower range anxiety, but not at the minimum. This was because the journeys are longer and the EV will typically need to charge en route. If the range anxiety is too low, there is a risk that there is no charge point in range when the EV starts to look for a charge point so the range anxiety increases allowing the EV to start to look for a charge point earlier. It is also noted in Figure 47 that the battery size also has an impact with the smaller batteries having a higher range anxiety.

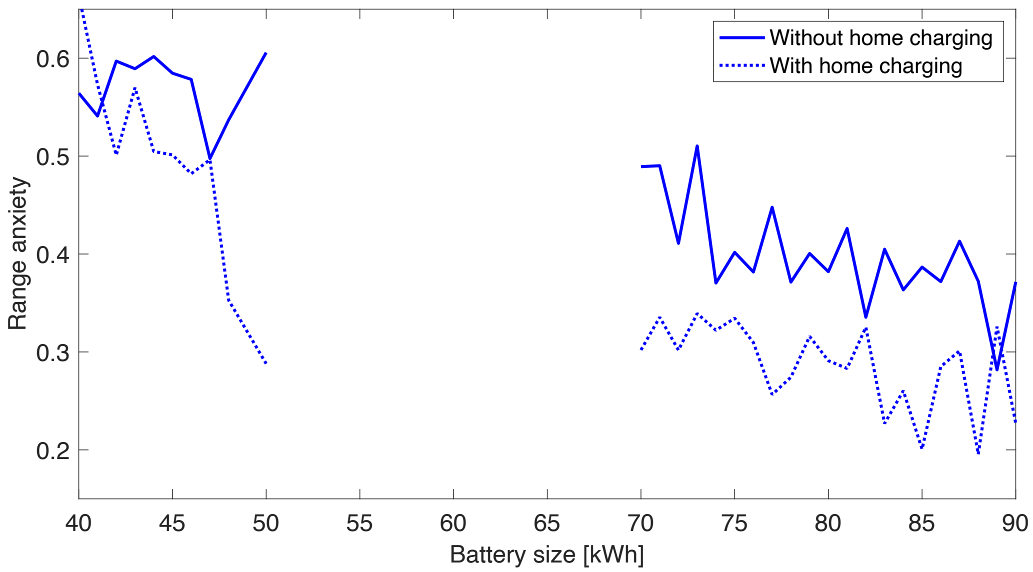

Figure 47: Impact of home charging on range anxiety (Turkey)

The variation of the range anxiety in this plot is a function of the number of EVs with different battery sizes since there is a normal distribution of battery sizes about two means.

6.9 Discussion comparing the city models and country models

The ABM has been calibrated to a range of locations that can be broadly grouped as city (Barcelona and Grenoble) and country (Turkey and Austria) models. This section will discuss general observations between the two groups of models and the differences in the groups can be summarised by:

- Length of journey: The country models tended to have much longer journeys.
- Ratio between local trips and inter-location trips: The city models tended to have more vehicles travelling between districts.
- Search radius: The search radius for finding a charge station was larger for country models as they the distances were larger.
- Interface with areas outside the model is more significant for the city models since the city model does not include vehicles coming from outside the region.

The average range anxiety and customer satisfaction is summarised in Table 7. Here it can be seen that the city models tend to have lower range anxiety than the country models, whilst the customer satisfaction is similar across the demonstration areas. The increase in range anxiety for country models probably related to the length of journeys where it is more likely for the EVs to get stranded. The similar customer satisfaction suggests that queues are not significant at the moment, but this may change as the number of EVs increase.

Table 7: Comparison between demonstration areas

Location	Average Range Anxiety	Average Customer Satisfaction
Austria	0.79	0.41
Barcelona	0.25	0.49
Grenoble	0.16	0.50
Turkey	0.64	0.49

7 CONCLUSION

7.1 Summary

An agent based model (ABM) has been developed for studying behaviour of electric vehicle (EV) drivers with respect to the charging infrastructure. The model has been calibrated against available data and demonstrates the trends seen at these demonstration sites.

The model has been successfully used to study the interactions between EVs, charging infrastructure, policies and market factors. The model has introduced the concept of range anxiety and customer satisfaction into the ABM paradigm to provide feedback on user behaviour.

Several results were intuitive, including:

- Range anxiety increases with increased numbers of EVs
- Range anxiety increases if EV driver is restricted to a sub-set of charge points, for example green charge points
- Range anxiety reduces with increased battery size
- Introducing legislation to encourage charge points to be released once the EV has charged can reduce range anxiety
- A number of booking systems were investigated before settling on a generic booking system. There were many ‘corner cases’ that had to be addressed to obtain realistic behaviour. Once configured, the response to the bookings were largely as expected, reducing range anxiety and improving customer satisfaction. It was also expected that as more people could book, the benefit would reduce, however within the parameters of the study this did not emerge.
- Home charging reduced the range anxiety. Extending this to consider the impact on different social demographics, it is likely that more affluent EV drivers will have less range anxiety than poorer EV drivers. This is more pronounced in cities where the journeys are short and being able to charge overnight can effectively remove range anxiety from the daily life.

Other results prompted more investigation to understand the interactions that led to the observed behaviour, including:

- Pricing has multiple effects: a high price for high power chargers would reduce the number of available charge points to drivers who are price sensitive, however this can then increase the range anxiety that increases the price they are prepared to pay. The model showed that if high power charge points were introduced, they would benefit the smaller battery vehicles more than the large battery vehicles since their range anxiety is higher and this raises the price they are prepared to pay for the high power charge.
- Additional charge points were introduced to improve customer satisfaction. It took a number of iterations to deliver the expected results since the response of the model could be masked by other factors. For example, adding expensive charge points had limited effect because EV drivers were not prepared to pay the extra and hence did not use them as expected.

7.2 Potential benefits and applications

The ABM can deliver benefits to:

- EV drivers as their user experience is at the core of this project. The ABM aims to improve visibility of that experience for the rest of the stakeholders, who are shaping the policies and infrastructure that the EV user experience relies upon.
- eMSPs by providing a “digital twin” of an EV user population that they can use to evaluate their service provision and what might influence the user perspectives on their services.

- CPOs by being able to evaluate the likely usage patterns for their facilities, and adjust and optimise their facilities accordingly, thus minimising wear and tear, and other operational costs.
- OEMs by having a means of identifying best- and worst-case scenarios in the usage of their equipment, thus optimising their designs accordingly.
- Local and national authorities and other policymakers by being able to build a “digital twin” on which to test their proposed policies and evaluate their impact on the user experience, stakeholder engagement, and other benefits and costs of such policies. The ABM would also be able to bring to their attention emergent behaviours that could possibly skew the outcomes of such policies and introduce unintended consequences that can then be avoided.

7.3 Future work

As with many simulation studies, the model could be refined further. For example, including user behaviour that emerges as the number of EVs increases, including use cases that are of interest to specific applications, adding additional rules/behaviours to the EV agent.

The model itself could be linked to live or updated data sets, leading to more accurate forecasting and and practical insights to adjust to rapidly evolving market structures.

Periodically update the model to reflect the advancements in battery technology, charging times and charge point configurations.

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9 ANNEX 1: DETAILED METHODOLOGY

9.1 Charge point location data

Additional details regarding data cleansing, by demonstration site.

9.1.1 Turkey (country)

The charge point data for Turkey was presented as a list of charging sessions which contained a range of characteristics relates to details of the charge station characteristics; Reservation Information, session start and end times, session durations and average charging power. The dataset also included the spatial coordinates of the charge station, the number of connectors, current type, socket type, the rated power output, and the city associated with the charge station.

The full list of charge station characteristics included: ['Transaction ID', 'Time Zone', 'Reservation(YES/NO)', 'Reservation Time','Reservation Start Date', 'Reservation End Date', 'Charging Year','Charging Month','Charging Week','Charging (YES/NO)', 'Charging Start Time', 'Charging End Time', 'Status', 'Charging Start Method', 'Parking Duration', 'Energy Delivered (kWh)', 'Average Charging Power (kW)', 'Initial SoC', 'Delivered SoC', 'Penalty Amount', 'Payment Status', 'Country', 'Charging End Method', 'Session Duration', 'Charging Duration']. 292 stations were included in this dataset and covered 20 different cities.

Data pre-processing

First, a subset of the data was selected out which contained only the 'DC' type charge points. Also, unused information in the extended list of charge station characteristics outlined above was removed from the dataset. This left a remainder of 123,183 charge sessions. The data, once grouped by city showed the charge stations were spread across 34 city locations. Next, some text preprocessing was conducted including the removal of certain text chunks and was manually cross-checked. The dataset was cleaned of repeated entries and session data was manually converted to individual station data.

The 'Connector' information in the original dataset could not reliably be used to determine charge point count at charge stations, due to the removal of 'AC' type charge points from the dataset. Charge points with identical latitude-longitude information were combined into stations and named sequentially by occurrence if associated with a certain city name, for all cities in the dataset.

The default values of the 'City' name column was the basis for 'Route' value assignments.

The main locations were taken as Ankara, Bursa, Kocaeli, Istanbul, Balikesir, Antalya, Aydin, Manisa, Izmir, Batumi, Artvin, Kayseri, Mersin, Diyarbakir, Kirklareli and Edirne.

locations with lower population counts and lay in-between the main locations included locations/cities such as: Bilecik, Isparta, Afyonkarahisar, Trabzon, Samsun, Corum, Eskesihir, Sakarya, Yalova, Bolu, Konya, Askaray, Mugla, *Aydin, Denizli, Usak, Adana, Malatya, and Gaziantep. Charge points associated with these locations were converted to Highway Charge stations between locations and labelled accordingly.

Missing data

Data records with no information on Power rating were filled using the modal value of charge point power rating in the appropriate city while data records with no spatial information were removed from the dataset completely. At the end of this process, 298 charge points remained.

The next step involved the validation the spatial coordinates of the charge stations by checking if they fell within the bounding box of Turkey. This region was defined as the area covered by the following ranges: Latitude 35.81-43.40 and Longitude 19.90-44.57 decimal degrees. The chargepoints were then assigned an x and y spatial coordinate for use in the model and compiled into the station location dataset.

The additional station characteristics dataset was also created using the chargepoint data and the default values assigned accordingly.

9.1.2 Austria (country)

The charge point data for Austria consisted of 3 months of charge point records (over 180,000) including with charge point location provided as a post code and description, AC or DC charger type, Max power, Start time, duration and energy delivered.

Data pre-processing

The post code was used to derive the geographical location for the charge point, with the first two digits used to assign a district or city to the charge points. As with the Turkey data set, the DC charge points were selected to study inter-regional trips.

9.1.3 Barcelona (city)

The charge point data for Barcelona consisted of charge point information under the headings of 'cp_ID', 'latitude', 'longitude and 'cp_power' and contained 97 charge points.

Data pre-processing

The data was checked for duplicate information and upon discovery, several duplicate records were removed, leaving a dataset of 79 records. This dataset was then manually inspected and labelled. Each charge point was assigned a 'district' value for the district it belonged to. Each charge point was also given a unique model-compliant name dependent on this district name.

9.1.4 Grenoble (city)

The Grenoble charge station dataset consisted of charge point information under the headings of 'Commune, 'CP', 'Adresse', 'Nom site', 'Nombre de bornes', 'Nombre de points de charge', 'PUISSANCE BORNE(kW)', 'Type borne', 'Pdc dédié à Citiz', 'Latitude', 'Longitude' and 'Précisions'. It contained thirty-two records.

Data pre-processing

Two charge points were removed from the dataset due to accompanying notes in the data indicating that development on these charge points had been postponed (postponed due to redevelopment, postponed due to not yet being created). The thirty remaining charge stations were sorted by 'Commune' and unused columns were removed from the dataset. It is important to mention that the dataset contained columns 'Nombre de bornes', 'Nombre de points de charge', they contained different values for each charge point record. Sometimes the value of 'Nombre de points de charge' (number of charge stations) was double the 'Nombre de bornes' (number of terminals), and at other times, the two columns contained the same values. The authors ultimately decided to treat each charge point as an individual charge station with one charge point. The charge points were then assigned model compliant charge point names.

Following preprocessing, the charge points in the dataset were assigned coordinates in model space, ensuring that all the charge point latitude and longitude information fall within the defined bounds of the study locale. Afterwards, the dataset was augmented with other charge point characteristics the route name, Chargepoint ID (CPID) and default values for Pricing, Greeness, Booking, Provider, resulting in 'Input chargestation dataset 2' for the locale.

9.2 Booking system

The model has an optional booking system which can be used by EV agents to book a charge session at a charge station on their current route before beginning a trip.

If booking is activated, the EV agents are assigned a booking status at the beginning of the simulation. A booking probability is set in the model configuration which determines the proportion of EVs which will have the Booking behaviour enabled. This parameter can be varied between 0 and 1 and the EV agents are assigned this boolean value in random order. These 'Booking EVs' interact with the Booking Agent and attempt to book charge sessions at charge stations on their route, prior to setting out on their daily trips.

9.2.1 Booking process

The EV attempts to book by first analysing how much battery will remain at the end of its trip for the day. If this battery level is below its battery usage threshold i.e. the battery level from which it would be in the 'Travel_low' state, it will attempt to make a booking. The battery at the end of the trip is calculated using the distance its intended trip covers and the EV's power consumption rate.

The EV agent compiles a list of candidate charge points, which are within driving range, relative to the EV agent's state of charge. It also checks whether the charge point is available at the estimated time of arrival of the EV at that charge point. A price suitability check is also conducted, comparing the EV's preferred price to the price associated with the charge point. If any eligible candidate charge points remain after these filters, the EV then attempts to book at the first one eligible charge point on the list of candidates.

Next, a booking is prepared with the relevant EV information including the EV's unique id, state of charge, preferred price, booked charge station and booked charge point. This booking is then sent to the Booking Agent which validates the start time and duration of the booked charge session and validates the request if there is availability on the booking schedule. Once validated, the booking is recorded by the booking agent and the EV then starts out on its daily trip.

The booking system allows one booked charge session, if more are needed for long journeys, the EV will look for free charge points in the same way as EVs without bookings.

9.2.2 Booked charge sessions

When the EV arrives at its booked charge station enroute its destination, it is added to the booked queue – a separate queue reserved for EV's with a booked charge session. The EV then goes to the charge point and any EV present and charging at the booked charge point is forced to end its charging session, removed from the charge point and subsequently resumes its trip.

At the end of each day, all information regarding booking is removed from all the EVs. The Booking Agent maintains a record of all valid bookings conducted throughout the model run.