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Are travel surveys a good basis for EV models? Validation of simulated charging profiles against empirical data

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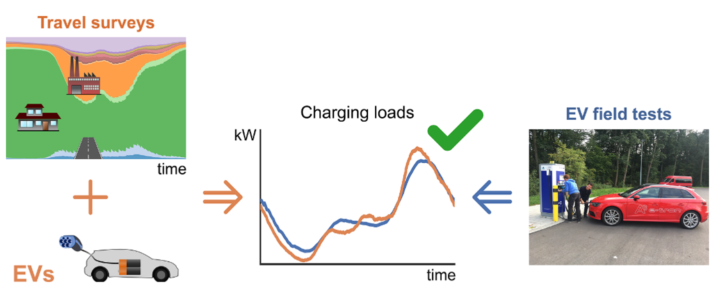
HIGHLIGHTS

- Current travel surveys can describe the mobility behaviour of EVs.
- Plug-and-charge schemes cause a high evening peak load at home.
- Charging profiles mostly depend on charging power, efficiency and battery size.
- Drivers' decision to charge is similar throughout different empirical contexts.
- Charging behaviour is stochastic and dependant on EVs' state of charge.

GRAPHICAL ABSTRACT



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ABSTRACT

The impending uptake of electric vehicles (EV) in worldwide car fleets is urging stakeholders to develop models that forecast impacts and risks of this transition. The most common modelling approaches rely on car movements provided in household travel surveys (HTS), despite their large data bias towards internal combustion engine vehicles. The scientific community has long wondered whether this characteristic of HTSs would undermine the conclusions drawn for EV mobility. This work applies state-of-the-art modelling techniques to the Swiss national HTS to conclusively prove, by means of validation, the reliability of these commonly used approaches. The cars tracked in the survey are converted to EVs, either pure battery or plug-in hybrids, and their performance is simulated over 4 consecutive days randomly sampled from the survey. EVs are allowed to charge at both residential and public locations at an adjustable charging power. Charging events are determined by a finely calibrated plugging-in decision scheme that depends on the battery's state of charge. The resulting charging loads corroborate the validation, as these successfully compare with measurements obtained from several EV field tests. In addition, the study includes a sensitivity analysis that highlights the importance of accurately modelling various input parameters, especially EVs' battery sizes and charging power. This work provides evidence that conventional HTSs are an appropriate instrument for generating EV insights, yet it adds guidelines to avoid modelling pitfalls and to maximise the simulation accuracy.

Abbreviations: ABM, Activity-Based Model; BEV, Battery Electric Vehicle; CP, Charging Profile (i.e. electricity demand from the grid while charging); CS, Charging Station; DSO, Distribution System Operator; DUOATS, Direct Use of Observed Activity-Travel Schedule; EV, Electric Vehicle (either BEV or PHEV); EVSE, Electric Vehicle Supply Equipment; HTS, Household Travel Survey; ICEV, Internal Combustion Engine Vehicle; MZMV, Mikrozensus Mobilität und Verkehr; PDF, Probability Distribution Function; PHEV, Plug-in Hybrid Electric Vehicle; SM, Supplementary Material; SOC, State Of Charge; UF, Utility Factor

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1. Motivation

The battle against climate change is pressing, and countermeasures must be deployed at a higher rate than ever before. Cutting CO_2 emissions is one of necessary key mitigation strategies [1]. Road transportation plays a vital role in this process since it accounts for 18% of total energy-related CO_2 emissions worldwide [2]. Different interventions — hybridisation, mode shift, autonomous driving — can contribute in alleviating CO_2 intensity of road transportation and only an interplay between them is likely to achieve the desired target. A major boost to achieve near-term climate objectives will come from electric light-duty vehicles (EVs) [1,3]. Contrary to other examples, the introduction of EVs is one of the few strategies which is judged on track to meet the 2025 interim benchmarks that are *likely* to keep global warming below 2° [3]. This progress is also confirmed by the substantial penetration of EV models in several developed countries [4].

As with every novelty, the introduction of EVs poses questions and challenges to various stakeholders of society, from policy makers to distribution system operators (DSO) and consumers. Particularly urgent is the call for estimations of future charging profiles (CP), i.e. the hourly electricity loads triggered by charging EVs. Their importance stems from their pivotal role as energy interface between the mobility and electricity sectors. In order to construct CPs, researchers have pursued two paths:

- public trials [5–10], where scientists provide the participants with actual EVs and charging stations (CS); researchers can then track EVs, measure current flows and extract any other measurable information;
- simulation models [11,12], where scientists design a digital transportation system that aims at emulating the real peer; researchers then have easy access to all data that are captured by the model, but the reliability of the simulations is always disputable.

Some studies employ a mixture of the two above procedures, for instance by grounding a model on data extracted from an EV trial [13–17]. The direct collection of information from users driving actual EVs certainly ensures the reliability of the acquired data. Their representativity is, however, more doubtful as the trials are necessarily limited in size, geography and demographics [8,9,18,19]. On the other hand, models can be designed in order to represent an arbitrary scenario, with customised demographics and geography. The model capability of capturing the real behaviour of EVs is, nevertheless, open to question.

The goal of this paper is to prove the possibility of building a methodology that takes the best of the two worlds, simulations and empiricism. This is achieved in the archetypal scientific way: by building a representative model with broad applications and validating it through trial-specific field measurements. The main purpose of the model is the construction of CPs, which will thus serve also as mean of comparison in the validation.

In the two following sections we provide a deeper dive into the topic, specifically:

- Section 1.1 details the types of models commonly used to describe the movements of cars and explains the choice made in this study;
- Section 1.2 presents an overview of current research that employs similar models to this study.

1.1. Types of EV models

A full overview of the existing models dealing with EVs usage is provided in [20]; following the classification there introduced, the model categories that better address the short-term interaction with the charging infrastructure are the so-called "Activity-based models" (ABM) and "Direct use of observed activity-travel schedules" (DUOATS). As their names suggest, both types of models rely on an activity schedule, which is assumed to be the fundamental principle behind the movement of people. In these models, people drive their EVs from a destination to another depending on their activities and they charge their batteries whenever they stop at a location equipped with a charging station (CS). CPs are thus the natural results of the interplay between the EV drivers' routines and the available charging network.

The core difference between ABM and DUOATS is the flexibility in building the activity-travel schedule: ABMs generate the schedule endogenously while optimising for specific key indicators, such as costs or travelling time; in contrast, DUOATS models employ an external activity-travel schedule, previously derived and not adjustable by the model. Typical activity-travel schedules used for DUOATS models are household travel surveys (HTS), national inquiries about the movement of people during one or multiple days. On one hand, HTSs usually contain enough entries to make robust and representative conclusions from the model; on the other hand, HTSs are performed on the general population without filtering for EVs, and are mostly composed of conventional cars. Therefore, HTSs may not reliably report the actual activity-travel schedule of potential EV drivers, but this entirely depends on future usage of EVs compared to current cars.

Yet, ABMs enjoy considerably more degrees of freedom and can potentially account for any distortion, such as mode shift of long trips or activities adjustments to accommodate longer charging. This flexibility can however be obtained only through a rich model, with multiple parameters and levers that emulate people's behaviour and the decision process behind the allocation of activities and trips. While this approach is in principle feasible and has been attempted [11,12], it poses serious challenges to the modeller. Furthermore, the complexity of such models introduces concerns in terms of reproducibility. On the contrary, DUOATS models directly follow from the realised outcome of people's decision process and they implicitly enclose all the complexity of human mobility behaviour. With the major drawback being that conventional cars are used. While some studies observe that range anxiety may impact the driving routine of EV users [21–24], others find this alteration not to be particularly significant, especially after longer driving experience [25–28]. This study employs empirical validation to conclusively prove that HTS-based DUOATS models can generate accurate CPs.

1.2. Usage of DUOATS models in literature

Our efforts to prove the validity of DUOATS models derives also from the remarkable success that they enjoy in literature. A typical case of DUOATS is given in [29,30], where the authors gather travel information of 877 candidates through online surveys and derived CPs based on different charging scenarios.

But the majority of DUOATS models relies on HTSs: Refs. [31,32] build HTS-based CPs and compare the results for different socio-spatial groups; while [33] uses the CPs to estimate the impact on the grid's substations. Refs. [34,35] provide more comparative analyses by building CPs from different European HTSs and conclude that, although some differences between countries exist, the biggest impact comes from assumptions on charging opportunity and behaviour. These aspects are thoroughly investigated in the sensitivity analysis included in this work.

Several researchers choose to describe the variable nature of private mobility through a stochastic formulation of their models. Ref. [8] derives CPs from the American HTS and then randomly samples some of those CPs from a selected pool of drivers. But the majority of works incorporates stochasticity by firstly deconstructing the HTS to its elementary variables - such as travelling times or mileage - and then restructuring the gathered information to obtain CPs. Refs. [14,36] extract univariate distributions of the necessary quantities (distance driven and parking times) and sample from these individual charging events. Refs. [37,38] recognise the importance of maintaining the interdependent structure linking those quantities and build charging events by conditionally sampling the necessary variables. Refs. [39,40] model the multivariate nature of mobility by employing copula functions: Ref. [39] then performs a Monte Carlo simulation, while [40] shows the effectiveness of using queueing theory to model CSs. Ref. [41] preserves the interdependency between travelling times and trip lengths by training artificial neural networks on the American HTS. The trained model is then used by a local aggregator to forecast EV travel behaviour and minimize the total cost of charging. Finally, some studies use the disaggregated information of the HTS to build new randomness-rich activity-travel schedules upon which they adopt conventional DUOATS models: Ref. [42] employs a Naive Bayes model, while [43–45] opt for Markov-chain simulations.

These last studies place a lot of emphasis on building a methodology that can capture the stochastic behaviour of private mobility; some of them also present a validation of such methodology against the original HTS [13,40,42,43]. While this verification is important, there is evidence that a big source of uncertainty concerning EVs' mobility is the charging behaviour of drivers [46]. However, most studies simplify this feature by either imposing a constant number of recharges per day (usually one [47]), or by assuming that EVs will be charged at every possible opportunity [48]. A more elaborate approach is proposed in [8,34], where the authors attempt to emulate charging decisions by introducing a time-dependent charging probability. Similarly, Ref. [13] uses the journey number of the day as proxy for the location of the vehicle, hence of its probability to charge. Other studies follow the recommendation of [46] to model the interaction between the EV driver and the battery's state of charge (SOC): Refs. [39,47,49,50] use fixed thresholds of SOC below which the drivers always decide to charge their EVs, while [43] introduces a SOC-dependent probability of charging that follows a logistic function. Ref. [51] proposes an advanced charging decision scheme that combines some of the above criteria with the cost of charging and the maximum rechargeable energy.

The present study assumes the availability of a conventional activity-travel schedule: it can be a raw or post-processed HTS, the outcome of a survey or a trial or an intermediate result of an ABM. The driving behaviour is thus taken as is, and no trip generator is developed. Rather, the focus of the modelling effort is on the inclusion of EVs' characteristics in those fixed patterns from the technical perspective (energy consumptions of EVs) to the behavioural one. Any model aiming at describing EVs' mobility should undergo a validation that captures both the simulation of car movements and the modelling of EVs' characteristics: CPs are the ideal candidates for this task and are accordingly chosen as exemplary goal of this work. However, we showed that most studies solely validate the trips generation, hence coming short of a comprehensive assessment. Very few works effectively present a comparison between CPs measured in a public EV trial and CPs built from a HTS. Ref. [14] compares CPs measured in a large EV trial in the UK [5] with the CPs built either from raw data of the trial itself or from the British HTS. The comparison predictably favours the CPs built from the trial itself, but also the HTS performs well, for instance by returning the same peak demand. However, the focus on the trial of the study did not allow space for refined DUOATS modelling of the HTS, and few adaptations would have improved the HTS's score. Researchers in [8] validate their DUOATS model from the American HTS against a small demonstration project in Austin, Texas. The quality of the comparison is remarkable although they employ normalised CPs and thus cannot assess the peak demand accuracy. Finally, although no HTS is employed, Ref. [13] compares the CPs obtained either by directly using data from an Irish EV trial [10] or by processing them with a refined stochastic model.

1.3. Outline of this study

This study presents the first systematic and quantitative validation of HTS-derived CPs, which are used as proxy for the performance of the entire procedure. The lack of previous quantitative assessments does not make comparisons with other works possible, but the new metrics allow the realisation of a comprehensive sensitivity analysis of the results. The quantification of the errors allows to understand which parameters impact the results the most and which should be paid attention to. The sensitivity analysis highlights the crucial role of charging behaviour hence supporting its accurate modelling. The model construction and all analyses were carried out with Python 3.5.

The paper is structured as follows. Section 2 presents the construction of the DUOATS model, from the cleaning of the HTS to the simulation of EVs mobility. Chapter 3 contains the results of this paper, including the validation of the methodology and the sensitivity analysis of the most important parameters. Finally, Section 4 summarises the most relevant findings and provides insights for future research. The potential applications of the designed model can in principle be spread out to include environmental and economic implications.

2. Methodology

This chapter is a step-by-step guide for the development of a CP-tailored model from a raw HTS. This process is split in two parts:

- Section 2.1 introduces the HTS used in this work together with a few preprocessing steps that should be considered before feeding a raw HTS to a DUOATS model;
- Section 2.2 describes the DUOATS model used in this study, from the technical assumption concerning EVs design to the modelling of charging behaviour.

2.1. From HTS to usable activity-travel schedule

This study builds on the 2015 outcome of the Swiss HTS, the *Mikrozensus Mobilität und Verkehr* (MZMV), carried out by the Swiss Federal Statistical Office (FSO) every 5 years [52]. The survey collected one day of travel information of 57,090 people, i.e. about 0.7% of the Swiss population [53]. The size of MZMV and the inclusion of a thorough weighting procedure allow the results to be representative for the whole Swiss population and for several subgroups (e.g. for different age groups or geographical areas). This HTS also fulfils most of the requirements that [54] considers crucial for effective investigations of EVs-infrastructure interaction. The only feature that MZMV lacks is the reporting of multiple days of travel information. Section 2.2.3 presents the specific strategy adopted to emulate multi-day mobility.

MZMV records include all relevant details for every single movement, which is here defined as stage: places of origin and destination, times of departure and arrival, mean of transport, purpose of the trip and many others. Specifically, temporal information comes with 1 min resolution, which is more than sufficient for the modelling of CPs. However, some aspects of the survey do not align with the inputs needed by a DUOATS model and we accordingly introduce the following preprocessing steps:

- conversion of the participants stages into car movements;
- attenuation of the human bias in the travelling times reported by the respondents;
- categorisation of car locations by place functionality (e.g. home, workplace, etc.).

2.1.1. From movement of people to movement of cars

MZMV, like many other HTSs, provides the daily movements of people; the standard procedure to extract movements of cars is to link together all and only the stages where the interviewed participant drove the same car. While this is a good first approximation, it leaves out any other movement where the car was driven by a person other than the respondent. The best approach to include these additional

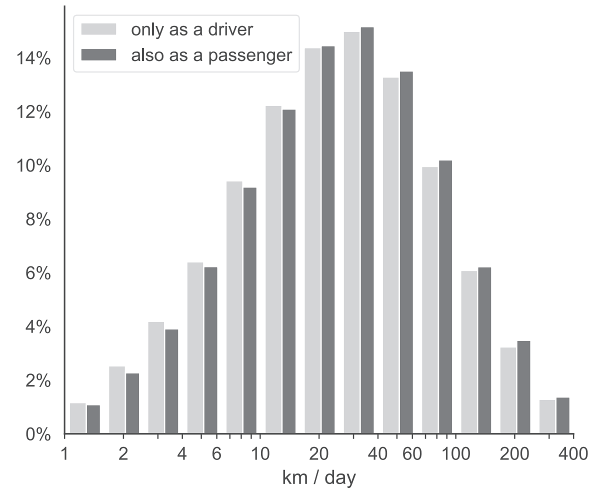

Fig. 1. Probability distribution functions of daily distance driven by car. The logarithmic scale on the x-axis makes the distributions look approximately Gaussian given their quasi-log-normal natural shape.

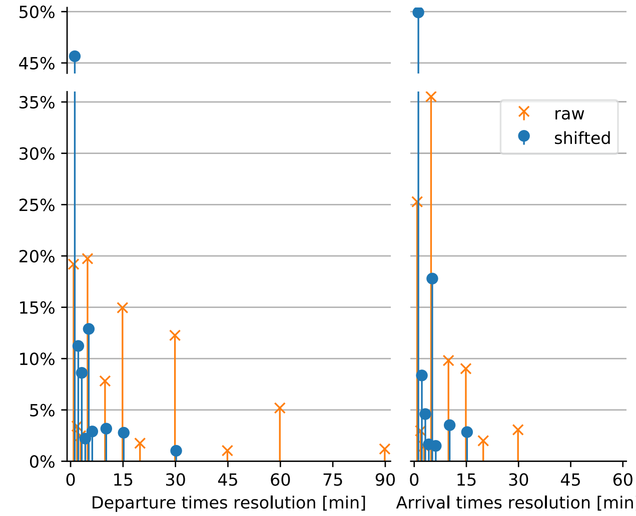

Fig. 2. Probability mass function of the time resolutions used by respondents while reporting travelling times. Time resolutions belonging to less than 1% of respondents are not shown for clarity. Clear peaks at 1 and 5 min are visible for both departure and arrival times.

stages is given by [55], where the authors use information about the other driving-license-holders of the same household to sample new car stages. Unfortunately, MZMV does not provide the same details as the HTSs employed in [55] and their approach is not strictly replicable.

However, MZMV reports all the stages where the respondent was a car passenger. If that car was also driven by the surveyed person on the same day, these passenger stages are added to the overall car movements of the day. Fig. 1 shows, on a logarithmic scale, the quasi-log-normal distance distribution of daily car trips [56–58]. The inclusion of passenger stages to the cars' mileage slightly shifts the distribution to the right, i.e. towards longer trips. Specifically, both the average and median daily distances increase by 4%. The overall procedure returns 23,434 one-day car trips, with an average distance of 48.7 km. It is important to highlight that these and all subsequent figures refer only to the active cars, i.e. cars that were used at least once on the interview day. For reference, the share of non-mobile cars on a given day is about 30% of the overall stock. A derivation of this estimate is provided in Section 1 of the supplementary material (SM).

Algorithm 1
Shift of departure and arrival times.

1: **for** i **in** trips **do**
2: $\quad$ $\text{resolution}_{\text{raw}} = \text{GCD}(t_{i,dep})$
3: $\quad$ **for** k **in** [60, 30, 15, 10, 5, 1] **do**
4: $\quad\quad$ **if** $\text{resolution}_{\text{raw}} \bmod k = 0$ **then**
5: $\quad\quad\quad$ $\text{resolution} = k$
6: $\quad\quad\quad$ **exit for loop**
7: $\quad\quad$ **end if**
8: $\quad$ **end for**
9: $\quad$ $\text{shift}_{\max} = \min(t_{i,dep}[1:\text{end}] - t_{i,arr}[0:\text{end}-1])$
10: $\quad$ $\text{shift}_{\max} = \min(\text{shift}_{\max},\ \text{resolution}/2)$
11: $\quad$ sample $X \sim \mathcal{U}(-1, 1)$
12: $\quad$ $\text{shift} = \text{truncate}(X \cdot \text{shift}_{\max})$
13: $\quad$ $(t_{i,dep}^{new},\ t_{i,arr}^{new}) = (t_{i,dep},\ t_{i,arr}) + \text{shift}$
14: **end for**

2.1.2. Smoothening of HTS reported times

Most of the fields in HTSs are directly filled with the respondents' answers. This is particularly the case for travelling times, which people tended to report rounded to the hour, half hour and quarter hour. Only few authors have acknowledged the problem and have proposed solutions to offset this distortion [8,59,60]. This work employs Algorithm 1 to reduce the bias and realistically disperse departure and arrival times. GCD computes the greatest common divisor and $t_{i,dep}$, $t_{i,arr}$ are the vectors of departure and arrival times for the i^{th} trip. We start from the assumption that every respondent had an inner time resolution and thus reported travelling times rounded to that resolution (line 2 in Algorithm 1). The share of participants with a given time resolution is plotted with × in Fig. 2. We separate departure from arrival times since the reported arrival times come with much finer precision than departure times. The likely reason for this is that respondents thought more in terms of trip duration, hence adding the latter to the departure time to estimate the arrival time. Overall, about 80% of respondents reported departure times with a resolution of 5 min or coarser. Following our approach, we can assume that the actual trips may have occurred at any moment falling within the respondents' time resolution around the reported times. Therefore, more diversity can be introduced by randomly shifting travelling times within their time resolution (lines 11, 12). We can also reasonably assume that respondents tended to round only to 5, 10, 15, 30 and 60 min and we accordingly reduce the set of possible resolutions (e.g. trips with apparent resolutions of 20 or 90 min are assigned resolutions of 10 or 30 min respectively; lines $3-8$). In order to maintain the original logistic structure of the trips, all daily movements of a trip are shifted by the same amount (line 13) and no shifted stage should overlap with the non-shifted neighbouring stages (lines 9, 10). The resulting time resolutions of trips are depicted with • in Fig. 2. Both distributions steadily improve, and arrival times exhibit time resolutions finer than 6 min for more than 80% of trips. This is crucially important to obtain sparse parking times, hence smoother CPs.

2.1.3. Classification of cars locations

HTSs do not necessarily report place of origin and destination in the format desired for simulating EVs. The final configuration of origins and destinations depends on the specific purpose of the EV model. CPs are usually presented, both when extracted from trials or built from DUOATS models, in an aggregated fashion by location function. Typical examples are CPs at private houses or at workplaces. MZMV does not readily provide these types of locations, but it gives the purpose of each stage. This information allows the construction of effective activity-travel schedules, where car movements alternate with parking periods at specific functional locations. Fig. 3 shows the result when all 23,434 car trips are converted into activity-travel schedules. The diagram depicts the parking locations of all active cars during an average day of the year. Importantly, MZMV is also representative for single days of the week, allowing to capture the typically different mobility behaviours between weekdays and weekends [10,17,61,62]. Some examples

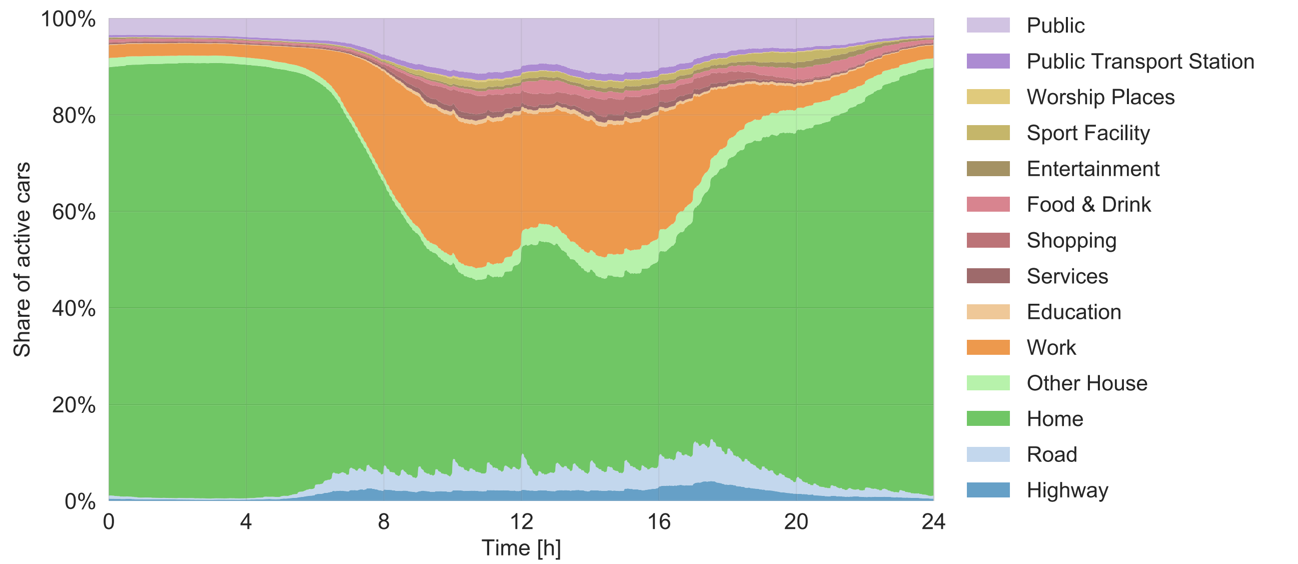

Fig. 3. Car locations and activities during an average day of the year. Only cars which are used at least once during the day are included.

of car locations' distributions on specific days of the week are presented in Section 2 of SM.

The portion of actively mobile cars is depicted by the Road and Highway shares and is almost always lower than 10%: EVs would thus have, in principle, plenty of time to charge while parked somewhere. The human bias in the reported departure times is still slightly visible in the Road segment, but more aggressive shifting procedures could jeopardize the original information; moreover, the CPs-relevant arrival times exhibit adequately smooth behaviour.

Rush hour is reached at the end of the working schedule, between 5 p.m. and 6 p.m., and it is followed by a quick increase of vehicles parked at Home: these concurrent events will trigger a considerable demand for electricity at home CSs. The other major opportunity for EV charging is at Work, where the share of vehicles parked in the mornings and afternoons reaches 40% on working days (see Section 2 of SM). However, the morning commute to work exhibits even more synchronised behaviour than the afternoon one and it could trigger, when not managed, an increasingly demanding load. The Public share clusters together all undefined locations, while the Public Transport Station portion represents the times when the driver transfers from car to public transport. Finally, evening CSs at leisure sites like Food & Drink and Sport Facility may represent interesting business models, but would not dramatically impact the system.

The above steps convert the Swiss HTS into a well-designed activity-travel schedule that can be employed in a DUOATS model to simulate the behaviour of EVs.

2.2. EV model

The activity-travel schedule provides one day of travelling information of 23,434 conventional cars. The task of the EV model is to return the CPs that those cars would produce if they were EVs. The model is thus structured according to Fig. 4, with the activity-travel schedule being converted to an EV-rich scenario where:

- the stock of active vehicles becomes massively electrified with widespread adoption of EVs;
- several locations offer the possibility of charging the EVs.

The first feature is addressed by a set of assumptions regarding the fleet composition in the activity-travel schedule. Thus far we have discussed EVs without differentiating between battery electric vehicles (BEV) and plug-in hybrid electric vehicles (PHEV). The reason for this is that the first part of the methodology concerns the construction of a database of trips and movements regardless of the powertrain. However, the following chapters treat the operation of the vehicles, and there the differences between BEVs and PHEVs play a crucial role. Further details regarding the powertrain scenario and the EVs' technical characteristics are described in Section 2.2.1.

The second required input is a set of assumptions concerning availabilities and power levels of CSs at different locations; further details are provided in Section 2.2.2.

This framework allows the EV model to be considered as black box, which for a given EV-rich scenario returns a full description of EVs behaviour and CSs loads. Such a flexible and lean formulation allows for agile validations against EV trials from different contexts and for compact sensitivity analyses.

Charging costs are not included in the current model. As described in Section 2.2.2, EV drivers are assumed to make charging decisions based on CS availability and range sufficiency. The cost of charging should be included in future specific works since it requires careful calibration of the EV drivers' elasticities and the monetization of range anxiety.

The following chapters provide the functioning principles of the DUOATS model:

- Section 2.2.1 details the powertrain scenario and the modelling of EVs while driving;
- Section 2.2.2 deals with the charging scenario and EVs' interaction with CSs; this includes the modelling of the charging behaviour of EV drivers;
- Section 2.2.3 explains how the EV model is run while taking into account multi-day mobility.

2.2.1. Vehicles design and energy consumption

The powertrain scenario is represented by a portfolio of vehicle segments with each share defined by:

- powertrain design, which can be ICEV, PHEV or BEV;
- nominal battery size expressed in kWh, if powertrain is BEV or PHEV.

The useful energy content of batteries is assumed to be 80% of the nominal value [63]. The SOC of EVs spans from 0% (empty) to 100% (fully charged), where both figures refer to its useful capacity. The designed powertrain scenario allows the simulation of mixed fleets with

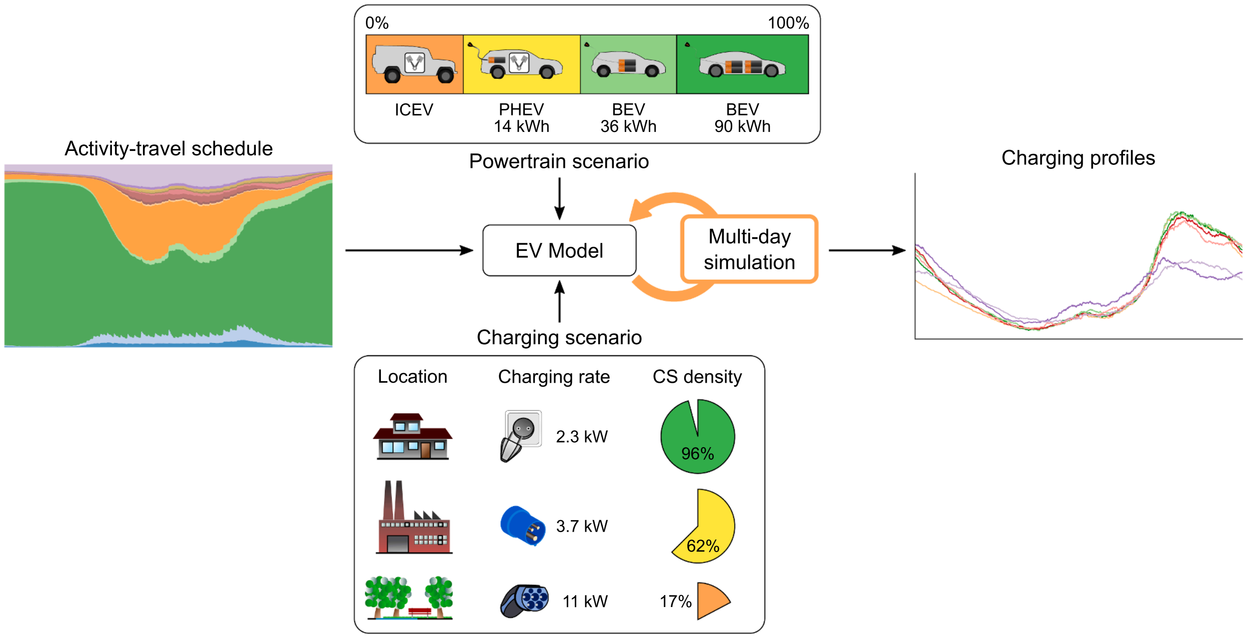

Fig. 4. General structure of the model used in this work. The activity-travel schedule is enriched with information regarding the stock of mobile vehicles and the charging capabilities of different functional locations. The whole setup allows the simulation of EVs behaviour within the predetermined activity-travel schedule. From the resulting EV movements a lot of information can be extracted, ranging from the electric share of PHEVs to the CPs triggered at different locations on different days. The numbers are just provided as examples and can be completely adjusted in this model.

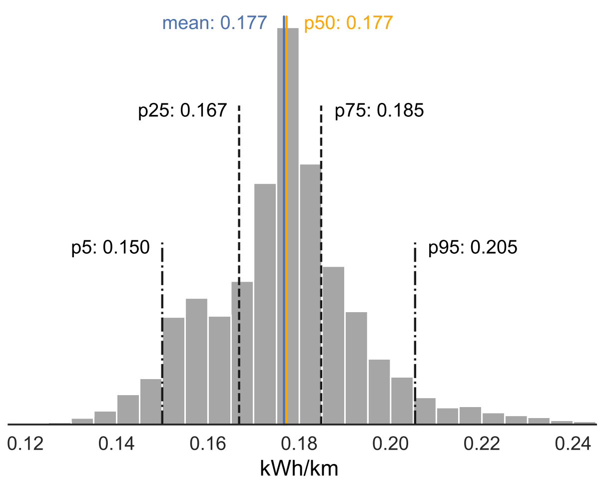

Fig. 5. Distribution of the specific electricity consumption at the battery output of all MZMV vehicles when converted to BEVs with 40 kWh battery capacity.

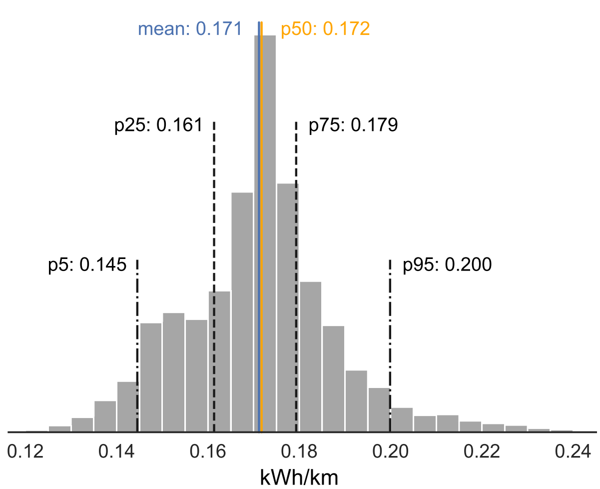

Fig. 6. Distribution of the specific electricity consumption at the battery output of all MZMV vehicles when converted to PHEVs with 13 kWh battery capacity.

multiple {powertrain, battery size} segments. However, the vehicles in the same fleet segment are not equal. We adopt the “intervention” concept from [63], where the *status quo* vehicles from MZMV undergo a conversion of the powertrain without affecting the car body. This approach reflects the idea that a person would buy an EV equivalent to their current car. This decision is also supported by statistical evidence that heavier cars tend to drive further than lighter ones, as reported in Section 3 of SM. In order to preserve this relation, each MZMV pair {*status quo* car, trip} is never split apart in the model.

Before starting the simulation, we randomly assign a vehicle design {powertrain, battery size} to each MZMV entry {*status quo* car, trip}. The probability for a {*status quo* car, trip} pair to be assigned a {powertrain, battery size} segment is proportional to the segment’s share in the powertrain scenario. The resulting powertrain mix of the MZMV entries mirrors the input powertrain scenario. Further details on the random assignment are provided in Section 4 of SM.

The new {*status quo* car, powertrain, battery size} vehicle is modelled according to the design rules of [63]. Each car is characterised by a kerb weight which is a function of the glider’s mass of the *status quo* vehicle and of the newly installed powertrain:

$$m_{\text{kerb}} = m_{\text{glider}}^{\textit{status quo}} + m_{\text{powertrain}}^{\text{new}}$$

However, the vehicle’s energy consumption depends on the actual mass of the vehicle, which includes the weight of the passengers aboard during each stage of the trip:

$$m_{\text{actual}} = m_{\text{kerb}} + m_{\text{passenger}} \cdot \text{occupancy}$$

The specific electricity consumption at the battery output [kWh/km] is computed as in [63] starting from the computation of the wheel energy demand on the Worldwide harmonised Light vehicle Test Cycle (WLTC). This estimation of the energy demand is primarily influenced by the actual vehicle’s weight m_{actual}. The converters’ efficiencies are then discounted by means of the empirically-derived Willans-line, which depends solely one the powertrain technology [63]. Finally the real-world energy factor 1.28 from [64] is applied to obtain the actual electricity consumption on the road of BEVs and PHEVs in charge depleting mode. Figs. 5 and 6 display the resulting energy consumptions of the entire MZMV fleet for two illustrative powertrain scenarios: all vehicles are BEVs with 40 kWh battery capacity or all are PHEVs with 13 kWh. Note that charging losses are not yet accounted for and all values must be regarded as electricity consumption at the battery output.

Two final remarks concerning the energy management of PHEVs and BEVs are necessary. PHEVs can be used in either charge sustaining mode — they run on the chemical fuel available on-board preserving the battery's SOC — or in charge depleting mode — they drain the battery and directly use the electricity for propulsion. In this work, PHEVs are assumed to always drive in charge depleting mode when possible, i.e. for any SOC > 0% [65]. If the battery is depleted, PHEVs continue driving in charge sustaining mode without constraints.

On the other hand, BEVs can solely be driven in charge depleting mode as they lack an alternative on-board fuel. This means that BEVs may run out of SOC during the simulation, hence failing to fulfil the assigned daily trip. When this happens, the trip is considered non-electrifiable and the car is replaced by its equivalent ICEV through a new intervention. For the purpose of this study there is no need to further detail the modelling of ICEVs.

2.2.2. Charging opportunities and behaviour

This section describes the handling of EVs whenever they reach their destinations. For this task the second set of exogenous assumptions, namely the charging scenario, is relevant. This input provides the following information for each type of functional place, i.e. for every location listed in Fig. 3:

- the density of CSs, expressed as the probability of finding an available charging point (also called Electric Vehicle Supply Equipment - EVSE) once the EV gets to a certain type of location. These probabilities can range from 100% (where it is always possible to charge) to 0% (where there are no CSs).
- the charging rate, i.e. nominal charging power (kW), of potential EVSEs at each type of location. Theoretically, any type of location may offer a variety of charging rates, but in order to keep the model leaner, we assume the same charging power for all CSs at the same location. This rate should also take into account the limitations of the employed EVs, whose on-board charger may constitute the actual bottle-neck in the charging process.

When an EV parks somewhere, a first random number is sampled from a uniform distribution ($X \sim \mathcal{U}(0, 1)$) to determine whether the current location hosts an available CS (X<CS density @ location). If successful, the decision to charge is up to the driver. For this two criteria are used:

- the stop must last long enough to make the charging seem sensible; i.e. there is a minimum time threshold under which the driver would not plug in the EV. This threshold conventionally ranges from 0 to 120 min [32,43,66] and is here set to 1 h.
- the decision to charge then depends on the SOC of the vehicle, which is more likely with a more depleted battery. This work employs a stochastic method similar to [43]. For PHEVs, a random number is sampled from a normal distribution ($X \sim \mathcal{N}(\mu, \sigma)$) and is compared to the SOC of the vehicle; if $\mathrm{SOC_{PHEV}} < X$ then the driver decides to charge. Similar decision process applies to BEVs although the normal distribution is truncated on the lower tail so that fully depleted BEVs are always charged. The difference between the two cases is illustrated in Fig. 7.

The normal distribution parameters μ, σ are also exogenous inputs to the EV model and have to be calibrated. Contrary to any previous study, in Section 3.2 we provide a detailed procedure to derive these parameters and results will show that EV drivers exhibit surprisingly similar behaviour in rather different contexts.

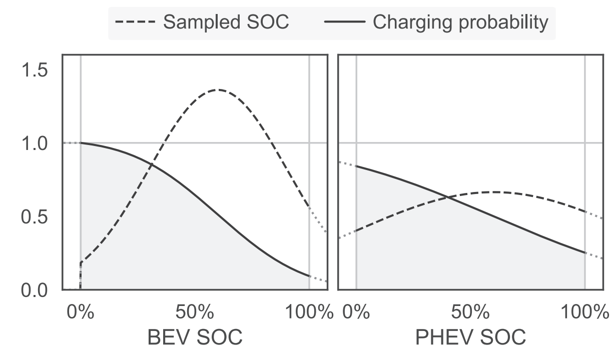

Fig. 7. With dashes, probability distribution functions (PDF) of sampled SOC during the charging decision process. With continuous lines, the reverse of the cumulative distribution functions, i.e. survival functions, which represent the probability of charging of an EV reaching the CS with a certain SOC. The BEV distribution on the left is truncated on the lower tail so that the survival function starts from 1 and forces drivers to always charge a fully depleted BEV. To the right, the survival function of PHEVs is non-truncated and starts from a fraction of 1, allowing the possibility of not charging even when fully depleted. The examples shown are computed for: $\mathrm{SOC_{BEV}} \sim \mathcal{N}(0.6, 0.3)$ truncated between $[0, +\infty]$ and $\mathrm{SOC_{PHEV}} \sim \mathcal{N}(0.6, 0.6)$.

Once the driver decides to plug in the EV, the car starts charging immediately at the power rate of the CS and it stops either when it leaves the place or when the battery is fully charged. This charging mechanism lacks any form of smartness, but is consistent with most of the charging data currently available [8,13,14,40,67]. However, if a future study wants to introduce demand-side management mechanisms, the proposed charging decision process may be regarded as a plugging-in decision process, thus determining whether the EV is connected and can participate in management scheme.

Charging losses are modelled according to the empirical Willans-line correlation found by [63]. The energy E_{CS} supplied by the CS relates to the change in energy content of the battery through the following linear equation:

$$E_{\mathrm{CS}}\,[\mathrm{kWh}] = 1.1992 \cdot \Delta\mathrm{SOC}\,[\mathrm{kWh}] + 0.1896$$

No constraints is assumed on the power supply side, neither from generation nor from the grid, because any impact downstream of CPs is beyond the scope of this paper. Moreover, the trials used for validation always involve low levels of EV penetration, which seem not to represent a threat for existing distribution grids, even in uncontrolled charging situations [33,44,68].

2.2.3. Multi-day mobility

In Section 2.2.1 we introduced the random assignment of a {powertrain, battery size} design to each {*status quo* car, trip} combination. However, a common issue faced when modelling EV routines is the initialisation of SOC in the morning. Most approaches include:

- EVs always start the day with a fully charged battery;
- EVs are assigned a random SOC which comes from measurements.

While the first approach is quite simplistic and assumes that all EVs are charged every night, the second one is bound to the specific context where measurements were taken. Moreover, these approaches do not ensure energy conservation during the simulated day and the assumed morning SOC may conflict with the designed charging scenario and behaviour. The authors of [32] resolve this issue by imposing the same SOC at the beginning and at the end of the day, but this strongly constrains the simulation.

Here we adopt the more flexible approach proposed by [13,39,42],

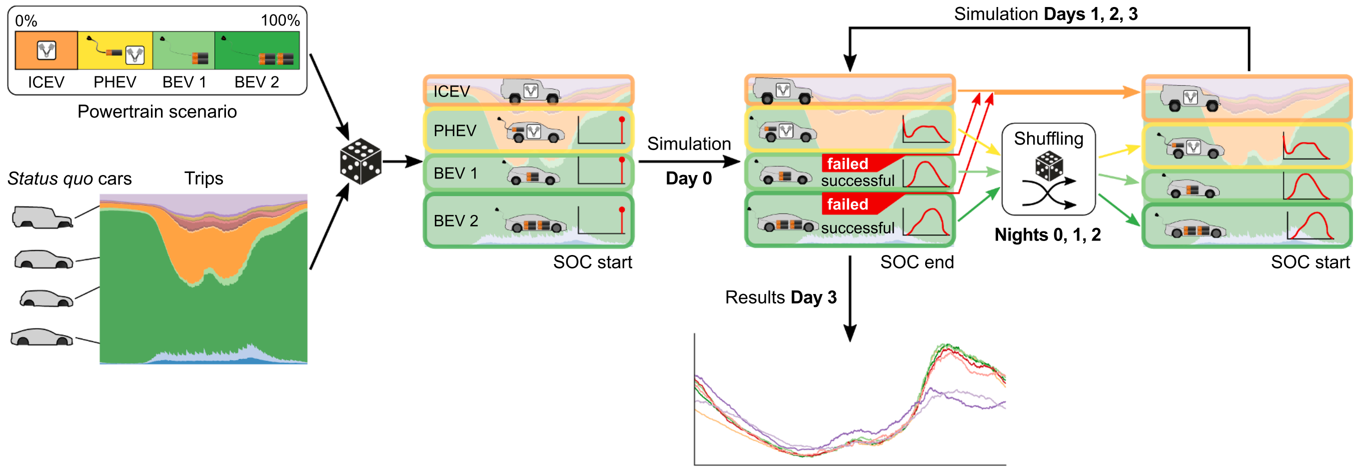

Fig. 8. Work flow of the simulation. From left to right: the model is first initialised with all EVs equipped with a fully charged battery; then a mobility day is simulated (**Day 0**) and the final SOCs are recorded. Overnight the powertrains are shuffled in order to assign to each {powertrain, battery size, SOC} triplet a new {*status quo* car, trip} couple. Then a new mobility day (**Day 1**) is simulated. The procedure is repeated 2 more times and the mobility patterns recorded on the fourth day (**Day 3**) are extracted for further analysis.

where multiple consecutive days are simulated to obtain a periodic boundary of SOC. Fig. 8 illustrates the overall procedure. On the first simulation day all EVs start with a fully charged battery, but from the second day they start with a random SOC derived from the final SOC distribution of the previous day. Every day we also repeat the random assignment of {powertrain, battery size} information to each {*status quo* car, trip} entry introduced in Section 2.2.1. The reshuffling excludes trips which were shown to be non-electrifiable and these trips are assigned a conventional ICEV for the following day. The results show that after the third day, the simulation reaches convergence — defined as observed periodicity of SOC and decreased rate of failing BEVs — and the fourth simulation day is then used for evaluation and analyses.

3. Validation and sensitivity analysis

The built model enjoys many degrees of flexibility and can simulate very different scenarios, either existing or artificial. In this work we focus on validating the model by comparing its outputs to real-world examples. This chapter provides both validation and sensitivity analyses in the following order:

- Section 3.1 introduces the real-world trials that form the basis of all subsequent investigations;
- Section 3.2 continues the modelling of charging behaviour from Section 2.2.2, using the trials to calibrate the behavioural parameters;
- Section 3.3 presents the qualitative comparison of the CPs from the trials and the model;
- Section 3.4 provides the quantitative sensitivity analyses of the model's parameters.

3.1. EV trials

This study employs the following 4 public EV trials for the validation:

- The “My Electric Avenue” Project (UK, 2013–15) [5,14];
- The North East's “Switch EV” electric vehicle trial (UK, 2010–15) [6,69];
- “The EV Project” from Nashville region (US, 2011–13) [7];
- The “Pecan Street” Smart Grid Demonstration Project (US, 2011–13) [8].

The My Electric Avenue and Pecan Street trials have been chosen since they constitute the bases for the few validation attempts found in literature [8,14]. On the other end, we include The EV Project and the Switch EV trial because they report the results with a functional spatial disaggregation that reflects the structure of the activity-travel schedule (home, workplace, etc.). They thus form the basis for a finer and disaggregated validation.

The original trials conditions are recreated in the simulation by solely operating on the exogenous inputs, namely the charging and powertrain scenarios. Table 1 summarises the original trial information used to set up the simulation and the resulting parameters settings. Nevertheless, the reader should bear in mind that all the trials represent open systems, where tracked EVs may charge at untracked CSs and vice versa. This means that our attempt of recreating the trials conditions may still neglect relevant environmental characteristics. This lack of control on the investigated system is one of the main reasons that discourages researchers from pursuing validations such as the one proposed here. We show that important conclusions can still be drawn even when the impact of external unknown variables becomes noticeable.

All simulation settings other than the powertrain and charging scenarios remain constant among different trials. However, one last important input yet to be discussed is the parametrisation of charging behaviour introduced in Section 2.2.2. The next section makes use of the EV trials to derive the behavioural parameters empirically.

3.2. Calibration of charging behaviour

Another key contribution of this work is the development of a detailed procedure to derive a SOC-dependent charging behaviour based on real data. The same procedure can in principle apply to both BEVs and PHEVs, but BEVs are first addressed since PHEVs require additional considerations.

The behavioural model employed in this work is depicted in Fig. 7, and assumes that the charging probability depends on the SOC upon arrival at a charging location. This function can be derived with Algorithm 2 and the graphical aid of Fig. 9. Provided we have access to the probability distribution function (PDF) of SOC before a charging event (line 1) and the PDF of SOC at any charging opportunity (line 2), we can obtain the charging probability as the ratio of these two functions (line 4). The ratio is then normalised to the peak (line 5) and set to 1 for all low SOCs (line 6) since the maximum charging probability for a BEV is 100% and occurs at low SOCs. The resulting function resembles

Table 1
Configuration settings of EV trials.

	Trial EV fleet	Powertrain scenario[a]
My Electric Avenue [14]	221 Nissan Leaf with 24 kWh battery	100% BEVs with 25 kWh battery
Switch EV [80]	15 Nissan Leaf with 24 kWh battery 20 Peugeot iOn with 16 kWh battery 9 other	43% BEVs with 25 kWh battery 57% BEVs with 18 kWh battery
The EV Project [81]	656 Nissan Leaf with 24 kWh battery 54 Chevrolet Volt with 16 kWh battery	93.5% BEVs with 25 kWh battery 6.5% PHEVs with 13 kWh battery
Pecan Street [8]	8 BEVs 25 PHEVs (primarily Chevrolet Volt)	30% BEVs with 25 kWh battery 70% PHEVs with 13 kWh battery
	Trial charging outlets installed	**Charging scenario[b]**
My Electric Avenue [14,62]	88 home charging outlets at 3.6 kW 13 work charging outlets at 3.6 kW	100% CSs at home at 3.6 kW 43% CSs at work at 3.6 kW 0% CSs anywhere else
Switch EV [67–69]	91 home charging outlets at 2 kW 268 public/work charging outlets at 2 kW 8 public/work charging outlets at 50 kW	100% CSs at home at 2 kW 83% CSs anywhere else at 2 kW
The EV Project [61,84,85]	596 home charging outlets at 3.76 kW 241 public charging outlets at 3.76 kW	100% CSs at home at 3.76 kW 11% CSs anywhere else at 3.76 kW
Pecan Street [8]	monitored home charging outlets at 3.3 kW limited work/public charging infrastructure	100% CSs at home at 3.3 kW 0% CSs anywhere else

[a] Input powertrain shares adjusted in order to obtain about the same shares as in the trial after elimination of failed BEVs during the four-day simulation. An example is shown in Section 4 of SM.

[b] The percentages refer to the CS densities at each location and the sum may exceed 100%. The densities take into account the relative frequency of different locations in the activity-travel schedule (for MZMV, home:work:non-home = 1:0.35:1.42) and are adjusted in order to obtain the same CS shares as in the trial. For public CSs, we assume 2.58 EVSEs (i.e. charging outlets) per charging location/site [82,83].

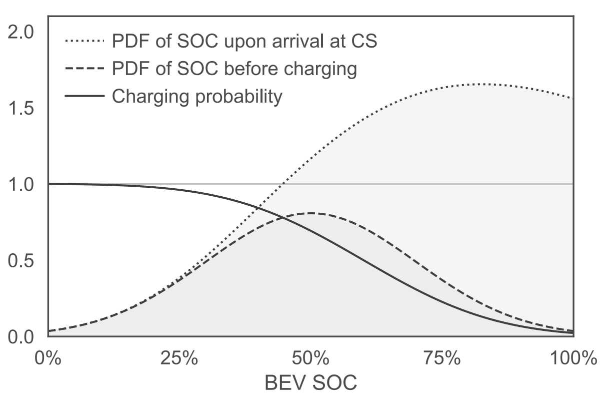

Fig. 9. Relation between characteristic PDFs and charging behaviour. The probability of charging at a given SOC (solid line) is the ratio between the times the BEV is plugged in starting from that SOC (dashed line) and all the times the BEV has a charging opportunity at that SOC (dotted line).

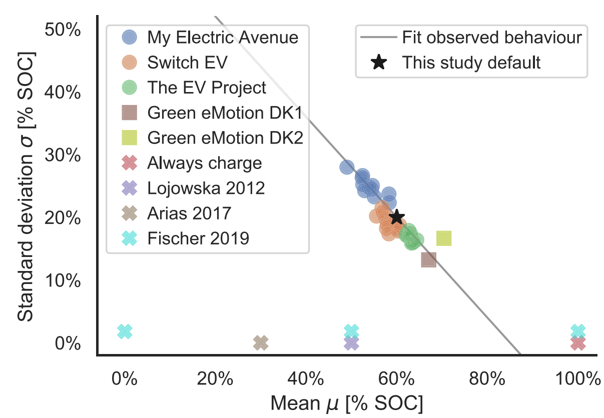

Fig. 10. Mean μ and standard deviation σ of the threshold SOC below which drivers connect their BEVs to the CS: approximations used in previous studies (×) and obtained from the trials through the methodology introduced in Section 3.2 (○, □). The weighted average of the trials thresholds is chosen as default behaviour. (★).

an S curve, which can be parametrised by fitting the survival function of a truncated normal distribution (lines 7, 8).

The procedure is short, but the two input PDFs require fully detailed records of SOCs at every CS-equipped stop, with or without a subsequent charge. While a simulation can provide this full insight, physical trials may lack some information. The majority of EV trials only reports the PDF of SOC at the beginning of a charge [46,69,62,70]. The closest examples in literature come from 2 Danish demonstrators carried out in the framework of the Green eMotion project [71]. The report on consumers' use of EVs [72] publishes, for the demo regions DK1 and DK2, both the PDFs of SOC before charge and the PDFs of SOC after trip event, i.e. at any stop. The latter may differ from the PDF at any charging opportunity thus affecting the estimation of the charging threshold. In addition, demo region DK2 involves a captive fleet composed by only 4 BEVs, while demo region DK1 employs 10 BEVs whose use case is unknown. The resulting estimates of charging behaviour are thus approximative and may not properly reflect the attitude of private BEV users. The parameters obtained when applying Algorithm 2 to these trials are indicated with □ in Fig. 10 and average $\mu = 0.69$, $\sigma = 0.15$.

Algorithm 2
Extraction of charging behaviour from characteristic distribution functions.

1: get empirical PDF of SOC before charge, c
2: get [empirical] PDF of SOC at charging opportunity (if unavailable, at any stop), s
3: smoothen c by fitting a normal PDF
4: get charging probability $p = c/s$
5: normalise $p = p/\max(p)$
6: set p for SOC < $\mathrm{SOC}_{\max(p)} = 1$
7: fit p with survival function of truncated normal distribution
8: get μ, σ of resulting truncated normal distribution

Algorithm 3
Iterative approach to derive charging behaviour from simulations.

set $\mu_{\mathrm{in}} = 0.69$, $\sigma_{\mathrm{in}} = 0.15$
for i **in** [1: N] **do**
  run 4-days simulation with inputs μ_{in}, σ_{in}
  extract PDF of SOC at charging opportunity s
  run **Algorithm 2** to get μ_{out}, σ_{out}
  set $\mu_{\mathrm{in}} = \mu_{\mathrm{out}}$, $\sigma_{\mathrm{in}} = \sigma_{\mathrm{out}}$
end for

To refine the result we make use of the trials introduced in the previous section. These demonstrators tracked the SOC only before a charge [62,69,70], but not at every charging opportunity. We accordingly extract the latter from the simulations of those trials. Since the model needs the behavioural parameters μ, σ as inputs, we initiate them according to the Green eMotion estimates and then apply Algorithm 2 iteratively. This procedure is summarised in Algorithm 3.

After the first three iterations, the behavioural parameters for each trial start converging towards similar values. The resulting μ and σ for every iteration of each trial are shown with ○ in Fig. 10. The Pecan Street trial does not provide information regarding the PDF of SOC before charge and its charging behaviour cannot thus be estimated. The three remaining trials exhibit lower charging thresholds than the Green eMotion demonstrators (lower μ). The trials also predictably show more variable behaviour (higher σ) since they involve private mobility, in contrast to the captive fleets used in DK2 and probably in DK1. Overall, the 5 demonstrators exhibit a linear trend between μ and σ, where lower mean thresholds correspond to more scattered behaviours. This joint shift of μ and σ indicates that the trials present more similar charging probabilities for loaded batteries than for depleted ones. Section 5 of SM shows in detail that the S curves in Figs. 7 and 9 of the different demonstrators look more alike at high SOCs. This pattern may be due to the different attitudes of people towards range anxiety, attitudes that emerge especially for lower SOCs. Moreover, BEVs are more likely to stop with a high SOC (trend of the dotted line in Fig. 9): this imbalance in the amount of information between low and high SOCs can cause the higher spread of charging probabilities for low SOCs. This empirical correlation between μ and σ is exploited in the sensitivity analysis (Fig. 15).

Fig. 10 also includes examples of BEV charging behaviours used in literature. All studies that employ a fixed charging threshold essentially assume no behaviour variability, i.e. $\sigma = 0$. On the other hand, a purely random charging threshold would entail $\sigma \to +\infty$ (out of scale in Fig. 10). While the results of our methodology still manifest a little volatility, these also prove that the introduced behavioural model can capture the charging attitude of BEV drivers from different contexts and that their behaviours converge towards very similar values. A weighted average that considers the higher trustworthiness of the simulated EV trials returns:

$$\mu_{\mathrm{BEV}} = 0.6 \quad \sigma_{\mathrm{BEV}} = 0.2$$

These two values, depicted with ★ in Fig. 10, are set as default charging behaviour of BEVs for the upcoming simulations and validations of all trials.

Charging behaviour of PHEVs can be estimated in a similar way, but their hybrid operation introduces an additional degree of freedom. Specifically, steps 5 and 6 of Algorithm 2 assume that a BEV driver would always charge for depleted batteries; this does not hold true for PHEV users, who can drive on liquid fuels after depletion of the battery. In other words, while BEVs owners necessarily charge all the electricity they consume, PHEVs drivers may indefinitely postpone charging while relying on conventional propulsion. This additional degree of freedom can be fixed by considering the utility factor (UF) of PHEVs or their average number of recharges per day. However, the complexity of the resulting procedure and the shortage of SOC distributions for PHEVs motivate us to adopt the same behavioural parameters as BEVs, hence:

$$\mu_{\mathrm{PHEV}} = 0.6 \quad \sigma_{\mathrm{PHEV}} = 0.2$$

It is important to remark that these parameters are not supported by empirical evidence. They are acceptable in the current framework mostly because the PHEVs employed in the trials have battery capacities comparable with the BEVs used in the calibration of charging behaviour (see Table 1).

3.3. Charging profiles and validation

This chapter presents the simulation results for the 4 EV trials obtained with the default settings, i.e. the powertrain and charging scenarios introduced in Table 1, and the charging behaviour derived in the previous section. For each trial we provide our CPs together with the reference CPs observed in the field and, whenever possible, with other simulated CPs from literature. In order to facilitate the comparison between simulated and empirical CPs, these are presented in the same units, i.e. in the way the reference CP was made available to the authors. Unfortunately, the 4 EV demonstrators report their CPs in different units (e.g. in kW or dimensionless) meaning that comparisons *between* trials cannot be confidently made. In the following validation we show which reporting units are more suitable to assess numerical and empirical CPs in order to provide a guideline for future similar works. Finally, for each trial we include the CPs resulting from multiple runs of our model so that the randomness built in the simulation can be appreciated.

Fig. 11 shows the CPs for the My Electric Avenue demonstrator. Both reference profiles come from [14] with the numerical CP obtained through Gaussian mixture models (GMM). The reference profiles are reported in absolute power demand [kW] per EV, but a deeper analysis of the original study suggests that EVs not charging during a day are neglected from the analysis. This comes from the absence of not-charging EVs in Fig. 1 of [14] and from the information that monitored EVs on average consumed 12.63 kWh/day, which translates to about 60 km/day, that is almost twice the average daily mileage of cars in England [73]. Therefore, all CPs plotted in Fig. 11 represent the average power demand for a *charging* EV, i.e. an EV that charges at least once during the day. All CPs are restricted to working days (Monday–Friday), but may originate at any location (in the default case, at home and workplace).

The CPs resulting from the proposed methodology slightly overshoot the reference peak load, but they capture the general trend closely during the day. The accuracy of our profiles from the Swiss HTS is notably comparable to the numerical CPs proposed by [14] which are based on tracking data of the same EVs that generated the empirical profiles. The local maximum around 1 p.m. is caused by Swiss residents

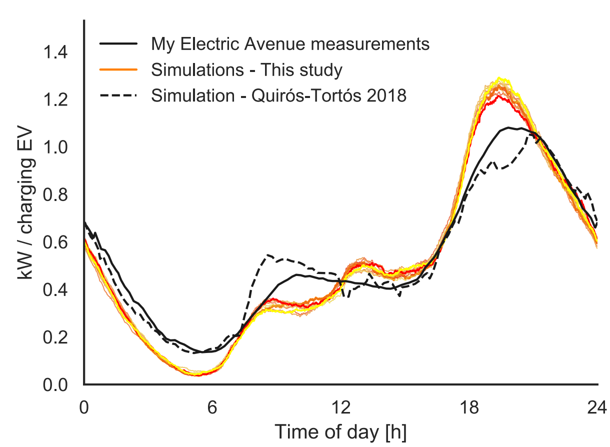

Fig. 11. CPs for the My Electric Avenue trial. The CPs represent the average power demand on a weekday for an EV that charges at least once.

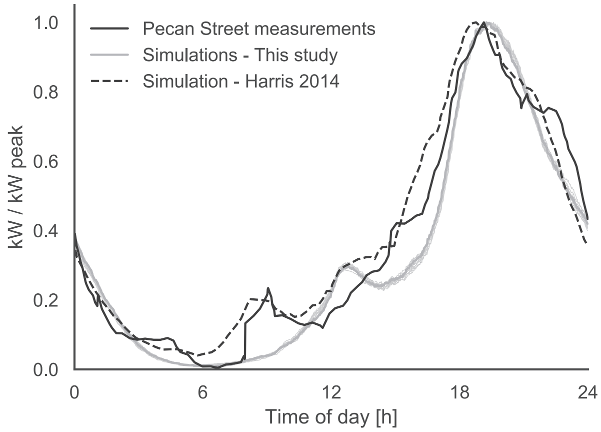

Fig. 12. CPs for the Pecan Street trial. The CPs represent the normalised power demand on a weekday for an EV charging at home.

returning home for lunch break or working part-time in the mornings (see Fig. 3). This can be explained by the higher share of part-time workers in Switzerland compared to most countries [74].

The stochasticity built in the model generates a multitude of slightly different CPs, which are depicted with various shades of orange in Fig. 11. The gradual transition from red to yellow in the evening peak has opposite direction compared to the morning local maximum (~8 a.m.), revealing that charging more at work helps to relieve the peak load at home (case of the red CP). The tendency of the colours actually suggests that the density of work CS has been underestimated in our simulations and this reflects the difficulty in translating the trials conditions into the model. The consequent overestimation of the peak load may impact the design of a local distribution grid with many EVs, but only if the total electricity demand (including non-EV applications) is also increased. However, the designs of each battery pack and charging station are not affected as they are dimensioned according to the *nominal* power exchanged while charging. This is the value reported in Table 1 and is constant for every EV regardless of the *average* charging power resulting from multiple EVs.

Fig. 12 presents the CPs for the Pecan Street project. Also for this example we provide an empirical and a numerical reference CP, where both profiles are extracted from [8]. All CPs consider only working days and home chargers. The authors of [8] propose a validation based on CPs normalised to the peak. The result is that all CPs follow a close pattern and distinguishing accurate simulations from deficient ones becomes a harder task. Our CPs exhibit a local maximum at noon, which is also mildly shown by the numerical profile of [8], but fail to capture the morning peak exhibited by both reference CPs. The empirical profile especially manifests a sharp increase around 8 a.m., which is quite unexpected from home chargers and may be due to some sort of control strategy. Such phenomena cannot be recreated by a DUOATS model that implements plug-and-charge strategies. This small mismatch is not relevant for the goal of this paper, which focuses on unscheduled charging. But future works should consider potential smart charging schemes when designing their models. Finally, the variability of our stochastic CPs is also reduced by the normalisation process.

Fig. 13 displays the CPs for the Switch EV trial for three different charging locations: home, workplace and public spaces. The empirical EV trials come from [67] and represent the charging distribution during an average day, i.e. the probability that a car is being charged at any hour. This means that all CPs are normalised to the area beneath the curves. Since MZMV deals mostly with individual mobility, the empirical CPs triggered by individual users of the Switch EV trial are adopted for the validation (Figs. 6–8 in [67]).

The comparison shows that the presented model manages to replicate all empirical CPs, capturing the specific charging features of each location. Home charging manifests the usual evening peak load already seen in My Electric Avenue and Pecan Street trials. Switch EV's peak is however smoother since the less synchronised weekend patterns are also included. On the other hand, work charging shows the highest *relative* peak load due to the high simultaneity characterising morning commuters. Finally, public chargers exhibit rather steady behaviour during all active hours. Overall, the CPs generated by the present model slightly miss the reference peak loads, but the normalisation of the profiles impedes further evaluations. Public CPs from the model manifest the biggest gaps from the reference profile, especially during the night (9 p.m.–5 a.m.), but the higher noise displayed also indicates the larger uncertainty surrounding this estimate. In addition, starting from 11 p.m. the reference public CP displays a slow night decay which resembles the domestic CP. This observation matches the findings in [67], whose authors determined that some Switch EV participants have used public CSs also for night charging.

Finally, Fig. 14 shows the CPs for The EV Project for two types of locations, private homes and public spaces, and differentiating weekdays from weekends. The empirical CPs come from the 2013 summary report on charging infrastructure of The EV Project [61] and more specifically from the Nashville region. There CPs are reported in terms of aggregated electricity demand through all charging units of the same type. With the available number of charging units per charger type (Table 1) the average empirical CP per charging unit could be derived. Therefore, in the following validation both empirical and numerical CPs are presented in terms of average power demand per charging unit, i.e. EVSE.

The first observation is that public CSs are used more rarely than domestic ones, and their average power demand is significantly smaller. This is confirmed by the lower utilisation rate of public charging units compared to residential ones reported in [61]. Secondly, while the simulated CPs reflect the general trends of the reference profiles, these also exhibit some differences. The peak loads at residential EVSEs are particularly divergent, but the differences have opposite sign on weekdays and weekends, signalling that these are not due to a calibration error. Analysing the Swiss and American HTSs [75] reveals that car drivers have opposite trends in the two countries: Swiss residents on average drive shorter distances than Americans on weekdays, but longer ones at weekends. This means that daily electricity demand of Swiss EVs is lower (or higher) than American EVs on weekdays (or on weekends). This fully explains the opposite shifts observed for domestic CSs, but also reveals the importance of checking the comparability of different data sources before attempting a validation. The investigations in [34,35] endorse the comparability between European countries, but the results of this study suggest that the same may not hold true for combinations of more diverse regions. Thirdly, the numerically simulated public CPs for weekdays nicely manifest the same three local maxima as the reference CP, while the net scaling mismatch points to a possible calibration error. As already mentioned, the adjustment of the CS density in public spaces is particularly difficult for open systems like EV trials. Finally, the simulated public CPs for the weekend accurately match the empirical profile from The EV Project.

Overall, the validation is satisfactory as the general charging trends in distinct locations and on different days are always well captured by the model. Only small differences arise, but they can mostly be explained by the usage of diverse datasets and cumbersome reporting units.

3.4. Sensitivity analysis

The previous chapter illustrates the good agreement between the outputs of the proposed model and empirical CPs when the default settings are used. The following sections reveal how the simulation responds to changes in the parameters and how a departure from the trial conditions impacts the performance of the model negatively.

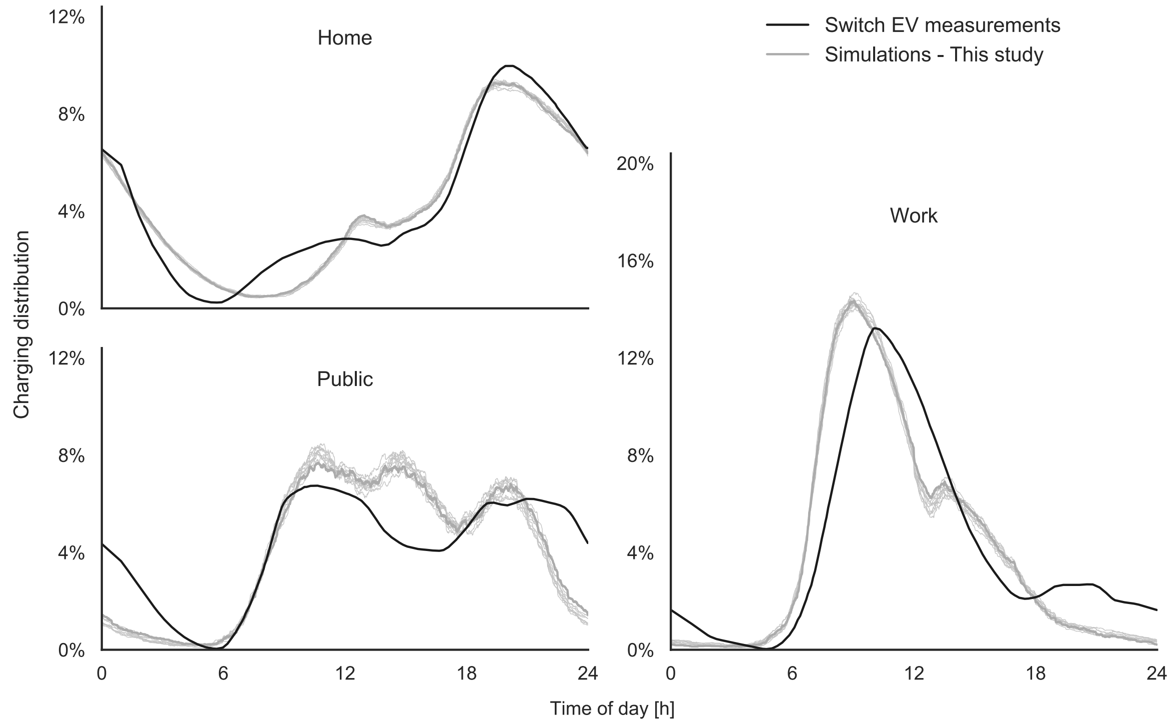

Fig. 13. CPs for the Switch EV trial at three different locations. All profiles are normalised by total daily energy and they thus represent the probability of charging at each hour. All CPs apply to an average day of the week.

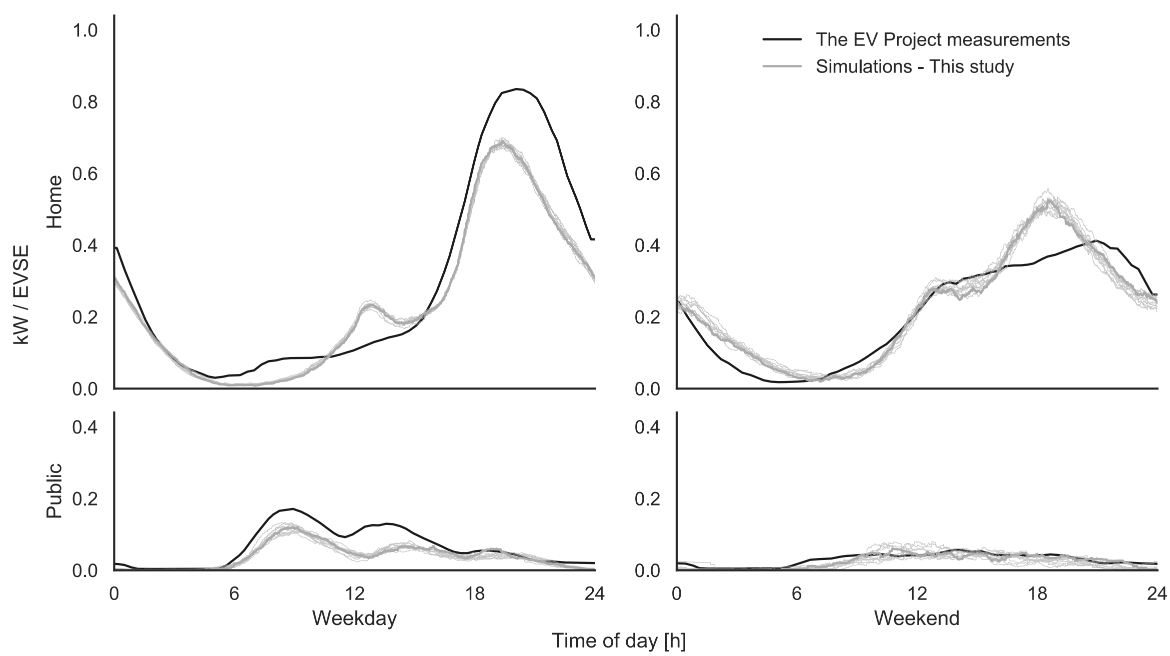

Fig. 14. CPs for The EV Project. All profiles illustrate the average daily power supplied by a single EVSE (i.e. charging unit). Top plots refer to private home chargers, while bottom ones to publicly accessible EVSEs (both at work or other locations). The left CPs apply to working days and the right ones to the weekend.

3.4.1. Metrics and nomenclature

Several measures are eligible to represent the effect of various input settings, e.g. changes in peak power load or in total daily energy supply. However, as the first study proposing a systematic sensitivity analysis, we opt for the coefficient of determination R^2, which describes the predictive power of the model when compared to empirical results. R^2 allows modellers to assess how close the numerical CPs follow the empirical profile during the whole day while still penalising a potential vertical mismatch in peak load. An examination of the predictive power during the entire day addresses more features of the model, such as charging behaviour or the car distribution among locations.

We perform two types of parametric analyses for each EV trial:

- a raw sensitivity analysis, where any quantitative input is adjusted by ± 10%;
- a set of exploratory scenarios, where particularly uncertain or evolving parameters are considerably modified.

The former helps to identify which parameters influence the output the most, and the latter investigates quantities with a broader space of

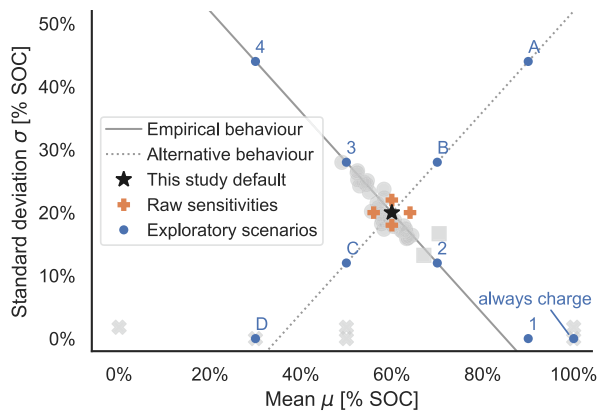

Fig. 15. Mean μ and standard deviation σ of the charging thresholds tested in this study: default case (★), variations of the single parameters by ± 10% (✚) and exploratory scenarios (•). These scenarios are either based on the observed behaviour (points 1–4 on the solid line) or on a hypothetical alternative behaviour antithetical to the former (points A–D on the dotted line). The "always charge" scenario is also tested. The points' labels link the sensitivities in Figs. 16 and 18 to the different behaviours. The background depicts the thresholds observed in trials or used in literature introduced in Fig. 10. More details are available in Section 5 of SM.

variability. For instance, vehicles energy consumption is slowly and measurably improving, but the density of public CSs is rarely well known and is changing quickly in many countries [4].

The scenarios chosen for the parametric analysis of the SOC charging threshold are shown in Fig. 15 and require specific commentary. For the raw sensitivity the input parameters μ and σ are individually adjusted by ± 10%. For the exploratory scenarios the linear behavioural pattern observed in Fig. 10 is utilised. Specifically, we design an "empirical behaviour" that fits the thresholds observed in the trials, and an "alternative behaviour" opposed to it. Conceptually, the empirical behaviour assumes that charging at high SOCs is well understood (as observed in the trials) and it spans the possible charging attitudes at low SOCs. On the other hand, the alternative behaviour assumes good agreement for low SOCs (that was not observed in the trials) and explores different charging reactions at high SOCs. For each trend we test 4 different points (1–4 with empirical behaviour, A–D with alternative behaviour). Additionally, we analyse the case where EV drivers always charge regardless of the SOC. The specific charging probabilities for all these scenarios are presented in detail in Section 5 of SM.

Figs. 16 and 18 show the R^2 results for both parametric analyses for all 4 trials. The red bars and lines indicate the scores of the default simulation settings, while all other colours refer to a change in a single input setting at a time. The grey bars depict the R^2 scores of previous validation attempts available in literature. Since The EV Project and the Switch EV demonstrator comprise CPs computed at different locations, their final R^2 coefficient is computed as a weighted average of the single scores at each location. For the weighting, we used the number of charging events per location detected during the trials [67,61].

3.4.2. Results of the sensitivity analysis

Fig. 16 presents the R^2 results for the My Electric Avenue and The EV Project trials as both are tested on CPs expressed in absolute power. In both demonstrators the CPs produced with the default settings rank among the best cases meaning that an uncalibrated setup of the simulations already allows for a very accurate reproduction of the empirical profiles. The raw sensitivities only marginally impact the quality of the results, with charging rate and losses playing a greater role as they directly impact the CPs without feeding anything back to the driving pattern. The delicate role of charging rate and losses observed in this study means that modellers must pay particular attention to these parameters when the goal of their EV model is the derivation of CPs.

This also justifies the choice not to investigate further the sensitivities of these parameters in the exploratory scenarios.

As expected, the exploratory scenarios heavily curtail the R^2 achieved by the model, because they span a much wider parametric space. The most significant impact is caused by variations in the powertrain fleet, as these changes drastically affect the total electricity consumption of EVs. The reader should notice that all BEVs used in the trials carry relatively small batteries (18–25 kWh) and can thus fulfil only the shortest trips of the HTS; this effect is important as it captures the likely use of the same BEVs in the real demonstrators. When replacing these BEVs with PHEVs with the same battery capacity, all previously unfeasible trips become possible as the driver would just switch to charge sustaining mode once the battery is drained. In other words, all trips that were deemed unfeasible with BEVs are now performed with PHEVs that finish the day with fully discharged batteries. Therefore, each new trip added to the analysis entails a total electricity consumption higher than the average trip already attainable by BEVs. The average daily electricity consumption per EV thus increases together with the daily electricity to be supplied by EVSEs. This causes longer and more frequent charges that negatively impact the R^2 of The EV Project. The same phenomenon is magnified in the My Electric Avenue trial, where days without charges are excluded from the analysis. The higher electricity consumption that accumulates on every driven day causes much longer charges on the few days the PHEV is plugged in, extending the simulated CPs and penalising R^2. This effect can be appreciated in Fig. 17, where the blue CPs represent the case where all cars are PHEVs. The same argument explains also the deterioration of R^2 when larger battery sizes are supplied to BEVs. The effect in this case is even stronger as the larger, heavier, batteries also entail a higher wheel energy demand.

Changing the density of work and public CSs also negatively impacts the predictive power of the model since it adds charging patterns that were absent in the trials. The EV Project case with no public CSs is the only scenario with an improvement of the score. This is due to two factors: firstly, the bad R^2 scores of the public CPs are excluded from the average, leaving it to the more accurate residential CPs. Secondly, the lack of public CSs forces EV drivers to charge more often at home, increasing the peak load especially during weekdays and reducing the gap with the reference profile.

Behavioural variations affect the results for the two demonstrators very differently. The major repercussion of behavioural tuning is a change in charging frequency, but the average energy to be supplied over time is only mildly impacted. The profiles reported for The EV Project depict the average daily electricity to be provided by each EVSE and a change in behaviour only lightly affects the overall magnitude of the CPs; the impact of charging behaviour is in this case limited to sharpening or shaving of peak loads. On the other hand, the profiles of My Electric Avenue consider only days where the EV is charged and a change in charging frequency causes a similar but opposite change in CPs magnitude. For instance, empirical behaviour 1 from Fig. 15 leads drivers to charge their EVs any time the SOC goes below 90%, causing more frequent and shorter charges. Both these effects are captured by the orange CPs in Fig. 17. In My Electric Avenue, the scenarios implementing an empirical behaviour expectedly show better alignment with the reference profile than the alternative ones. Notably, cases 3 and 4 improve the R^2 score compared to the default model, suggesting that the charging threshold for My Electric Avenue should have been fixed at lower μ and higher σ. Figs. 10 and 15 show that this is exactly the direction where the empirical SOC thresholds from My Electric Avenue are located with respect to the point chosen as default behaviour. This is particularly remarkable considering that no information is exchanged between the two investigations, i.e. no empirical distribution of SOC is used to compute the numerical CPs, and no empirical CP is used to derive the SOC thresholds. This good agreement between the two analyses is a strong argument in favour of the methodology used to derive the charging thresholds and the way they are included in the EV model.

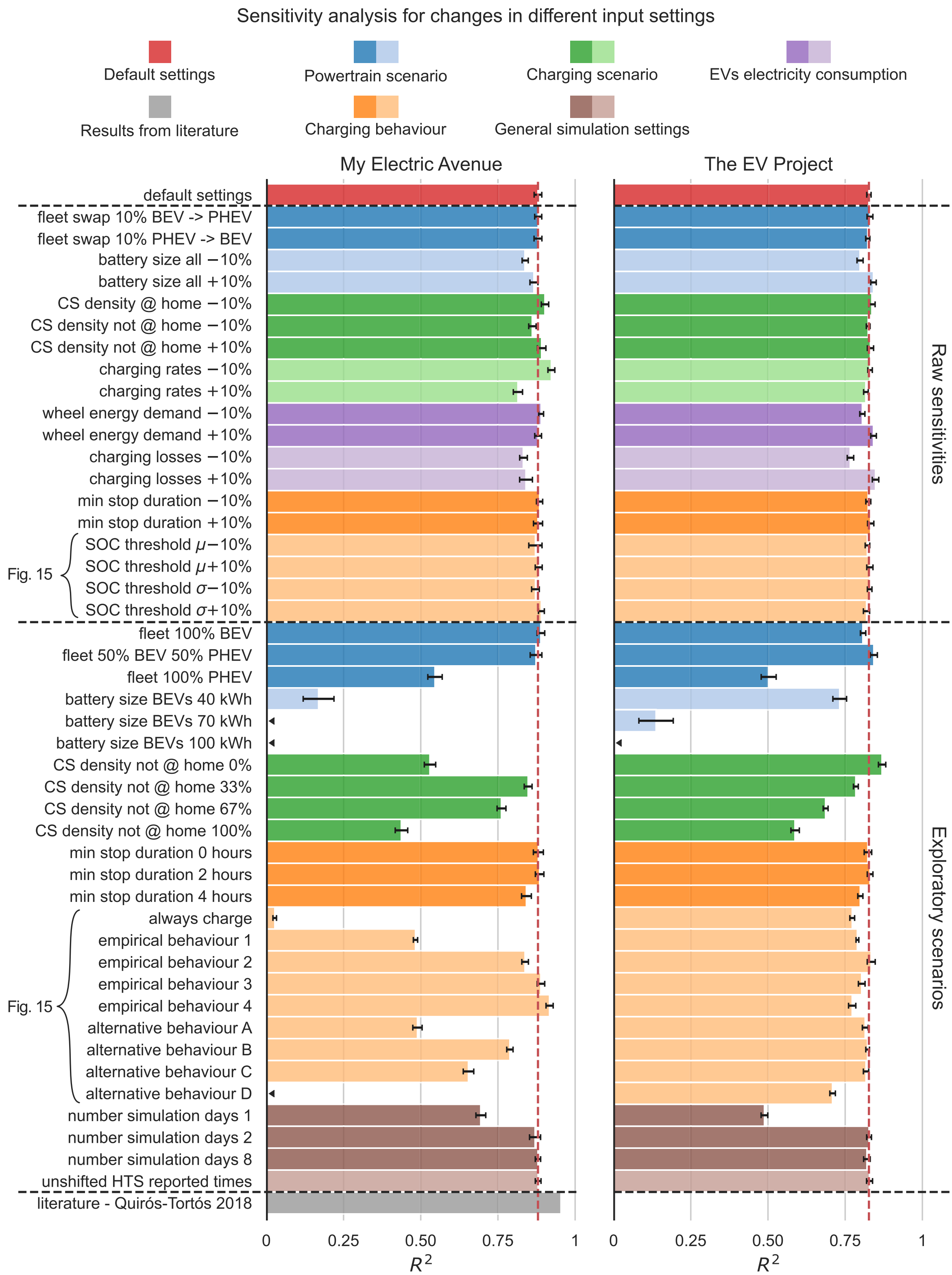

Fig. 16. Sensitivity analyses for the simulations of My Electric Avenue and The EV Project trials. The bars use the coefficient of determination R^2 to show the closeness of the simulated CPs to the empirical ones from the trials. The R^2 values shown for The EV Project are an average of the coefficients computed at each location, weighted with the number of charging events. Note that in few cases the R^2 score is negative.

The sensitivity analysis of the number of simulation days per run simply confirms that four days are more than sufficient to reach convergence, at least in terms of CPs. Finally, the employment of the original time series as reported in the HTS does not affect the general CPs patterns and leaves R^2 untouched. The impact is however appreciable at smaller scale where CPs exhibit a serrated behaviour with a frequency of 5 min. This is consistent with the probability mass distribution for *arrival* times shown in Fig. 2: indeed the shift of stages helps to reduce the number of trips reported with 5 min resolution. Although the overall impact seems small, the reader should observe that the highest

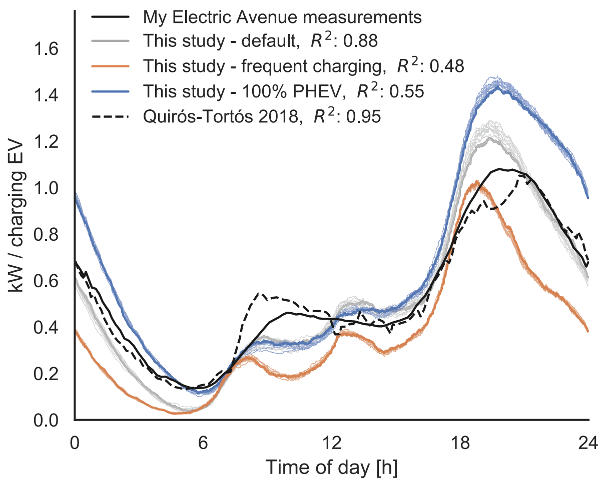

Fig. 17. Examples of My Electric Avenue CPs obtained with different settings. In blue the case with all cars being PHEVs with the original battery size; in orange the case with empirical behaviour 1 from Fig. 15, i.e. with more frequent charging.

benefit from shifting stages is the spread of *departure* times which becomes of primary importance when charging schemes smarter than the one here proposed are employed.

For the My Electric Avenue demonstrator Fig. 16 also reports the R^2 score of the numerical CP proposed in [14] and depicted in Figs. 11 and 17. The profile performs better than any CP proposed by this study, mostly because it does not overshoot the peak load. However, the reader should note that the CP from [14] is computed with data extracted from the same My Electric Avenue trial used as reference, while the present model employs the Swiss HTS as input. Most importantly, the improvement of [14] with respect to the CP generated with default settings is small when compared to other possible modelling imprecisions such as the ones investigated in the parametric analysis.

Fig. 18 reports R^2 scores for Pecan Street and Switch EV projects since all their CPs undergo some kind of normalisation. The peak load normalisation applied to CPs from the Pecan Street demonstrator particularly helps any numerical CP to closely approach the empirical profile, often resulting in R^2 greater than 0.90. To appreciate the different R^2 scores of the parametric analysis we thus magnify the x-axis scale of the Pecan Street demonstrator in Fig. 18. The simulations involving a change in the powertrain scenario are the only ones which exhibit lower R^2. As explained for the two previous trials, switching a BEV with a PHEV or expanding the BEVs' battery size both cause an increase in daily electricity consumption. This affects the extension of the CPs more than their peak load and the mismatch with the reference profile is thus retained also after normalisation.

In the Pecan Street trial the CPs obtained with the default settings are among the best performing numerical profiles, supporting the design of the model and its capability to reproduce the on-field trial conditions accurately. The simulated CP from [8] achieves a higher R^2 score, thanks mostly to its capability to capture the morning peak at 8 a.m.. As discussed in 3.3, a DUOATS model solely with home chargers is not capable of reproducing the same peak without a smart charging scheme.

The Switch EV trial exhibits a diversity in R^2 results comparable to Fig. 16, meaning that normalisation of CPs to the area does not level out the profiles as much as the peak load normalisation. The highest sensitivity is shown for changes in charging rate, charging losses and BEV battery size, which reflects most of the observations made for Fig. 16. Two additional comments are however necessary. Firstly, the simulated public CPs of Switch EV are often the worst performing in terms of R^2 as is observable in Fig. 13. The relative flatness of the reference public CP makes it an easy target for an horizontal fit. Since the coefficient of determination R^2 compares the goodness of the simulated profile to a hypothetical horizontal fit, it becomes a stricter parameter when the latter fits better the reference profile, such as in the case of public CP. This means that a lot of the variance observed in the sensitivity analysis is ascribable to changes in the R^2 score of the simulated public CPs. Secondly, the mismatches characterising home and work CPs are small but with an opposite sign. This means that even important parameter changes may affect the R^2 results of the two profiles in opposite directions, neutralising the overall impact on the metric. This is the case for the variations in powertrain scenarios, which usually imply longer average charges. When normalising to the area, these longer CPs also manifest a lower peak; consequently, a better reproduction of the reference work profile is offset by a worse performance of home CPs. An example of this effect is presented in blue in Fig. 19 for the case with only PHEVs.

The exploratory scenarios of the Switch EV demonstrator occasionally perform better than the default case. The main outlier is the scenario with no public or work CSs, but the main reason is the exclusion of the poorly performing public CPs from the computation of the overall R^2. In other words, the R^2 score plotted for this test indicates the approximate R^2 generally achieved by the numerical home CPs. A second scenario that performs better than the default case is where the minimum parking time for charging is increased to 4 h. This change mostly affects stops at public spaces as these locations are more likely to host short parking times. The variation of this parameter does not play an important role in the other 3 trials because of the lower relevance of public CPs in those demonstrators[1]. However, in Switch EV, the R^2 performance of public CPs is a dominant factor of the overall score. Increasing the minimum parking time for charging eliminates several short charges smoothening the synthetic public CPs and reducing the gap with the reference profile. This improvement strongly boosts the overall R^2 result for the scenario.

The last Switch EV scenario that performs better than the default case is when charging behaviour is shifted to point C of Fig. 15: this point lies on the alternative behaviour line and entails less likely charges for high SOCs compared to default. This adjustment mostly impacts stops during the day as EVs are always more likely to charge at home (regardless of behaviour) and end up driving with more depleted batteries in the afternoons than in the mornings. This means that public and work CPs are mostly affected by the behavioural shift to point C, with morning charges becoming less frequent. The orange profiles in Fig. 19 illustrate these changes, with morning peaks of all three locations being reduced. The CP improvements at work and public places are particularly responsible for the higher R^2 achieved by this scenario.

All the other scenarios of the Switch EV trial perform similarly to or worse than the default case, hence further validating the architecture of the EV model.

3.4.3. Summary of the sensitivity analysis

The above examples demonstrate that the model responds logically to changes in the input parameters although *a priori* the outcome is not always intuitive. The sensitivity analysis shows also that, in few cases, a careful adjustment of some parameters would allow to close the gap with the empirical CPs. However, a more important conclusion is that the uncalibrated model always ranks among the best test cases, managing to capture all important patterns at any location on any day. This work does not intend to promote the use of fine tuning to perfectly match the experimental data; rather, it provides evidence that the construction of a thought-out model that genuinely describes EVs' driving behaviour is sufficient to replicate the CPs from different contexts accurately.

[1] Note that public EVSEs in The EV Project account for recharges at both workplaces and public spaces.

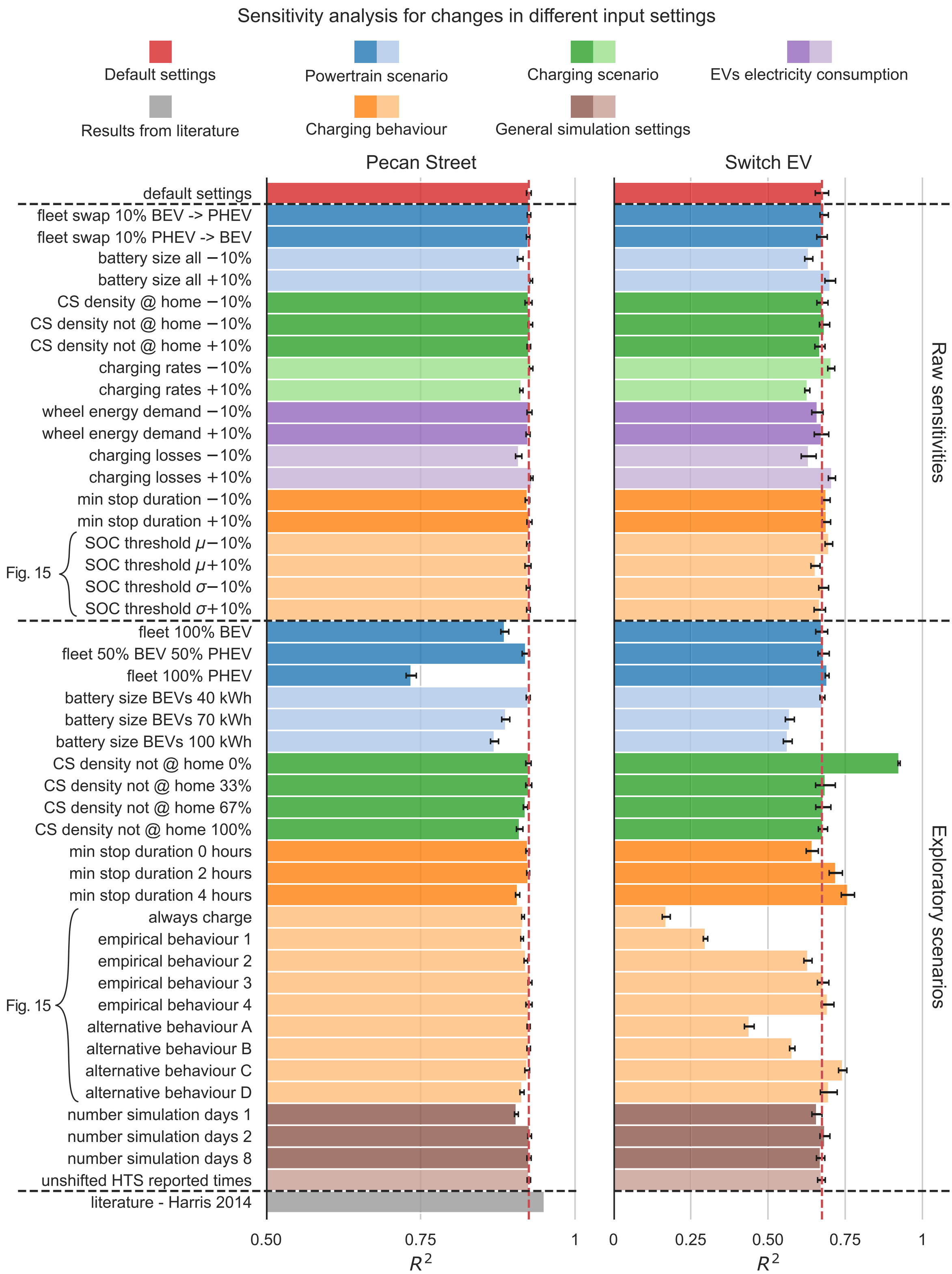

Fig. 18. Sensitivity analyses for the simulations of Pecan Street and Switch EV trials. The bars use the coefficient of determination R^2 to show the closeness of the simulated CPs to the empirical ones. The R^2 values shown for Switch EV are an average of the coefficients computed at each location, weighted with the number of charging events. Note the different x-axis scale used for the Pecan Street demonstrator.

4. Conclusions

This study demonstrates that an EV model constructed out of conventional household travel surveys (HTS) can accurately reproduce EVs' driving and charging behaviours from different environments. Policy makers or grid planners that have access to HTSs or other reliable travel diaries may thus employ EV models of the kind proposed to make sensible estimates of the expected electricity demand from EVs. The eligibility of such approach is conclusively proved in this study with the support of multiple empirical validations. Specifically, the model presented in this work accurately reconstructs the charging loads measured in four EV field tests, achieving an average coefficient of

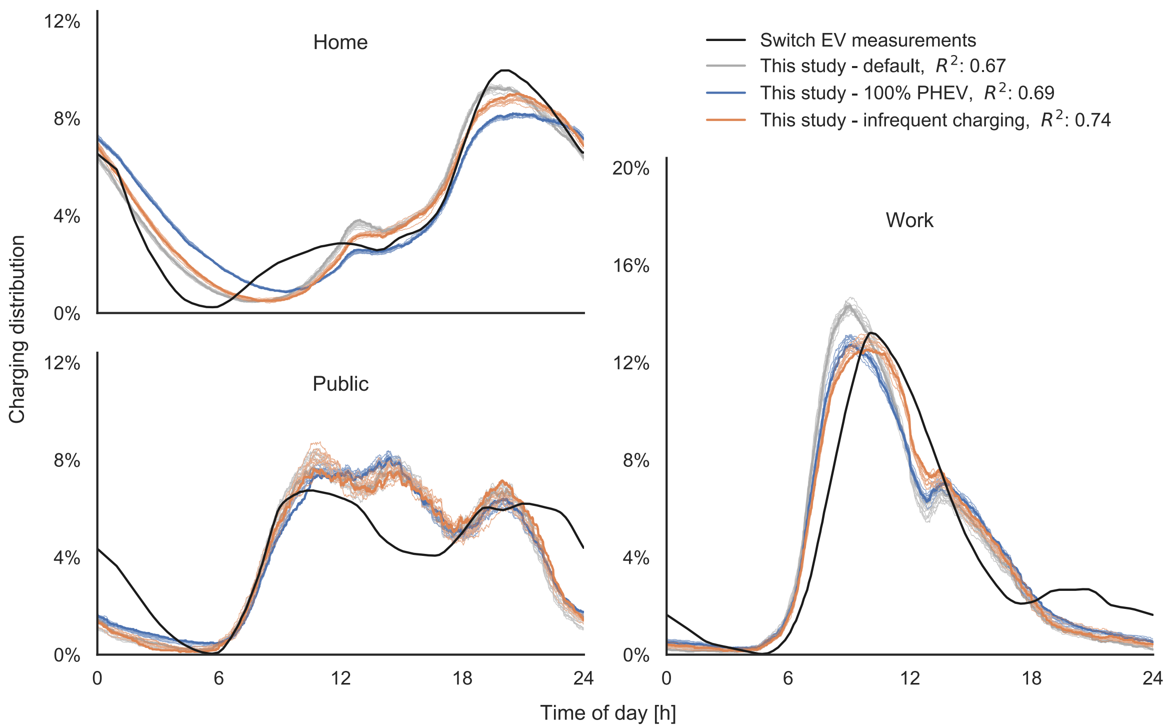

Fig. 19. Examples of Switch EV CPs obtained with different settings. In blue the case with all cars being PHEVs with the original battery size; in orange the case with alternative behaviour C from Fig. 15, i.e. with less frequent charging for high SOC.

determination R^2 equal to 0.83.

The manuscript shows that no extensive restructuring of HTS raw data is necessary to achieve good predictive power. The scientific community should thus put less modelling effort in recreating driving data as existing HTSs and other travel diaries usually provide sufficiently accurate and abundant empirical information. However, there is more uncertainty regarding the introduction of EVs and this study provides an assessment of the relevance of different specific EV features. The results indicate that the most sensitive parameters are charging losses, charging rates and powertrain design (i.e. battery size and possibility of driving on liquid fuels) since these all directly shape the energy demand once the EV is plugged in.

Importantly, the simulations achieve the highest accuracy when run with settings closely resembling the trails' conditions. When the input parameters are purposely perturbed, the average R^2 score drops to 0.70. This finding proves that the model accurately captures the dynamics of the real system without requiring fine tuning.

A decisive feature expanded in this work is the modelling of charging behaviour through a plugging-in decision process that depends on the EV's state of charge. This study introduces a calibration mechanism which combines empirical data commonly available from EV trials with the richer insights from simulations in order to generate realistic charging behaviours. This approach shows that participants in the examined EV trials tended to plug in their pure battery EVs when the state of charge fell below a normally distributed threshold with parameters:

$$\mu_{\text{BEV}} = 60\% \quad \sigma_{\text{BEV}} = 20\%$$

of the actual battery capacity.

These values differ considerably from previous estimates attempted in literature. However, employing the calibrated charging threshold markedly increases the simulations' accuracy and predictive power.

4.1. Limitations of the study

In this study, the model is employed and validated under the following specific circumstances:

- cars are privately owned and individually used,
- EVs have relatively small battery sizes,
- EVs are charged through plug-and-charge schemes.

The first choice is motivated by the goal of endorsing HTSs, which usually describe individual private mobility. However, the model in principle can accommodate any travel diary and return the respective charging loads. When HTSs are employed, the researcher should be aware that the resulting charging demand will be more accurate for private houses than public spaces, where types of mobility other than private may interfere. More generally, in models relying on exogenous travel diaries the outputs intrinsically depend on the driving behaviour captured by those travel surveys. Caution is thus always necessary when the inferred charging loads and the source travel diaries take place in different locations or ages. However, there is evidence that some countries and different time periods may share similar mobility patterns [34,35,76].

The second and third choices are driven by the EV field tests employed for the validation. The small battery capacities are mainly due to the typical car segments provided to participants in EV trials, which are constrained by economical considerations. In addition, the EVs available in the market when the field tests were conducted had smaller batteries on average. However, the field tests employed in this study are chosen for their transparency and supply of detailed information, which enable the thorough validation proposed here. The same reason explains the choice of EV trials with simple plug-and-charge schemes, which are unequivocally defined and easier to replicate.

Future field tests and modelling studies should examine contexts that exceed the three above conditions in order to generate insights applicable to the wider range of current and future realities.

4.2. Outlook

Some difficulties encountered during the work provide recommendations for further studies in the area. Firstly, there is a need for more standard reporting techniques from both EV trials [77] and numerical simulations. Charging loads are often published with different units, which make comparisons and analyses more cumbersome. The authors recommend not using normalised charging profiles because, while easier to replicate, these do not allow assessment of absolute peak load, which is a fundamental research question in the field. Charging loads should always be reported in absolute power and with a clear reference basis, e.g. charging demand [kW] per used EV.

Secondly, the scientific community should gather more knowledge regarding day-to-day mobility. Any conventional or novel vehicle (from EVs to fuel-cell cars) can cover ranges that go beyond the average daily driven distance. These vehicles do not need to refuel every day, but the energy demand triggered when that is the case depends heavily on the vehicles usage on consecutive days. Only few surveys collect this kind of information, such as the British HTS [78] for passenger cars or the Swiss *Gütertransporterhebung* [79] for freight transport.

Finally, there is a need to address the shortage of validations in the field of fleet EV modelling. There are many proposed models in literature, but very few undergo a thorough validation procedure. The major obstacle is the difficulty in collecting the right type of empirical data. Beyond the reporting problem described above, EV demonstrators are intrinsically open systems with undefined borders. This complicates the reproduction of the exact trial conditions and impedes the actualisation of a thorough validation. This paper partially succeeds in validating a Swiss HTS-based model with empirical data from different countries, but some observed discrepancies cannot be plainly attributed to the model or to the trials replicas. Future works in the field should stem from synergic collaborations between modellers and trial organisers where both parties have a concordant understanding of the system boundaries and of the mobility patterns within.

CRediT authorship contribution statement

Giacomo Pareschi: Conceptualization, Methodology, Software, Validation, Formal analysis, Visualization, Writing - original draft, Writing - review & editing. **Lukas Küng:** Methodology, Software. **Gil Georges:** Software, Funding acquisition, Project administration, Writing - review & editing, Supervision. **Konstantinos Boulouchos:** Resources, Project administration, Writing - review & editing, Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.apenergy.2020.115318.

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