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User behaviour and electric vehicle charging infrastructure: An agent-based model assessment

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HIGHLIGHTS

- Novel approach simulates impact of individual behaviour on charging infrastructure.
- Business model based on parking fees is more superior than power sales.
- At today's low penetration of electric vehicles, profitability is highly uncertain.
- Future competition can have substantial adverse impact on profitability.

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ABSTRACT

The transition to electric mobility is accelerating, and, thus it is increasingly important to be able to anticipate and adapt future development of the electric vehicle charging infrastructure. A novel agent-based simulation framework coupled with a detailed geo-referenced digital model of the built infrastructure is developed and applied. The charging behaviour of individual electric vehicle users as well as the spatial distributions of electric vehicles are accounted for in the simulation framework. More than 2500 scenarios of the transition to electric mobility in a mid-size city in Switzerland are assessed. The time to break-even of the electric vehicle charging infrastructure is up to 50% shorter when users are charged on the basis of parking fees rather than power sales. However, the revenues from parking fees are shown to be more sensitive to the behaviours and preferences of the users. At today's low penetrations of electric vehicles, the profitability of the charging infrastructure is very uncertain, and thus entrants into the marketplace will have substantial financial exposure until the penetrations are of order 10%. Additionally, it is shown that, at specific transformers, public charging considerably increases grid loads by up to 78% during peak hours; these local increases, rather than the average city-wide increase in load, are the critical determinant of the required upgrades to the distribution grid. Overall, this novel simulation framework facilitates the planning of electric vehicle charging infrastructure that will support a successful transition to electric mobility.

1. Introduction

Worldwide sales of new Electric Vehicles (EVs) surpassed 1 million units in 2017, a 54% increase compared to sales in 2016 [1]. Indeed, the global stock of EVs is expanding rapidly, having crossed the threshold of 3 million vehicles in 2017. There are a number of drivers for this transition to EVs, including policies and incentives, cost reductions and more stringent CO2 targets for cars. From the perspective of policies and incentives, targets such as the European Union's proposed 40% reduction in greenhouse gas emissions by 2030, rebates to EV owners in the state of California, and cost-free license plates for EVs in Shanghai, are amongst the drivers for transition. The cost of batteries used in EVs is now decreasing faster than suggested by historical data [2,3] and together with the entry into the EV market of traditional manufacturers of internal combustion engine vehicles [3,4], substantial cost reductions of EVs coming into the market are anticipated. Cities such as Cologne, Hamburg, and Stuttgart, amongst many others, have undertaken clean city initiatives that limit or completely ban diesel or petrol cars. Indeed, up to now the growth in the number of EVs has been driven primarily by their increased use in cities [4].

Thus, for cities, and in particular, distribution system operators (DSOs), there are significant challenges in the EV transition. One of the main challenges for DSOs is to anticipate the development in electric mobility, and then to adapt, in advance, the infrastructure for the

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Nomenclature

C_{inv}	investment costs
C_{maint}	annual maintenance costs
DSO	Distribution Service Operator
EV	electric vehicle
NPV	net present value
P^{Base}	base fee
P^{Fee}	parking charge
$\Delta P^{Surcharge}$	surcharge
r	discount rate
SOC	state of charge
t	time
t_{BE}	time to break-even
α_{DSO}	cost share of DSO

anticipated development. Planning tools that can accurately assess the impact of EVs on the infrastructure and that can optimise the finances of DSOs, in order to assure the best benefit-to-cost ratios, are required to support a successful transition to EVs. However, the development of such tools is challenging as the deployment of EVs is accompanied by new technologies and by changes in the perceptions and habits of current and future EV users. Fast chargers, new grid management solutions – such as 'controlled charging' and 'smart charging' –, individual preferences in regards to charging at home, at work or at public chargers, etc translate into significant economic and technical uncertainties around which DSOs must make planning decisions for both short- and long-term.

Different approaches have been used to assess the impacts of increased EV penetrations. Ref. [5] coupled a MARKAL model with a static transportation model to show that EVs have little effect on the energy system. The behaviour of EV users and the characteristics of EVs have been assessed on a 34-node IEEE test feeder model in [6], who show that peak loads may be of concern. Using two real distributions grids, with assumed charging and driving behaviours of EV users, [7] showed that peak hour charging had the main impact of the distribution grid. The placement, size and operation of public charging stations have been investigated in a number of different studies. A genetic algorithm technique has been used by [8] to find a layout that minimised the total cost of deploying charging stations. The formulation of a classic set covering problem was used to investigate and optimize the utilisation of charging stations [9]. Recently, the optimal layout of multi-types of public chargers, derived using a two-step equivalence method, has been investigated [10]. Using a 31-bus distribution system, the overall cost of the EV charging infrastructure has been demonstrated to be reduced with the optimal layout. Coupled models of the distribution and transportation networks have been used to identify locations of the least expensive charging stations [11]. A K-means clustering method has been used to determine the optimal number, location and capacity of public charging stations that maximise the profits of a distribution system operator [12]. Considering the characteristics and number of EVs and the technical specifications of charging stations, [13] assessed the locations and sizes of charging stations on the Italian highway system. Ref. [14], used a Markov chain model coupled with geospatial maps to estimate the charging load arising from electric vehicles in a city; three distinct charging profiles (home, work and other) were modelled and applied on a model of the city of Uppsala, Sweden.

Some previous studies have focused issues that arise from EV charging at home. The coordination of EV charging at homes in order to avoid grid congestion and voltage problems has been examined [15]. As exact forecasting of household loads is not possible, stochastic models of load profiles have been studied to develop optimal charging profiles that minimise the power losses associated with the charging of EVs at homes [16]. A stochastic bottom-up model that accounts for socio-economic, technical and spatial factors was developed in [17], and it was shown that uncoordinated EV charging at home has a profound impact on the distribution grid. The economic rational of EV charging infrastructure has not been extensively studied. Ref. [18] examined the uncertainties of EV rollout and showed that at low EV penetrations the investment in fast charging infrastructure is hardly profitable. Ref. [19] showed that the needs of specific EV users should be accounted for in the development of networks of standard chargers. Ref. [12] observed that the profits of a DSO do not necessarily increase with increased EV penetration, as the costs of establishing parking lots is often higher.

It is evident from above that a number of different behavioural, economic, technological and sociological factors are driving the EV transition. In order to holistically plan and assess an EV charging infrastructure that will support a successful transition to EVs, we develop a novel simulation approach in this work. Compared to prior works, the present work is novel in the following regards:

1. Agent-based population and mobility models are used to simulate, respectively, the activities of individual agents and the agents' travel between his/her locations of activities. The use of agent-based models means that our novel simulation approach has several advantages to prior studies. Firstly, the agent-based models distinguish the characteristics and behaviours of all individuals in the population. Second, the agent-based models can account for the interactions between agents, between agents and the infrastructure, and between agents and the environment. And third, unlike models that are based on past statistical data, and which therefore do not account for future changes, in the agent-based framework, future changes can modify the behaviours of agents.

2. *A priori*, for current and future penetrations of EVs, the users of EVs are most often unknown. We have developed a stochastic model of EV users, such that realistically plausible distributions of EVs in a population can be generated, and therefore uncertainties related to EV adoption can be accurately assessed. Thus, even in the absence of surveys of EV use or EV ownership, or in locations where there is not yet penetration of EVs, our novel simulation approach may be used to plan EV charging infrastructure.

3. Human patterns of EV charging behaviour are stochastically modelled. Thus, by running multiple simulations while varying charging behaviour, both the average impact, as well as the uncertainties due to certain behavioural patterns, can be established.

4. Our novel simulation approach uses digital twins of the actual built infrastructure with all physical components. For the test-case city, all 14,000 buildings in the city, all locations of activities (that is of living, working, leisure, etc.), all parking lots, and all transformers, all middle-voltage lines and all low-voltage lines of the distribution grid are geo-referenced and modelled. Furthermore, to accurately assess the population and mobility, all individuals of the country's population, including the city's inhabitants and commuters, are modelled using agent-based simulations. For the first time, using a recently developed GPU mobility simulator [20], large-scale agent-based simulations are combined with the high-resolution digital model of a DSO's infrastructure to assess the technological and financial impacts of the deployment of electric vehicles from the perspective of a DSO, with a focus on the consequences of different customer behaviour. Furthermore, this novel methodology has been validated using measurement data.

The structure of this paper is as follows. In the next section, the methodology is described in detail. The results of validation studies and the outcomes of different scenarios are then described. The paper concludes with a summary of the main findings of this work.

2. Methodology

Our in-house agent-based simulation framework, EnerPol, is extended in the present work. EnerPol is a bottom-up simulation framework, which in previous work has been demonstrated as suited for scenario-based assessments to support decision-making for a broad range of stakeholders, including: transportation [20], policy makers [21], developers of infrastructure for electricity transmission systems [22], gas systems [23], and urban planners [24]. In the present work, we integrate into the EnerPol framework (i) new stochastic models of EV use and of the charging behaviour of EV users, and (ii) a new deterministic model to evaluate, at the level of the distribution grid, the electrical demand arising from EV charging. These novel models utilise EnerPol's already existent agent-based population and mobility models; thus, for sake of completeness, while details of the latter can be found elsewhere, [21] and [20], below both the existent and novel models are described. With this extended simulation framework, for a given scenario, the daily activities of all individuals of a population, including the driving and charging of EVs, are simulated with one-second temporal resolution over a week-long period. Based on the simulation outcomes, the technical and economic impacts on the EV charging infrastructure can be accurately assessed.

2.1. Agent-based population model

In the agent-based population model [21], a synthetic population of individual agents is generated from population statistics at the municipal level and from databases of housing stock and activities. Characteristics such as total population, age distribution, income distribution, household structure, employment status, etc., are amongst the population statistics, and features such as the availability of a parking garage, the structure of the building, etc., are in the database of housing stock. Examples of the locations of activities of individual agents in the synthetic population include office workplaces, shops, schools, etc. Each individual agent is linked to a household, and is assigned a dwelling and, if relevant, a workplace. The demographics and the locations of activities of each individual agent are the basis for generating the activity-based demand, which is comprised of a set, typically three, of daily plans for each individual agent; each daily plan consists of travel start times, destinations, and the preferred mode of transport.

2.2. Stochastic EV use model

For a given penetration of EVs, the total number of EVs is determined, and multiple different sets of distributions of these EVs are generated in the stochastic EV use model. In each set, the EVs are randomly assigned to eligible agents of the working population. An agent is eligible to have an EV assigned to him/her, if the EV has a range that is equal to or greater than twice the distance between the agent's dwelling and workplace. As the users of EVs are generally not known a priori, this stochastic EV use model allows the extended EnerPol framework to be applied even in geographic areas where either no survey of EV use or ownership exists, or where there is as of yet no penetration of EVs in vehicle fleet.

2.3. Stochastic behaviour model of EV user

The human patterns of EV charging behaviour are stochastically modelled. In this regard, when the battery state of charge is less than 50%, the probability of charging is determined. In this work, we consider two different behaviours – a price-driven behaviour and a comfort-driven behaviour – and the respective probabilities of charging at a given instant in time are modelled as follows:

A. Price-driven behaviour: the probabilities are assumed to be inversely proportional to the price of charging at home, work, or public charger at the time of the opportunity to charge; and
B. Comfort-driven behaviour: the probabilities are derived from a recent analysis of surveys of EV charging behaviour [25]. These probabilities are summarised in Table 1. For example, the probabilities of an agent, who lives in a single-family house, charging at home, work, or public charger are respectively, 81%, 9% and 10%.

Table 1
Summary of probabilities of charging at home, work or public charger, when an agent with comfort-driven behaviour has an opportunity to charge his/her EV. k is scaling factor.

Place of charging	Dwelling type		
	Single-family	Multiple-families	
		No garage	With garage
Home	0.81	0.00	k · 0.81
Work	0.09	0.09	k · 0.09
Public charger	0.10	0.91	k · 0.10

Scaling factors are applied to ensure that the sum of probabilities is unity.

It is worth noting here that the use of stochastic models, as described above, can result in uncertainties in the outcomes; sometimes this can be a challenge to interpret.

2.4. Agent-based mobility model

The activity-based demand that is generated in the agent-based population model is used in EnerPol's agent-based mobility model [20]. This mesoscopic, queue-based model is multi-modal, and simulates, with one second temporal resolution, vehicular transportation. In a mobility simulation, with one daily plan per agent, the agents perform their daily activities and travel between locations of activities. Each mobility simulation is scored based on a cumulative utility function that accounts for the travel times of all agents. Based on a given probability, a sample of the agents modify or leave as is their individual daily plans; re-routing on account of traffic congestion or changing mode of transportation are two examples of modifying the daily plans. The daily plans of the agents are iteratively varied until the population reaches a Nash equilibrium. For EVs, the simulated driven distance, travel time and time of arrival at home/workplace are subsequently used to quantify the electric consumption of each EV.

2.5. Deterministic EV charging infrastructure model

The top 10 EVs in terms of 2017 sales in Switzerland [26,27], Table 2, are included in the model.

Consistent with other studies (for example, [1,28]), the three charging options, of at home, work, or public charger, are modelled as follows:

- Home charging: charging duration of more than 4 h using standard home AC plugs;

Table 2
Characteristics of electric vehicles.
Sources: [26,27].

EV model	Share of sales [%]	Autonomy range [km]	Consumption [kWh/(100 km)]
Tesla S	39.8	528	23.6
BMW i3	21.5	160	16.8
Renault Zoe	12.0	240	14.6
Nissan e-NV200	5.6	170	15.8
Mercedes B 250	5.5	200	24.9
Nissan Leaf	4.6	250	18.6
Kia Soul EV	4.0	212	19.8
VW E-Golf	3.4	190	17.4
Smart Fortwo	2.0	145	15.1
Mitsubishi i-Miev	1.6	150	18.6

- Workplace charging: charging duration of more than 4 h using wall-boxes; and
- Charging at public chargers, with a minimum charging duration of 15 min, using either:
  - o AC chargers (having a nominal power of 15–20 kW) that are installed in public parking lots; or
  - o Fast DC chargers (having a nominal power of 100–150 kW) that are installed at hotspots

The public chargers are assumed to operate with a conversion efficiency of 90%. Tapering of the charging speed occurs from a battery state of charge (SOC) of 80%, and charging end when the battery SOC reaches 95%.

The investment and annual maintenance costs of the EV charging infrastructure are summarised in Table 3. It should be noted that discount factors are applied when multiple chargers are installed at the same location [29].

2.6. Optimised placement of public EV charging infrastructure

In this work, for the purpose of assessing new EV public charging infrastructure, the EnerPol simulation framework is further extended by embedding the agent-based mobility model within an optimiser, which optimises the placement of the EV public charging infrastructure across the city. The optimal placement maximises the load factor of public chargers.

As shown in Fig. 1, for a given penetration of EVs, a sequence of placement and mobility simulations is used to determine this optimal placement. Initially, similar to the approach used in the modelling of power systems in EnerPol [22], a Voronoi tessellation centred on the locations of the low-voltage transformers is established. Then, in a first step of the sequence of simulations, one public charger is allocated to each Voronoi cell, and then in a second step of the sequence, a mobility simulation is conducted in order to assess the usage of the public chargers. In subsequent iterations of the sequence, public chargers are added or removed with the goal of maximising the load factor of the public chargers. In particularly busy locations, which have more than 20 users per day, AC chargers are substituted with DC fast chargers, in order to minimise the queuing time of EV users. Further, if the load factor is less than 1 h per day, then chargers are removed. A Monte Carlo approach is employed, as in each iteration one of the sets of randomly distributions EVs, for the given penetration of EVs, which are generated in the stochastic EV use model, is used. The iterative sequence of placement and mobility simulations is considered converged when there is less than 5% difference in the successively predicted: electricity supplied for charging at (i) all homes, (ii) all workplaces, and (iii) all public chargers; (iv) usage of each charging station; (v) number of required public chargers; and, (vi) share of agents not able to find an available public charger. The agent-based mobility model, as well as agent-based population model, are run on GPUs and, therefore, provide high resolution simulations in a reasonable amount of time. Since our methodology is based on agent-based mobility and population simulations, very detailed data and high-performance computing resources are required.

2.7. Databases

In the present work, the entire population of Switzerland, 8,534,667 individuals, [21], is considered, with a focus on the city of St. Gallen that has 75,500 inhabitants. The entire Swiss driving population of 5,200,000 agents [20] is simulated, and for the city of St. Gallen there are 23,000 internal daily commuters and 39,000 external commuters circulating by car in the city each weekday. The characteristics of individual buildings and the locations of activities are extracted from highly detailed databases such as the Swiss Federal Registries of Residential Buildings and Dwellings [30,31] and the Swiss Federal Registry of Economic Activities [32]. A geo-referenced digital model of the city's distribution grid that includes 185 transformers, and all of the city's middle-voltage (10 kV) and low-voltage (400 V) lines is developed. When assessing the impact of EV demand on grid load, the additional electric demand is aggregated at low-voltage transformers and compared to the predicted demand derived from power flow simulations without EVs.

2.8. Scenarios

For the case of the existing EV charging infrastructure in the City, 1260 scenarios have been evaluated, in which the EV penetration, the source of revenues, the charging behaviour of EV users, and the preferences of EV users are varied. For the case of new EV charging infrastructure in the City, 1308 scenarios have been assessed.

The simulation parameters can be described as follows:

- EV penetrations. The ratio of EVs and the entire vehicle fleet circulating to or within the City that are simulated are 0.3%, 2%, 5%, 10%, 15% and 20%. The EV penetration of 0.3% is the 2018 EV penetration in Switzerland [33]; the EV penetration of 2% is the 2020 goal for the City [34]; and the 20% EV penetration is the City's 2030 goal and the EV penetration that is anticipated for Europe in 2030 [1]. In the 20% EV penetration case, 12,078 EVs are simulated. For all EV penetrations greater than 0.3%, on account of the expected improvements in technology, the efficiencies of EVs are increased up to 25% over the baseline case used in the 0.3% EV penetration case [28] and the conversion efficiency of chargers are increased to 94%.
- Source of revenues. Two alternative options are considered. In the first option, EV users are charged by the amount of power used to charge the EV. The power charge is a multiple of the average Swiss electricity price (which was 0.20 Swiss Francs/kWh in 2018 [35]). The marginal gain for the DSO is assumed to be a multiple of 0.16 Swiss Francs/kWh, which is the difference between the European Energy Exchange wholesale electricity price in Switzerland and the electricity price for households [35]. In the second option, EV users are charged by parking duration. The parking charge is $P^{Fee} = P^{Base} + \Delta P^{Surcharge}$, where the base fee, P^{Base}, is the same as the City's current market price for parking of traditional vehicles, which is 2 Swiss Francs/hour, and the surcharge, $\Delta P^{Surcharge}$, is 2 Swiss Francs/hour.
- Charging behaviour of EV users. As described above, a price-driven behaviour and a comfort-driven behaviour are simulated, each with respective probabilities of charging at home, work or public charger.
- Preferences of EV users. Three charging preferences of EV users are considered: (i) leaving the parking space immediately after completion of charging; (ii) leaving the EV plugged in for a buffer time; and (iii) moving the EV after work.

2.9. Evaluation of profitability of EV charging infrastructure

The profitability of the EV charging infrastructure is evaluated in terms of time to break-even (t_{BE}) (Eq. (1)). This period between the first year of operation and break-even year, is determined when the net present value of the infrastructure is equal to or greater than 0. A

Table 3
Modelled charging elements and associated investment and maintenance costs.

Charging option	Element	Power (kW)	Investment (Swiss Francs)	Annual maintenance (Swiss Francs)	DSO cost share α_{DSO} (%)
Home	Plug	2.3	–	–	0
Workplace	Wall Box	10	6000	1200	20
Public	AC (2018)	15	20,000	1200	100
	AC (future)	20	25,000	2000	
	DC (2018)	70	100,000	2500	
	DC (future)	150	110,000	2500	

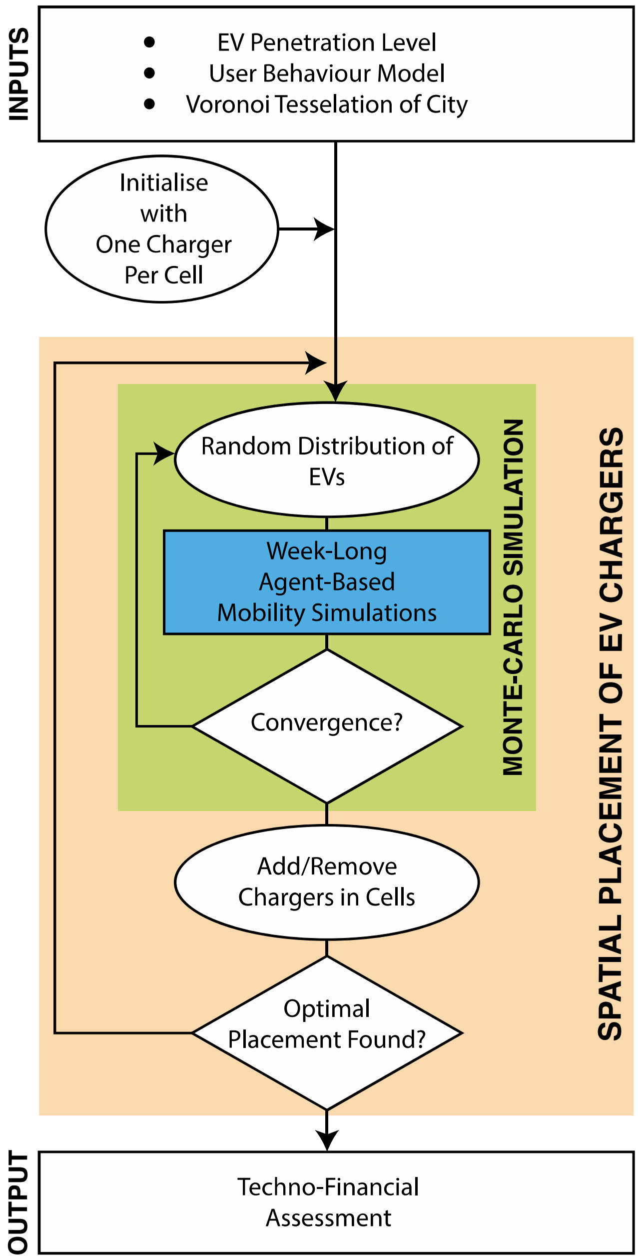

Fig. 1. Schematic of iterative sequence of placement and mobility simulations that is integrated into the EnerPol framework.

discount rate r of 5% is used. The revenues and costs of all components of the infrastructure (chargers and wall-boxes) are considered; thus, it is possible that EV users who charge at home may also payback for the investment in public chargers. From the DSO's perspective, this approach provides the most complete evaluation of profitability.

$$0 = NPV\,(t_{BE}) = -C_{Inv}\cdot\alpha_{DSO} + \sum_{t=0}^{t_{BE}} \frac{(Revenues - C_{Maint}\cdot\alpha_{DSO})}{(1+r)^t} \tag{1}$$

3. Results

3.1. Validation

Fig. 2 compares the predicted and actual monthly charging cycles in 2017 at the four most widely used public charging stations of the City. The geographic locations of the 4 charging stations are also shown in Fig. 2. In 2017, the City had a total of 23 public chargers and the EV

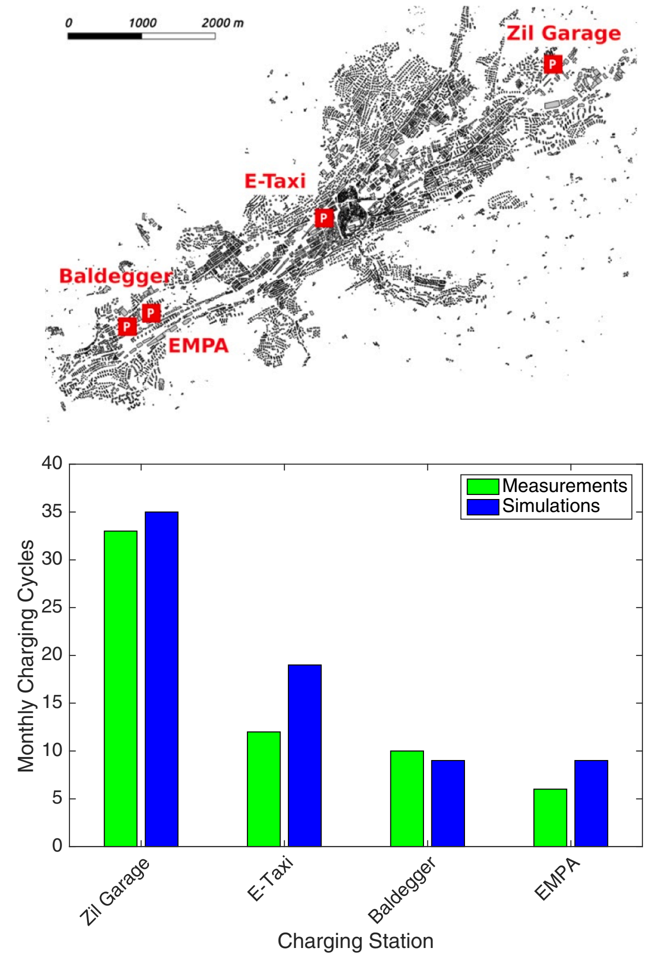

Fig. 2. Locations (upper) and comparison of predicted and actual monthly charging cycles (lower) in 2017 at the 4 most widely used public charging stations of the City.

penetration was 0.3%. In the simulations a price-driven charging behaviour of the EV users is assumed. It can be seen, that there is overall good agreement between the predicted and actual monthly charging cycles. For all public chargers, simulations predict an average of 106 charging cycles per month, a 4.3% difference to the actual average of 110.8 charging cycles per month. For the City's 23 public chargers, the predicted and actual monthly supplied electricity are 1.18 MWh and 1.05 MWh, respectively; a difference of 12%. This overall good agreement between predictions and data validates our novel agent-based simulation methodology.

3.2. Existing infrastructure

In the following, we assess scenarios where, as the EV penetration increases, the City's existing EV infrastructure of 23 public charging stations is unchanged. Fig. 3 compares the DSO's revenues from charging at home, work, and public chargers, for the two options of paying for the use of public chargers – sales of power and parking duration. In the first option, power sales, the price of charging is 0.20 Swiss Francs/kWh, which is the 2018 market price for EV charging in the City, and in the second option, parking fees, the price of charging of 4 Swiss Francs/hour is the City's current market price for the parking of traditional vehicles. Further in Fig. 3, the two different charging behaviours of EV users – price-driven behaviour and comfort-driven behaviour – are assessed. It can be seen that for a given EV penetration, the DSO's revenue from parking fees is greater than the revenue from power sales, both for price-driven and comfort-driven charging behaviours. Even though a business

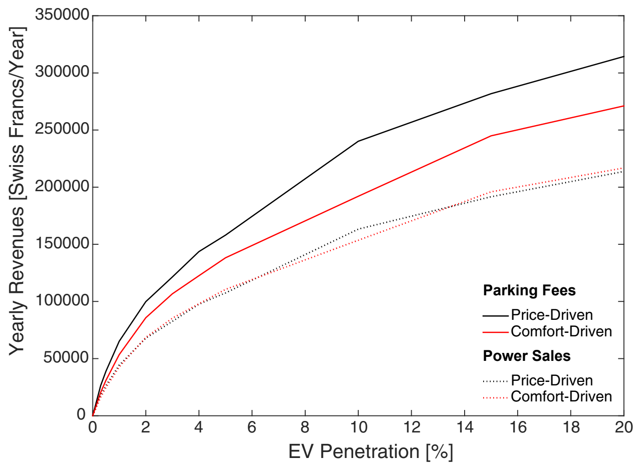

Fig. 3. Comparison, for EV users with price-driven and comfort-driven charging behaviours, of the effect of EV penetration on the DSO's revenue for EV charging based on parking duration (solid lines) and power sales (dotted lines).

model based on parking fees rather than power sales generates more revenue, this business model shows greater sensitivity to the charging behaviour of EV users, and the revenue is lower for comfort-driven charging behaviour compared to price-driven charging behaviour. This observation highlights also an advantage of agent-based models in comparison to models that forecast based on historical statistical data, as agent-based models can account for the interactions between agents and their environment, whereas statistically-based models do not account for such interactions. Because of the feedback included in our agent-based simulation framework, changes in pricing systems affect the choices of EV users and, in turn, the design, costs and revenue of the EV charging infrastructure. For example, doubling the electricity price neither doubles revenue nor halves the time to break-even.

The effect of EV penetration on the time to break-even of the City's existing EV infrastructure is shown in Fig. 4. Two business unit cases are compared: (i) the business unit manages all EV charging infrastructure; and (ii) the business unit manages only the public EV charging infrastructure. In both cases, the DSO's revenues come from parking fees, and the EV users have price-driven charging behaviour. Whereas a business unit that manages all EV charging infrastructure will have a time to break-even of 11 years at today's EV penetration of 0.3%, and subsequently shorter times to break-even as the EV penetration increases, a business unit that manages only public EV charging infrastructure will only break-even when the EV penetrations are 4% or higher.

Recently, it has been announced that private companies plan to enter the market of public EV chargers in St. Gallen [36]. In Fig. 5, the impact of 10 proposed privately-owned public chargers on the DSO's existing infrastructure is assessed. In the assessment, the DSO's revenues are based on parking fees, and the EV users are assumed to have a price-driven charging behaviour. It can be seen that the privately-owned public chargers have a substantial adverse impact, with a 35% decrease in load factor for a 2% EV penetration, on the DSO's revenue from its existing infrastructure, Fig. 5 (a). At two representative public charging stations of the DSO, the impact of competition on the annual revenue is shown in Fig. 5 (b). It can be seen that at both public charging stations, there is an adverse impact on the DSO's revenue, even at high penetrations of EVs.

3.3. Future infrastructure

In the following, we assess scenarios in which the City's EV infrastructure of public charging stations is expanded as the EV penetration is increased. Fig. 6 shows the optimised placement and number of public charging stations for EV penetrations of 2% (Fig. 6 (a)), 10% (Fig. 6 (b)), and 20% (Fig. 6 (c)). These optimised placements ensure both that sufficient EV charging is available to all EV users and that the load factor of the public chargers is maximum. The revenues from EV charging are based on parking duration, a price-driven charging behaviour of the EV users is assumed, and different preferences of EV users – that are: leaving the parking lot immediately after charging; leaving 30, 60, 120, 240 or 480 min after charging; and, leaving at the end of the EV user's workday – are assessed. As can be seen from Fig. 6, and summarised in Table 4, the median number of required chargers increases with EV penetration. It is noteworthy that at busy locations, in order to minimise the queuing time of EV users, DC fast chargers are deployed in place of AC chargers. As a guideline, a ratio of 10 public chargers to 100 EVs has been targeted in Europe [1]. For an EV penetration of 10%, the simulations show that this target is reached, whilst the number of public chargers is in excess of the target for lower EV penetrations. As there are different preferences of EV users, in terms of when the EV user leaves the EV charger, there is an uncertainty in the median number of required chargers; it can be seen in Table 4 that the uncertainty in the median number of required chargers increases with increased EV penetration.

For an EV penetration of 2%, the effect of elasticity in demand on the DSO's revenue for EV charging and the time-to-breakeven for the EV charging infrastructure are compared in Fig. 7. Both the DSO's total (that is from charging at home, work, and public chargers) revenue and the revenue from public chargers alone are shown in Figs. 7–9. Thus, in Figs. 7 and 8, the revenue is normalised relative to the total revenue based on power sales at the reference price (of 3.5 Swiss Francs with power sales and 2 Swiss Francs with parking fees). For each option, different charging behaviours of EV users – price-driven behaviour and comfort-driven behaviour – are examined. Further, for each option, different preferences of EV users – that are: leaving the parking lot immediately after charging; leaving 30, 60, 120, 240 or 480 min after charging; and, leaving at the end of the EV user's workday – are assessed; the impact of these preferences of EV users is shown as uncertainty bars in Figs. 7–9.

It can be seen that, similar to the case of an unchanged EV public charging infrastructure, as the public charging infrastructure is expanded the DSO's revenue from parking fees is always greater than the revenue from power sales, both for price-driven, Fig. 7, and comfort-driven, Fig. 8, charging behaviours. Furthermore, for both charging behaviours of EV users, the DSO's revenue is less sensitive to changes in price, as EV users that are price-driven tend to charge, even more, at home as the price of charging is increased. Even though a business model based on parking fees rather than power sales will generate greater revenue, it can be seen that in the uncertainty in revenue, for

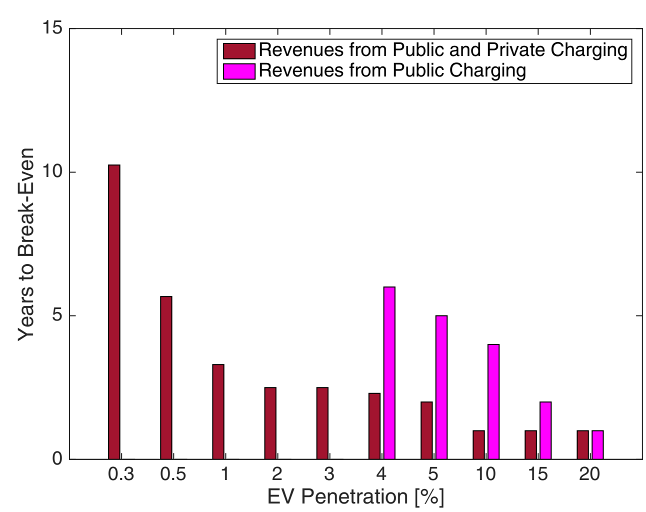

Fig. 4. Comparison of time to break-even for the cases when revenue comes from all EV charging infrastructure and from when revenue comes only from public EV chargers are considered. The revenue comes from parking fees, and the EV users have price-driven charging behaviour.

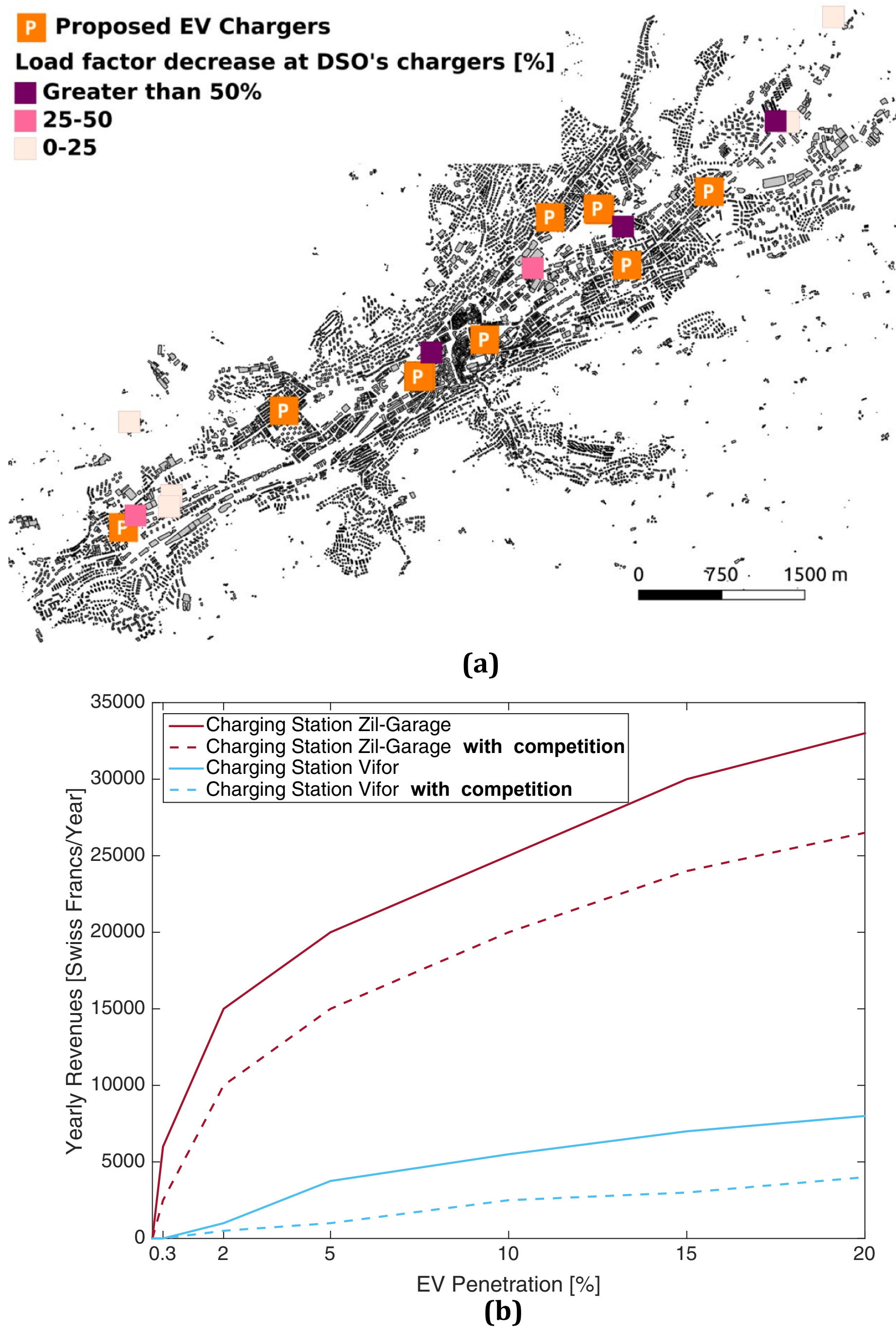

Fig. 5. (a) Locations of 10 proposed privately owned public chargers and their impact on the load factors at the DSO's existing public chargers and (b) comparison of revenue, at two of the DSO's public charging stations, without and with competition from the privately-owned public chargers.

public chargers in the case of price-driven charging behaviour, Fig. 7, and for both total and public charging revenue in the case of comfort-driven charging behaviour, Fig. 8, increases with increased prices. This increase in uncertainty occurs as EV users with a comfort-driven charging behaviour tend not to adapt their charging behaviour, as their behaviour is more driven by comfort and less so by price.

Fig. 9 shows the effect of elasticity of demand on the time to break-even of the whole EV charging infrastructure. As the time to break-even accounts for the revenues, the investments costs, and the operations and maintenance costs, the time to break-even, rather than the generated revenue, is considered a more robust assessment of the profitability of business models. Despite the increased uncertainty in revenue for a business model that is based on parking fees, a business model based on parking fees is preferred to a business model based on power sales, as the latter business model only breaks-even if the price of charging is five times the market price for EV charging in the City; even then, the time to break-even is substantially larger than for the power sales business model. It is noteworthy that while the business model based on parking fees does not break-even with sales at the reference price (which is the City's current market price for the parking of traditional vehicles), with prices of 10% or more above the reference price, the business model breaks even, and the time to break-even decreases as the sales price increases.

Fig. 10 compares the impact of EV penetration on the time to break-even, for the business model based on parking fees, for both the price-driven and comfort-driven charging behaviours. This business model

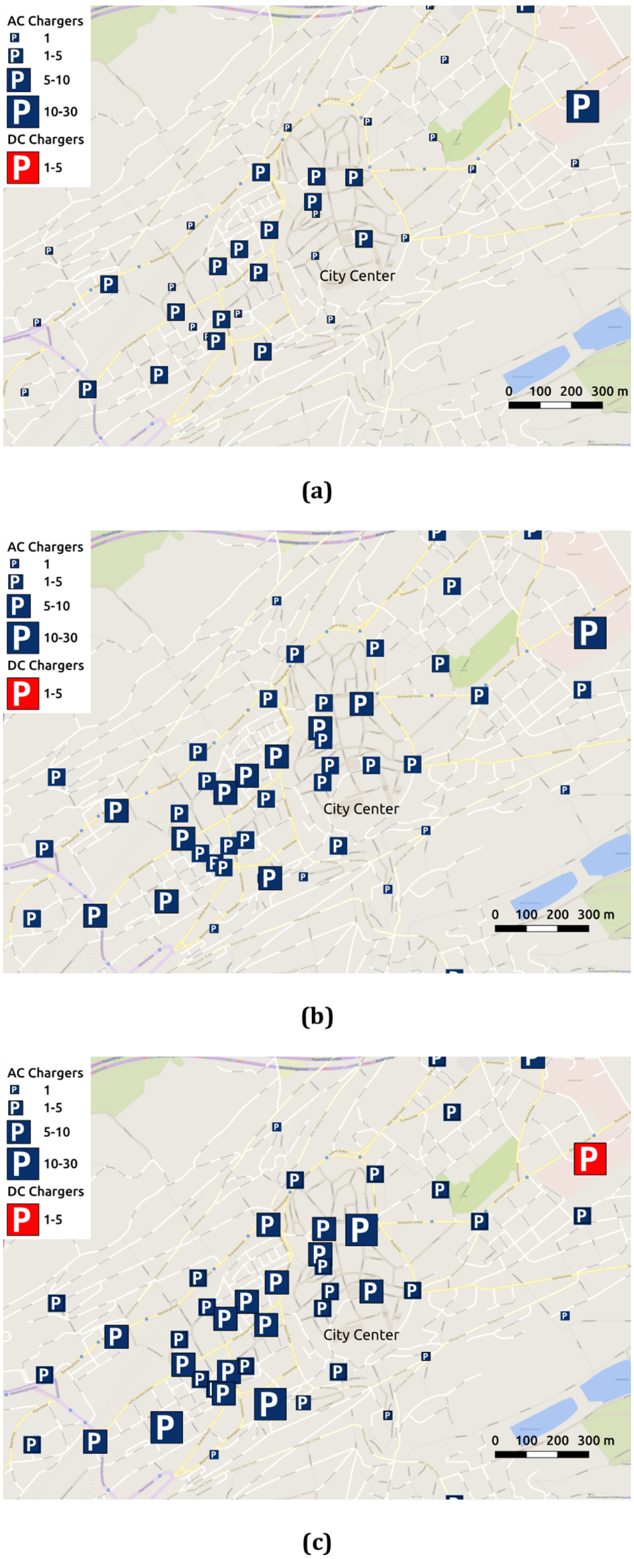

Fig. 6. Optimised placements of public EV charging infrastructure for EV penetrations of (a) 2%, (b) 10%, and (c) 20%. The size of the symbols is indicative of the number of chargers.

has been identified above as the most profitable. However, with sales at the City's prevailing market price for the parking of traditional vehicles, at the current EV penetration of 0.3%, no break-even is possible for either price-driven and comfort-driven charging behaviours of EV users. At an EV penetration of 2%, this business model is profitable only if the EV users exhibit comfort-driven charging behaviour. Thus, even though revenue increases with increased EV penetration, early entrants into the EV charging marketplace have substantial financial exposure if knowledge of the charging behaviour of EV users is unknown. Only for EV penetrations of 10% or larger is the financial exposure due to the charging behaviour of EV users reduced, and is the uncertainty due to the preference of when EV users leave a parking lot smaller.

Fig. 11 quantifies, by source, the additional electricity demand that is arises from EV charging. The EV penetrations are 2% (Fig. 11 (a)), 10% (Fig. 11 (b)), and 20% (Fig. 11 (c)) and a business model based on parking fees is used for EV users with both price-driven and comfort-driven charging behaviours. The time-series, with 1-minute temporal resolution, covers the duration of a week. It is evident that the characteristics of charging at work, home, and public chargers are different. While charging at work and at public chargers show sharp peaks in electricity demand at morning peak hours, the time-series of charging at home has less distinctive peaks, and has maxima during evenings. Over the range of EV penetrations that have been assessed, charging at home is the largest source of the additional electricity demand, and quantitatively charging at home, work, and public chargers account for 47%, 45% and 8% of the total additional electricity demand due to EV charging. It can also be seen in Fig. 11 that as our agent-based simulation framework differentiates between the activities of all individuals in the population, the trends in the additional demand differ between workdays and weekends.

For a 20% EV penetration, the maximum increase in load, at the City's low-voltage transformers is shown in Fig. 12. The increase is determined at the time of the largest hourly increase in load, and for the transformer that has the largest increase in load. It is evident that the largest hourly increase occurs in the case of price-driven behaviour, which has an increase of approximately 78% compared to 22% for the case of comfort-driven behaviour. This larger increase occurs as more EV users charge in the City in the case of price-driven behaviour. It can also be seen in Fig. 12 (a) that in the case of the price-driven behaviour, public chargers account for 80% of the hourly increase in load, whereas in the case of the comfort-driven behaviour, charging at work and public chargers are approximately equal, each accounting for 40% of the maximum hourly increase in load. In Fig. 12 (b), the load increase averaged over the City at the hour of the maximum increase in load is shown. It is useful to highlight three observations. First, it can be seen that the City-averaged increase in load of 6.1% is less that the local increase in load that is shown in Fig. 12 (a). Furthermore, averaged over the City, it is evident that EV users charging at work account for the largest increase in load, as both residents of the City and external commuters are considered. Lastly, in comparison to the case of local load increases, there is little difference averaged over the City due to the different behaviours of EV users. Overall, Fig. 12 highlights the importance of using a digital model of the actual built infrastructure, as bottlenecks in the grid, can then be reliably identified.

4. Conclusions

In this work, a novel agent-based simulation framework coupled with a detailed geo-referenced digital model of the built infrastructure is used to assess the impact of user behaviour on electric vehicle charging infrastructure. This novel approach is demonstrated in scenarios of the transition to electric mobility in a mid-size city in Switzerland. The main findings are as follows:

- For a Distribution System Operator that plans to deploy public chargers, the revenue from parking fees is larger than the revenue from power sales. Thus, a business model based on revenue from parking fees has a much shorter time to break-even. However, revenue from parking fees is more sensitive to the charging behaviour and preferences of electric vehicles users.
- For the investigated test-case, at today's electric vehicles penetration of 0.3%, the break-even of the existing public charger infrastructure

Table 4
Summary of impact of EV penetration on optimised public EV charging infrastructure.

EV penetration [%]	Median number of required public chargers	Ratio of median number of public chargers to 100 EVs	Uncertainty in median number of public chargers
2	146	12	34
5	402	13	83
10	552	9	109
20	824	7	127

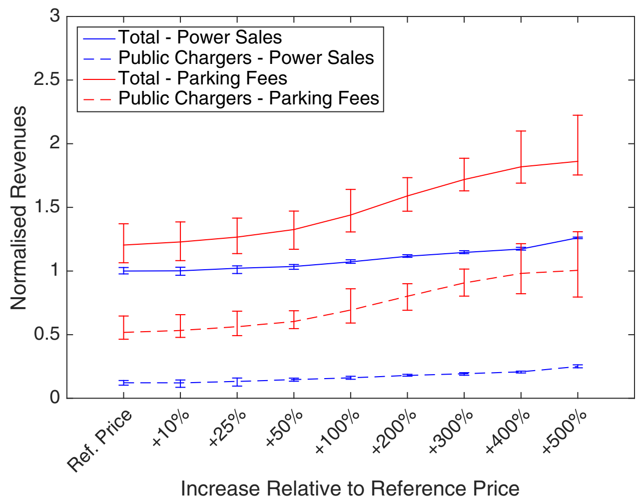

Fig. 7. Comparison, for EV users with price-driven charging behaviour, of the effect of elasticity of demand on the DSO's revenue for EV charging based on power sales and parking duration. The total revenue is from charging at home, work, and public chargers. The revenue is normalised relative to the total revenue based on power sales at the reference price. The EV penetration is 2%. The vertical bars show the uncertainty due to the preference of when EV users leave.

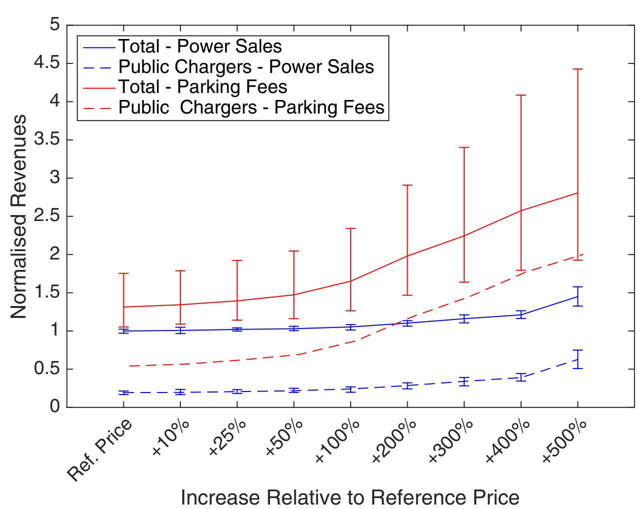

Fig. 8. Comparison, for EV users with comfort-driven charging behaviour, of the effect of elasticity of demand on the DSO's revenue for EV charging based on power sales and parking duration. The total revenue is from charging at home, work, and public chargers. The revenue is normalised relative to the total revenue based on power sales at the reference price. The EV penetration is 2%. The vertical bars, for sake of clarity not shown for public charger parking fees, show the uncertainty due to the preference of when EV users leave.

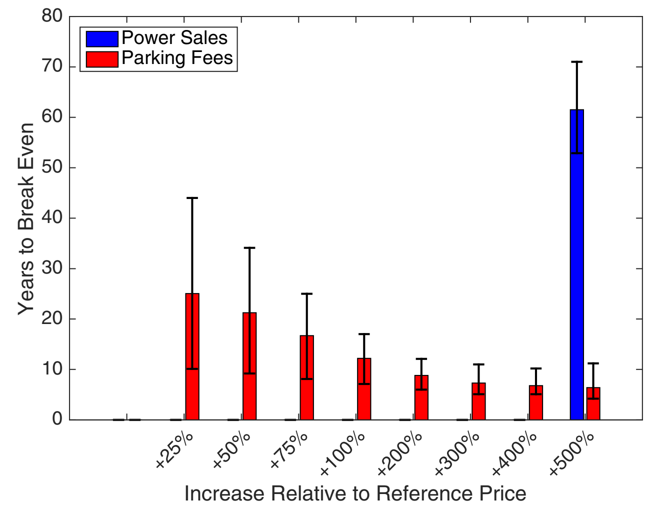

Fig. 9. Comparison of the effect of elasticity of demand on the time to break-even of the EV charging infrastructure for EV charging based on power sales and parking duration. The EV penetration is 2%. The vertical bars show the uncertainty due to the preference of when EV users leave.

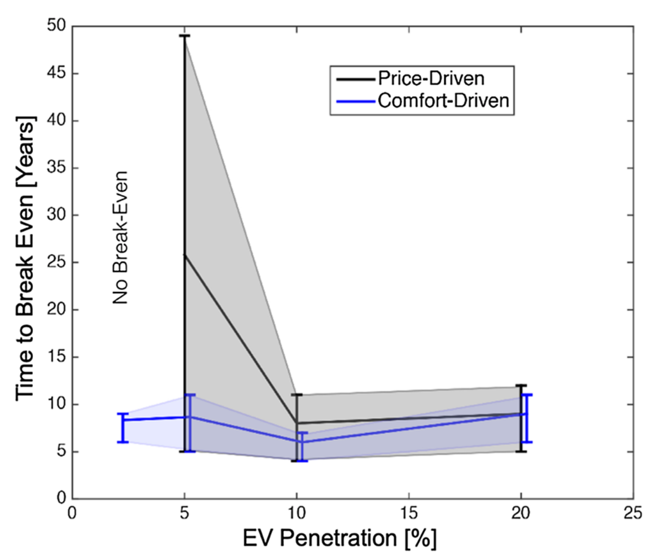

Fig. 10. Comparison, or the business model based on parking fees, the impact of EV penetration on the time to break-even for both the price-driven and comfort-driven charging behaviours. The vertical bars show the uncertainty due to the preference of when EV users leave.

of the distribution system operator is, at best, 10 years, when the business unit manages all charging infrastructure (that is from charging at home, work, and public chargers). Otherwise, break-even can only be reached if the electric vehicle penetration is 4% or greater. Moreover, competition in the public charging marketplace can decrease revenue substantially, up to 35% decrease in load factor at an electric vehicle penetration of 2% in the present test case. Thus participants in the marketplace have substantial financial exposure, when penetrations of electric vehicles are low.

- Charging at home and at work are the largest sources of the additional electricity demand due to EV charging. While charging at work is characterised by sharp peaks in electricity demand at

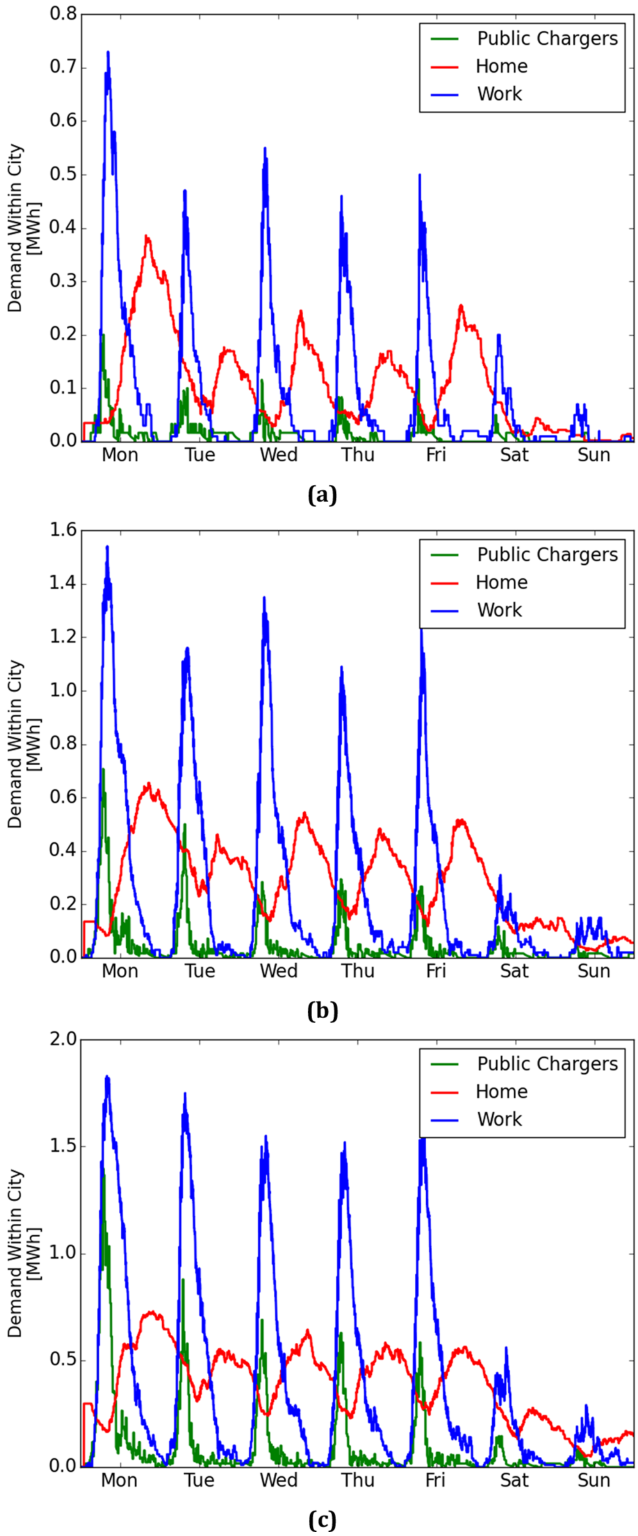

Fig. 11. Comparison of the sources of the additional electricity demand that is due to EV charging, for EV penetrations of 2% (a), 10% (b), and 20% (c).

morning peak hours, on the otherhand charging at home has less distinctive peaks with maxima during evenings.

- Local increases in the grid loads may be up to 78% during peak hours, whereas the increase in grid load averaged over the city may be only 6%. Thus, in order to reliably identify what specific upgrades are required in the distribution grid, it is important to use a digital model of the actual built infrastructure.

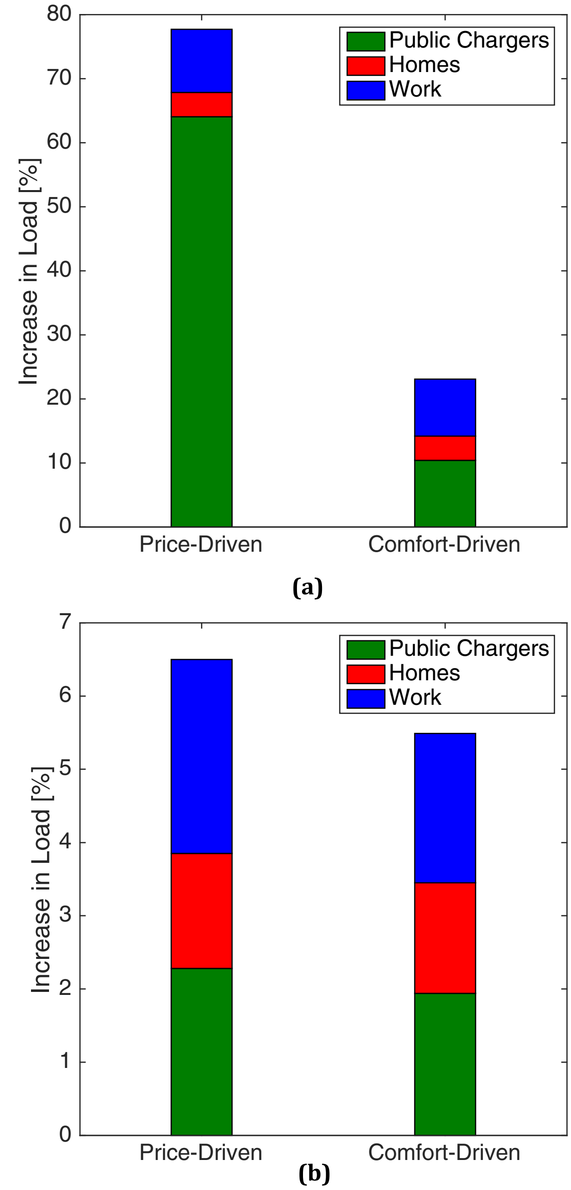

Fig. 12. (a) Comparison of the maximum increase in the peak load due to EV charging across the City that is. (b) Comparison of the increase in peak load at peak hour due to EV charging averaged over the City.

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