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Research paper

Electric vehicle charging strategies in residential communities: Permissible penetration levels and emissions

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ABSTRACT

This study investigates the impact of three electric vehicle (EV) charging strategies on distribution transformer overloading and charging emissions. Real-world GPS-tracked mobility profiles are used to simulate EV charging, and power balance simulations quantify transformer overloading for combinations of seven residential community sizes, four driver groups and five EV penetration levels. High spatio-temporal resolution emissions intensity data inform EV charging emissions estimates. Findings indicate that while all three charging strategies allow 20% EV penetration, greater penetration depends on community size and the charging strategy. The results further illustrate how grid operators can update transformer sizing conventions to accommodate 100% EV penetration. In the absence of local photovoltaic generation, charging slowly overnight minimizes transformer overloading but maximizes emissions, insinuating trade-offs. However, even with current levels of local PV generation, charging during sunshine hours may, on average, already emit and overload the least, mitigating trade-off concerns between distribution grids and the environment.

1. Introduction

Electric vehicles (EVs) are both: A promising technology to help decarbonize the transportation sector, and a considerable challenge to the electrical grid. The distribution grid infrastructure faces particular overloading issues since it has typically been planned and installed to operate for multiple decades (IEA, 2023) with assumptions of only modest increases in demand (Navarro Espinosa and Ochoa, 2015). Electric vehicles may double or even triple residential loads (Gilleran et al., 2021; Fischer et al., 2019), and may overload distribution network equipment very quickly, creating a potential bottleneck to the diffusion of electric vehicles (IEA, 2023).

The overloading of line feeders and transformers on the distribution grid is directly dependent on the employed charging strategy — controlled or uncontrolled (Sun et al., 2020; Amjad et al., 2018; Mangipinto et al., 2022; Elmallah et al., 2022). Moreover, the choice of the charging strategy has been shown to directly impact the emissions arising from EV charging (Arvesen et al., 2021). Studies that center around grid impacts of EV charging strategies are especially prevalent (Papadopoulos et al., 2012; Watson et al., 2016; Papaefthymiou and Dragoon, 2016; Parchure et al., 2017; IEA, 2019; Verhoog et al., 2020; Rahman et al., 2022; Nour et al., 2020; Xi et al., 2023; Unterluggauer et al., 2023), as are investigations on the emissions related to EV charging (Chen et al., 2018; McLaren et al., 2016; Arvesen et al., 2021; Mehlig et al., 2022). However, few studies consider both grid impacts and emissions together when considering controlled and uncontrolled charging strategies. Charging strategies that may minimize local charging peak loads may also shift charging to periods of the day with greater emissions intensity of the electricity generation mix. Therefore, whether a trade-off exists between transformer overloading in the local distribution grid due to a charging scheme and the emissions caused due to charging requires more comprehensive and generalizable analyses. Insights into whether trade-offs emerge require a clear understanding of how different EV charging strategies lead to differently shaped EV charging profiles that, together with residential load profiles, affect local distribution network loading. In this work, we use real-world mobility data to investigate these trade-offs in a systematic manner across three EV charging strategies, varying EV penetration levels in residential communities, and two driver categories involving two mutually-exclusive driver groups each.

The real-world, high resolution mobility profiles employed in this work allow the simulation of EV charging demand profiles under varying charging strategies to fulfill the same underlying mobility

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needs in different manners. Furthermore, high-resolution emissions intensity of the electricity mix used in this work helps account for spatio-temporal variations, crucial in the accurate estimation of EV charging emissions. Estimating EV charging emissions with such data and comparing against the transformer loading helps understanding the trade-offs between local grid overloading, represented by the distribution transformer in this work, and the emissions due to EV charging which in general have a global impact.

1.1. EV charging impacts on distribution transformers

An extensive body of research on the integration of EVs into existing power distribution networks exists, see for instance (Nour et al., 2020; Xi et al., 2023; Unterluggauer et al., 2023). In particular, electric vehicle charging has been shown to increase peak loads in various studies (Fischer et al., 2019; Mangipinto et al., 2022; Rahman et al., 2022). This increase in peak loads may lead to transformer overloading, consequently leading to a reduction in the service life of the transformer and necessitating either the upgrade of infrastructure to meet increased demand, or limiting permissible EV penetration. Muratori (2018) estimated that uncontrolled charging of a share of 60% 200-mile range EVs and 40% 40-mile range plug-in hybrid EVs led to local distribution transformer overloading even at low penetration levels (1 EV in 6 households) and low charger powers (6.6 kW). Unterluggauer et al. (2023) showed that 40% EV penetration levels already posed overloading challenges to cables and transformers on the low voltage distribution network in Frederiksberg, Denmark. Qian et al. (2015) developed a methodology to determine that while EV penetration levels less than 10% are not detrimental to the life of the transformers, the loss of life increases as the penetration level increases further. Other works have estimated the impact of overloading on transformer hotspot temperatures and the consequent degradation and loss of life (Roy et al., 2023; Razeghi et al., 2014). Pagani et al. (2019) find that low voltage network transformers supplying EVs may experience an increase of up to 78% in the peak load, and emphasize the vital significance of evaluating localized load increase rather than relying solely on city-wide averages when assessing the need for distribution system upgrades.

While the average city- or region-wide load increase due to EVs is significant and needs careful planning, a large number of EVs lead to smoother EV profiles and low per EV peak demand from the perspective of the transmission system (Guo et al., 2020; King and Datta, 2018). With more than 50 EVs, the share of EVs charging simultaneously (coincidence factor, CF) falls to less than 25% (Bollerslev et al., 2022). Conversely at the distribution system level, fewer EVs could create significant local overloading with concentration of charging demand (Muratori, 2018) and increased variance (a greater probability of higher coincidence factors) leading to less smooth EV charging profiles and large per EV demand (Guo et al., 2020; Razeghi et al., 2014). Therefore, understanding the impact of EV charging on distribution transformers is particularly important, since not all distribution grid operators are aware of their network characteristics due to the 'fit-and-forget' approach taken for the distribution system (Unterluggauer et al., 2023) and lack of active monitoring (Unterluggauer et al., 2023; Navarro Espinosa and Ochoa, 2015). Even though each low voltage distribution network is different and must be analyzed individually (Unterluggauer et al., 2023), it may not be feasible for distribution system operators (DSOs) and utilities to do so. The lack of knowledge of network topology makes load flow analyses difficult, and collecting data to perform such analyses may be time consuming and costly. An analysis using real-world EV data to evaluate the impact of different EV on local distribution transformers may provide relevant indications on EV penetration levels that can be sustained in typical distribution networks supplying residential households. This can be helpful for utilities and grid operators to keep up with the energy transition, until detailed analyses on their networks can be performed.

1.2. Emissions attributed to EV charging

EVs bring high hopes for decarbonization of the transportation sector. Lifecycle analyses (LCAs) of EVs show that they emit less than internal combustion engine vehicles (ICEVs), by some estimates 30% (Hall and Lutsey, 2018) and by others 13.4% (Wu et al., 2018). EVs also have lower emissions in the use phase, due to high-efficiency motors and the ability to use clean electricity (Hall and Lutsey, 2018; Lutsey, 2017). However, the variation in use-phase emissions from charging EVs, due to variations in the electricity mix, directly impacts the LCA results (Wu et al., 2018). Studies have shown that emissions from EV charging depend on the time and location of charging (Chen et al., 2018; McLaren et al., 2016), as well as the electricity generation mix considered, which is the most important factor affecting CO2 emissions (McLaren et al., 2016). Understanding the variations in carbon intensity of the electricity mix across the day can be helpful in further reducing the environmental impact of EVs. For instance, Dixon and Bell (2020) and Mehlig et al. (2022) show that controlled charging can help reduce battery electric vehicle emissions compared against a 'dumb' charging scenario. Two studies from Taiwan (Tseng and Hsieh, 2023) and the United States (McLaren et al., 2016) report that daytime charging leads to lower emissions than nighttime charging. Arvesen et al. (2021) also show that daytime charging emits between 33%–50% less than nighttime charging, due to high shares of clean electricity from solar PV in the day and dirtier electricity from gas power plants in the evening and night. They emphasize that EV charging policies and emissions assessments must account for the time of charging and the variation in electricity mixes over the day. Mehlig et al. (2022) further support this argument by quantifying that non-temporal CO_2 emissions underestimate EV charging emissions by 4.4% as compared to high resolution profiles. These studies highlight the importance of accounting for temporal variations, so that coincident peaks of EV charging demand and the emissions intensity of the electricity mix are accounted for.

Additionally, spatial variation in the emissions intensity of the electricity mix is also relevant. Kamiya et al. (2019) highlight the importance of considering zonal electricity generation mixes in evaluating lifecycle emissions reductions from using EVs — regions with lower emissions intensities have greater emissions reductions. Ensslen et al. (2017) further show how charging EVs in France results in only 10% of the emissions of charging in Germany. Therefore, they suggest the importance of distinguishing "regional boundaries in which emissions are investigated" since the energy mix depends on factors "such as local resources, climate, and energy policy" (Ensslen et al., 2017, p.265). However, few studies account for both spatial and temporal high-resolution emissions intensity data in estimating the emissions from different EV charging strategies.

1.3. Research gaps and contributions

The majority of existing studies investigating EV charging impacts on distribution grids rely on assumptions about trips — for instance, distributions of the times that EV users arrive at and depart from home, and trip distances which translate to energy consumed from the battery (Fischer et al., 2019; Pagani et al., 2019; Muratori, 2018; Liao et al., 2023). Other studies base these timings on trip diaries, typically collected via national transport surveys (Sachan et al., 2020). As assumptions and self-reported mobility behavior data are prone to bias and lack accuracy, some studies have relied on real-world GPS-trajectory data, addressing varying objectives. Tu et al. (2016) and Hu et al. (2018) rely on data collected from taxis to optimize charging station locations and evaluate the feasibility of taxi electrification, respectively. Kontou et al. (2019) investigate charging infrastructure coverage and the opportunity to charge, while Yi et al. (2022) optimize the layout of public charging stations. Sun et al. (2020) conduct statistical analyses on spatio-temporal characteristics of EV data. März et al.

(2022), Li et al. (2023) and Lei et al. (2022) all investigate charging patterns of an EV fleet, while Hartvigsson et al. (2021) rely on GPS data to estimate EV charging coincidence. However, only a select few have relied on real-world GPS or charging station data to estimate grid impacts of EV charging (Powell et al., 2020; Shokrzadeh et al., 2017; Diaz-Londono et al., 2022). Of these studies, Powell et al. (2020) focus on workplace transformers on weekdays only, hence missing out on home charging, which is projected to continue to be the main EV charging location (Hardman et al., 2018). Shokrzadeh et al. (2017) only observe typical summer days with a fixed transformer size, while Diaz-Londono et al. (2022) only consider one week of charging. Since EVs are relatively new, a clear understanding of the variation in load, similar to diversity factors for the typical household electrical profiles, is lacking. Crozier et al. (2021) stress the importance of local mobility information due to the large variation in peak demand of small EV fleets, and Unterluggauer et al. (2023) also mention how one-shot simulation analyses are unable to capture variations in EV charging demand which can be significant in estimating grid bottlenecks.

The use of high resolution GPS-tracked real-world mobility profiles help address the aforementioned challenges of assumed and self-reported mobility behavior as well as capture variations in mobility profiles. Such profiles consist of accurate vehicle location, trip distance and trip duration data, and therefore an accurate estimation of an EV's energy needs are possible. Furthermore, an advantage of mobility profiles when compared against measured electric vehicle charging profiles, typically from charging stations, is that the mobility profiles can be used as a starting point for evaluating different charging strategies to fulfill the same given mobility demand. However, few research works combine real-world mobility needs with multiple charging strategies to estimate the impact of EV charging on the local distribution transformer and simultaneously report the associated emissions from charging, investigating potential trade-offs between grid overloading and emissions. Therefore, in this work, we rely on a real-world GPS-tracked dataset to answer the following research questions:

1. *Under given real-world mobility needs, how do different charging strategies impact the load profile of EV charging, and how does the load profile differ for different driver groups?*
2. *What EV penetration levels can typical installed distribution transformers sustain, depending on the charging strategy?*
3. Answering these questions help in answering the key question we raised: *Do trade-offs emerge in the choice of charging strategies, considering transformer overloading and carbon emissions?*

To answer these questions, we analyze and systematically compare the effects of EV charging at home under three charging strategies: Uncontrolled, Flat and Daytime. To that end, we utilize real-world GPS-tracked mobility data collected from 1000 internal combustion engine cars in the Northern region of Italy over a duration spanning nearly two years, from July 2007 to June 2009. This dataset provides precise information regarding the energy requirements for mobility as well as details regarding parking locations and durations. Leveraging this information, we simulate the demand for electric vehicle (EV) charging and assess the overloading of local distribution transformers across various sizes of residential communities and levels of EV penetration using typical residential load profiles within Italian neighborhoods. Finally, we analyze the emissions stemming from EV charging across three different charging strategies. Our findings reveal permissible EV penetration levels within residential communities depending on the charging strategy employed and highlight inherent trade-offs between transformer overloading and carbon emissions, offering insights into selecting optimal charging strategies aligned with the objectives and preferences of EV fleet and grid operators.

2. Data and methodology

2.1. Mobility data

We rely on real-world mobility profiles measured anonymously on 1000 internal combustion engine vehicles (ICEVs) in Northern Italy, between July 2007 and June 2009 (two weeks short of two years). The data was measured in support of a car insurance product, with no demographic or car information recorded. All cars have high-resolution data point measurements at every 2 km driven as well as on every change in the ignition state of the engine. Data points include the location, speed, engine state, date and time, and the road-type (highway, urban or extra-urban). Accounting for 91 cars with deficient data, we end up with data from 909 cars. Overall, the data used in this study includes more than 4 million trips and more than 46.5 million km traveled, and has been employed in previous works by other researchers (Wenig et al., 2015, 2019; Sodenkamp et al., 2019).

2.1.1. Driver groups

We segment the observed mobility behavior into k = 8 driver types, following the k-means cluster analyses conducted in previous work by Wenig et al. (2019). This is based on segmentation variables derived from the GPS data on mobility attributes such as trip and round-trip distances, trip duration, number of round-trips per month, number of stops per round-trip, parking periods, and variance of speed. For details, the reader is referred to Wenig et al. (2019). The resulting eight driver types and their nine segmentation variables are shown in Table 1. The eight distinct types of drivers are further categorized into two larger groups labeled (1) 'Private', which constitutes 77% of the fleet, and (2) 'Commercial', which consists of 23% of the fleet, due to similarities in the underlying identified types of drivers. This may help observe differences in charging profiles based on the underlying differences in mobility profiles of the two groups, as seen by differences in arrival and departure times in Figs. A.1(b) and A.1(c) in Appendix. In line with Wenig et al. (2019), the location with the longest parking duration is defined as 'Home', the second as 'Work', and all others as Public locations. For commercial drivers, the longest-parked locations may technically be referred to as 'depots', but we retain the term 'Home' for consistency. While the focus of this work is on residential communities, commercial vehicles are retained to capture charging diversity.

Additionally, we also segregate drivers by the location of their homes, into Rural and Urban driver groups - based on the subdivision of the NUTS-3 classified units of the EU into the local administrative units (LAU) (Eurostat, 2023). The LAUs consist of three degrees of urban classification — predominantly urban, predominantly suburban and predominantly rural. Cars in the predominantly suburban and predominantly rural categories are merged into and labeled as one 'Rural' group comprising 47% of the fleet, while 'Urban' drivers comprise 53% of the fleet. Drivers with urban home location types show a distinct behavior as compared to the created rural group. For details, see Fig. A.1 in Appendix., which shows the share of cars arriving at or departing from the home location every hour of the day. The Private and Commercial driver groups are mutually exclusive, as are the Rural and Urban groups. Most Commercial cars are based in urban areas, while Private cars are split nearly evenly between rural and urban locations (Table 2).

2.1.2. Sample representativeness

Overall, the driving patterns in the dataset are very similar to recent Italian mobility studies from 2019 and 2023. The proximity of the aggregated time series values of the dataset to these Italian mobility studies supports its use in this work. For example, the median distance driven per working day (18.12 km), mean trip distance (11.41 km), and median driving duration per working day (37.5 min) in the dataset closely match the respective values of 20.28 km, 11.2 km, and 35.5 min reported in the 2019 Italian mobility survey (Carminucci

Table 1
Eight driver types and their segmentation variables.
Source: Adapted from Wenig et al. (2019).

Segment type	Private driver types				Commercial driver types			
	FLD	OD	SC	UC	CR	SV	LDDV	SDDV
Segment Size	149	101	173	278	84	35	49	40
Segmentation Variables								
Median Round-trip Distance (km)	10.18	57.76	29.11	21.25	207.55	66.70	98.88	0.65
Median Round-trip Duration (h)	2.15	10.07	6.22	4.39	9.29	4.35	7.34	0.29
Round-trip driving to parking ratio	0.22	0.07	0.13	0.16	0.85	1.26	0.46	0.49
Median Variance Round-trip speed	347.89	761.71	241.46	496.20	357.53	368.31	122.83	207.33
Average Round-trips per month	54.12	11.44	33.68	30.87	23.38	48.10	30.96	58.01
Average stops per Round-trip	3.58	5.84	3.65	4.62	8.70	6.79	16.10	8.41
Median trip distance (km)	3.01	9.61	7.74	3.91	12.85	9.36	2.33	1.59
Median home parking duration (h)	4.77	15.07	10.40	11.25	11.81	1.51	14.06	1.56
Median non-home parking duration (h)	0.36	1.24	1.13	0.48	0.28	0.21	0.15	0.18

FLD: Frequent Local Driver; OD: Occasional Driver; SC: Steady Commuter; UC: Unsteady Commuter; CR: Company Representative; SV: Service Vehicle; LDDV: Long-distance Delivery Vehicle; SDDV: Short-distance Delivery Vehicle.

Table 2
EV fleet and driver group sizes.

	Urban	Rural	Total
Private	342	359	701
Commercial	140	68	208
Total	482	427	909

et al., 2020). Likewise, the 2023 survey (Carminucci et al., 2023) found that the average per-capita daily distance traveled by all modes was 28 km, of which motorized vehicles (bikes and cars) comprised 80% (i.e., 22.4 km)—again in a very similar range.

Some differences to Italian mobility surveys are present in this dataset. For example, the median weekend driving distance is 7.68 km, which is considerably lower than the 24.95 km reported in the 2019 survey (Carminucci et al., 2020). In addition, only 53% of cars in the dataset have their home location in urban regions, compared to 72%–80% of the Italian population living in such areas (Macrotrends, 2025; Eurostat, 2025). This results in an under-representation of urban driving behavior. Even so, the dataset captures a broad spectrum of mobility patterns, as illustrated by the distinct driver groups in Table 1 and the variation in arrival and departure times across the four broader groups shown in Fig. A.1 in Appendix. Finally, the nearly two-year observation period provides insight into the real, uninhibited mobility needs of 909 households—–an advantage over smaller datasets based on early EV adopters, EV charging stations or self-reported data.

2.2. EV driving energy and charging profile simulation

We utilize real-world driving data to represent genuine mobility demand instead of relying on synthetic or survey-derived mobility patterns. To translate ICEV energy demand originally satisfied by fossil-fuels into electrical demand, we build on the methodology employed by Wenig et al. (2019). We map the original low-resolution measured speed data points to higher resolution speed profiles from driving cycles for the three road types on which the vehicles may drive (urban: ECE-15, extra-urban: EUDC or highway: EMPA T130) (Barlow et al., 2009). This provides acceleration and deceleration values for the vehicle. Together with vehicle characteristics assumed to be that of an electric Renault Zoe (EV Database, 2021), the electrical demand of the vehicle is derived. All vehicles are assumed to be Renault Zoes with a vehicle weight of 1625 kg (including a 75 kg mass for driver and package) and a frontal area of 85% of the rectangular outline of the car front, 2.37 m^2. Vehicle rolling resistance coefficient (0.011), air drag resistance (coefficient 0.31) and regenerative braking (50%) are also included in the calculation of the driving energy demand, along with an assumed 90% vehicle efficiency. The resulting electrical energy consumption values on a per km basis are 144.41 Wh/km for extra-urban regions (EUDC), 108.79 Wh/km for urban regions (ECE-15) and 233.91 Wh/km for highways (EMPA T130). These lie within performance data estimates of a Renault Zoe (EV Database, 2021). The use of the real-world dataset therefore allows us to estimate the electrical energy demand for driving based on the road-type of the vehicle, making the trip electrical energy consumption estimates more realistic as compared to singular Wh/km consumption values typically assumed in other works. We additionally integrate auxiliary energy consumption in the vehicle from Needell et al. (2016), improving the energy consumption model of Wenig et al. (2019). This includes a 100 W constant demand for electrics, as well as heating or cooling demand to maintain a comfort range of 20–24 degrees C inside the car, dependent on the outside temperature values taken from EnergyPlus (EnergyPlus, 2023).

We assume a 37.6 kWh battery size and the presence of EV chargers at home locations with 11 kW of rated power which enables to generate state of charge (SOC) profiles for the vehicles. To account for instances where the assumed vehicle battery lacks sufficient energy for long-distance trips, we adopt an approach in line with Wenig et al. (2019), assuming the existence of a gasoline-powered range extender that activates when necessary, so as to prevent the loss of trip data. Considering the anticipated investment in public fast-charging infrastructure (IEA, 2022, 2020), such trips may well be feasible, and therefore we retain them in our analysis.

2.3. Charging strategies

We choose three different charging strategies to evaluate — Uncontrolled, Flat and Daytime, as outlined in Table 3. In all three strategies, charging is only possible at the home location for two reasons: First, the majority of EV charging is projected to be at home (Hardman et al., 2018). Second, we thus evaluate the worst effect on the local transformer, since this results in greater charging demands at the one location where charging is allowed. In the Uncontrolled charging strategy, cars only plug-in to charge after the last trip of the day is over, which can happen at any time of the day, but for most cars happens in the evening. Charging happens uncontrolled, that is, as fast as possible, depending on the charger capacity. Once the battery level reaches 80% SOC, the charging slows down to one-third the charging power to maintain operational safety, in line with other research (Wenig et al., 2019; Gschwendtner et al., 2023b; Pagani et al., 2019; Amjad et al., 2018; Schäuble et al., 2017). Since controlled charging has been shown to be beneficial in managing the impact of EV charging on the local grid (Mangipinto et al., 2022), we implement a Flat charging strategy — charging happens at the end of the last trip of the day as slowly as possible (with the lower limit of 1.22 kW) so that the SOC reaches 100% on departure (i.e., taking advantage of the cars' idle time as much as possible, without reducing the SOC on departure). It is assumed that the EV owner has exact knowledge of their time of departure and inputs it

Table 3
Charging strategies and share of trips completed.

Charging strategy	Explanation	Trips completed with home charging	Share of trips completed (Strict - charging only in defined hours)	Average charging duration
Uncontrolled	Charge after last trip of the day, until 100% SOC, as quickly as possible	86.81%	83.12%	2 h 49 min
Flat	Charge after last trip of the day, until 100% SOC, as slowly as possible	86.56%	82.64%	5 h 28 min
Daytime	Charge between 9 AM–4 PM, until 100% SOC, as quickly as possible	86.82%	74.12%	1 h 36 min

to the EV charger, which controls the EV charging. For a third strategy, we emulate daytime charging, so that the increased demand coincides with local solar PV generation within the community. It is assumed that if the EV is at the home location between 9 AM to 4 PM (a simplifying proxy for sunshine hours), owners always plug-in and leave their EVs to charge. Like the Uncontrolled charging strategy, charging happens as fast as possible (with a reduction to one-third the charging speed after 80% SOC). Table 3 provides an overview of the three charging strategies considered in this work.

Across all three strategies, the maximum charger delivered power is fixed at 11 kW, to emulate level 2 (L2) charging at home. Faster charging, such as 22 kW L2 and DC fast charging at levels of 50 kW and above are not explicitly considered in this work, since the focus is on home charging. Since EV charging profiles are simulated from ICEV mobility data with assumed battery sizes, some trips become infeasible. In all charging scenarios, if the battery SOC is insufficient for upcoming trips until the next home-charging opportunity, the vehicle is allowed to charge at home until the SOC covers those trips, even outside the defined charging hours of the charging strategy. For example, if a car is home at noon with a depleted battery but still has trips left, it will charge enough to complete those trips until it is at the home location to charge again . This caveat avoids unnecessary trip loss and reflects realistic driver behavior — EV owners will go out of their established habits of plug-in in case the battery level is not enough for upcoming trips. Nonetheless, small battery capacities and trips not ending at home prevent 100% trip completion (Table 3). For comparison, we also simulate 'strict' strategies disallowing the exception to charge outside the defined hours, to report the difference in trip completion rates. (Table 3).

2.4. Transformer sizing and overloading estimation

2.4.1. Transformer sizing

To evaluate the impact of EV charging on local distribution transformers, we assume residential communities sized between 5–100 households. In line with Freitas et al. (2018), we size the distribution transformer for each community with the following equation commonly applied for transformer sizing:

$$P_{PT} = \sum_{i}^{N} P_{contracted,i} \times C_{diversity} \times F_{safety} + P_{over} \tag{1}$$

where P_{PT} stands for the transformer power capacity, N represents the number of residential households in the community, $P_{contracted,i}$ the contracted peak demand of a household i (set to 3 kW for Italy), F_{safety} a safety margin set to 1.5 to oversize the transformer to account for future load growth and power factor, and P_{over} the oversized transformer capacity defined by the next available transformer available from commissioning, in this work considered from Schneider Electric's range of low voltage transformers (Schneider Electric, 2023). The diversity factor $C_{diversity}$ for residential households is given by the following equation (from Freitas et al., 2018):

$$C_{diversity} = 0.2 + \frac{0.8}{\sqrt{N}} \tag{2}$$

As Eq. (2) shows, the diversity factor decreases as the number of households increases. This captures the lower risk of load coincidence as the community size increases, and conversely, the high risk of load coincidence in communities with very few households. This may have implications when the load drastically increases, such as when the penetration level of EVs increases, especially for large residential communities.

2.4.2. Transformer overloading

Transformer overloading depends on transformer type and operating conditions such as ambient temperature, prior loading levels, and transformer age. Oil-type transformers may be overloaded up to 120% of rated power for 60 or 90 min, if previous load levels were 75% or 50% of rated power respectively (Schneider Electric, 2025b). The respective durations for dry-type transformers are 17 and 27 min, respectively (Schneider Electric, 2025a). Transformer overloading is measured using three metrics. First, the peak load ratio, which is the ratio of the peak load flowing through the transformer to the transformer size (nominal capacity). Second, the number of hours overloaded above 120% nominal capacity, and third, the number of hours the transformer is consecutively overloaded, since transformers are designed to be overloaded for short periods of time (Kannan and Au, 2010; Schneider Electric, 2025a,b). Although transformers can be safely overloaded to greater load levels for limited periods, we adopt a conservative and static limit of 120% of rated power for 60 min as the maximum permissible transformer loading, irrespective of transformer type or condition. This enables a generalized and comparable assessment of transformer overloading across community sizes.

2.5. Simulation of residential communities with EV penetration

To evaluate the impact of EV charging on local distribution transformers, the baseload from residential households must be accounted for. We employ the hourly-resolution standardized 24-hour residential load profile for Italy, taken from Lazzeroni et al. (2020), due to the lack of availability of high-resolution real-world smart meter data. Using this as the load profile for every household, we simulate hourly power balances in residential communities sized between 5–100 households, since the typical residential community consists of not more than 100 households (Pimm et al., 2018). Intra-hour peaks, phase imbalances, current flow and over-/under-voltages are not considered. Within each residential community simulated, we add hourly-resolution EV charging loads according to EV penetration rates of 20%, 40%, 60%, 80%, and 100%. We perform a Monte-Carlo inspired sampling of EV charging profiles from the full set of 909 EVs, as well as sub-fleets of Private, Commercial, Rural and Urban driver groups, simulated to populate the residential communities with EV loads. We repeat this 100 times for each residential community and each penetration level, and report the average and maximum values of the three transformer overloading metrics. Overall, seven community sizes are simulated with EV charging load profiles based on the number of EVs from 5 EV penetration levels for the three charging strategies, resulting in a total of 105 combinations of communities with EV charging loads. To observe the impact of a mixed EV fleet as well as the congregation of specific driver groups on the local transformer, the analyses is conducted by sampling over the entire fleet consisting of all driver groups, as well as separately for the four driver groups individually. Fig. 1 showcases the methodology employed in this work.

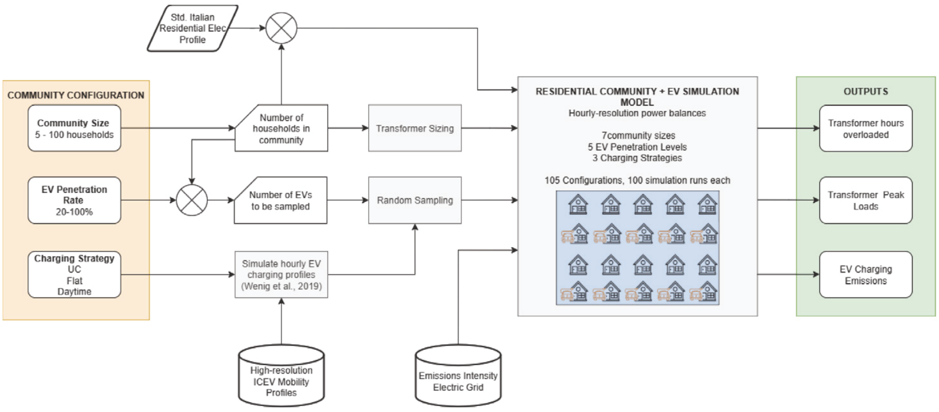


Fig. 1. A schematic of the methodology.

2.6. Emissions intensity data from Italy

To evaluate the impact of the electricity mix and resulting EV charging emissions, we account for the spatial distribution of the fleet across Italy's six market bidding zones (Fig. 2) (Pecinovsky and Boerman, 2023; Gestore Mercati Energetici, 2023). The Center-North (IT-CNO) is the least emitting zone, while Sardinia (IT-SAR) is the most. We use hourly average emissions intensity (AEI) data from 2022 at both national and zonal levels from Electricity Maps (2025), focusing on direct (operational) emissions to capture the use-phase "fuel" consumption of EVs. For details, the reader is referred to Electricity Maps (2025). Home locations of vehicles are mapped to zones, with 803 and 87 cars located in IT-NO (North) and IT-CNO (Center-North) respectively. Emissions are calculated by multiplying the hourly charging demand with AEI (nationally, zonally, and under counterfactuals where all EVs charge in the cleanest or dirtiest zone). The average emissions intensity is reported as the fraction of total emissions over the total energy consumed for charging.

While some studies advocate the use of marginal emissions intensities (MEI) to estimate the additional emissions from a marginal increase in the load due to EV charging, we adopt AEI. Estimating the veracity of MEI (i.e., the true generator that supplied the additional load) is extremely complex due to complex operation of the grid (50Hertz, 2025). Moreover, the MEI focusses on the immediate, short-term impact of additional load, which does not capture long-term changes in grid infrastructure to meet the additional demand. Instead, the use of the AEI enables emissions estimation by assuming future generation deployment in the same proportion as existing generation, providing a conservative but long-term perspective aligned with grid planning for rising EV loads. Additionally, the AEI is also more intuitive as a policy signal to encourage eco-friendly EV charging during low-AEI periods (e.g., daytime solar peaks) even when MEI may paradoxically rise due to fossil plants covering residual load, resulting in greater short-term emissions estimates (Corradi, 2022).

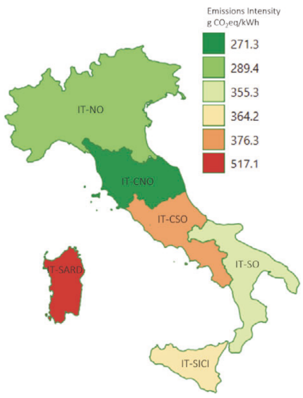


Fig. 2. Italy zonal boundaries and emissions intensity. *Source:* OpenStreetMaps (Italy) and Pecinovsky and Boerman (2023) (Zonal boundaries).

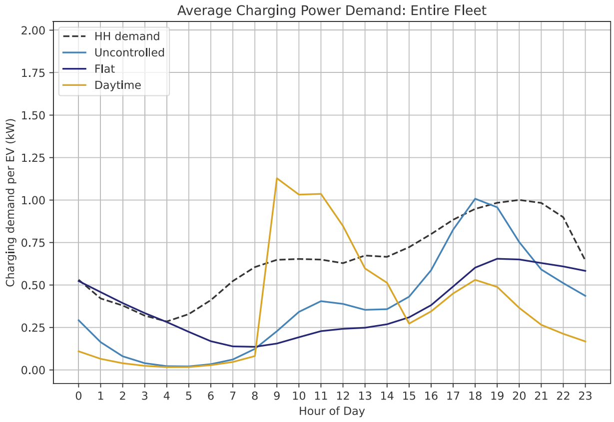
3. Results

In this section, we first present the quantified average EV demand profiles, both for the entire fleet and by driver groups. Second, we report on transformer overloading for different EV fleet sizes and penetration levels within residential communities. Finally, we present the emissions caused due to EV charging, both at national and zonal spatial resolutions for Italy.

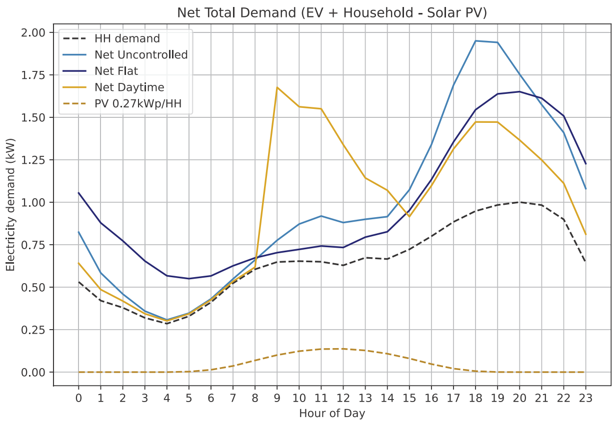
3.1. Average EV power demand by charging strategy

The charging strategy strongly shapes the average EV demand profile, as seen in Fig. 3(a). In the Uncontrolled strategy, the large share of evening arrivals home (Fig. A.1) lead to a demand peak of 1.01 kW/EV at 18:00, coinciding with household evening peaks and doubling total demand (Fig. 3(b)). The maximum coincidence factor of 23% at 18:00 when the majority of EVs arrive home falls to 1% by 06:00 (Fig. 4), since vehicles charge as fast as possible at maximum power of 11 kW. Conversely, the Flat charging strategy yields a lower peak of 0.65 kW/EV at 19:00 but long average charging session length (5 h 28min, Table 3). This results in sustained high coincidence factors, with up to 39% of EVs connected and charging between 19:00–22:00 and a drop to the minimum CF of 10% at 08:00. Therefore, the Flat strategy observes the greatest average overnight charging demand. The Daytime strategy produces the highest peak across the three strategies, 1.13 kW/EV at 09:00. For the fleet in consideration, a large share of cars are at home and able to charge in the morning and early afternoon, as seen by the high coincidence factors between 09:00–15:00 (see Fig. 4). A smaller evening peak of 0.53 kW/EV appears at 18:00 for vehicles unable to fully charge earlier or must charge more to not lose subsequent trips, since the charging sessions in the Daytime strategy are the shortest (1 h 36 min, see Table 3). Despite these contrasting profiles across strategoes, trip completion rates are similar (86.56–86.82%) because vehicles may charge outside defined hours if SOC is insufficient for upcoming trips. Under strict rules disallowing such exceptions, completion falls to a minimum of 74.12% (Daytime) to 83.1% (Uncontrolled) (Table 3).

Private vs. Commercial cars. The distinct mobility patterns of private and commercial drivers create starkly different charging profiles. Private cars follow typical workday rhythms — departing in the morning, returning in the evening, and often making midday home stops,



(a) Charging Power Demand for All Cars under different charging strategies



(b) Total power demand (average profile) as seen by the distribution transformer, inclusive of average residential PV generation and residential demand

Fig. 3. Average EV charging demand across different charging strategies — EV only, and net demand inclusive of average residential PV production and EV charging.

presumably for lunch (Fig. A.1). This results in charging peaks of 0.93 kW/EV at 18:00 (Uncontrolled), 1.06 kW/EV at 09:00 (Daytime), and 0.53 kW/EV at 22:00 (Flat). By contrast, commercial vehicles leave after midnight, return in the morning, and remain parked until late evening. Their charging is bimodal: peaks of 1.29 and 1.59 kW/EV at 11:00, and 1.30 and 1.07 kW/EV at 17:00 under Uncontrolled and Daytime strategies, respectively. Under Flat charging, high coincidence factors create an evening peak of 1.15 kW/EV at 18:00–19:00.

Rural vs. Urban cars. An interesting distinction is seen when comparing the charging demand profiles of cars with homes in rural regions against those with homes in urban regions. Urban cars have more prominent secondary peaks in the morning hours, with more cars being home and able to charge under the different strategies. This is not the case for rural cars. Therefore, rural cars have higher peaks in the evening than urban cars for all strategies — 1.11 kW/EV vs. 0.92 kW/EV at 18:00 in the Uncontrolled strategy, 0.66 kW/EV vs. 0.647 kW/EV at 19:00 in the Flat strategy, and 0.59 kW/EV vs. 0.476 kW/EV at 18:00 in the Daytime strategy. In contrast, the Daytime strategy produces a higher morning peak for urban cars (1.16 vs. 1.09 kW/EV at 09:00), reflecting greater presence at home in the mornings.

3.2. Distribution transformer overloading by EV penetration level

Differences in mobility profiles strongly affect the timing of charging peaks and thus transformer overloading. Yet, due to low coincidence, the fleet-average demand remains modest: across all 909 cars, charging peaks at only 1.13 kW/EV, and even the 208 commercial EVs do not exceed 1.59 kW/EV in the Daytime strategy—far below the 11 kW charger rating. Smaller fleets, however, show higher per-EV peaks (Fig. A.3): below 100 EVs, peak loads reach 1.39 kW/EV (Flat), 5.98 kW/EV (Uncontrolled), and 6.53 kW/EV (Daytime). Since distribution transformers typically do not serve more than 100 households, we analyze communities of this size under varying penetration levels to assess whether the transformer can sustain the additional EV loads under the three charging strategies. Importantly, PV generation within residential communities is excluded here to isolate EV charging load impacts. However, we acknowledge that local PV generation can synergize with supply EV loads and reduce net electricity imports, ameliorating overloading issues. This is further discussed in Section 4.

Table 4 summarizes three transformer overloading metrics over the 100 simulation runs across all 105 configurations (without any solar PV generation in the communities). The first, the peak load ratio, measures transformer loading relative to capacity, with values less than 1.2 over 60 min considered as the limit. Peak load ratios under this value are highlighted in green, while ratios between 1.2–1.3 are highlighted in yellow. All other combinations of EV penetration levels and community sizes overload the transformer to unacceptable levels and are highlighted in red. Two other key metrics that help determine permissible EV penetration levels in residential communities are the number of hours overloaded at or above peak load ratios of 1.2, and the number of hours of overload at or above peak load ratios of 1.2 for the second consecutive hour or more. Combinations with less than 60 min of consecutive overloading are highlighted in green, as a very strict threshold for potential permissible combinations. For more information on the results, the reader is referred to Appendix A.4. Table 5 condenses the three overloading metrics into permissible ('Y') or non-permissible ('N') configurations, or borderline ('(Y)') outcomes. Combinations that exceed peak load ratios of 1.2 or have more than one hour consecutively overloaded above 120% nominal capacity are deemed non-permissible and are assigned 'N'. In a few special cases, we assign '(Y)' (borderline yes, in yellow) to combinations that are very close to the permissible criteria.

Table 5 shows that, on average over 100 simulation runs, a 20% EV penetration level is feasible across all strategies and community sizes. As the EV penetration level increases, permissible EV penetration depends both on the community size and the charging strategy. The Flat charging strategy is the most transformer-friendly, causing the least overloading across combinations. Communities with 10 and 60 households can achieve 80% penetration levels, with communities sized 10 having a possibility to achieve 100% penetration as average peak load ratio does not exceed 1.2, even though on average the transformer is overloaded for 1.4 additional hours consecutively (rightmost panel in Table 4). Communities with 20 and 40 households can achieve 60% EV penetration. Very small (5) and very large communities (≥ 80) can support 40% EV penetration. The Uncontrolled and Daytime strategies have similar permissible EV penetration levels — communities with 10 and 60 households can achieve 40%. With the Daytime strategy, communities sized 20, 40, and 100 households can also achieve 40% EV penetration, even though peak load ratios are greater than 1.2 (1.27, 1.24 and 1.28, respectively, shaded in yellow in Table 4), since they are barely overloaded consecutively for more than an hour (rightmost panel, Table 4).

Comparing across charging strategies, Flat charging leads to the lowest share of overloaded hours (middle panel in Table 4). Even though daytime charging indicated the greatest peaks attributed to EV charging demand, transformer overloading is more frequent with

Table 4
Averages of transformer overloading metrics (without solar PV) — peak load ratio, hours overloaded above 120% rated capacity, hours overloaded for the second consecutive hour or more above 120% rated capacity.

Charging strategy	Community size	Transformer capacity (kVA)	Available EV hosting capacity (kVA)	Transformer peak load ratios					No of hours overloaded					No of hours of overload for the second consecutive hour or more				
				EV penetration levels					EV penetration levels					EV penetration levels				
				20%	40%	60%	80%	100%	20%	40%	60%	80%	100%	20%	40%	60%	80%	100%
Uncontrolled	5	15	2.00	1.06	1.55	1.79	2.03	2.19	0.0	16.9	44.7	101.3	146.5	0.0	8.2	26.6	66.6	95.9
	10	30	2.00	0.91	1.19	1.37	1.54	1.72	0.0	1.5	12.7	24.5	49.5	0.0	0.5	6.5	13.3	28.4
	20	45	1.25	0.99	1.25	1.46	1.67	1.87	0.1	3.5	21.0	67.9	155.5	0.0	1.1	10.1	41.3	110.0
	40	75	0.88	0.98	1.29	1.49	1.71	1.92	0.0	6.5	38.0	147.5	302.1	0.0	2.7	21.4	109.1	248.2
	60	112.5	0.88	0.93	1.16	1.38	1.61	1.80	0.0	0.8	20.9	114.6	252.7	0.0	0.1	10.7	79.3	205.9
	80	112.5	0.41	1.18	1.49	1.78	2.06	2.30	1.5	77.2	353.4	711.5	1095.6	0.4	51.3	301.6	659.2	1045.1
	100	150	0.50	1.07	1.35	1.62	1.86	2.13	0.1	24.1	180.1	489.6	808.3	0.0	12.0	138.1	442.3	764.4
Flat	5	15	2.00	0.93	1.06	1.28	1.35	1.48	0.0	1.2	7.8	13.5	24.2	0.0	0.9	5.6	10.4	19.0
	10	30	2.00	0.71	0.88	0.98	1.06	1.16	0.0	0.0	0.1	0.6	2.2	0.0	0.0	0.1	0.3	1.4
	20	45	1.25	0.77	0.93	1.07	1.22	1.33	0.0	0.1	0.4	5.7	14.1	0.0	0.0	0.2	3.8	10.2
	40	75	0.88	0.83	0.98	1.11	1.26	1.41	0.0	0.0	0.4	11.1	38.2	0.0	0.0	0.1	7.6	29.3
	60	112.5	0.88	0.79	0.92	1.06	1.19	1.33	0.0	0.0	0.1	1.5	20.7	0.0	0.0	0.0	0.9	15.0
	80	112.5	0.41	1.00	1.20	1.38	1.54	1.74	0.0	3.5	57.0	259.5	674.6	0.0	2.2	45.5	234.5	647.5
	100	150	0.50	0.93	1.09	1.27	1.43	1.57	0.0	0.0	10.8	111.6	346.3	0.0	0.0	7.0	95.8	322.0
Daytime	5	15	2.00	1.05	1.63	1.90	2.17	2.44	0.0	18.3	54.0	84.9	162.5	0.0	8.0	26.8	39.1	88.9
	10	30	2.00	0.94	1.20	1.46	1.63	1.79	0.0	1.5	10.5	27.2	48.2	0.0	0.2	2.5	9.3	17.8
	20	45	1.25	0.97	1.27	1.51	1.71	1.97	0.0	2.1	17.4	49.8	135.7	0.0	0.3	5.1	18.3	65.4
	40	75	0.88	0.96	1.24	1.50	1.77	2.03	0.0	2.1	22.9	92.2	234.3	0.0	0.2	6.7	42.0	133.3
	60	112.5	0.88	0.89	1.13	1.37	1.65	1.89	0.0	0.3	8.4	55.3	182.7	0.0	0.0	1.5	23.5	101.4
	80	112.5	0.41	1.12	1.41	1.75	2.07	2.40	0.4	22.0	167.7	511.7	957.4	0.1	6.5	90.2	359.5	770.2
	100	150	0.50	1.02	1.28	1.57	1.90	2.20	0.0	4.0	68.8	285.4	652.1	0.0	0.7	30.0	181.3	487.5

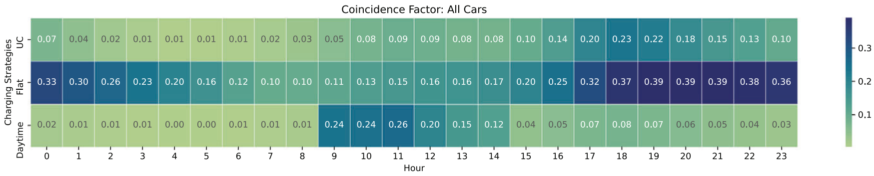
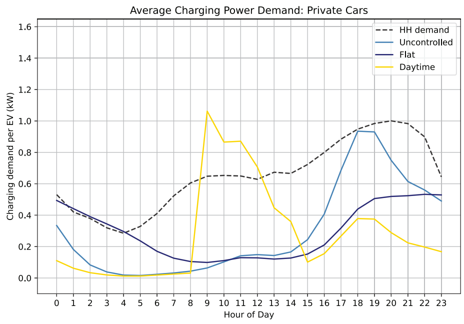
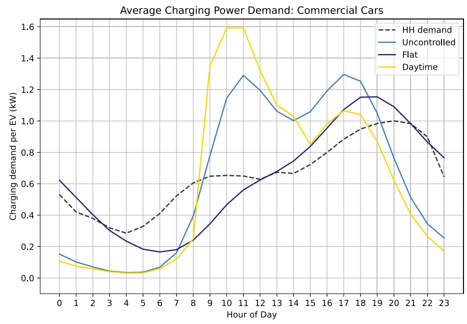


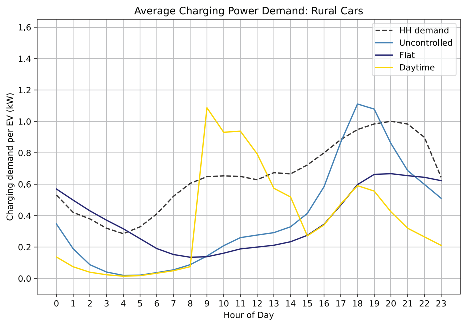
Fig. 4. Coincidence factors for EV charging, all cars.



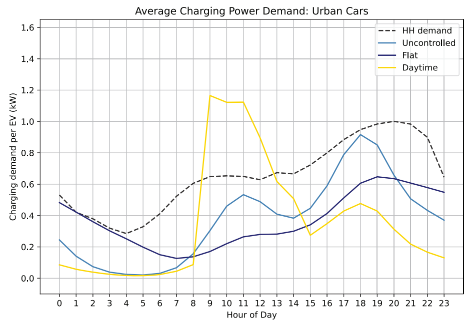
(a) Charging Power Demand for Private cars under different charging scenarios



(b) Charging Power Demand for Commercial cars under different charging scenarios



(c) Charging Power Demand for cars with Rural homes under different charging scenarios



(d) Charging Power Demand for cars with Urban homes under different charging scenarios

Fig. 5. Average EV Charging Demand across different scenarios for the different driver groups.

Uncontrolled charging, due to greater congruence of the EV charging demand and the household demand (see Fig. 3(a)).

Among driver groups, commercial cars generate the highest number of overloaded hours across charging strategies—on average, six times more than private cars across community sizes (see Table A.2). The penetration levels in Table 5 apply to all groups except commercial cars. While 40% penetration is feasible for mixed fleets under some strategies, a fleet composed solely of commercial cars causes excessive transformer overloading, making 40% penetration infeasible. Rural cars produce slightly more overloaded hours than urban cars under the Uncontrolled strategy, though the reverse holds for Daytime charging. However, differences remain within four percentage points annually when considering shares of overloaded hours over the entire year. Grid and fleet operators may therefore benefit from identifying the prevalent driver groups within their networks, particularly to be aware of the degree of homogeneity of the fleet. Fleets of commercial cars which arrive and depart in sync, can create overloading issues even with flat charging strategies. Such fleets would need careful charging and infrastructure planning.

3.3. Emissions intensity of EV charging

Fig. 6(a) shows emissions intensity of electricity used for EV charging under different strategies in Italy, considering both national averages and the highest and lowest emitting zones, over one year of mobility needs. The comparison between national and zonal emissions intensities illustrates how charging location affects emissions outcomes.

Estimating emissions with the national electricity mix (middle bars in Fig. 6(a)), Flat charging emits the most at 0.333 kg CO_2eq/kWh. Uncontrolled and Daytime strategies emit 2.3% (0.325 kg CO_2eq/kWh) and 9.1% (0.302 kg CO_2eq/kWh) less, respectively. Relative to the aggregate national average which does not differentiate by time of day (0.322 kg CO_2eq/kWh, dotted line), Flat and Uncontrolled emit 3.3% and 0.9% more, as both rely on dirtier nighttime charging, while Daytime emits 6.1% less due to cleaner daytime electricity. These results highlight the importance of using high-temporal-resolution emissions intensity data for greater accuracy in emissions accounting.

In addition to the importance of the high temporal resolution, we also quantify the importance of high spatial resolution in estimating EV charging emissions. If all EVs charged in the least-emitting zone (IT-CNO, 0.271 kg CO_2eq/kWh, 15.8% lower than the national

Table 5
Permissible (Y), likely permissible ((Y)) and non-permissible (N) EV penetration levels for communities sized with 5–100 households (without solar PV) across the three charging strategies. Results based on average values of peak load ratios and number of hours overloaded above 120% transformer rated capacity.

		EV penetration level				
	Community size	20%	40%	60%	80%	100%
Uncontrolled	5	Y	N	N	N	N
	10	Y	(Y)	N	N	N
	20	Y	N	N	N	N
	40	Y	N	N	N	N
	60	Y	Y	N	N	N
	80	Y	N	N	N	N
	100	Y	N	N	N	N
Flat	5	Y	Y	N	N	N
	10	Y	Y	Y	Y	(Y)
	20	Y	Y	Y	N	N
	40	Y	Y	Y	N	N
	60	Y	Y	Y	Y	N
	80	Y	(Y)	N	N	N
	100	Y	Y	N	N	N
Daytime	5	Y	N	N	N	N
	10	Y	(Y)	N	N	N
	20	Y	(Y)	N	N	N
	40	Y	(Y)	N	N	N
	60	Y	Y	N	N	N
	80	Y	N	N	N	N
	100	Y	(Y)	N	N	N

average), emissions from Uncontrolled, Flat, and Daytime would be 16.1%, 15.6%, and 17.2% lower than the national mix, respectively. By contrast, charging in the most-emitting zone (IT-SARD, 0.517 kg CO_2eq/kWh, 60.6% greater than the national average) raises emissions by 60.7%, 60.8% and 57.5% respectively. High spatial resolution is therefore critical for accurate EV charging emissions estimates.

For the most accurate possible estimation of emissions from our case study, we map the home location of each EV to the emissions intensity from each zone in Italy and calculate the emissions, and report them in Fig. 6(b) for the fleet as well as segregated by the driver groups. The Uncontrolled, Flat and Daytime strategies lead to 0.293, 0.298 and 0.279 kg CO_2eq/kWh emissions (that is, compared to Flat charging, uncontrolled and Daytime strategies can save 1.67% and 6.37% emissions, respectively). Emissions calculated with national level emissions data (middle bars in Fig. 6(a)) overestimate all three strategies by 11.04%, 11.56% and 8.29% respectively. Across groups, the Daytime strategy emits the least, while the Flat strategy emits the most. Driver groups able to charge predominantly only in the evening or night hours (Private and Rural drivers) produce between 1.96–18.94 g CO_2eq/kWh (or between 0.7–6.7%) more emissions than groups able to charge more in the morning and afternoon hours (Commercial and Urban drivers). The Commercial driver group, due to their natural mobility profiles enabling them to charge during the day due to daily trips ending in the day (see Fig. A.1(c)), emit the least across all groups and charging strategies.

4. Discussion

With the rise of EV penetration, EV charging will pose considerable challenges for the distribution grid in particular, but research on the impact of different charging strategies on distribution grid infrastructure like transformers, and in terms of carbon emissions, especially using real-world mobility data, is still emerging. In this work, we simulate EV charging demand across three charging strategies — Uncontrolled, Flat and Daytime — and report the average power demand curves for the entire fleet, as well as sub-fleets of the four driver groups. The three strategies lead to quite differently shaped load profiles, with differences in the magnitude and timing of the peak load as well. We further discuss the implications of overloading transformers that result in permissible EV penetration levels, depending on the community size, and the emissions associated with charging the EVs following the three strategies.

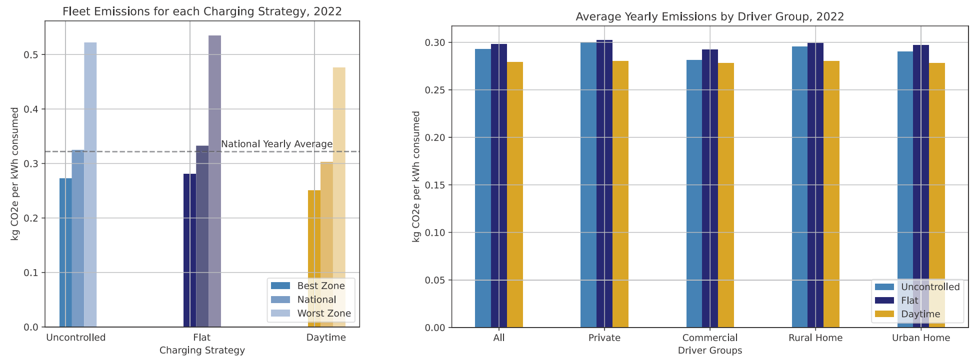
4.1. EV charging demand and permissible EV penetration levels

The results help outline EV penetration limits for communities of different sizes under various charging strategies. In general, all strategies permit at least 20% EV penetration without transformer overloading (Table 4). The Flat charging strategy enables the highest penetration due to lower charging power levels: from 40% up to 100% depending on community size. In contrast, the Daytime strategy supports 40% penetration in most communities, while the Uncontrolled strategy reaches this level only in one case, with most communities limited to 20%. These threshold ranges across the charging strategies resonate with findings from other studies in the range of 15%–45% permissible EV penetration (Muratori, 2018, Shokrzadeh et al., 2017 and Awadallah et al., 2016 reported transformer overloading at 16.66%, 20% and between 30%–40% EV penetration respectively, at 6.6 kW charging. Quiros-Tortos et al. (2023) and Razeghi et al. (2014) reported that 40% and 45% EV penetration levels would lead to transformer overloading, respectively). Given that EV uptake in Italy is projected to reach only 15% by 2030 (School of Management - Politecnico di Milano and Energy & Strategy Group, 2022), DSOs and utilities may still have time to plan grid upgrades or deploy smart EV charging. Nevertheless, affluent communities may already exceed 20% EV penetration, at which point transformer overloading risks become significant according to the findings of this work. The findings therefore provide a pragmatic criterion based on EV penetration to determine the timing of necessary grid infrastructure upgrades to further support EV adoption. Since community size and charging strategy both determine permissible EV penetration levels, blanket policies promoting a single strategy may be inadequate. Instead, DSOs and policymakers should develop more granular, community-specific incentives that consider household numbers, EV penetration levels, and user characteristics.

For example, our results show that a policy successful in incentivizing all EV owners in a community to adopt daytime charging (e.g. through time-of-use tariffs) may limit permissible EV penetration levels to 20%–40%, similar to the Uncontrolled strategy where EV charging occurs predominantly in the evening and night. However, it may lead to a very high ramp-up in demand by artificially constructing high coincidence factors (see Fig. 4). Average total demand (per household and EV) rises from 0.68 kW at 08:00 to 1.77 kW at 09:00, a 158% increase within an hour, much greater than for the other two charging strategies (Fig. 3(a)). While PV generation is not explicitly modeled in this work, assuming PV generation with the Italian residential average installed PV capacity of 0.27 kW per household (see Appendix A.5) and the average PV generation profile for northern Italy would worsen the average ramp up to a 171% increase from 0.62 kW at 08:00 to 1.68 kW at 09:00 (see Fig. 3(b)). This strategy therefore brings into question such hard-set time-of-day rules that aim to create simplified incentives for EV owners to charge their cars in particular periods of the day but may have unintended and undesired effects on grid infrastructure. Approaches such as scheduling charging or employing time-of-use pricing in stages, or identifying driver groups and adjusting charging start times to cascade after a few minutes may work better to avoid such ramp-ups of EV charging demand.

On the other hand, a successful implementation of the Flat charging strategy can afford greater EV penetration levels, up to 60%–80%, potentially postponing distribution transformer upgrades. Yet it requires the technical implementation of EV charging control (requiring smart electricity meters and smart chargers) to limit charging speeds as well as EV user acceptance of such charging strategies, promoted for instance through cheaper overnight tariffs.

While policy incentives such as time-of-use tariffs to promote daytime charging or special, cheaper tariffs to promote overnight Flat charging may create favorable conditions for EV charging considering charging costs and grid constraints, the inclusion of social and behavioral dimensions of EV users' decision-making to charge (Shariatzadeh



(a) Average Emissions Intensity across different charging strategies, for Italy's national average as well as its highest and lowest emission zone

(b) Average emissions intensity for EV charging across driver groups and varying charging strategies, with zonal level emissions intensity data for 2022

Fig. 6. Average Emissions Intensity and Total EV Charging Emissions across different scenarios.

et al., 2025) are equally important and fertile ground for future research. Furthermore, policy approaches other than tariffs may also provide adequate solutions, such as the categorization of EVs as controllable loads in Germany to allow DSOs to slow charging down to a minimum of 4.2 kW to relieve grid stress (Bundesamt für Justiz, 2025). Such policies may enable greater EV penetration even with Uncontrolled charging strategies. New business models as combinations of tariffs and compensation for EV charging control may emerge. While a techno-economic analysis was out of scope, future work should consider the inclusion of the cost of implementation, user acceptance and operation of EV charging control against transformer and grid upgrade costs to shed further light on the design of EV charging strategies.

The simulated EV penetration levels implicitly reflect future scenarios of high adoption under current grid infrastructure. This highlights when existing infrastructure may become overloaded, which is critical given the 20–30 year lifetime of distribution transformers. Future developments – such as greater deployment of renewables, BESS, heat pumps, load-control algorithms, and demand-side flexibility – will influence these outcomes. While electrification (e.g., heat pumps) may raise demand and strain transformers, higher PV and BESS penetration could offset demand locally and reduce charging emissions. Smart algorithms integrating local generation and storage could further optimize loading, dynamically enabling higher EV penetration than allowed under the static limits assumed here. Thus, our results serve as practical guidelines for estimating safe EV hosting capacity in the absence of such technologies, while future work should incorporate them to provide refined recommendations for DSOs.

In addition to the permissible EV penetration levels in residential communities, the findings also have implications on the sizing of distribution transformers. Even though a transformer peak load ratio limit of 1.2 provides a strong indicator of the permissible EV penetration level, a consideration of the amount of overloaded hours under the different strategies provides a very interesting insight, as the duration of overload is crucial to estimate deterioration of a transformer's operational lifetime. For all charging strategies in communities with 10–60 households, the number of hours overloaded is not greater than 0.433% of the hours of the year (that is, 38 h, in the combination: Uncontrolled charging, 40 households, 60% EV penetration, see Table 4). On the other hand, in communities with 80 or 100 households, 60% EV penetration overloads transformers for many more hours (353.4 h in the combination Uncontrolled charging, 80 households, 60% EV penetration). Increasing EV penetration further increases the number of hours of overload, much more in 'Large' communities with 80 or 100 households as compared to 'Small' communities with 60 or fewer households. A key reason is evident in Table 4 where we report the available EV hosting capacity per household (calculated as the available transformer capacity after accounting for residential load), which decreases with increasing community size: Transformer sizing conventions lead to a less than linear increase in transformer installed capacities as community size increases. Even though EV charging does not have high coincidence factors, the high power levels of EV chargers (11 kW) leapfrog diversity factor calculations typically taken to size local transformers without EVs. This may imply a rethink of the transformer sizing conventions by grid operators for the electrification era, and points to the importance of real-world measured data for appropriate sizing. To achieve 100% EV penetration, transformer sizing conventions in communities up to 100 households generally need a scaling factor of 2.30 (Uncontrolled), 1.74 (Flat) and 2.44 (Daytime), derived from Table 4 as the greatest peak load ratios across the community sizes considered. That is, a scaling factor of 1.74–2.44 may account for the EV charging loads on the distribution transformer, in the absence of further increases in load, such as with heat pumps. In line with the results of this study, in order to manage existing networks and avoid dangerous transformer overloading that may lead to loss of load, grid operators should first focus on larger residential communities where one distribution transformer supplies 80 or more households. Solutions like smart charging become relevant for these cases if upgrades are to be avoided; or limited resources should first be invested for such cases if upgrades are unavoidable. For smaller residential communities, grid operators may not face extended periods of transformer overload as soon, especially consecutively, which may be manageable by simpler techniques to control EV loads such as even direct messaging EV owners on especially high-demand days to avoid charging at peak hours.

Differences in mobility patterns across the different driver groups inevitably lead to differences in charging demand. Homogeneity in mobility profiles, in the absence of multiple charging locations, may be particularly problematic due to larger coincidence factors of charging. Compared to Urban drivers that have more variance in arrivals home, a majority of the Rural driver group only return home (and plug-in to charge) in the evening, leading to larger coincidence factors. Therefore, the Rural driver group has 20.65% greater demand peaks than Urban drivers in the Uncontrolled strategy. EVs in rural regions following the Uncontrolled strategy are therefore more likely to overload the local distribution transformer and other grid infrastructure, as has also been shown with the greater number of overloaded hours in Table A.2. Such driver groups should be considered as primary candidates for controlled charging approaches like flat charging (as considered in this work) or other smart charging techniques like charging scheduling and fleet-wide peak minimization.

These findings raise justice and equity concerns regarding the nature of the energy transition. A critical discussion around the roll-out of EV charging infrastructure may be necessary, especially in large communities with installed transformers that have low EV hosting capacities, to ensure that early EV adopters do not create grid constraints for subsequent EV adopters. The installation of EV chargers could be made contingent upon a prior evaluation of the local network, and charger power limits within communities could be imposed. Conversely, smaller communities may hold an inherent advantage due to existing larger transformer capacities, raising concerns about fairness and access when comparing different communities. Therefore, a mechanism to fairly allocate existing grid capacity or a smart charging scheme that accounts for the dynamics of EV adoption within communities connected behind the same transformer (or other limiting distribution grid infrastructure) may be necessary to enable the fast EV adoption needed for the decarbonization of transport sector, and at the same time ensure a just and equitable transition by not leaving poorer and late-adopting households behind.

4.2. Emissions from EV charging

A clear implication from the emissions associated with the different charging strategies is that the Daytime strategy charging leads to the lowest emissions (0.302 kg CO_2eq/kW) while Flat charging leads to the greatest emissions (0.333 kg CO_2eq/kW), since the electricity mix in Italy is greener in the day. Compared to Flat charging, the Uncontrolled and Daytime strategies save 2.3% and 9.1% when considering the national electricity mix, respectively. With the current Italian national electricity mix, the use-phase emissions of EVs account for 55%–60% of the entire lifecycle emissions (Bieker, 2021). Adopting Daytime charging therefore has the potential to reduce EV lifetime emissions by approximately 5.0–5.4%, as compared to Flat charging. In other countries, depending on the electricity generation mix, the difference between the strategies may be different. A charging strategy that limits emissions in one country may not necessarily limit emissions in another country; a blind uptake of charging strategies in other regions based on these results is therefore not recommended unless a comprehensive feasibility study is implemented to understand the differences between geographical regions.

An inspection of emissions of the different driver groups, in Fig. 6(b), reveals two interesting insights. First, the Daytime charging strategy leads to the lowest emissions across all driver groups (between 1.08–6.37% lower than Uncontrolled and 4.83–7.32% lower than Flat charging), and has a spread of only 2.1 g CO_2eq/kWh, even though some charging sessions occur in the evening hours to fulfill trip needs (secondary peaks in Fig. 6(b)). This implies how tapping into the flexibility for charging EVs due to their long parking periods, even within the hard constraints of mobility needs as represented in this work with real-world profiles, can contribute to a meaningful reduction in emissions by charging when the electricity is cleaner. Second, the commercial driver group, by virtue of being able to charge the most during the morning and afternoon hours, has between 3.27–6.75% lower emissions than private drivers, across the charging strategies. This indicates that some driver groups may naturally be well suited to certain charging strategies due to inherent mobility patterns. Identifying such driver groups and assigning charging strategies accordingly can offer an approach to quickly reducing emissions from transport with the least efforts.

4.3. Trade-offs between emissions and transformer overloading: Practically non-existent

In general, while the Flat charging strategy leads to the greatest emissions from charging across driver groups, it has the least overloading impact on the distribution transformer, allowing greater permissible EV penetration levels than Uncontrolled and Daytime strategies. Flat charging leads to 2.3% and 10% more emissions than the Uncontrolled and Daytime strategies, respectively; but leads to 77.82% and 74.14% lower hours overloaded on average across community sizes with 100% EV penetration level, respectively. It is the only strategy that allows 100% EV penetration (for community size 10). On the other hand, the Daytime charging strategy leads to much greater overloaded hours (under the assumption of absence of local PV generation), can only achieve a maximum of 40% of EV penetration, but has the lowest emissions across driver groups. Therefore, this insinuates a trade-off between grid overloading and charging emissions: Choose the Flat charging strategy to limit overloading, or the Daytime strategy to limit charging emissions. Since the Uncontrolled charging strategy leads to even greater hours overloaded and has greater emissions than the Daytime strategy, it is neglected in this discussion about trade-offs.

It must be noted that the emissions savings derived from choosing the Daytime strategy over Flat charging imply approximately 5–5.4% emissions reductions over the entire EV lifecycle, assuming that the current Italian national electricity generation mix does not change. While this is a large difference considering the large base of transportation sector energy consumption and emissions, this savings potential may reduce as the average generation mix further decarbonizes. Therefore, in the absence of any local PV generation (as assumed in the transformer overloading analyses in this work), it may be worthwhile to focus entirely on deferring transformer and grid upgrades until very high EV penetration levels by following the Flat charging strategy. Detailed analyses are necessary to consider the changing electricity generation mix, local (renewable) electricity generation and local distribution network topologies, EV user behavior and acceptance of charging strategies.

Nevertheless, accounting for currently installed average residential PV levels of 0.27 kW per household and the daily average generation from such a system imply that the total peak load borne by the transformer is almost the same in the Daytime and Flat strategies (see Fig. 3(b)). With projections of increasing residential solar PV installations, Daytime charging is poised to have lower total peak load on the transformer than Flat charging. Therefore, if local PV generation exists within the residential community behind the distribution transformer, Daytime charging strategy is the superior choice, both in terms of charging emissions and allowing high EV penetration. That is, the Daytime charging strategy leads to minimal trade-offs between charging emissions and transformer overloading.

Infrastructure and policy challenges may hinder the adoption of daytime EV charging. Limited availability of chargers at homes or workplaces can restrict feasibility, while some policies may also discourage daytime charging. For example, direct subsidies or indirect mechanisms such as reduced feed-in tariff rates to promote self-consumption for residential PV–BESS systems may reduce local solar generation available for EVs. Policies to incentivize EV adoption with flat or discounted tariffs (for instance, at night) for EV charging may disincentivize EV owners to plan to charge in the daytime. EV and home owners may prioritize personal financial incentives (clearer available information and ability to control) at the expense of grid infrastructure or charging emissions (lack of information and understanding). Additionally, EV owners may simply want to charge at night out of habit or for ease of process. Conversely, supportive measures such as time-of-use tariffs aligned with solar peaks, workplace charging facilities, and incentives for PV–EV integration could make daytime charging both practical and attractive. A coherent policy framework is therefore essential to ensure intended outcomes and avoid unintended behaviors.

4.4. Limitations and future work

This work is not without limitations. First, while the dataset provides detailed mobility patterns for 909 vehicles, we assume these persist in the transition from ICEVs to EVs. It is conceivable however, particularly in the early adoption period, EV use may involve behavioral changes due to range anxiety, re-routing to chargers, or shifting trip times to avoid congestion at charging stations. Newer datasets measured on EVs may better capture the exact driving and energy consumption profiles, and include EV driver behavior, enabling more accurate estimates of the impact of EV charging on distribution transformers and on emissions. For instance, EV drivers may charge less frequently (e.g., once or twice a week), creating coincident high-demand events not captured in our daily-charging assumption. This may result in greater peak load ratios and potentially longer durations with more than 120% overload than the 60 min considered in this work as an overloading metric, depending on the frequency of coincident charging events. The inter-relationship between charging demand, charging frequency and EV battery size is non-trivial. Therefore, incorporating charging preferences, randomness, and behavioral adaptation is a key direction for future research, potentially through agent-based models that simulate such dynamics (e.g., Gschwendtner et al., 2023a). These issues may lessen over time with larger batteries and wider charging access, but remain important for interpreting our results. Moreover, our analysis is limited to Italian driving profiles, which may not reflect other regions with different travel behaviors or household load profiles.

Second, the study focuses on home charging and three predefined strategies, omitting the potential role of workplace and public charging — especially in urban contexts, where greater charger availability could reduce the stress on transformers feeding residential communities. Similarly, we do not explicitly model local solar PV generation profiles(and their sensitivity to installation orientation, location, and weather) which may temporally align with EV charging demand, potentially reducing the impacts of the Daytime charging strategy. Alternatively, in case of adverse weather conditions, the Daytime charging strategy may inadvertently exacerbate grid impacts. However, these limitations allow the inspection of worst-case charging impacts due to home charging.

Third, the absence of high-resolution Italian residential demand data required combining standardized load profiles with high-resolution EV charging profiles. While this may underestimate local transformer stress, the study emulates transformer sizing according to conventions followed by grid operators, thereby reporting how existing practices and diversity factor calculations affect permissible EV penetration levels in residential communities. Additionally, the transformer overloading metrics in this work do not capture real-time power flow or thermal dynamics. Advanced approaches such as winding hot-spot temperature models could refine overload estimates, and support dynamic transformer ratings, thereby providing DSOs with instantaneous input to manage EV charging loads. At the same time, transformer overloading is influenced by multiple factors, including previous loading, phase balances, wiring materials, transformer age, and ambient temperature. For instance, older or heavily-loaded transformers may not sustain the EV penetration levels reported as permissible in this analysis. While we do not model these explicitly, reporting peak load ratios and overloaded hours allows us to deliver a comprehensive analysis and offer generalized recommendations on permissible EV penetration levels in residential communities.

5. Conclusion

In this work, we rely on real-world GPS-tracked mobility profiles from 909 vehicles to simulate three different electric vehicle charging strategies – Uncontrolled, Flat, and Daytime – evaluating charging demand profiles for the full fleet and driver sub-groups. We provide a comprehensive analysis of EV charging demand under the three charging strategies, quantify the overloading faced by distribution transformers supplying residential communities across 105 configurations of varying size, EV penetration level, and charging strategies. EV charging emission estimates are reported considering national and zonal emissions intensities, illustrating spatio-temporal differences in emissions estimations. The findings provide generalized estimates for permissible EV penetration levels in residential communities that do not overload distribution transformers, and estimate the emissions intensity of EV charging.

The results show that 20% EV penetration levels are permissible regardless of community size or the employed charging strategy. Higher penetration depends on both strategy and community size: Uncontrolled and Daytime allow up to 40% in some cases, while Flat charging enables even 100% in a 10-household community. Therefore, personalization for the case at hand is important — a charging strategy appropriate for one residential community may not be appropriate for another. The results also suggest transformer sizing conventions need updates to keep up with the transition to electric vehicles. Transformers supplying 80 or more households end up with smaller available EV hosting capacities, by virtue of lower diversity factors. EV charging leapfrogs existing load growth calculations and necessitates the inclusion of a scaling factor of 1.74–2.44 to allow 100% EV penetration levels in residential communities.

This study also sheds light on potential trade-offs between transformer overloading and the emissions attributed to EV charging. While the Flat charging strategy has the least impact on transformer overloading, it leads to the greatest emissions. Conversely, Daytime charging cuts emissions by 10% relative to Flat charging, by virtue of cleaner electricity during the charging hours, but leads to a large share of overloaded hours. Charging EVs with the Daytime strategy may end up emitting between 5.0–5.4% lower lifetime emissions than with Flat charging, assuming the current electricity generation mix. However, consideration of local solar PV generation behind the transformer at the average installed Italian residential capacity of 0.27 kW/household results in very similar total peak loads imposed by the Flat and Daytime strategies. Hence, Daytime charging stands as an optimal choice already today when considering charging emissions and enabling high EV penetration without overloading the grid, and is likely to become even more advantageous as PV penetration increases.

These findings are relevant for utilities, distribution system operators, residential communities, EV fleet managers, and policymakers. Utilities and DSOs can use the penetration thresholds as practical guidelines and prioritize upgrades and management of grid infrastructure and EV charging control in residential communities larger than 80 households. Fleet operators can assess the trade-offs between emissions and grid impacts at different penetration levels. Policymakers, particularly in regions with electricity mixes similar to Italy, should pair EV adoption policies with incentives for daytime charging to encourage charging emissions reductions and afford greater EV penetration levels while delaying or even avoiding grid upgrades altogether.

CRediT authorship contribution statement

Prakhar Mehta: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Verena Tiefenbeck:** Writing – review & editing, Supervision, Funding acquisition, Conceptualization. **Thorsten Staake:** Writing – review & editing, Supervision.

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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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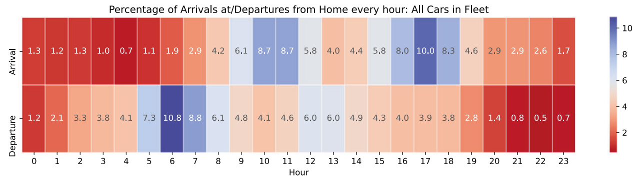
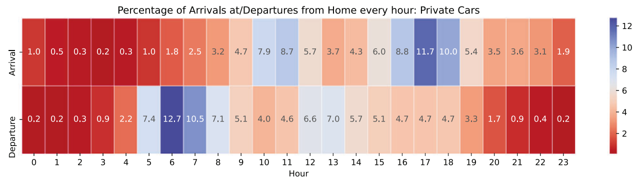
Appendix

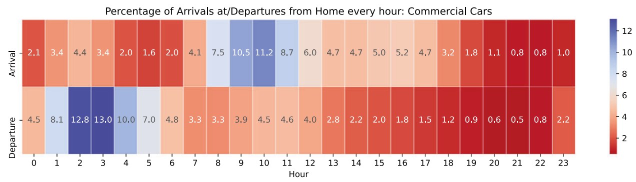
A.1. Arrivals and departures from home



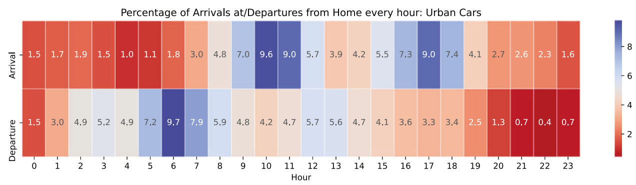
(a) All Cars



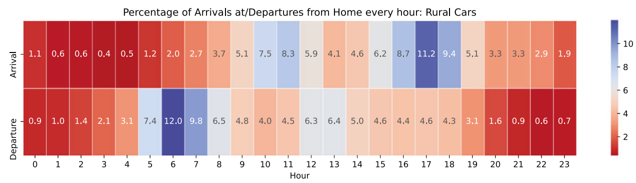
(b) Private Cars



(c) Commercial Cars



(d) Urban Cars



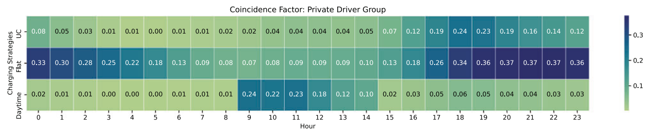
(e) Rural Cars

Fig. A.1. Fraction of EVs arriving at and departing from home.

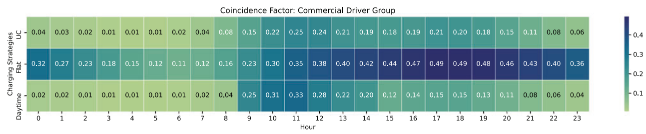
Fig. A.1 shows the fractions of arrivals at and departures from home locations, for the entire fleet A.1(a) as well as the driver groups (Figs. A.1(b), A.1(c), A.1(d), A.1(e)). The Private driver group follows more typical arrivals at and departures from home, with the majority departing early morning and arriving in the evening. A considerable share of cars also make a trip home in the middle of the day, presumably for lunch. On the other hand, the Commercial driver group operates mostly overnight, leaving the home location between 01:00–05:00 and arriving home in the morning between 08:00–12:00. Comparing the Urban and Rural driver groups, the Urban driver group shows greater heterogeneity as the shares of cars are more distributed across the hours of the day. Rural cars have larger fraction arriving at and departing from home at the same time, leading to larger charging demand peaks, as seen in Fig. 5(c).

A.2. Coincidence factors

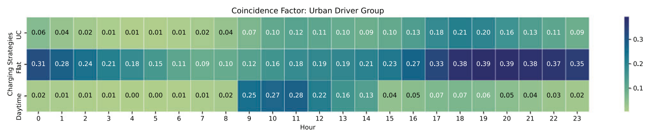
Fig. A.2 shows the coincidence factors (CFs) for all four driver groups for all three charging strategies. Key differences exist between the Private and Commercial driver groups. Since commercial driver groups arrive at their home locations in the late morning and plug-in to



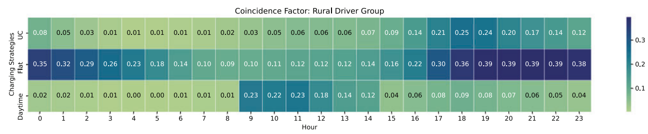
(a) Coincidence Factors for Private cars



(b) Coincidence Factors for Commercial cars



(c) Coincidence Factors for Rural cars



(d) Coincidence Factors for Urban cars

Fig. A.2. Average EV Charging Demand across different scenarios for the different driver groups.

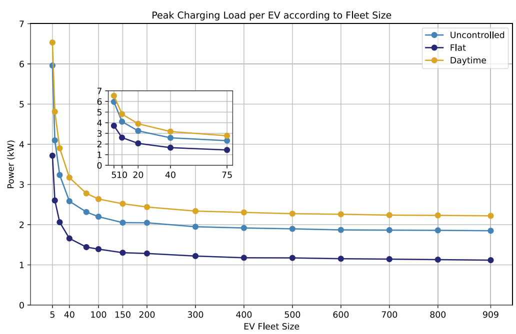


Fig. A.3. Peak charging demand per EV as the fleet size increases.

Table A.1
Averages of the peak load (Load) and peak coincidence factor (CF), as well as peak overload ratios (PLR) over 100 runs for all community sizes (without solar PV) and EV penetration levels across all three charging strategies, with all driver groups.

			100%			80%			60%			40%			20%		
	#HHs	Xmer kVA	Load	PLR	CF	Load	PLR	CF	Load	PLR	CF	Load	PLR	CF	Load	PLR	CF
Uncontrolled	5	15	32.86	2.19	0.84	30.39	2.03	0.92	26.85	1.79	0.96	23.30	1.55	1.00	15.97	1.06	1.00
	10	30	51.49	1.72	0.69	46.26	1.54	0.75	41.24	1.37	0.81	35.56	1.19	0.91	27.29	0.91	1.00
	20	45	84.32	1.87	0.56	75.03	1.67	0.62	65.50	1.46	0.66	56.23	1.25	0.75	44.49	0.99	0.91
	40	75	143.86	1.92	0.50	128.40	1.71	0.52	111.73	1.49	0.56	96.47	1.29	0.62	73.53	0.98	0.71
	60	112.5	202.54	1.80	0.47	181.50	1.61	0.49	155.74	1.38	0.51	130.97	1.16	0.55	104.40	0.93	0.66
	80	112.5	259.21	2.30	0.45	232.22	2.06	0.46	199.83	1.78	0.49	167.49	1.49	0.52	132.99	1.18	0.60
	100	150	319.57	2.13	0.44	279.34	1.86	0.45	242.44	1.62	0.47	201.76	1.35	0.49	160.52	1.07	0.58
Flat	5	15	22.18	1.48	0.97	20.30	1.35	1.00	19.16	1.28	1.00	15.95	1.06	1.00	13.97	0.93	1.00
	10	30	34.68	1.16	0.88	31.89	1.06	0.92	29.29	0.98	0.96	26.31	0.88	1.00	21.22	0.71	1.00
	20	45	59.67	1.33	0.78	54.83	1.22	0.81	48.29	1.07	0.86	41.98	0.93	0.92	34.63	0.77	0.99
	40	75	105.44	1.41	0.69	94.22	1.26	0.71	83.18	1.11	0.76	73.38	0.98	0.80	62.35	0.83	0.92
	60	112.5	150.04	1.33	0.67	133.51	1.19	0.68	119.26	1.06	0.70	103.72	0.92	0.75	89.07	0.79	0.86
	80	112.5	195.24	1.74	0.65	173.21	1.54	0.66	154.74	1.38	0.69	135.27	1.20	0.72	112.61	1.00	0.81
	100	150	235.50	1.57	0.63	214.08	1.43	0.64	190.87	1.27	0.66	163.68	1.09	0.70	139.51	0.93	0.77
Daytime	5	15	36.58	2.44	0.90	32.52	2.17	0.97	28.51	1.90	0.98	24.50	1.63	1.00	15.82	1.05	1.00
	10	30	53.83	1.79	0.74	48.97	1.63	0.80	43.68	1.46	0.86	35.89	1.20	0.96	28.33	0.94	1.00
	20	45	88.67	1.97	0.63	77.00	1.71	0.65	67.96	1.51	0.71	56.93	1.27	0.80	43.62	0.97	0.95
	40	75	152.24	2.03	0.54	133.07	1.77	0.57	112.77	1.50	0.61	93.17	1.24	0.67	72.04	0.96	0.80
	60	112.5	213.02	1.89	0.51	185.74	1.65	0.53	154.67	1.37	0.56	127.48	1.13	0.61	100.26	0.89	0.71
	80	112.5	270.07	2.40	0.49	233.17	2.07	0.51	197.11	1.75	0.53	158.92	1.41	0.56	125.48	1.12	0.66
	100	150	329.45	2.20	0.48	284.29	1.90	0.50	235.26	1.57	0.51	191.91	1.28	0.55	153.04	1.02	0.63

Table A.2
Average number of hours overloaded above 120% of transformer nominal capacity (without solar PV), for all community sizes, charging strategies and driver groups, at 100% and 40% EV penetration levels.

		100% EV penetration							40% EV penetration						
	Community size/ Driver type	5	10	20	40	60	80	100	5	10	20	40	60	80	100
Uncontrolled	All Cars	146.49	49.46	155.54	302.09	252.74	1095.56	808.29	16.85	1.46	3.54	6.49	0.79	77.24	24.14
	Private	112.63	37.04	102.63	210.02	171.73	972.75	719.05	13.95	0.65	1.53	2.05	0.40	46.64	12.13
	Commercial	540.69	318.93	779.50	1390.03	1353.02	2853.61	2560.89	65.02	8.79	28.14	38.51	16.00	403.94	157.45
	Rural	189.62	64.93	181.66	443.54	378.64	1273.88	977.88	19.73	1.49	4.36	5.76	2.67	112.58	44.04
	Urban	166.17	40.32	123.95	228.46	168.44	988.78	677.94	19.37	1.01	1.67	4.20	0.39	40.96	10.61
Flat	All Cars	24.18	2.20	14.10	38.16	20.67	674.64	346.28	1.23	0.00	0.05	0.01	0.00	3.50	0.02
	Private	12.99	0.28	1.14	2.37	0.48	170.20	49.02	0.38	0.00	0.00	0.00	0.00	0.04	0.00
	Commercial	236.88	92.75	390.46	840.21	875.28	2168.15	1832.91	15.14	1.35	3.14	8.98	4.10	250.93	109.17
	Rural	33.14	2.95	10.14	41.93	22.14	654.27	352.00	1.36	0.00	0.19	0.05	0.00	3.23	0.35
	Urban	26.09	2.22	13.15	40.37	23.07	674.91	366.22	0.62	0.03	0.03	0.03	0.00	1.82	0.05
DAYTIME	All Cars	162.53	48.23	135.65	234.26	182.68	957.44	652.07	18.31	1.54	2.13	2.12	0.27	21.99	3.98
	Private	102.65	35.78	76.95	134.40	107.17	523.66	341.22	9.77	0.80	1.05	1.21	0.21	14.30	2.91
	Commercial	566.63	331.23	788.43	1406.46	1450.04	2892.02	2602.76	61.60	8.20	23.92	38.57	12.22	346.92	133.40
	Rural	171.00	57.24	133.86	232.47	192.95	902.49	599.27	16.64	1.65	2.76	2.93	0.51	32.68	7.58
	Urban	160.32	61.58	155.23	256.33	210.57	1042.82	729.54	15.42	1.51	3.12	1.41	0.25	19.43	3.33

charge, the CFs are greater than Private driver groups in the morning and early afternoon hours (07:00–17:00) across charging strategies. Due to greater homogeneity in the Private driver group, in the Uncontrolled strategy, the CF is greater than for the Commercial driver group in the evening hours due to more arrivals home. In the Flat charging strategy, the Commercial driver group stays connected longer due to greater energy needs, leading to larger CFs until the early morning hours, when Private driver groups have greater CFs since they started charging much later. Between the Rural and Urban driver groups, more rural cars finish their daily trips in the evening and therefore show slightly greater CFs between 17:00–02:00 in the Uncontrolled charging strategy. Since a share of Urban cars are already done with all trips of the day quite early, they charge more in the morning and afternoon hours between 08:00–15:00 and have greater CFs.

A.3. Electric vehicle charging demand per EV at varying fleet sizes

Fig. A.3 shows the peak charging demand per EV as the fleet size increases, for the three charging strategies with a maximum charging power of 11 kW. In small fleets, the peak charging demand per EV is very high, as there is a greater chance of the few EVs coinciding to charge at the full rated charger power. As the number of EVs increases, the demand per EV decreases. Post 300 EVs, the demand per EV is almost constant.

A.4. Transformer overloading metrics

In evaluating transformer overloading, we also report the peak loads faced by the transformers across charging strategies. Table A.1 shows, for each charging strategy, the averages of the peak load and the coincidence factor over 100 simulation runs of EV charging over a full year, for every residential community size and EV penetration level. The ratio of the peak load to the transformer nominal capacity, the peak load ratio (PLR), is highlighted for each EV penetration level. As transformers can withstand loads up to 120% of nominal capacity for short periods, we focus on cases where the PLR is 1.2 or greater. While the PLR increases with increasing EV penetration level, the degree of overload depends on the choice of charging strategy and the size of the community. Across strategies, transformers supplying very small communities (5 households) and large communities (80 and 100 households) bear the greatest PLRs. Consequently, for the Uncontrolled and Daytime strategies, even 40% penetration levels exceed PLRs of 1.2, while the Flat strategy allows up to 60% penetration. In 5-household communities across penetration levels 20%–100%, the small number of EVs (1–5) have a greater chance of high coincidence factors, as seen with the peak CF being the greatest across all community sizes. Therefore, the transformer capacity of 15 kVA is more likely to be overloaded by the EV charging demand further coinciding with residential demand peaks. In larger communities with 80 or 100 households, even though the CFs are relatively lower (in the range of 44%–72% across penetration levels and charging strategies), it is the transformer sizing that rather becomes the bottleneck, with a capacity of only 1.4–1.5 kVA per household, leading to low available hosting capacities for EVs. Introducing EVs in such communities quickly overloads the transformer, even at low penetration levels of 40%. Communities between 10–60 households, in general, experience lower PLRs at all penetration levels, due to greater hosting capacity available for EVs. Between charging strategies, the Flat charging strategy has the lowest PLRs, while the Daytime strategy has the greatest.

Table A.3
Extension of Table 4 with 95% confidence interval margins included with average values of transformer overloading metrics — peak load ratio, hours overloaded above 120% rated capacity, hours overloaded for the second consecutive hour or more above 120% rated capacity.

Charging strategy	Community size	Transformer peak load ratios					No of hours overloaded					No of hours of overload for the second consecutive hour or more				
		EV penetration levels					EV penetration levels					EV penetration levels				
		20%	40%	60%	80%	100%	20%	40%	60%	80%	100%	20%	40%	60%	80%	100%
Uncontrolled	5	1.06 ± 0.003	1.55 ± 0.040	1.79 ± 0.044	2.03 ± 0.055	2.19 ± 0.056	0.00 ± 0.000	16.85 ± 5.168	44.72 ± 12.028	101.28 ± 18.197	146.49 ± 18.197	0.00 ± 0.000	8.20 ± 2.859	26.58 ± 9.584	66.61 ± 15.966	95.89 ± 14.403
	10	0.91 ± 0.023	1.19 ± 0.032	1.38 ± 0.042	1.54 ± 0.040	1.72 ± 0.045	0.00 ± 0.000	1.46 ± 0.584	12.70 ± 5.165	24.51 ± 7.798	49.46 ± 11.379	0.00 ± 0.000	0.47 ± 0.256	6.52 ± 3.210	13.34 ± 5.757	28.38 ± 8.766
	20	0.99 ± 0.021	1.25 ± 0.026	1.46 ± 0.034	1.67 ± 0.041	1.87 ± 0.042	0.06 ± 0.068	3.54 ± 1.395	21.03 ± 5.022	67.89 ± 11.424	155.54 ± 18.468	0.02 ± 0.040	1.10 ± 0.477	10.07 ± 3.124	41.34 ± 8.539	109.97 ± 15.859
	40	0.98 ± 0.015	1.29 ± 0.026	1.49 ± 0.024	1.71 ± 0.038	1.92 ± 0.037	0.00 ± 0.000	6.49 ± 2.392	38.03 ± 7.167	147.53 ± 20.517	302.09 ± 27.371	0.00 ± 0.000	2.66 ± 1.447	21.40 ± 5.114	109.13 ± 18.254	248.22 ± 26.942
	60	0.93 ± 0.014	1.16 ± 0.017	1.38 ± 0.022	1.61 ± 0.028	1.80 ± 0.032	0.00 ± 0.000	0.79 ± 0.280	20.93 ± 5.326	114.57 ± 14.169	252.74 ± 21.705	0.00 ± 0.000	0.12 ± 0.136	10.69 ± 3.630	79.31 ± 12.308	205.92 ± 21.479
	80	1.18 ± 0.016	1.49 ± 0.022	1.78 ± 0.026	2.06 ± 0.032	2.30 ± 0.036	1.51 ± 0.754	77.24 ± 13.037	353.43 ± 29.504	711.54 ± 33.041	1095.56 ± 31.696	0.43 ± 0.363	51.27 ± 10.585	301.57 ± 29.757	659.17 ± 34.270	1045.13 ± 32.745
	100	1.07 ± 0.013	1.34 ± 0.016	1.62 ± 0.020	1.86 ± 0.023	2.13 ± 0.028	0.06 ± 0.084	24.14 ± 5.298	180.10 ± 14.896	489.56 ± 24.433	808.29 ± 26.480	0.02 ± 0.040	12.05 ± 3.441	138.09 ± 13.832	442.26 ± 25.743	764.41 ± 27.827
Flat	5	0.93 ± 0.039	1.06 ± 0.044	1.28 ± 0.049	1.35 ± 0.054	1.48 ± 0.050	0.00 ± 0.000	1.23 ± 1.087	7.79 ± 4.855	13.46 ± 6.342	24.18 ± 9.094	0.00 ± 0.000	0.91 ± 0.880	5.55 ± 3.828	10.42 ± 5.733	18.99 ± 8.002
	10	0.71 ± 0.019	0.88 ± 0.026	0.98 ± 0.029	1.06 ± 0.034	1.16 ± 0.035	0.00 ± 0.000	0.00 ± 0.000	0.11 ± 0.112	0.55 ± 0.371	2.20 ± 1.292	0.00 ± 0.000	0.00 ± 0.000	0.07 ± 0.106	0.32 ± 0.250	1.42 ± 0.932
	20	0.77 ± 0.016	0.93 ± 0.022	1.07 ± 0.027	1.22 ± 0.030	1.33 ± 0.034	0.00 ± 0.000	0.05 ± 0.071	0.38 ± 0.197	5.65 ± 3.312	14.10 ± 5.120	0.00 ± 0.000	0.00 ± 0.000	0.25 ± 0.158	3.82 ± 2.732	10.17 ± 4.228
	40	0.83 ± 0.014	0.98 ± 0.017	1.11 ± 0.018	1.26 ± 0.026	1.41 ± 0.023	0.00 ± 0.000	0.01 ± 0.020	0.37 ± 0.280	11.14 ± 4.668	38.16 ± 9.309	0.00 ± 0.000	0.00 ± 0.000	0.14 ± 0.141	7.64 ± 3.642	29.30 ± 8.103
	60	0.79 ± 0.012	0.92 ± 0.014	1.06 ± 0.016	1.19 ± 0.016	1.33 ± 0.018	0.00 ± 0.000	0.00 ± 0.000	0.05 ± 0.059	1.48 ± 0.520	20.67 ± 5.791	0.00 ± 0.000	0.00 ± 0.000	0.00 ± 0.000	0.86 ± 0.382	15.01 ± 4.989
	80	1.00 ± 0.012	1.20 ± 0.017	1.38 ± 0.018	1.54 ± 0.020	1.74 ± 0.019	0.01 ± 0.020	3.50 ± 1.487	57.04 ± 12.108	259.52 ± 26.348	674.64 ± 36.353	0.00 ± 0.000	2.18 ± 1.002	45.46 ± 11.185	234.46 ± 25.830	647.48 ± 37.143
	100	0.93 ± 0.011	1.09 ± 0.011	1.27 ± 0.013	1.43 ± 0.017	1.57 ± 0.016	0.00 ± 0.000	0.02 ± 0.040	10.84 ± 2.879	111.55 ± 15.674	346.28 ± 25.322	0.00 ± 0.000	0.02 ± 0.040	7.00 ± 2.167	95.77 ± 14.704	322.00 ± 25.232
DAYTIME	5	1.05 ± 0.008	1.63 ± 0.039	1.90 ± 0.050	2.17 ± 0.051	2.44 ± 0.062	0.00 ± 0.000	18.31 ± 4.843	54.03 ± 12.164	84.93 ± 12.134	162.53 ± 19.339	0.00 ± 0.000	7.98 ± 2.852	26.84 ± 9.384	39.14 ± 8.540	88.87 ± 15.016
	10	0.94 ± 0.017	1.20 ± 0.033	1.46 ± 0.034	1.63 ± 0.043	1.79 ± 0.042	0.00 ± 0.000	1.54 ± 0.614	10.45 ± 2.283	27.18 ± 4.989	48.23 ± 6.723	0.00 ± 0.000	0.16 ± 0.146	2.51 ± 0.854	9.26 ± 2.825	17.75 ± 3.662
	20	0.97 ± 0.021	1.26 ± 0.024	1.51 ± 0.029	1.71 ± 0.036	1.97 ± 0.042	0.04 ± 0.039	2.13 ± 0.717	17.38 ± 3.326	49.79 ± 6.537	135.65 ± 13.426	0.00 ± 0.000	0.26 ± 0.230	5.09 ± 1.846	18.34 ± 4.024	65.38 ± 9.957
	40	0.96 ± 0.016	1.24 ± 0.021	1.50 ± 0.025	1.77 ± 0.033	2.03 ± 0.034	0.02 ± 0.040	2.12 ± 0.722	22.85 ± 3.433	92.15 ± 9.959	234.26 ± 15.418	0.00 ± 0.000	0.22 ± 0.168	6.68 ± 1.992	41.98 ± 6.905	133.31 ± 12.068
	60	0.89 ± 0.013	1.13 ± 0.016	1.38 ± 0.021	1.65 ± 0.029	1.89 ± 0.030	0.00 ± 0.000	0.27 ± 0.112	8.38 ± 1.294	55.26 ± 5.640	182.68 ± 11.283	0.00 ± 0.000	0.02 ± 0.040	1.51 ± 0.449	23.52 ± 4.233	101.35 ± 9.397
	80	1.12 ± 0.018	1.41 ± 0.020	1.75 ± 0.026	2.07 ± 0.027	2.40 ± 0.029	0.40 ± 0.246	21.99 ± 3.144	167.68 ± 13.568	511.68 ± 23.024	957.44 ± 32.132	0.06 ± 0.088	6.54 ± 1.666	90.24 ± 10.777	359.54 ± 22.205	770.20 ± 33.605
	100	1.02 ± 0.014	1.28 ± 0.015	1.57 ± 0.020	1.90 ± 0.025	2.20 ± 0.028	0.04 ± 0.063	3.98 ± 1.055	68.75 ± 5.948	285.41 ± 14.558	652.07 ± 26.971	0.00 ± 0.000	0.71 ± 0.408	29.95 ± 4.090	181.26 ± 12.080	487.49 ± 26.949

Transformer overloading hours based on the driver group are shown in Table A.2. It shows the number of hours the transformer is overloaded over 120% of the nominal capacity, for the three charging strategies, all driver groups and all community sizes, for 40% and 100% EV penetration levels.

Table A.3 shows the averages of the three transformer overloading metrics together with the 95% confidence interval margins.

A.5. Assumptions on installed residential PV capacity in Italy

In 2022, Italy had a total installed capacity of 4949 MW of PV systems sized less than 12 kW, which typically make up residential installations (Bellini, 2023). This included a growth of 1.1 GW in 2022 (Bellini, 2023). We assume an optimistic 2023 with Italia Solare's expectation of doubling installations, and assume an additional 2 GW of added residential capacity (Bellini, 2023). With 25.7 millions households in Italy (Istituto Nazionale di Statistica, 2021), the residential PV capacity per household amounts to 0.27 kW.

Data availability

The data that has been used is confidential.

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