Representative empirical, real-world charging station usage characteristics and data in Germany

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***Abstract*—Electric vehicle (EV) charging infrastructure is a new type of consumer in the power grid. Oftentimes, theoretical models have to be used to understand the impact of these new assets since little empirical data of charging station usage is available. This paper aims to increase understanding of charging station usage by providing empirical data collected from 26,951 charging station connectors in Germany. We demonstrate that currently the usage intensity of stations is overall between 15 % and 20 % and therefore relatively low, but depends strongly on weekday and hour of the day. Fast-chargers are generally occupied less time compared to slower chargers while each charging event also takes significantly less time. A key challenge in optimizing real-world asset usage are EVs which are parked significantly longer at charging stations than the actual charging process takes. We show that an unexpectedly high share of charging events requires between 8 and 10 hours indicating that people park their EVs before going to work and then picking them up after they finished working.**

Keywords—Electric vehicles (EVs), Charging station, empirical data, Germany

I. Abbreviations

Abbreviation	Explanation
EV	Electric vehicle
EVSE	Electric vehicle supply equipment
CapEx	Capital Expenditure or investment
OpEx	Operational Expenditure or maintenance

Abbreviations used in multiple chapters. Abbreviations used only in a single chapter are introduced in that chapter.

II. Introduction

To allow for the widespread use of electric vehicles (EVs), publicly accessible recharging infrastructure is indispensable. As public chargers are quite expensive, with fast-chargers costing up to and more than 100,000 $ [1], a balance must be made in infrastructure planning between minimizing required hardware while simultaneously maximizing user comfort. To do so, researchers and planners often employ simulations to estimate the usage pattern of stations. This has been done in a variety of ways including the usage of traffic counters, socio-economic data, electric vehicle usage data, surveys, or sampled charging station profiles. The key challenge here is to create a model that accurately corresponds with real-world behaviour while simultaneously there is limited empirical data to compare the models with. This paper aims to support researchers and planners alike by providing usage patterns based on a vast real-world database where the occupation of 26,951 charging points in Germany was monitored over 3 months. The resulting patterns can be used by researches either by directly applying the usage pattern in their models or by verifying that theoretical models result in a pattern comparable to the empirical models reported in this paper.

A. Literature review

In literature, some examples exist where authors collected data from a large amount of charging stations and performed pattern analysis on the data. Especially in the Netherlands[2, 3] and in the UK/USA [4], significant efforts were made to characterise how public charging infrastructure is used. To our best knowledge, no other example of comparable scale exists where the charging infrastructure of an entire country is systematically analysed. Other authors focused their analysis on smaller regions such as in Shanghai, China [5] or Jeju island, South Korea [6]. While the results appear very promising for specific sites, it is not clear how representative the obtained results are and it is consequently not possible to transfer the results to other, larger areas or different cultures. A third source of real-world charging station usage data are reports or databases from governmental agencies such as the city of Palo Alto, USA [7] or Nebraska, USA [8]. While these datasets allow for people to perform own analysis, they are again limited in geographical scope and cannot serve as a guideline for general charging station usage of states or countries. Concluding one can state that limited large-scale, real-world, empirical data or the analysis thereof of charging station usage is available worldwide. Lastly, several organizations exist which likely possess large-scale charging station usage data and offer consulting or other services based on said data. Examples are ElaadNL, CIRRANTiC, SemaConnect, ChargePoint, and many more. For science, the problem with these institutions is that access to the data is limited and often involves payment.

If no real-world charging station usage data was available, authors used a number of ways to generate charging profiles:

- Traffic counter data [9, 10]: It is assumed that electric vehicles are a fixed share of all moving traffic and of that again a certain share is in need of recharging.
- Socio-economic data and expert opinions [11, 12]: A model is built that derives charging needs from

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- assumptions of how socio-economic data translates into localized charging needs
- Electric vehicle usage data [13–16]: From the movement of EVs, the actual or possible charging processes can be found through analysis of idle times

The key challenge in these approaches is to ensure that the resulting models correspond with real charging station usage. Otherwise, a risk of unrealistic model behaviour exists which, if used for investment planning, could lead to inefficiently allocated resources.

B. *This paper in the context of literature*

We believe that using large-scale, real-world data and then interpreting the patterns one can observe is the path with least systematic errors when trying to understand public charging station usage. To do so, researchers and practitioners require diverse datasets and analysis from around the world. With this paper, we therefore would like to contribute by showing results for Germany, a country for which, to the best of our knowledge, no comprehensive analysis over the usage patterns for charging stations on a national level has been executed. Next to the presented analysis, we actively invite other researchers to get in touch with us to perform other analyses together with them using our dataset.

III. Material and Methods

This paper shows charging station usage data, collected between December 21, 2019 and March 10, 2020. The dates were chosen to include the effect of public holidays (Christmas and New Year) while not altering results by changes in travel behaviour due to the Corona crisis starting mid-March. The data has been collected in a Python environment using automated requests from various web portals. The sources are the maps of various roaming

Table 1: Characteristics of observed connectors. From here onwards, the different sets are referenced by their respective power rating.

Power rating	Most frequently occurring rating in set	Observed connectors	Average share of time during which status was known
P≤4kW	3.7 kW (47 %), 3.0 kW (40 %)	2,079	68.9 %
4kW<P≤12kW	11 kW (100 %)	2,400	82.7 %
12kW<P≤25kW	22 kW (100 %)	19,228	81.1 %
25kW<P≤100kW	50 kW (93 %)	3,233	81.0 %
P>100kW	175 kW (73 %)	11	99.7 %

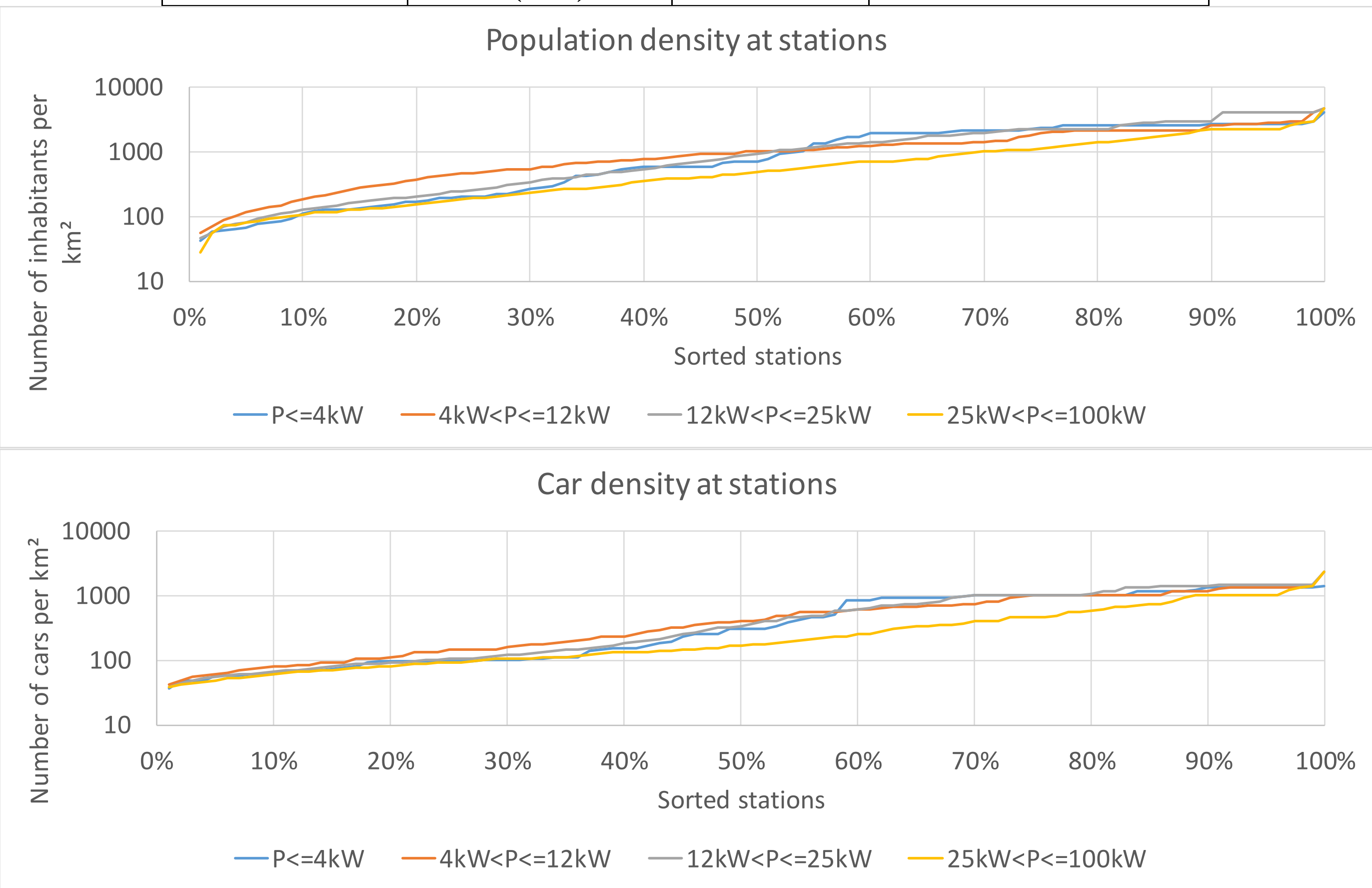

Figure 1: Characterisation of dataset a) by population density near each station and b) by car density near each station. Example how to read: 70 % of stations with power ranging between 25kW and 100kW have equal to or less than 410 registered cars per km² near them. P > 100 kW not shown for data protection reasons.

platforms where the status of many charging stations in Germany can be observed. Of those websites, all stations of which the status was visible were made part of the database and no further selection process applied. Given that, 26,951 connectors were observed in this study compared to 25,434 reported connectors in the country [17], it appears justified to assume that the trends found are representative for Germany as a whole, particularly for public connectors with low power levels. Note that not all stations in existence appear in [17] and that there are possibly some duplicate stations in our dataset since we collected data from several sources. Duplicates were removed based on location data and station characteristics, but this process might not see all duplicates. In comparison, Chargemap reported 61665 connectors at the time of writing this document [18].

The instantaneous status was requested either every 5 minutes or every 20 minutes, depending on the portal used. The obtained raw data was compiled into a database that forms the basis of all results presented in this paper. Using the method described above, Table 1 shows the number of stations for which the status was known on average over time. The connectors were split into 5 power ratings where each corresponds to one of the typical ratings of an EV charger. As can be seen from the share of power ratings already, the dataset does not include many high-power chargers. The reason for this is that the live status of fast-chargers was not shown on the observed platforms. To the authors best knowledge, large companies such as IONITY or Fastned do not share their stations availability publicly, at least not on their own websites [19, 20] or any of the platforms observed. Additionally, Figure 1 shows the population density and car density (incl. non-EVs) near the stations. As supporting material, the number of cars and inhabitants near the charging stations was collected from [21] and [22] and matched to the location of the charging stations using data obtained from [23] (© GeoBasis-DE / BKG 2019, with license dl-de/by-2-0). Further, the land use type per station was found by matching station location with the land use given in the Corine land cover database covering most of Europe and created with funding by the European Union [24]. Since the number of land use categories is larger than what appears sensible to be put into a regression model, several supercategories as shown in Table 2 were created. 71 parks were matched to land usage areas, which do not seem sensible for charging stations. Further, note that the areas sometimes are very close to each other so that for individual stations some uncertainty exists concerning the area type. Given the large number of stations in this study however, this uncertainty does not exist on the aggregated level.

Table 2: Overview of grouping of Corine categories into supercategories.

Corine categories	Supercategory	# parks
Continuous urban fabric	Urban	2,171
Discontinuous urban fabric, green urban areas, sport and leisure facilities	Suburban	24,112
Industrial or commercial units, port areas, airports, mineral extraction sites, construction sites	Industrial	7,695
Road and rail networks and associated land, port areas, airports, mineral extraction sites, dump sites, construction sites, green urban areas, sport and leisure facilities, non-irrigated arable land, vineyards, fruit trees and berry plantations, pastures, complex cultivation patterns, land principally occupied by agriculture, with significant areas of natural vegetation, broad-leaved forest, coniferous forest, mixed forest, natural grasslands, moors and heathland, transitional woodland-shrub, beaches, dunes, sands, inland marshes, peat bogs	Uninhabited	2,662
Dump sites, construction sites, green urban areas, sport and leisure facilities, non-irrigated arable land, vineyards, fruit trees and berry plantations, pastures, complex cultivation patterns, land principally occupied by agriculture, with significant areas of natural vegetation, broad-leaved forest, coniferous forest mixed forest, natural grasslands, moors and heathland, transitional woodland-shrub, beaches, dunes, sands, inland marshes, peat bogs, water courses, water bodies, estuaries, sea and ocean	Non-fitting	71

A. *Data structure (Charging station – Electric vehicle supply equipment (EVSE) – Connector)*

In this paper, we largely follow the 3-tier data structure outlined in the Open Charge Point Protocol [25]. The structure distinguishes between a charging stations, EVSEs and connectors. A charging station or “park” may contain multiple EVSEs. Each EVSE in turn may contain multiple connectors, but only one of them can be active at any moment in time. The connectors are the point that electric vehicles connect. In practice, a connector often appears as a socket on a pillar, which in turn is an EVSE. One or more of these pillars in close proximity form a charging station. The results presented in this paper are always on the level of connectors.

B. *Events*

In this paper, some of the results are given in terms of events. We consider an event the period in which a single connector remains in a specific status. Such an event consists of three components: the start (i.e. the timestamp where the status differed from the previously reported status), the end (i.e. the timestamp just before the status changes to something else again), and the duration (the difference between the two timestamps + the observation interval). If for instance a connector reports "Available" until 1:00 PM, is observed as "Occupied" at 1:05 PM and switches back to "Available" at 1:45 PM, we assume that the start of occupation occurred randomly between 1:00 PM and 1:05 PM and the disconnect occurred randomly between 1:40 PM and 1:45 PM. This yields on average a connection time of 40 minutes.

IV. THEORY AND CALCULATION

The results presented in this paper are intentionally without excessive modification, but rather try to distil as much information from the raw data as can reasonably be transported in the format of a scientific paper. The following methods have been applied to compile results into a format generating as much insight for the reader as possible.

A. *Share of charging stations occupied*

The share of charging stations occupied has been found by dividing all charging stations marked as occupied at each moment in time by the total number of stations for which the status was known at that moment in time. As indicated in Table 1, it was not always known for each station what the status was, partly due to server unavailability (e.g. one data source performed regular maintenance at around 2:10 meaning that certain stations could not be monitored) and partly due to short internet connectivity interruptions on our side. Given the overall high share of time when the status of the stations was known, we do not regard this as a severe problem concerning the reliability of the results of this study.

B. *Duration distribution*

The duration distribution was found by aggregating all event durations for all stations in a specific power group. Events are defined as described in III.B.

C. *Number of events*

The number of events per day was found by counting how often any charging station in a specific power group would switch to the given status. In practice, a charge event is counted any time an EV driver connects to a charging station and an available event is counted any time an EV driver disconnects from a charging station.

D. *Charging station costs*

The costs of the charging station were assumed as the sum of investment costs (CapEx) in annualized form and operational expenditures (OpEx) for maintenance. Investment costs for the year 2020 were taken from [26] and confirmed by industry experts as realistic. A lifetime of 10 years and an interest rate of 7% were assumed. The resulting annuity factor given in eq 1 was used to annualize the investment. OpEx was also taken from [26]. The cost per station, c_{sttn}, is found using equation 2. $t_{visible}$ is the time in which each station was observed by our monitoring application.

$$ANF = \frac{(1+i)^n * i}{(i+1)^n - 1} \approx 0.142 \qquad (1)$$

$$c_{sttn} = (ANF * CapEx + OpEx) * \frac{t_{visible}}{1\ year} \qquad (2)$$

E. *Power consumption model*

The dataset collected for this work does not contain information about the actual power flow between charging station and vehicle, but only whether a vehicle is connected at any moment in time or not. To be able to derive statements about actual energy consumption and costs per unit of energy, a simple power flow model was developed where it was assumed that each vehicle consumes a certain amount of energy from the grid. The charged energy levels E_{charge} were chosen as 8 kWh, 20 kWh, 40 kWh, and 60 kWh per charging process. If the duration of the charge event was too short to supply the respective energy, the energy charged was reduced such that it can be found from connected time and rated power as given in equation 3.

$$E_{charge\_possible} = \min(t_{connected} * P_{rated}, E_{charge}) \qquad (3)$$

8 kWh were chosen in line with [2], but since both vehicle energy capacity and charging power have significantly gone up since the publication in the observed period between 2012 and 2016, higher energy levels were also considered. With most EVs consuming between 15 kWh/100km and 25 kWh/100km [27] and Germans driving on average 39 km/day [28], a 20 kWh charge would mean 2 recharges per week for an efficient vehicle and 60 kWh result in a single recharge per week even for an inefficient vehicle. It was assumed for all charger types that the vehicles could charge at rated power P_{rated}. The charging and idle duration can be found as given in equations 4 and 5.

$$t_{charge} = \frac{E_{charge\_possible}}{P_{rated}} \qquad (4)$$

$$t_{idle} = t_{connected} - t_{charge} \qquad (5)$$

This model intentionally does not employ a random distribution of E_{charge} around a central value. The reason is that given the extremely large dataset, the introduced randomness reduces itself into noise in the macro analysis used in this paper. There is consequently no gain of knowledge from introducing randomness.

F. *Linear regression model*

A simple linear regression model was used to distinguish and quantify the effects already visualized using the methods mentioned in IV.A - IV.C. The methodology is identical to a previous work and we therefore choose to repeat the same explanation of methodology [29]: "We choose to use linear probability models in this part because they are simple in their interpretation and especially robust to misspecification. Therefore, we estimate linear probability models of the following form by ordinary least squares[1]

$$y_{it} = \beta_o + \beta_1 x_{it}^1 + \ldots + \beta_k x_{it}^K + \epsilon_{it} \qquad (6)$$

Here, y_{it} represents the charging status of station i in period t, x_{it}^1 until x_{it}^K represent K charging station's properties that are likely to affect its usage. β_1 to β_k are the parameters

[1]Sampling frequency of 5 minutes is much higher than a typical charging duration (ranging from 10's of minutes to hours).Therefore, the usage state is likely to depend on the past usage state because charging cycles often last multiple data periods.

to be estimated reflecting the impact the specific property has on the likelihood of the charging station to be used. Because of the linear functional form, the β-estimates can be interpreted directly as the marginal change in the conditional probability of the charging station's usage when the specific characteristic x^k is present. Lastly, ϵ_{it} represents the error term."

Note that a linear model is clearly an oversimplification of the real world. We can for example observe that the fluctuation over a day is significantly weaker on a weekend than it is on a weekday. It would be possible to construct various such non-linear connections leading to a generally more accurate model. This is one of the strengths of models using for instance neural networks. The problem with such a representation however would be that the number of variables quickly becomes very large and that it does not provide the kinds of insights, which we would like to provide in this paper. The β-values therefore provide a trend and a general tendency, but not an exhaustive form of modelling the provided data.

V. RESULTS

In the following chapters, the results corresponding to the theory and calculations outlined in IV are given. Since frequent reference is made to figures and their underlying data, the reader is invited to take a closer look at the data used to generate the figures which is attached to this publication.

A. *Share of charging stations occupied*

Figure 3 shows a first overview of how charging station connectors are in use at each instance of time. A few trends can already be observed from the given graph such as the following:

- Connectors with low power rating are occupied more frequently than are those with higher power ratings.
- During public holidays (24 – 26 December, 31 December, 1 January in Germany) and on the weekend charging station usage is significantly below the remaining time periods for stations with P ≤ 25 kW.
- Connectors with power levels between 25 kW and 100 kW appear to be used mostly for traveling and/or recreational shopping on the weekends and therefore have an almost inversed weekend/weekday-pattern compared to lower power levels.
- A clear day-night pattern can be observed. The difference between usage during the day and during the night is especially pronounced for high power ratings.
- Overall, the connector usage is quite low. For all stations observed, the overall usage was rarely above 20 % during midday-peak and mostly in the order of 15 %.
- Fast-chargers with P > 100 kW in our sample do not have a clear repeating pattern over the course of a day or week.

A quantitative statistical justification of the above-described qualitative effects can be found in Appendix XI.B.

Figure 4 shows a similar picture as Figure 3, but focussing on the location of the station. The different categories are described in Table 2 and in subchapter III. The trends to be observed are:

- Industrial areas are mostly used by people arriving in the morning as can be seen from the steep increase of charging stations connectors occupied early in the morning. Rural areas show this behaviour as well, but experience an additional peak in the early evening, likely because of people returning home and charging near their home. Suburban and uninhabited areas generally experience significantly lower fluctuations.
- The overall usage is highest in rural areas, possibly because of the dual use of people working and living in the same areas and therefore reducing the inhomogeneity in usage.

For an overview of typical statistical parameters, see Table 5, Table 6 and subsection XI.A, XI.B and XI.D. The latter provides an overview of the standard deviations appearing as a result of aggregating the timeseries data into daily and weekly data. We recommend considering these when applying the data in the readers own models.

B. *Duration distribution*

Figure 5 provides an overview over the durations a charging station connector is typically used or available. The figure again allows for the derivation of a few general trends:

- The higher the power of a connector, the shorter a vehicle stays connected. This behaviour can be split into distinct behaviour for fast (P > 25 kW), medium (4kW < P ≤ 25kW) and slow (P ≤ 4kW) chargers.
    - Fast: Virtually all charging processes require less than 1 hour, most less than 20 minutes. The vehicle consequently only remains connected for the time required for charging
    - Medium: The shape of the curve is almost identical for charging processes up to 40 minutes. During these charging events, the full available power is probably used. Afterwards the curve is significantly flatter which could be an indication that vehicles stay longer than they need to. Especially the slight peak between 8 and 10 hours indicates that vehicles are effectively parked for either a full workday or overnight. This can also be observed in the analysis done in section XI.C where the effect is quantified.
    - Slow: Not surprisingly, most charging events on slow-chargers take several hours. The pronounced peak between 8 and 10 hours further hints at cars being parked for either a full workday or overnight.
- For all connector types, the availability duration follows a similar pattern of an exponentially decaying curve. The slower chargers experience a slightly higher share of availability events around 16 h as compared to the exponentially decaying trend. This behaviour appears fitting to the 8 h peak for charging events if we assume that daily patterns typically repeat cyclically.

Table 3 shows what share of time that the vehicles spend connected to charging infrastructure is used for charging using the assumptions introduced in IV.E. Some conclusions to be drawn from this are:

- Across all power levels, the share of time spent charging is proportionally higher at higher amounts of energy per charge event. This means that there are very few events in the dataset where the connected time would be insufficient to recharge the vehicle at rated connector power. A higher amount of energy transferred per event consequently increases utilization.
- The usage patterns of connectors in the medium power range is nearly identical. The higher charging power consequently does not result in higher amounts of energy transferred, at least at current usage patterns. The extra cost of 22 kW stations compared to 11 kW stations should consequently be low. Otherwise the result shown in Table 3 results where the actual charging time is simply shortened and replaced by idle time while not serving more customers.
- Despite overall short time in usage for high-power chargers, they appear to fulfil their purpose as fast recharge opportunities since a high amount of energy is transferred.

Table 3: Share of time that the connector is active as a function of connector power and energy charged using the power model introduced in IV.E.

		Maximum energy charged per charge event in kWh			
		8	20	40	60
Power of connector	P<4kW	18.3%	31.7%	42.9%	48.8%
	4kW<P P≤12kW	8.7%	18.9%	30.5%	38.0%
	12kW<P P≤25kW	4.1%	9.5%	16.8%	22.5%
	25kW<P P≤100kW	7.1%	16.2%	25.0%	29.7%

C. *Number of events*

Figure 6 shows the number of charge events over the course of a week and a day. The additional insights are:

- Fast-chargers with a charging power above 25 kW have more charging events per day as compared to other chargers. For connectors with less than 25 kW the pattern is not as clear, particularly for low-power chargers with P < 4 kW.
- The usage patterns over the course of the day are different for the different power levels. Whereas the lower power chargers follow a curve with a similar shape as the share of connectors occupied (see Figure 3), the very high-power chargers experience a usage pattern which resembles commuters somewhat more with a peak in the morning and in the early evening.
- Fast-chargers have most charging events on Saturday and to a lesser degree on Friday and Sunday. This is the opposite pattern of what can be observed for the slower charger types, which record most charge events during the workweek.
- Not visible in these graphs is that charge events are comparable for Sundays if the day is a public holiday.

D. *Economics*

Figure 7 and Figure 8 show some key indicators regarding the economics of operating charging stations by showing how much an operator would have to charge if the operator wanted to earn back their initial investment by either charging a premium per kWh transferred or per minute that a vehicle is connected to the connector. These two models are also the most typical billing models in the German market next to the also popular flat fee [30].Taking a closer look at Figure 7 one can derive the following conclusions:

- To increase the overall efficiency of the system it makes sense if the users are encouraged to charge larger amounts of energy per charge event. Especially for low total amounts of energy transferred, the station is mostly inactive.
- In Germany, charging at public charging stations typically costs between 30 and 50 €ct/kWh [30]. Given that this also has to refinance the energy costs of around 20 €ct/kWh to the operator, only very few stations were operating profitably in the observed time window. For the more expensive customer prices of 50 €ct/kWh depending on the assumed typical energy sale, only between 2.5% and 38% of the charging station earned back their hardware investment. For lower sales prices, this value drops to almost zero.

Focussing on Figure 8, a different perspective is taken where we assume that the station operator intents to earn its investment back through a time-based tariff.

- The costs for AC-stations with power ratings below 25 kW are comparable while DC charging stations are much more expensive per minute, which is mostly a result of the significantly higher investment.
- Given that most real-world tariffs for AC-charging are in the order of 1 – 5 €/h [30] (~17 – 83 €ct/h) the share of charging stations able to earn back their investment costs is significantly higher than for the energy model shown in Figure 7. Depending on power level and customer price, between 30 and 75 % of the AC stations are in a profitable range.
- For DC-charging, the fees are in the order of 0.06 - 0.5 €ct/min [30]. This would also allow up to 50% of fast-chargers to operate profitably using a time-based tariff system.

When analysing these numbers one limitation has to be kept in mind: The billing model for the stations observed in this paper is not known. Time-based tariffs would incentivise a user to shorten its stay, but charge as much energy as possible while energy-based tariffs have the opposite effect. The user will optimize his*her behaviour according to the tariff model. This adaption cannot be compensated for in the data since the tariff structures are unknown.

For an overview of average, maximum, minimum and median costs, please check Table 7 and Table 8.

E. *Linear regression model*

Table 4 shows the result of the linear regression model. The first five variables are static properties of a charging station. Since the β-values represent the linearized marginal change of the variable impact, these values can be interpreted as follows taken power as an example:

For every kW of power a connector has, the usage of it decreases by 0.3 %

The following variables are all dummy variables. If for instance the impact of time of the day is of interest, a possible interpretation is:

At hour 12 (i.e. between noon and 1PM), the usage of connectors was 2.63 % above the usage at midnight.

For hour, weekday and land usage type, the respective reference midnight, Monday and non-fitting are not listed as they have a β-value of zero. For a visualization of the dummy variables, please refer to Figure 2. Note that these results slightly differ from the results given in Figure 3 since the linear regression model is sensitive to missing data.

*Table 4: Results of linear regression model. ** indicate a p-value lower than 0.01 and three asterisk a p-value lower than 0.001.*

Variable	Unit Variable	β-Value	Std. dev.
Connector power***	kW	-2.79e-03	1.29e-05
Population density***	$\frac{\#persons}{km^2}$	-3.99e-05	8.86e-08
Connector density***	$\frac{\#connectors}{km^2}$	0.0173	0.001
Share pluggable vehicles***	$\frac{\#EV + \#PHEV}{\#all\ cars}$	22.7628	0.046
Vehicles per inhabitant***	$\frac{\#all\ cars}{\#inhabitants}$	-0.3909	0.001
Industrial***	$True \vee False$	-0.0909	0.017
Urban**	$True \vee False$	-0.0529	0.017
Suburban***	$True \vee False$	-0.0852	0.017
Uninhabited***	$True \vee False$	-0.126	0.017
Hour1***	$True \vee False$	0.0017	0
Hour2***	$True \vee False$	0.0044	0
Hour3***	$True \vee False$	0.0063	0
Hour4***	$True \vee False$	0.0076	0
Hour5***	$True \vee False$	0.0076	0
Hour6***	$True \vee False$	0.006	0
Hour7**	$True \vee False$	-0.0013	0
Hour8***	$True \vee False$	-0.0108	0
Hour9**	$True \vee False$	-0.007	0
Hour10***	$True \vee False$	0.0027	0
Hour11***	$True \vee False$	0.0076	0
Hour12***	$True \vee False$	0.0083	0
Hour13***	$True \vee False$	0.0072	0
Hour14***	$True \vee False$	0.006	0
Hour15***	$True \vee False$	0.0053	0
Hour16***	$True \vee False$	0.0032	0
Hour17	$True \vee False$	-0.0007	0
Hour18***	$True \vee False$	0.0021	0
Hour19***	$True \vee False$	0.0114	0
Hour20***	$True \vee False$	0.014	0
Hour21***	$True \vee False$	0.012	0
Hour22***	$True \vee False$	0.0053	0
Hour23	$True \vee False$	-7.43e-05	0
Tuesday	$True \vee False$	-0.0004	0
Wednesday***	$True \vee False$	0.0109	0
Thursday***	$True \vee False$	0.0148	0
Friday***	$True \vee False$	0.0122	0
Saturday***	$True \vee False$	-0.0021	0
Sunday***	$True \vee False$	-0.0025	0
Public holiday***	$True \vee False$	-0.0476	0.001
Constant***	1	0.4849	0.017

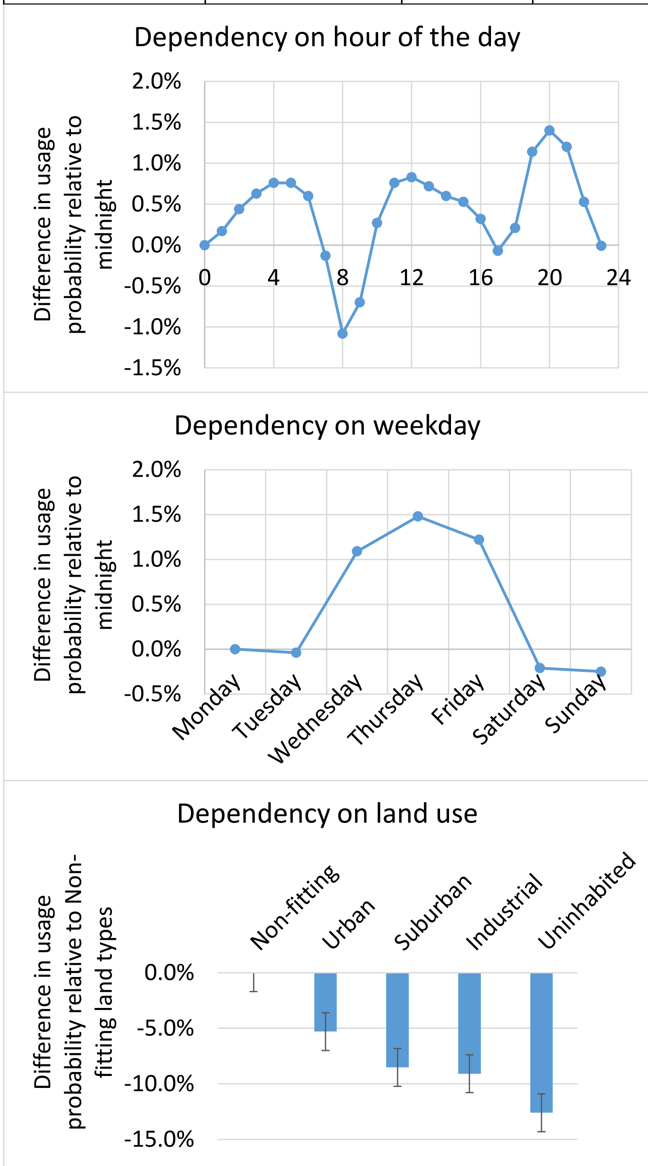

Figure 2: Visualization of time variables given in Table 4.

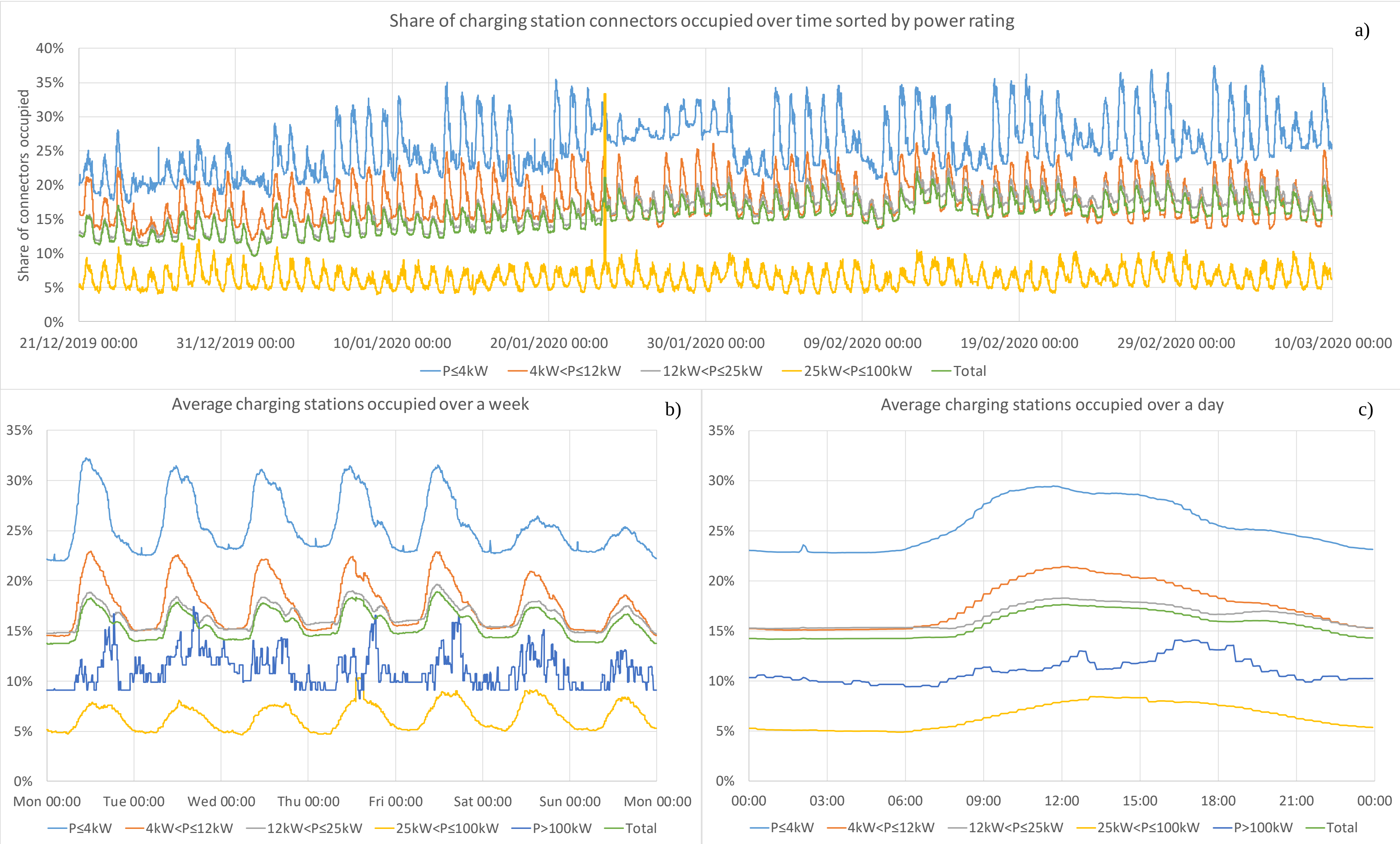

Figure 3: Share of charging station connectors which are occupied at each moment in time by power rating. For each power rating, the number of connectors marked as occupied was divided by the sum of connectors for which the status was known. a) shows the occupation rate over the entire observed period, b) aggregated on a weekly level and c) aggregated on a daily level. Note that the peak on 23/01/2020 as well as the small peaks at around 2:10 in the morning were reported by the observed websites, but likely represent a fault in the IT system on the remote end.

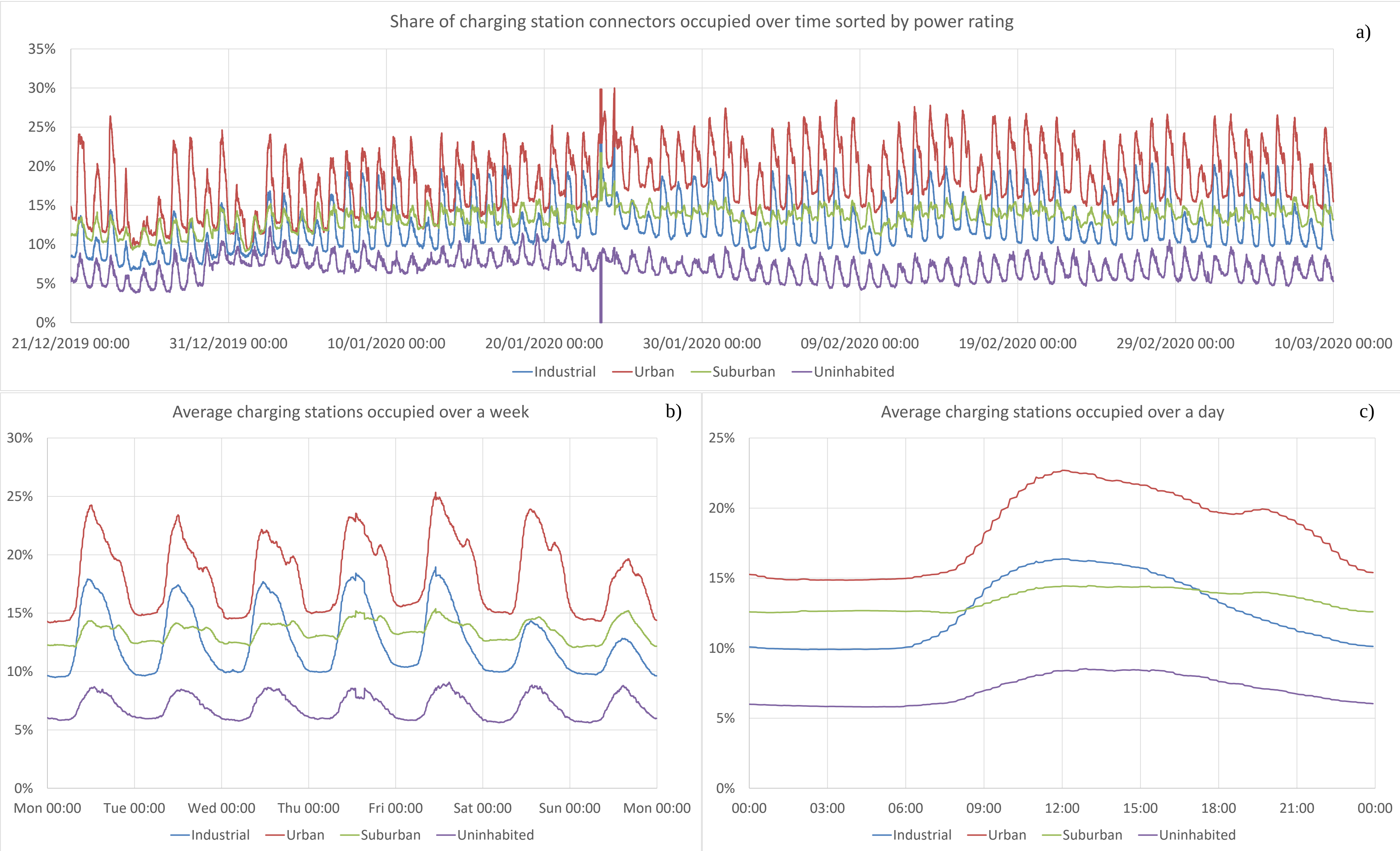

Figure 4: Share of charging station connectors which are occupied at each moment in time by location of the charging station. The graph logic is otherwise identical to Figure 3.

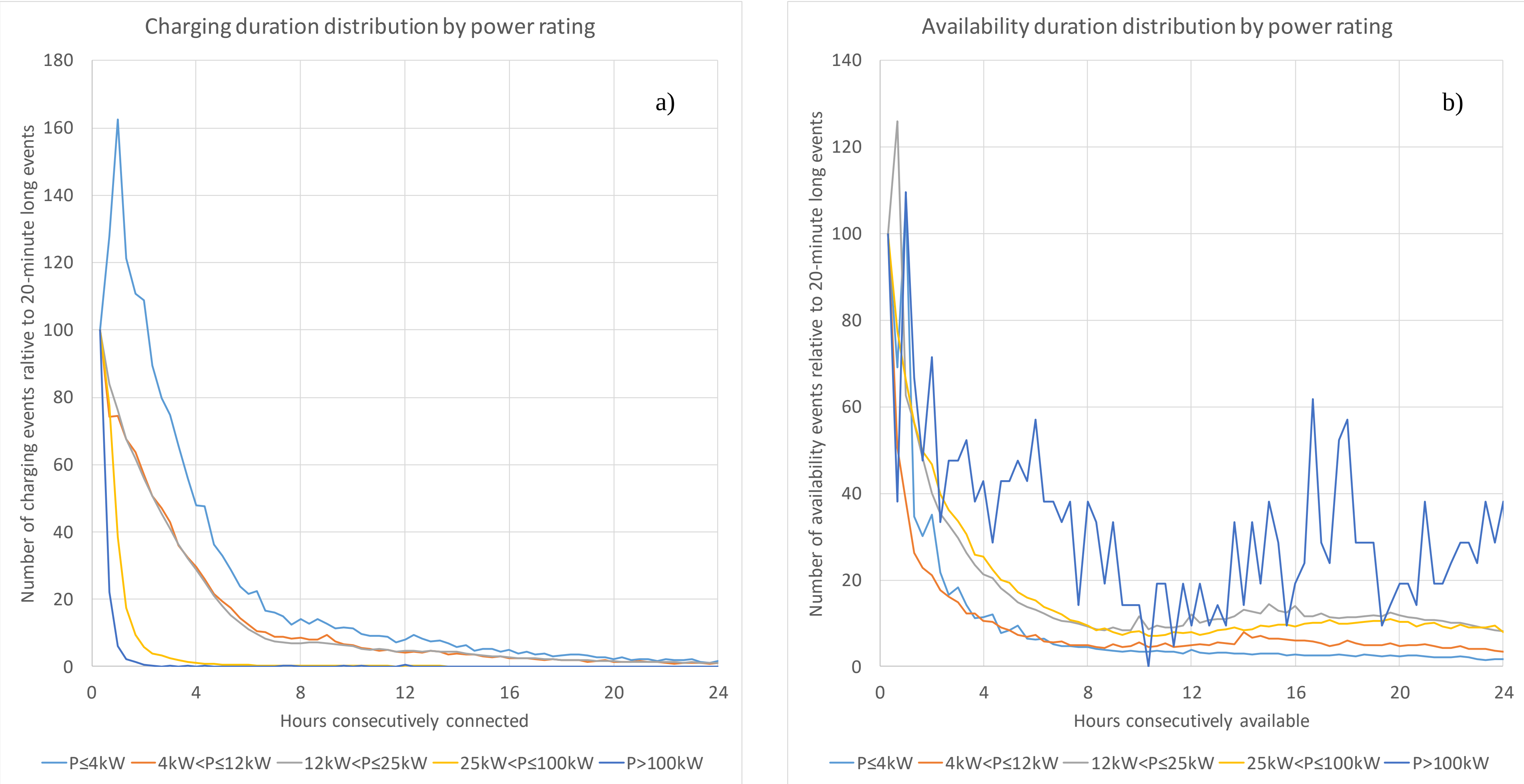

Figure 5: a) shows how long charging stations where typically used with a duration of up to 20 minutes serving as reference point valued as 100. The step size of the graphs is 20 minutes. Example how to read: The point (4h, 29) of line 12kW<P≤25kW means that for every 100 charge events which took up to 20 minutes, 29 events occurred which took between 3:40h and 4:00h. b) follows the same pattern, but displays how long stations where available on average.

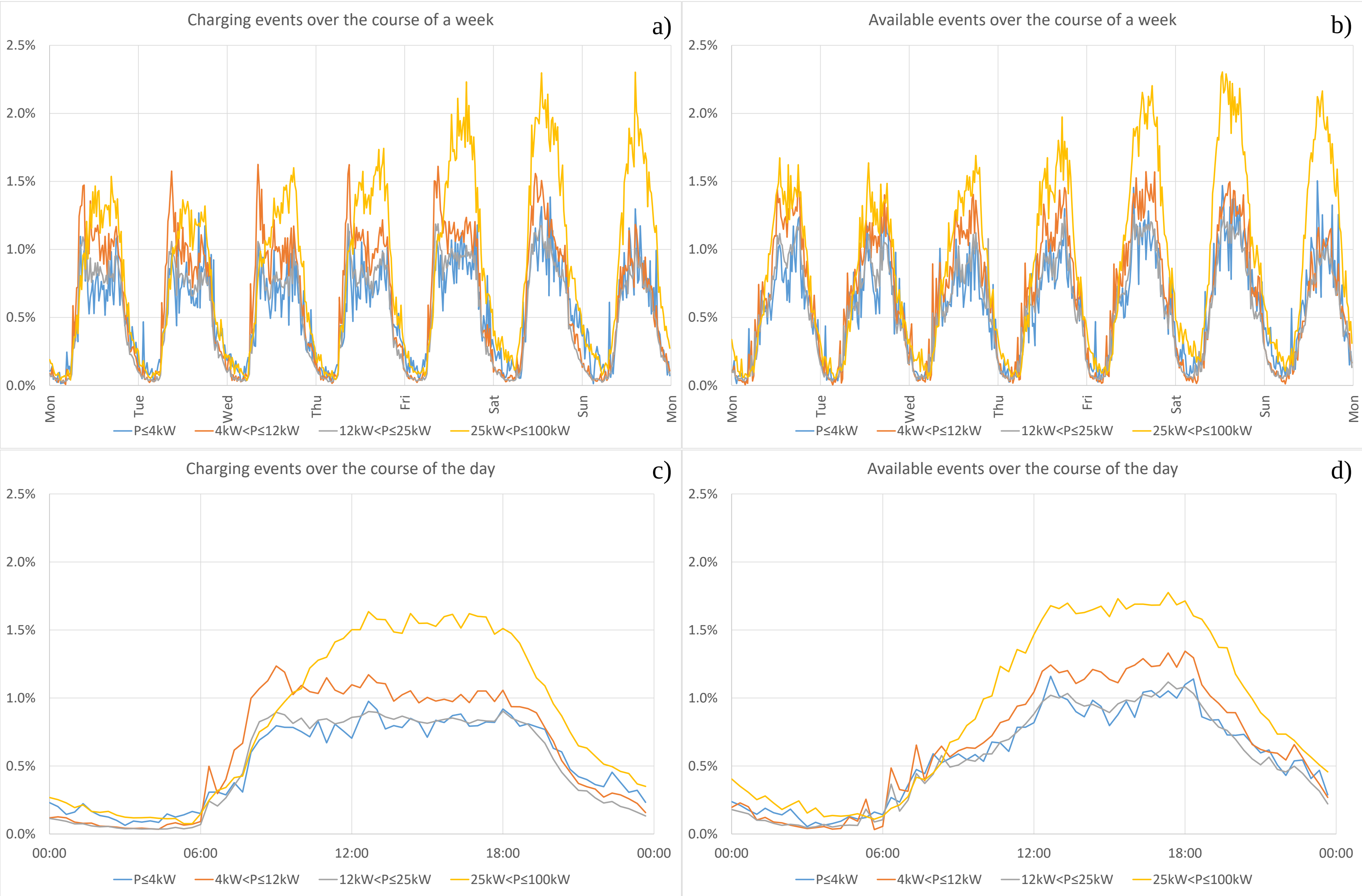

Figure 6: Charge and available events recorded over the observed period. Each curve shows the average share of stations observed which experienced such an event in a 20-minute timeframe. Please note that due to occasional communication loss, the values should be looked at mostly with respect to each other. With regards to the absolute value, the authors are not fully able to guarantee accuracy. Example how to read: on a typical Monday between 4:20 PM and 4:40 PM, 1.54% of charging stations with a power rating of 25 kW < P ≤ 100 kW experience a charge event.

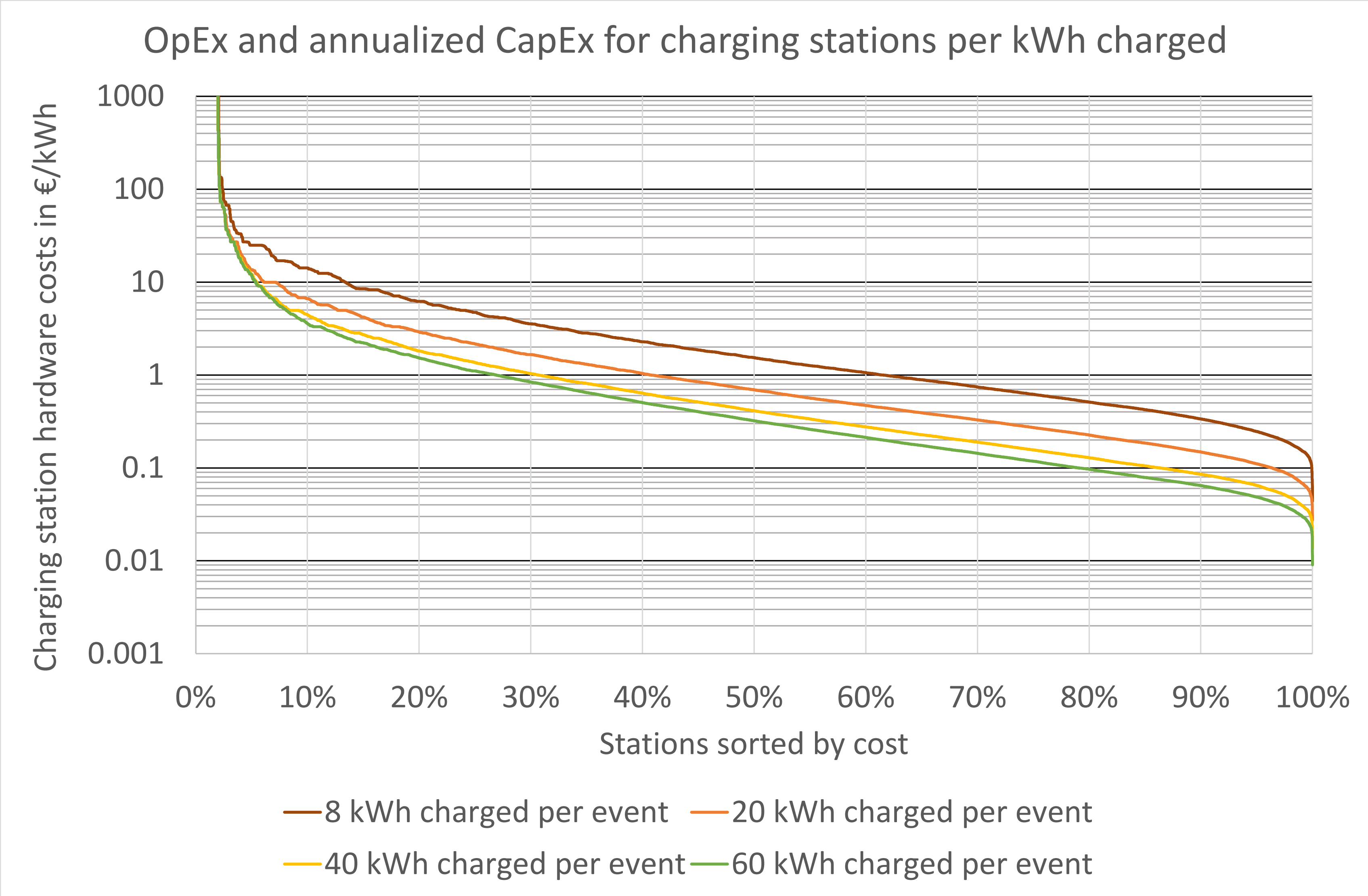

Figure 7: Annualized investment and OPEX costs for providing a kWh of energy. Value shown does not include purchase cost of electricity. A charging station operator would have to charge the displayed premium compared to electricity purchase costs to earn back the funds required for installing and maintaining the hardware. The different lines show the value using different assumptions about the maximum amount of energy transferred per charge event. Since no charging events were recorded for 1.9% of stations, no cost per kWh could be determined as no kWh were transferred. Example how to read: If at every charging event a maximum of 8 kWh was charged, around 60% of charging stations would have to charge at least 1 €/kWh + electricity purchase costs if all investment and maintenance costs should be earned by through energy sale alone.

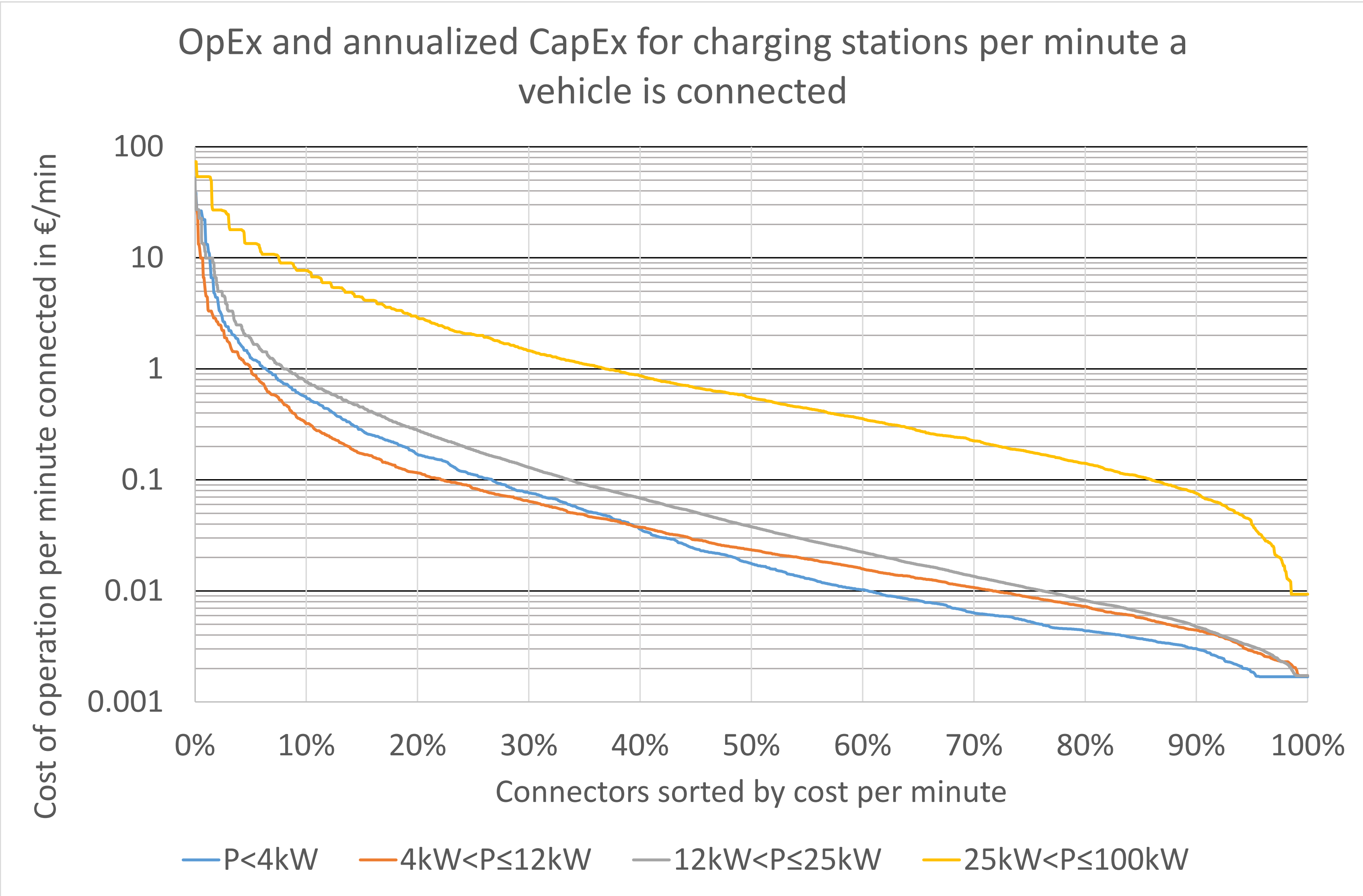

Figure 8: Annualized investment and OPEX costs for operating a charging station per minute that a vehicle is connected to a connector by power level. A charging station operator would have to charge the displayed amount per minute for any connected vehicle to earn back the funds required for installing and maintaining the hardware. Charging stations without any charging events are not displayed., but similar to Figure 7 are about 4% of the stations. Example how to read: For charging station connectors with 12 kW – 25 kW power rating, 50% of the stations would have to charge at least 40€ct/min that a vehicle is connected to cover costs for installing and maintaining the hardware.

VI. Discussion

The results shown in this paper provide a first understanding of how charging stations in Germany are used.

The results are overall in line with what was reported in previous studies where low-power chargers experience a higher occupation and charging events are significantly more probable to start during the day and on the weekdays Monday - Friday [2, 29]. Since the different papers focus on a different country each (i.e. Netherlands and Republic of Ireland), it is probable that the observed trend is typical for EV usage at least in Western Europe.

A difference to previous results can be seen Table 4. Properties, which correspond with urban settings such as high population density and connector density, correlate with lower charging station usage instead of higher usage. A possible explanation for this phenomenon could be that many inner cities have imposed maximum charging durations at public chargers to prevent unnecessary blocking of connectors. Since the shown data looks at occupation and not at actual usage, the parking behaviour in more urban areas without time limitations could cause the occupation rate to be higher.

A. Limitations

The results reported in this paper are based on data obtained from publicly accessible portals. The authors do not have any way of verifying the data obtained and consequently cannot guarantee the accuracy of the presented results. We have found individual stations in the dataset with extremely long occupation periods. This could either be a result of somebody parking their vehicle or of some other reason such as the charge point operator wanting to block the station. Which of the two is true cannot be checked from the outside. These stations remain in the dataset.

Additionally, our sampling frequency was set to 5 or 20 minutes. It is possible that for some station, a vehicle left and another one arrived between two observations. In our dataset, this would appear as a continuous charging process. Given the low overall station usage, we however do not believe this to happen frequently. Similarly, extremely short occupations are also not detected.

Lastly, the presented results only show occupation and not actual power flow. Care should therefore be taken if our results are used for grid modelling or alike. Our suggestion here is to refer to [2] or [7] for a comparison between connected time and real power flow. Once such a relation is derived, it can be applied to our results to estimate power flows in specific settings. Alternatively, the simple power flow model shown in IV.E could be used.

VII. Conclusion

The results of this paper show some clear trends in how charging stations are used in Germany. Since the infrastructure expenses per station needs to be refinanced through energy sales or a time-based tariff+, it would be desirable that charging stations were occupied as much time as possible and of the occupation time would spend as much time as possible actively transferring power. From the results shown in this paper, several conclusions can be drawn about how stations are used how usage could possibly be improved:

A. Charging station usage depends strongly on time of day and weekday

The charging station occupation during the day is on average several percent higher across all connectors with $P \leq 100$ kW. That day-peak is much more pronounced on weekdays than on weekends. During off-peak times such as the weekends or between 6 PM and 8 AM, many chargers remain unused. The stations could therefore be offered to customers at favourable conditions such as reduced price or longer allowed parking duration without significantly reducing the availability of stations for spontaneous charging.

B. Charging stations are frequently used for parking

Especially at chargers with $P \leq 25$ kW, vehicles remain much longer than charging processes typically take. This could be explained by vehicles not being able to absorb the full available power and therefore requiring long recharge times, e.g. because their on-board-charging is of Type1 (single-phase) while the station offers Type2 (3-phase) charging or especially for higher powers it could be a battery limitation. The slight peak at 9 hours occupation duration however indicates that EV users instead leave their car parked for their workday. The vehicle consequently blocks the asset while not actually using it, which should be avoided.

C. Overall usage is low

Overall, the occupation rate is between 5 % and 35 % for all connector types. The current system is consequently able to service more customers than the ones currently using the infrastructure. Especially if the inhomogeneity over time as mentioned in VII.A and the "parking" as mentioned in VII.B are solved, significantly more vehicles could be on the road without need for much additional hardware.

VIII. Data availability

The data used for making the plots in the main body of this paper (i.e. all point coordinates in the plots) will be published alongside the article itself. We further invite other researchers to reach out to us so that joint analyses can be performed on the full dataset.

IX. Acknowledgements

We thank colleagues working at the ISEA for supporting our work. This work was not funded by an external source.

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XI. Appendices

A. Statistical values

In the following, several typical statistical parameters such as averages and means are provided where applicable. Each table directly relates and expands the information shown in Figure 3 - Figure 8.

Table 5: Average, maximum, minimum, and median charging station occupation by power level or land usage type. Values are directly related to Figure 3 for power levels and Figure 4 for land usage type.

	Ø	Max	Min	Median
P≤4kW	26%	38%	17%	25%
4kW<P≤12kW	18%	26%	10%	17%
12kW<P≤25kW	16%	23%	10%	17%
25kW<P≤100kW	6%	33%	4%	6%
P>100kW	6%	Insufficient data		
Industrial	13%	27%	7%	12%
Urban	18%	30%	9%	18%
Suburban	13%	22%	9%	14%
Uninhabited	7%	12%	0%	7%
Total	16%	22%	10%	12%

Table 6: Average (Ø) and median (M) durations during which a vehicle is connected to a station or during which the stations are available. The displayed information relates to Figure 5. The much longer averages are the result of very long charging events which were not displayed in the figure.

	Connected		Available	
	Ø	M	Ø	M
P≤4kW	19:12	2:40	1:50	2:05
4kW<P≤12kW	13:02	2:45	20:43	6:05
12kW<P≤25kW	6:05	2:35	16:05	8:25
25kW<P≤100kW	2:44	0:45	9:55	6:25
P>100kW	0:50	0:25	15:50	14:05

Table 7: Average (Ø), maximum (Max), minimum (Min), and median (M) of OpEx and annualized CapEx for charging stations per kWh charged. The data in this table directly relates to Figure 7. Connectors without any event in the entire period are excluded.

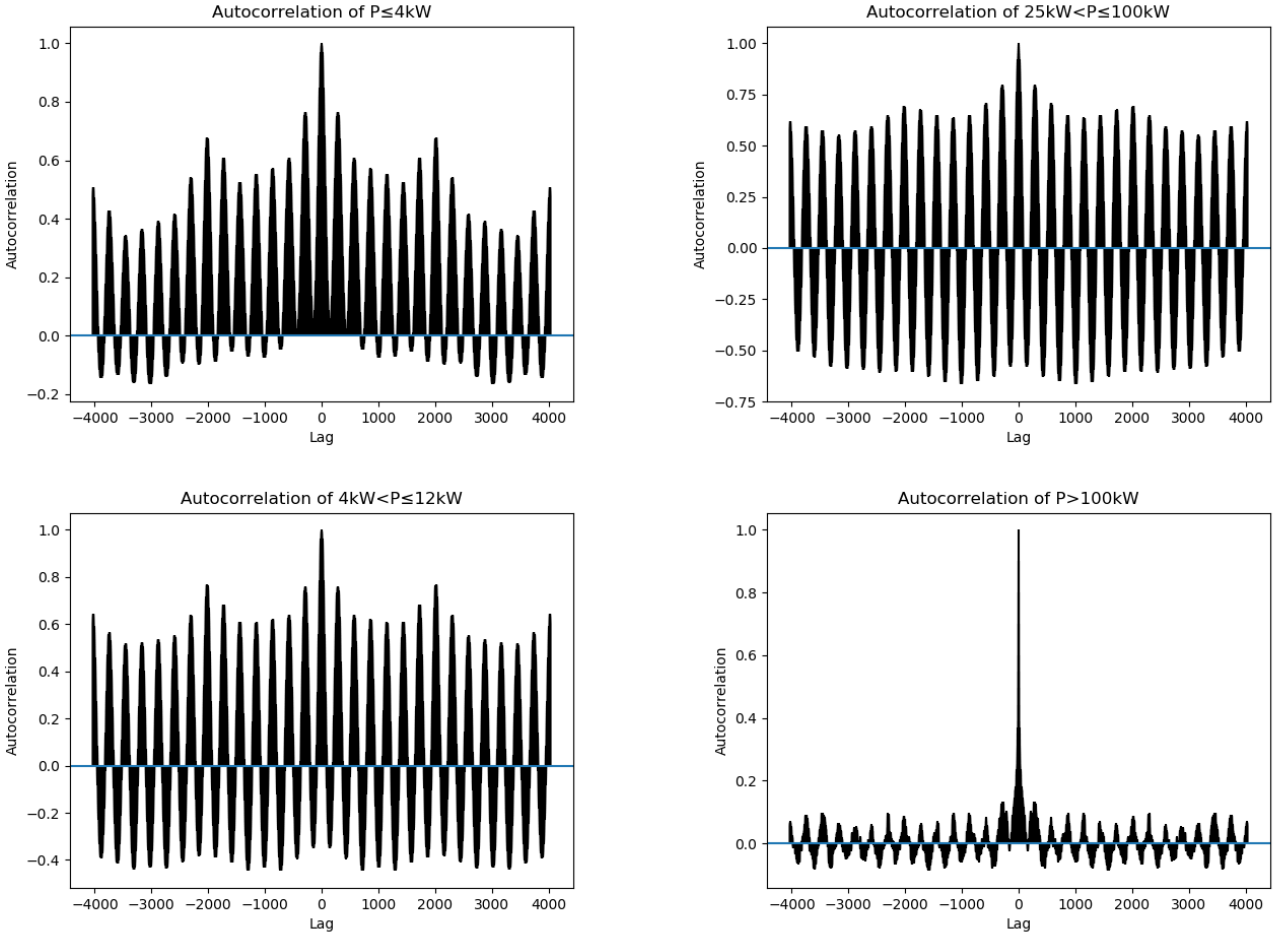
Energy charged per event	Ø in €/kWh	Max in €/kWh	Min in €/kWh	M in €/kWh
8 kWh	4.77	143.55	0.04	1.53
20 kWh	2.76	256.24	0.03	0.69
40 kWh	2.18	256.24	0.01	0.41
60 kWh	2.02	256.24	0.01	0.32

Table 8: Average (Ø), maximum (Max), minimum (Min), and median (M) of OpEx and annualized CapEx for charging stations per minute a vehicle is connected. The data in this table directly relates to Figure 8. Connectors without any event in the entire period are excluded.

Connector power	Ø in €/min	Max in €/min	Min in €/min	M in €/min
P≤4kW	0.49	38.69	0.00	0.02
4kW<P≤12kW	0.30	36.23	0.00	0.02
12kW<P≤25kW	0.54	36.76	0.00	0.04
25kW<P≤100kW	3.02	73.45	0.01	0.55

B. Autocorrelation and seasonality

In Figure 9, the correlation plots of usage probability by power level are provided. For low power levels with $P \leq 100$ kW, the weekly and daily autocorrelation already outlined in V.A can be observed. The also mentioned non-correlated pattern for ultra-fast-chargers ($P > 100$ kW) results in a much lower autocorrelation between day and night pattern. Given the overall low number of ultra-fast chargers in the dataset, some caution should be taken when generalizing the results.



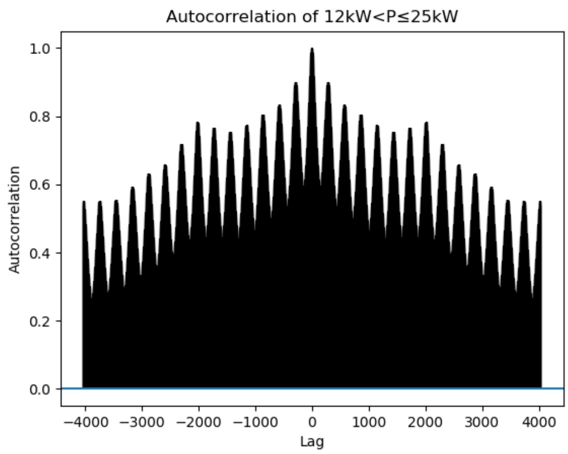


Figure 9: Correlation plots by power level corresponding to Figure 5. A single leg corresponds to the basic 5-minute interval used in this study. A day is consequently equivalent to 288 lags and a week corresponds to 2,016 lags.

Along a similar line, Figure 10 shows the additive seasonal decomposition of the same time series shown above. The composition was created using the seasonal timeseries analysis tools of statsmodels in Python. The tool is a classic or naïve decomposition which applies a convolution filter to the data to calculate the seasonality. The additive approach was chosen since the number of long-term parkers and the size of daily or weekly fluctuations cannot be presumed to be linearly correlated which the multiplicative decomposition would require. The full mathematical model to be fitted is given in equation 7:

$$observed(t) = trend(t) + seas\_d(t) + seas\_w(t) + \epsilon (7)$$

In all cases, the daily and weekly seasonality already showing in Figure 9 can be further quantified to be between 2% and 5%. This is in line with the qualitative observations made in V.A.

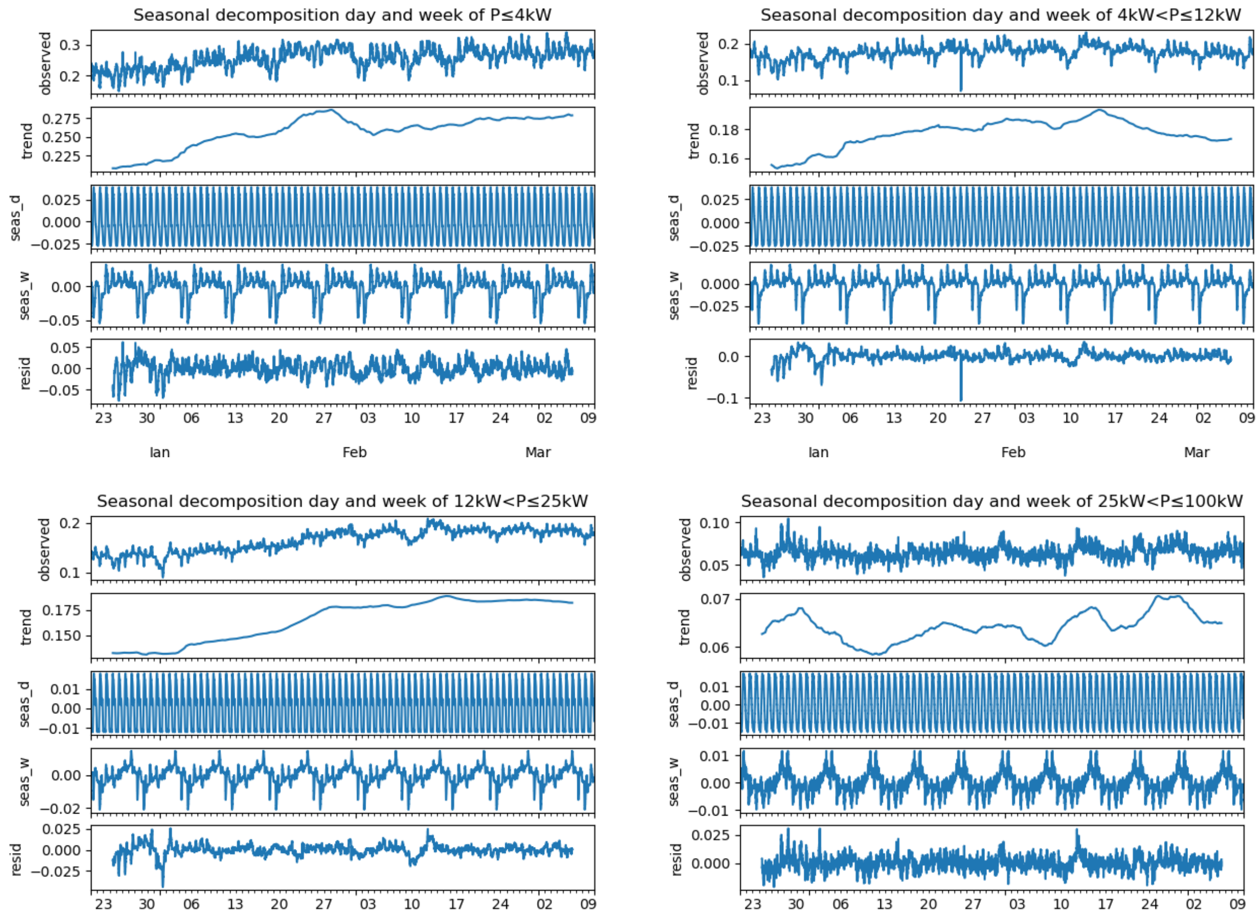


Figure 10: Additive seasonal decomposition of the time signals shown in Figure 4. The daily seasonality seas_d was calculated first and subtracted from the signal. The weekly seasonality seas_w was calculated in a second step.

C. *Curve fits*

Table 9 shows an exponential fit obtained fitting the data given in Figure 5 to equation 8. Given the overall high adjusted R^2, the exponential model appears suitable.

$$y(x) = a * e^{b*x} \tag{8}$$

Table 9: Exponential fits of the data given in Figure 5. In brakets, the 95% confidence interval is given.

		a	b	Adj R^2
Occupation duration fit (Figure 5 a)	P≤4kW	160.6 (152.7, 168.5)	-0.2787 (-0.2973, -0.2602)	0.9522
	4kW<P≤12kW	103.3 (101, 105.6)	-0.314 (-0.3234, -0.3046)	0.9901
	12kW<P≤25kW	108.1 (106, 110.3)	-0.3369 (-0.346, -0.3278)	0.9919
	25kW<P≤100kW	174.9 (167.8, 182)	-1.507 (-1.574, -1.441)	0.9830
	P>100kW	439.1 (416.3, 462)	-4.441 (-4.586, -4.297)	0.9995
Available duration fit (Figure 5 b)	P≤4kW	125.1 (114.7, 135.6)	-0.6451 (-0.7133, -0.577)	0.8929
	4kW<P≤12kW	111.4 (99.09, 123.6)	-0.8521 (-0.9664, -0.7377)	0.8182
	12kW<P≤25kW	115.2 (102.6, 127.9)	-0.4096 (-0.469, -0.3502)	0.7597
	25kW<P≤100kW	90.09 (82.77, 97.41)	-0.2913 (-0.3231, -0.2594)	0.8496
	P>100kW	55.46 (48.26, 62.65)	-0.04827 (-0.05846, -0.03808)	0.5023

When subtracting the exponential fit from the original data, Figure 11 is obtained. Any deviation of the residuals above the exponential fit can be understood as a deviation from the expected norm. As already outlined in V.B this is a clear indication that a non-random amount of charging processes takes more than 8 hours indicating that stations are used for parking over the day. Periods lasting up to 24h can also be observed.

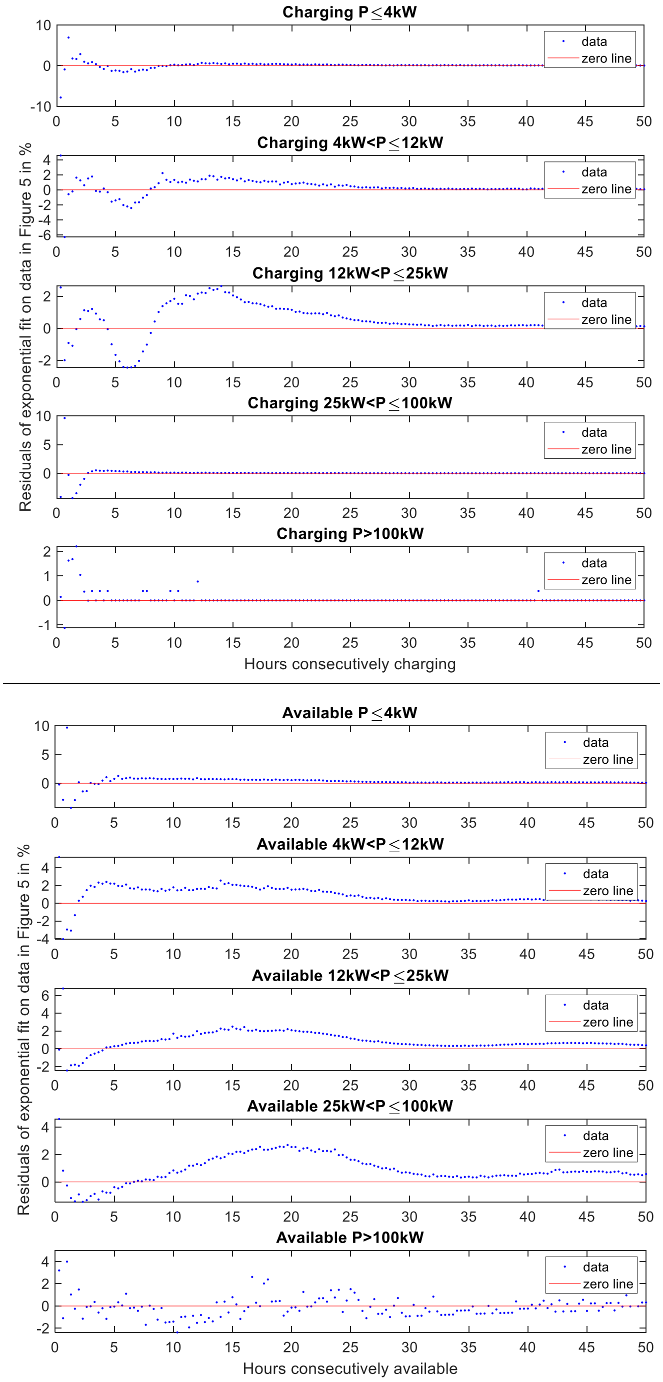


Figure 11: Residuals obtained when subtracting the fitted functions given in Table 9 using equation 8 from the data shown in Figure 5.

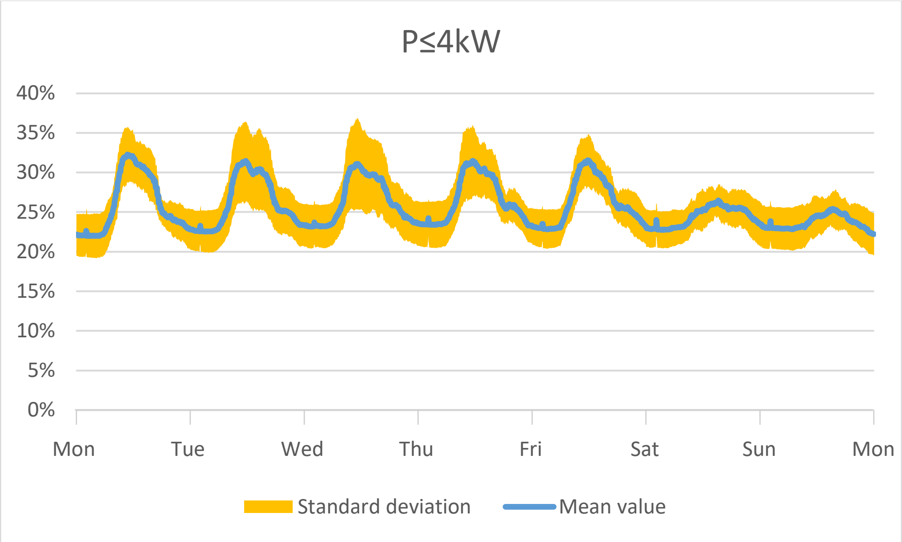
D. Standard deviation of connector occupation

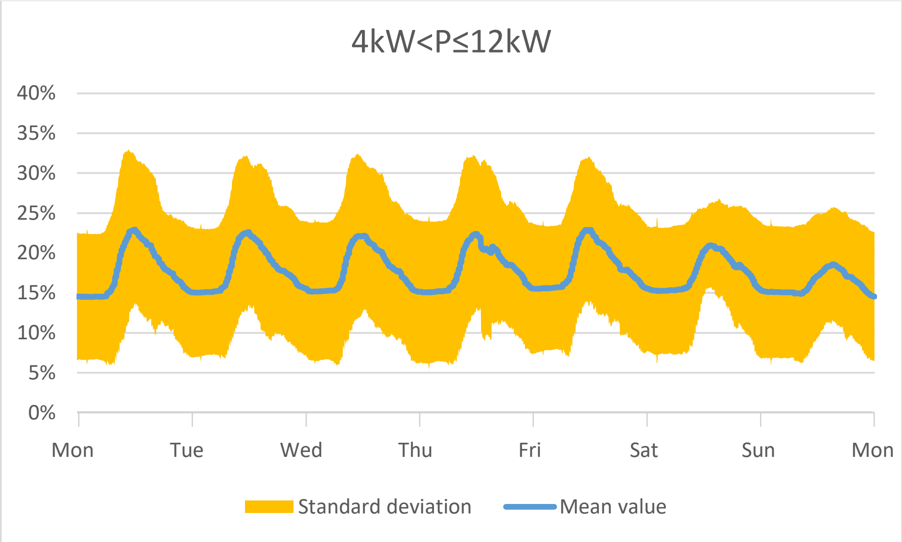
Figure 12 shows the standard deviation of the mean values displayed in Figure 3.b. The blue line shows the mean and the yellow-shaded areas shows the standard deviation in positive and negative direction. It can be seen quite well that the standard deviation is quite large compared to the base predicted value, which is the result of the overall quite inhomogeneous usage patterns. This can in part be explained by the fact that the observed period included public holidays and a vacation period, which inherently have a different usage pattern.

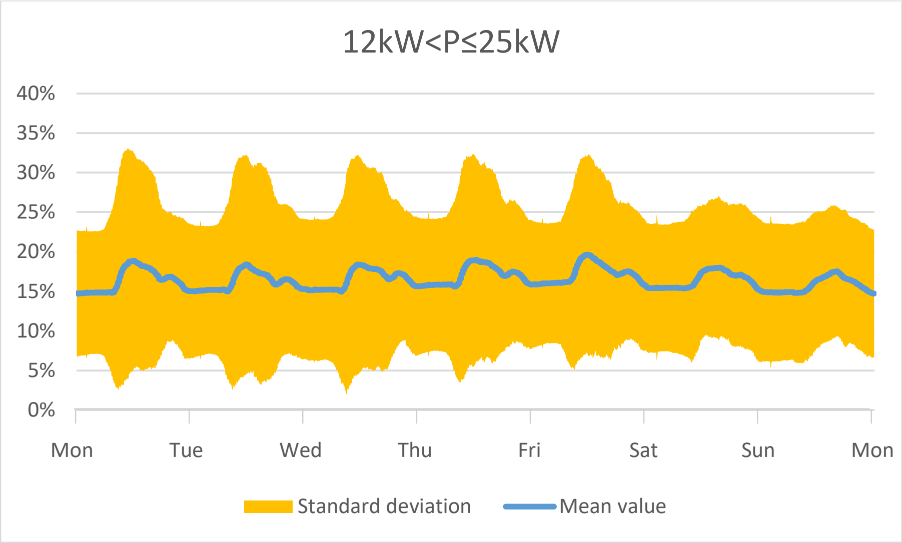
For conciseness, the visualisation is not repeated for Figure 3.c and Figure 4.a and b and the reader is referred to the dataset published alongside this paper.

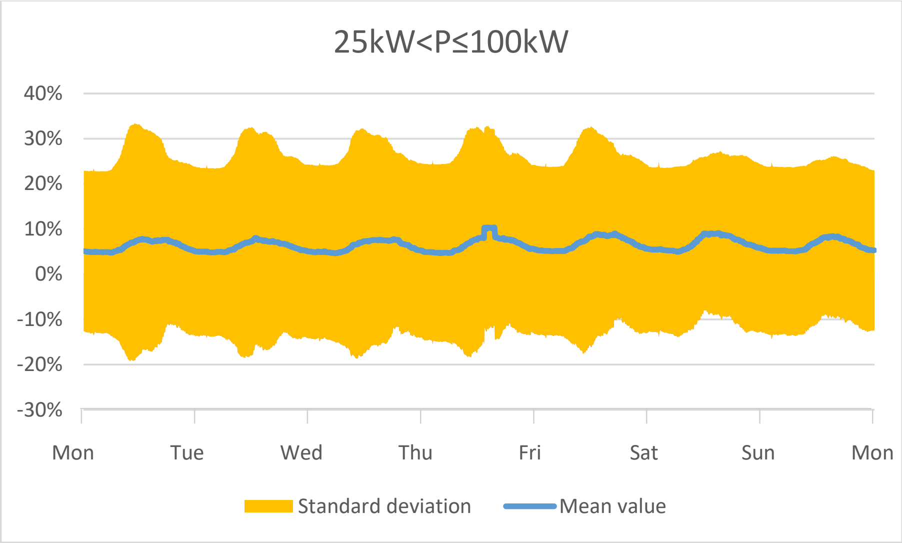
Table 10: Standard deviation on the weekly and daily basis for the daily and weekly aggregations displayed in Figure 3 and Figure 4.

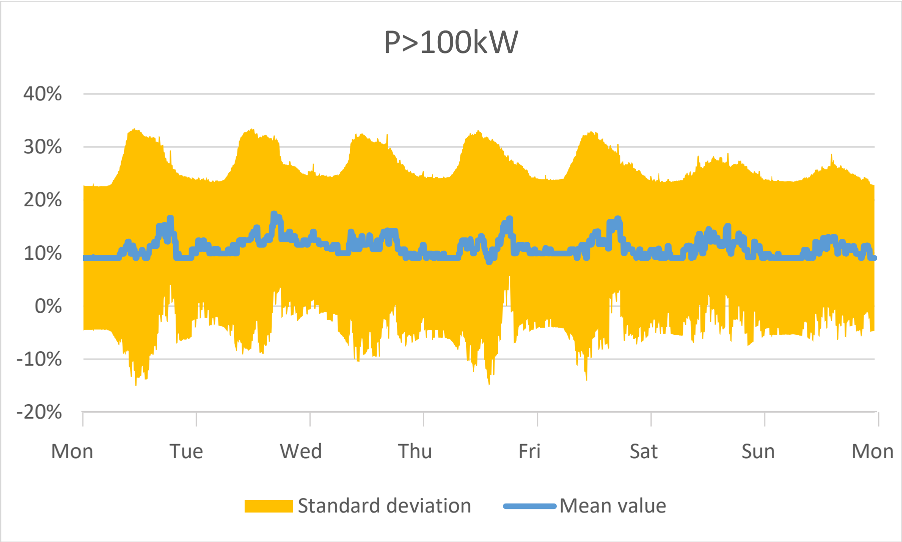
	Weekly	Daily
P≤4kW	2.9%	3.2%
4kW<P≤12kW	8.5%	8.2%
12kW<P≤25kW	9.8%	9.4%
25kW<P≤100kW	20.1%	19.3%
P>100kW	15.8%	15.2%
Total	10.6%	10.2%
Industrial	1.7%	2.0%
Urban	6.5%	6.4%
Suburban	2.6%	2.2%
Uninhabited	6.0%	5.7%


P≤4kW
40%
35%
30%
25%
20%
15%
10%
5%
0%
Mon
Tue
Wed
Thu
Fri
Sat
Sun
Mon
Standard deviation
Mean value


4kW<P≤12kW
40%
35%
30%
25%
20%
15%
10%
5%
0%
Mon
Tue
Wed
Thu
Fri
Sat
Sun
Mon
Standard deviation
Mean value


12kW<P≤25kW
40%
35%
30%
25%
20%
15%
10%
5%
0%
Mon
Tue
Wed
Thu
Fri
Sat
Sun
Mon
Standard deviation
Mean value


25kW<P≤100kW
40%
30%
20%
10%
0%
-10%
-20%
-30%
Mon
Tue
Wed
Thu
Fri
Sat
Sun
Mon
Standard deviation
Mean value



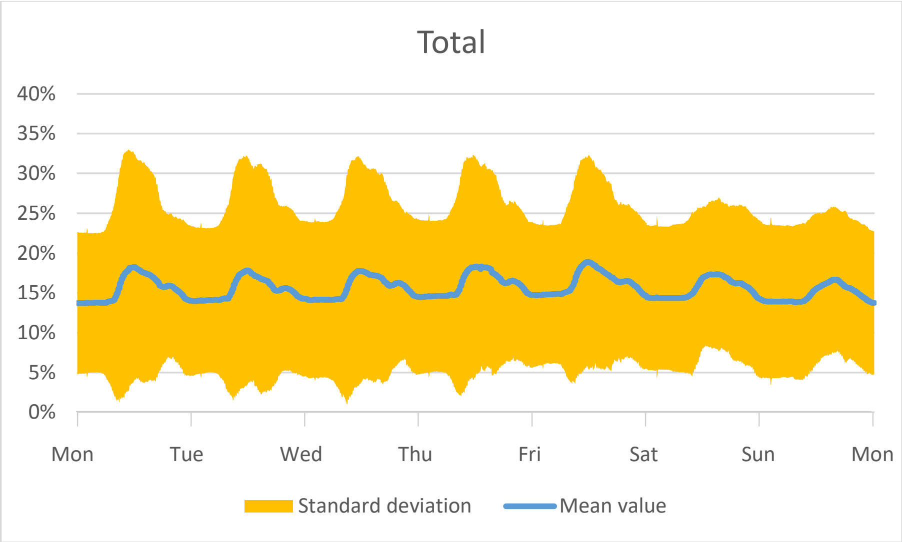


Figure 12: Mean values from Figure 3.b) with their respective standard deviations. The standard deviation was calculated by comparing each combination of weekday and time with all instances of that weekday and time in the dataset. Example: The population out of which the standard deviation was calculated for a Monday morning 8 AM were all Monday mornings at 8 AM in the dataset.