CHARGING OR IDLING: METHOD FOR QUANTIFYING THE CHARGING AND THE IDLE TIME OF PUBLIC CHARGING STATIONS

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ABSTRACT

The study at hand presents a methodology to determine the utilization of public charging infrastructure by the proportion of effective charging time and idle time. The results of the study can be used by decision makers to better understand the usage behavior of public charging infrastructure and to align the provision of charging infrastructure with the behavior of users. The user behavior is analyzed using charging areas and scenario-based analysis of charging sessions. More than 300,000 charging sessions at AC and DC charging stations in the urban area of Munich in 2020 were recorded as the data basis for the study. The methodology takes the available vehicle models in the study area as well as the characteristic charging behavior of plug-in electric vehicles (PEV) with a decreasing charging power at high states of charge of the battery into account. The results show a high proportion of idle time at AC charging stations. The outcome of a correlation analysis additionally indicates a correlation between the share of idle time and the proportion of high-density urban living in the survey area.

Keywords: Plug-in Electric Vehicles (PEVs), Public Charging Stations, User Behaviour, Hogging, Idling

INTRODUCTION

In recent years, the amount of plug-in electric vehicles (PEVs) sold increased steadily (*1*). In the meantime, public administrations faced the task to supply charging infrastructure that on the one hand meets charging demand and on the other hand adheres to building regulations and does not exceed the power network's capabilities. Thus, the demand-oriented and economic development and operation of public charging infrastructure (CI) is an urgent field of action for cities. This article investigates the utilization of charging infrastructure as it has been built up in Munich, Germany. The infrastructure is characterized predominantly by 22 kW AC charging points and few 50 kW DC chargers in the city. As a decision support for the future rollout of charging infrastructure, the utilization of the available charging stations is investigated. Utilization in this regard can be differentiated into two parts:

1. an active part, i.e. the effective charging time, in which the PEV's battery is charged.
2. a passive part, i.e. the idle time, in which the PEV is parked until it is needed for the next trip.

Both parts are inherent to charging as it takes place during parking stops between different trips, which follow specific purposes (*2*). As a proxy for utilization, in addition to the amount of energy transferred, the charging duration is investigated, as it allows to determine the active part of charging at public charging points. In this study, a method is presented to quantify the effective charging time and the idle time at public charging points using a qualitatively limited data basis. The results from the analysis are linked to geographic information from the city of Munich to identify a correlation between location factors of charging stations and usage behavior and conclusions are drawn about the required future capacity of charging points at different types of location. The remainder of this paper is structured as follows: Section 2 discusses relevant literature and highlights the research gap. The available data is described in Section 3. Section 4 describes the applied methodology and Section 5 presents results, which are discussed in Section 6.

RELATED WORK

In this section, an overview of publications focusing on usage behavior at public charging infrastructure is given. The results are summarized in Table 1. The studies are based on data collected from charging sessions at public charging points. For a better understanding, the number of charging sessions recorded, the study period, the information content of the data based as well as results are given with regard on several criteria. The first five criteria structure the information content of the dataset. The criterion *User ID* indicates whether the charging sessions can be ascribed to individual customers, allowing for individual usage behavior to be analyzed. The *Vehicle ID* indicates whether information about the vehicle such as the type of plug-in electric vehicle (battery electric vehicle BEV or plug-in hybrid PHEV) or the usable battery capacity is available. The criteria *Connection Time* and *Charging Time* enable the temporal delimitation of the connection with the public charging point or the period in which the charging point has transferred energy. If only the connection time is available, the share of the charging time or the share of the idle time cannot be inferred directly from the data. In addition the *Charged Energy* indicates the amount of energy transferred during the charging process. The two remaining criteria are used to categorize the results of the studies. The criterion *Idle Time* determines whether the idle time of the connection has been quantified in the studies. *Land Use* states whether an analysis of the charging locations in relation to the quantified idle time of the charging stations has been carried out.

(*3*) represents an early investigation of user behavior of PEVs at public charging points.

TABLE 1: Overview Related Literature

Authors	Charging Sessions	Period	User ID	Vehicle ID	Con. Time	Charg. Time	Charg. Energy	Idle Time	Land Use
van den Hoed et al. (3)	135,000	2012 - 2013	✓	-	✓	✓	✓	✓	-
Wolbertus et al. (4)	1.6m	2014 - 2015	✓	-	✓	✓	✓	✓	-
Wolbertus and van den Hoed (2)	1.3m	2016	✓	✓	✓	✓	✓	✓	-
Wolbertus et al. (5)	2.6m	2014 - 2016	✓	✓	✓	-	✓	-	-
Gerritsma et al. (6)	8,000	2017 - 2018	✓	✓	✓	✓	✓	-	-
Almaghrebi et al. (7)	17,000	2013 - 2018	✓	-	✓	✓	✓	✓	-
Almaghrebi et al. (8)	27,000	2013 - 2019	✓	-	✓	-	✓	-	-
Almaghrebi et al. (9)	27,000	2013 - 2019	✓	-	✓	✓	✓	-	-
van der Kam et al. (10)	1m	2016 - 2018	✓	✓	✓	-	✓	✓	-
Hecht et al. (11)	-	2019 - 2020	-	-	✓	-	-	-	-

The study is based on data from the Dutch city of Amsterdam. In addition to the identification of individual customers and the amount of energy transferred per charging process, the data set already included a differentiation of the connection time into charging time and idle time. However, the detailed differentiation of charging time and idle time was only possible for two months in 2013. The utilization of the public charging points is defined as the percentage of the effective charging time in relation to the available connection time and averaged to just 12 to 18%.

One of the most comprehensive data sets on charging sessions at public charging points is recorded by the Amsterdam University of Applied Sciences (AUAS). The data set includes several million charging sessions in the Amsterdam metropolitan region and the cities of Amsterdam, Rotterdam, the Hague and Utrecht. The data collection and processing was initiated in the course of the research project "Intelligent datadriven optimization of charging infrastructure" (IDO-Laad) and serves as the basis for several publications (*2, 4, 5*).

In (*4*), the effective use of public charging infrastructure by charging PEVs is quantified with 20%, where the effective charging period is directly derived from the collected data. In (*2*), the idle time at public charging points is specifically investigated. In the context of the study, the term "charging station hogging" is introduced to describe a behavior in which the PEV users utilize a public charging station longer than necessary when solely considering active charging. The analysis includes at which locations, by which user group and over which time period charging station hogging takes place. The data set used here is very detailed, since in addition to the pseudonymous identification of unique customers, information is available about the PEV including the usable battery capacity and the effective charging time. The analysis shows that charging station hogging occurred mainly in the city of Amsterdam, with the share of idle time varying strongly between individual locations. A more detailed analysis of individual locations was not performed. The low number of public parking spaces in the city of Amsterdam and the resulting high parking pressure, as well as existing carsharing services with electric vehicles, were named as one cause, which accounted for a large part of the idle time. Hogging thus occurred mainly during charging on public holidays and overnight charging, where the vehicle was connected to the public charging point in the evening between 5 p.m. and 8 p.m. and not disconnected until the next morning. Additionally, different approaches to avoid charging station hogging are explained and classified. In (*5*), an evaluation of the connection time is performed using a multinomial regression analysis. For this purpose, five different categories were formed based on the length of the connection time: stop & charge, park & charge, work & charge, home & charge, and long charge.

In (*6*), charging session data from 21 charging stations in the city of Utrecht, NL, over a year beginning in August 2017 were analyzed in order to quantify a) the potential for delay in charging and b) eventually the flexibility in charging sessions to postpone charging of PEVs without negative impacts on usage. By differentiating between local and visiting BEVs and PHEVs, respectively, usage behavior between these vehicle classes is analyzed and differences in plug-in times and ending times especially between PHEVs and BEVs are derived. Furthermore, the charging powers of both vehicle classes are analyzed and the differences are shown. Based on the given data, the potential for changes in charging power during the charging session is disclosed, showing high potential especially for BEVs during the day and in the evening. Less pronounced, but still relevant potential was identified with PHEVs as well, a notable result since this vehicle class exhibits high shares in the given dataset. After all, the data was utilized as basis for a Monte Carlo simulation for different scenarios, representing the growing amount of PEVs in the fleet as well as different charging methods. Results show that 59% of charging sessions can be delayed by over 8 hours, while peak energy demand could be lowered by a third in the simulation, just by utilizing different charging strategies with delays. The flexibility analyzed in this paper reflects directly the high impact of idle time at public charging points, since the time PEVs are connected to a charging point without charging is utilized to substitute the charging towards.

In (*7–9*) , charging sessions collected over a long 7-year period from 2013 to 2019 at public charging points in the US state of Nebraska were evaluated. In (*7*), charging time and idle time are evaluated in a differentiated manner, with the individual time shares again emerging directly from the collected data. The evaluations show a high share of idle time at the public charging points, whereby no differentiated evaluation of the idle time has been made according to individual charging stations or charging locations. In (*8*), the data was analyzed to investigate relationships between charged energy, time of day, and location factors at the charging point using a regression analysis. In (*9*), the existing data set is used to evaluate different approaches that predict the energy demand of electric vehicles at the captured public charging points.

In (*10*), billing data from the company *NewMotion* is used to support the rollout strategy for charging infrastructure for decision-makers from politics by providing specific recommendations for action. The recommended actions are structured using a decision tree, where specific actions mainly depend on the share of idle time or the share of charging time in the total connection time. If the share of charging time is high, its suggested to increase the number of public charging points in the affected area. If the share of idle time is high, the cost efficiency of the public charging points should be improved. As a specific measure for the concerned charging points, a stronger integration into the energy grid, i.e. in the context of vehicle-to-grid (V2G) concepts, is suggested in order to reduce the energy costs or the load for the distribution grid. Since the charging time or the idle time cannot be directly derived from the data used, the values were estimated by means of a simplified procedure in which the smallest nominal charging power from the vehicle and public charging point was used to calculate the charging time that was necessary to transfer the billed energy from the charging process. Thus, this approach did not consider the charging curve typical for electric vehicles with decreasing charging power at high State of Charge (SoC) of the vehicle battery. As in (*2*), the evaluations show a spatial concentration of public charging stations with a high proportion of idle time, although no more detailed analysis of the individual locations was carried out in this study either.

In (*11*), data from public charging stations in Germany, collected from websites of several roaming platforms, is analyzed. The data essentially includes the connection time at individual charging points without information about the customer and the amount of energy transferred during the connection. Based on a high proportion of long connection times between 8 and 10 hours, the authors formulated the thesis that the public charging points concerned have a high proportion of idle time. The correlation between location-specific parameters and the duration of the connection has not been performed, hence there is no indication included to why users parked that long.

In the studies listed, the idle connection time was only quantified if the time components were directly derived from the data set. An exception is van der Kam et al. (10), where a simplified approach with linear charging power over the entire charging area of the vehicle battery was applied. In addition, no analysis of the charging locations as a function of the idle connection time was carried out in the investigations. In this study, a methodology is presented to quantify the effective charging time and the idle connection time, respectively, based on a limited data set. In addition, a location analysis is performed as a function of these time components. The results can be used as a basis for decision-making in order to better determine charging stations based on the expected user behavior or depending on objective location factors.

DATA DESCRIPTION

The objective of the study presented here is to quantify the idle time of public charging points. The data basis for the study are the 2020 charge detail records of public charging points provided by *Stadtwerke München* (SWM), the largest operator of public charging stations in the city area of Munich. Due to corporate confidentiality requirements regarding competitive data by the data provider, no evaluations were made that allow direct conclusions to be drawn about the profitability of the public charging stations.

Table 2 includes information about the data set. The analyses are based on over 300,000 charging sessions recorded at 1,156 charging points of 577 charging stations in 2020. The data contains basic information required for billing the public charging sessions: the amount of energy transferred and the connection time. As only this data is available, a method needs to be developed to infer the idle time. The raw data was subjected to a logical check beforehand, whereby connections in which no energy was transferred were not evaluated. In addition, charging sessions with a transferred energy quantity of more than 100 kWh were not evaluated, as there were no electric vehicles in series with a corresponding useable battery capacity during the recording period. Figure 1 shows a map of the locations of the investigated AC and DC charging stations in the city of Munich. The data set includes charging sessions from 1,150 AC charging points and 6 DC charging points. The ratio of AC and DC charging points is also reflected in the number of charging sessions recorded. Over 99% of the recorded charging sessions were AC charging sessions (approx. 302,000) and only 1% were DC charging sessions (approx. 2,000).

TABLE 2: Description of the Dataset

Variable Name	Description	Unit
EVSEID	Identification of charging point	Unique ID
Startdatetime	Start time of the connection	dd:mm:yyyy hh:mm
Enddatetime	End time of the connection	dd:mm:yyyy hh:mm
Duration	Duration of the connection	Seconds
Quantity	Charged energy during the connection	kWh
Address	Address of the charging station	street name, street number, postal code and city
Type	Information whether it is an AC or DC charging point	AC or DC
Power	Nominal charging power of the charging point	kW

When considering connection times separately for AC and DC charging sessions, different connection behavior can be observed. Figure 2 shows the connection times separately for AC and DC charging sessions. A high proportion of short connection times can be seen for both charging types. At the same time, AC charging processes have a significant share of long connection times. For example, about one third of the AC charging processes have a connection time of 2 hours or less and one third have a connection time of 5 hours or more. The intermediate peak at about 12 to 13 hours of connection time of the AC charging sessions results from connecting the PEV overnight, where the vehicles are connected to the charging point in the evening and not disconnected until the next morning. That the intermediate peak in Figure 2a results from charging

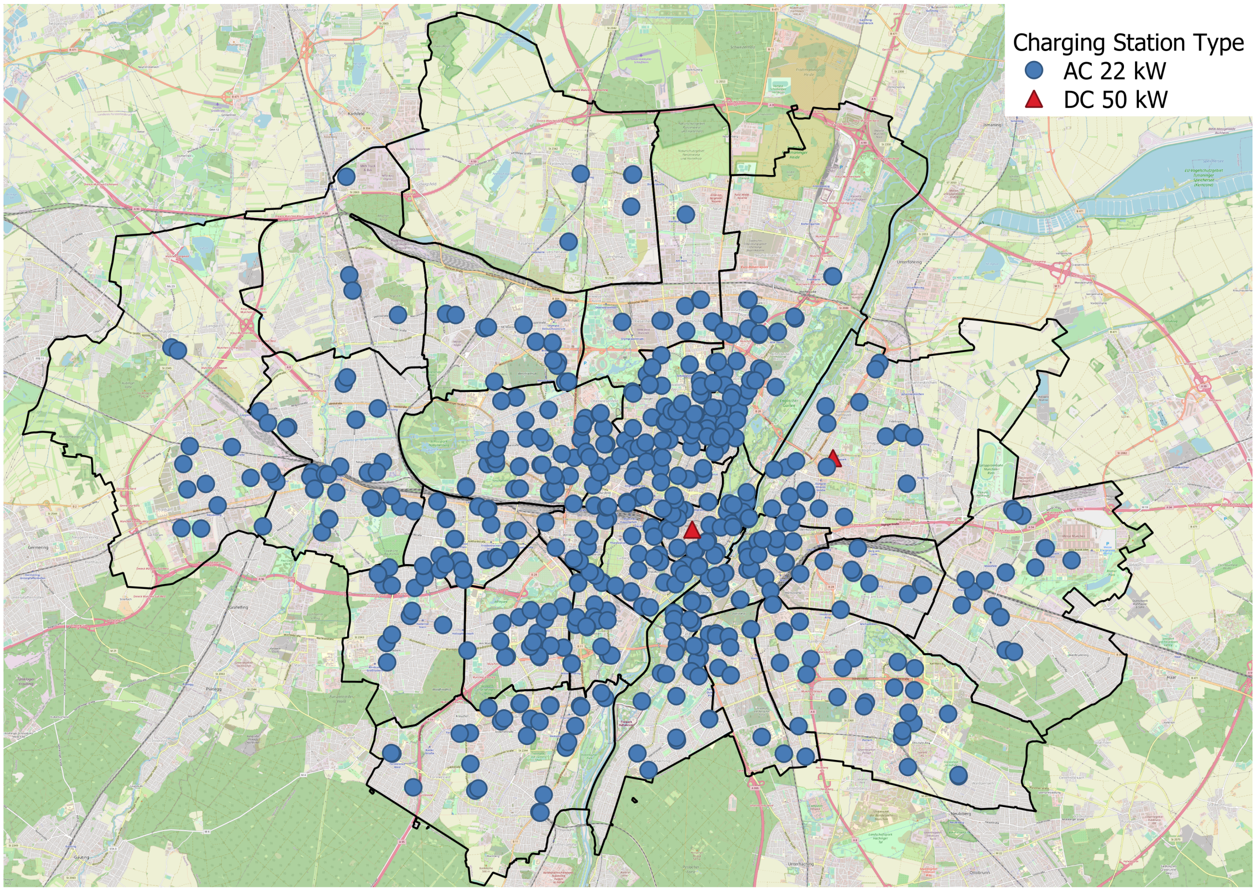
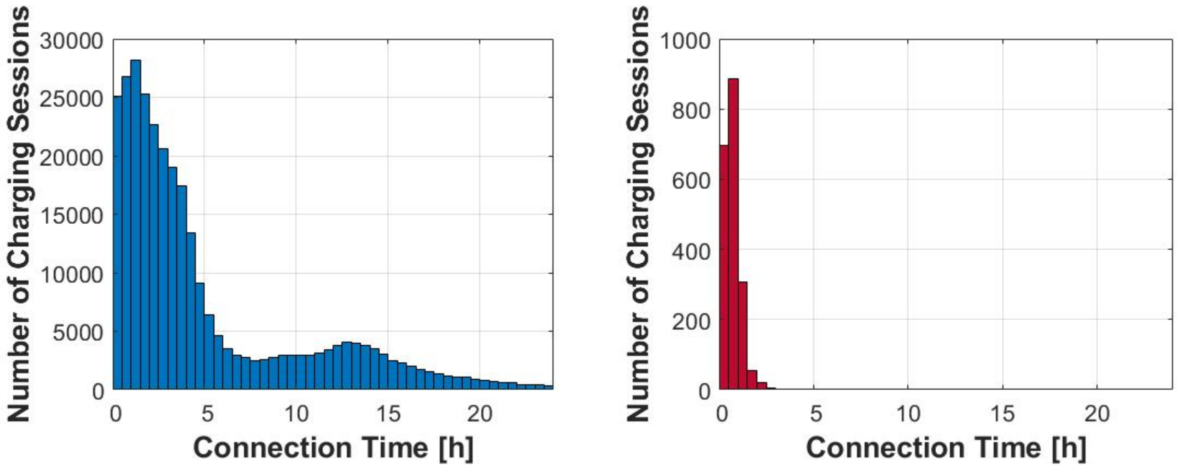


FIGURE 1: Locations of the Investigated Charging Stations in the City of Munich

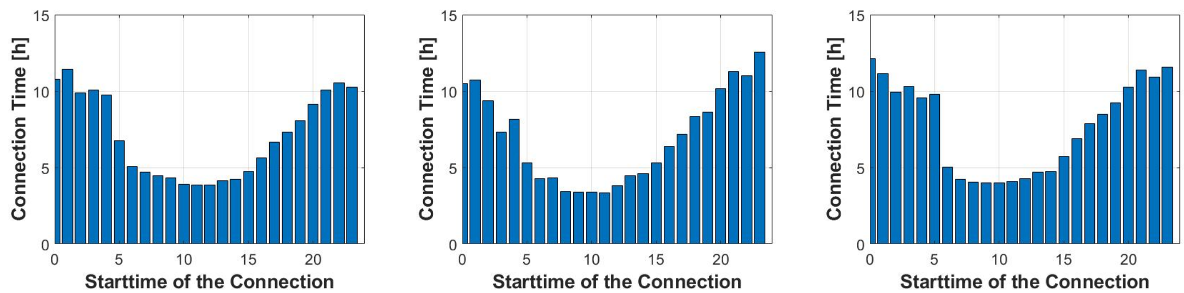
sessions over night can be deduced from Figure 3. The diagrams show the relationship between the start of the connection and the average connection duration for different types of days. In Figures 3a and 3d, connections are evaluated on workdays from Monday to Friday, in 3b and 3e for Saturdays, and in 3c and 3f for Sundays and regional holidays. In addition to the differentiation according to day types, a differentiated view between charging sessions at AC and DC charging stations takes place.

AC charging sessions show a long connection duration for charging sessions that start at night between 0 and 5 a.m. or in the late evening between 5 and 11 p.m.. The connection duration here is about 10 hours on average. At the same time, the average connection duration decreases significantly for charging sessions that start during the rest of the day. One possible reason for this is the parking time regulation in the city of Munich. PEVs are allowed to park at charging stations between 8 a.m. and 8 p.m. for up to 4 hours. Thus connections that start between 6 a.m. and 4 p.m. have an average duration of only about 3 hours. A different behavior with regard to the connection duration and the distribution over the day can be seen at DC charging sessions. Due to the shorter connection times, the scaling of the y-axis was adjusted to 3 hours. In contrast to the AC charging sessions, the duration of the connection times does not result in a clear distribution. Due to the low number of 2,000 DC charging sessions, there are no connection starts at certain times of the day, which have therefore been evaluated as 0 in the diagrams.

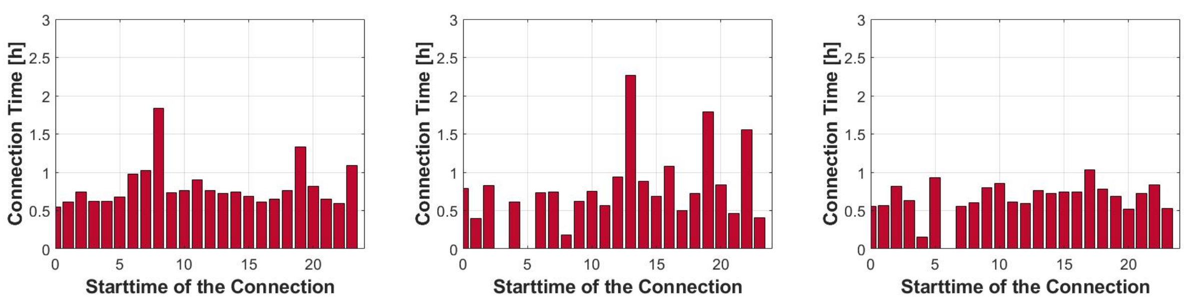


(a) Connection Time of AC Charging Sessions (b) Connection Time of DC Charging Sessions

FIGURE 2: Connection Time of AC and DC Charging Sessions



(a) AC Monday till Friday (b) AC Saturday (c) AC Sunday



(d) DC Monday till Friday (e) DC Saturday (f) DC Sunday

FIGURE 3: Distribution of Connection Duration of AC and DC Charging Stations

METHODOLOGY

The following section explains the methodology for dividing the connection time into charging time and idle time for a detailed evaluation of the usage of public charging stations by PEV drivers. The required data basis for the methodology is the connection time and the amount of energy transferred for the individual charging sessions. Figure 4 shows a scatter plot, in which each point represents a charging session defined by the value pairs connection time and amount of energy transferred. For a differentiated assessment, AC charging sessions are shown as small blue dots and DC charging sessions as big red dots. A cluster of charging sessions with low energy quantity and connection time can be seen in the lower left corner. The cluster of AC charging sessions with a connection time of 12 to 13 hours can also be found in this evaluation. It is noticeable that the charging processes form different linear ranges, whereby one linear range can be seen for the DC charging processes and several linear ranges for the AC charging processes. The linear ranges result from the accumulation of charging sessions with identical vehicle-specific charging power. It is pointed out that the nominal charging power for the public AC charging points is 22 kW and for the public DC charging points is 50 kW. This corresponds in each case to the first linear range from the left for the AC and DC charging sessions. The formation of the additional linear ranges therefore results from a reduced vehicle-specific charging power, which occurred primarily with AC charging sessions.

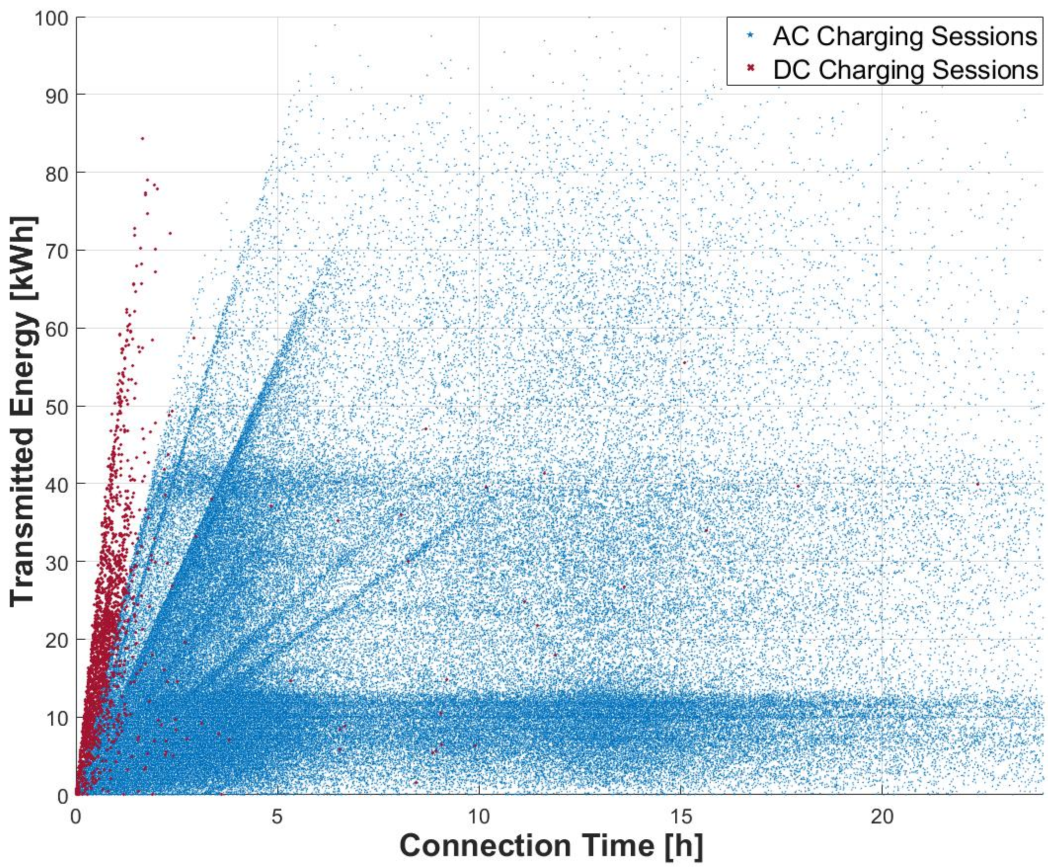


FIGURE 4: Data Distribution of Charging Sessions According to Connection Time and Transmitted Energy

Figure 5 shows an exemplary charging process with a nominal charging power of 7 kW. In this case, the vehicle is connected to the charging point for 10 hours, whereby the connection time

t_{CON} can be differentiated into a charging time t_{CHARGE} and an idle time t_{IDLE}. The charging time from 0% to 100% State of Charge (SoC) is completed after about 5 hours. The vehicle remains at the charging point for another 5 hours after completion of the charging process before the vehicle leaves the public charging point again. This second section corresponds to the idle time. The connection time at the charging point is thus composed of the charging time and the idle time and can be described as follows in Equation 1.

$$t_{CON} = t_{CHARGE} + t_{IDLE} \tag{1}$$

This paper models the charging process according to the so-called IU charging behavior of lithium-ion battery cells according to (*12*). The charging behavior is also referred to as CCCV for constant current constant voltage. In the I-phase, the lithium-ion cells are charged with a constant current and the cell voltage increases only minimally. At a defined SoC switch point SoC_{Switch}, the cells are charged with a constant voltage. This subsequent phase is called U-phase, where the voltage is defined to be the end-of-charge voltage of the cell U_{CE} and the current decreases exponentially. A value of 75% has been defined as the SoC switch point SoC_{Switch}. The charge process is terminated when the charge current reaches the defined charge cutoff current value I_{CE}. As a resultant behavior, the battery is charged with a constant charge power in the first phase, which decreases exponentially in the second phase after the charge switch point is reached. Hence, the charging process can be assumed to be linear up to an SoC_{Switch} of 75%. This charging section with constant charging power over time and hence, higher amounts of energy transferred corresponds to the linear areas in Figure 3.

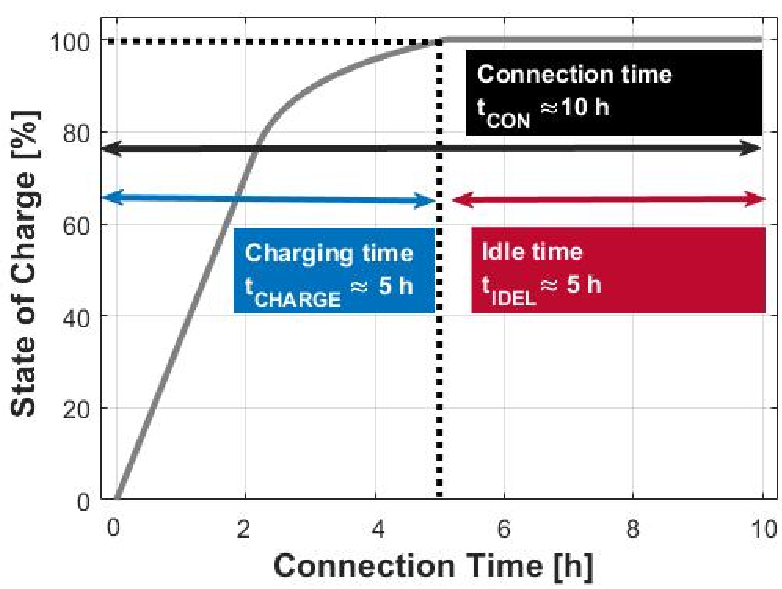


FIGURE 5: AC Charging Session with Charging time and idle time

In Equation 2, the charging power is calculated after exceeding the charge switch point SoC_{Switch}. If the SoC is below the defined switch point SoC_{Switch}, the vehicle battery is charged with the nominal charge power of the electric vehicle P_N.

$$P_{Charge} = P_N \cdot e^{\frac{SoC_{Switch} - SoC}{C_{Charge}}} \tag{2}$$

The charge correction factor C_{Charge} is defined according to Equation 3 and ensures that the defined charge cut-off current I_{CE} is reached at a battery state of charge of 100% and thus at the end of the charging process.

$$C_{Charge} = \frac{100 - SoC_{Switch}}{\ln(\frac{P_{Const}}{P_{CE}})} \tag{3}$$

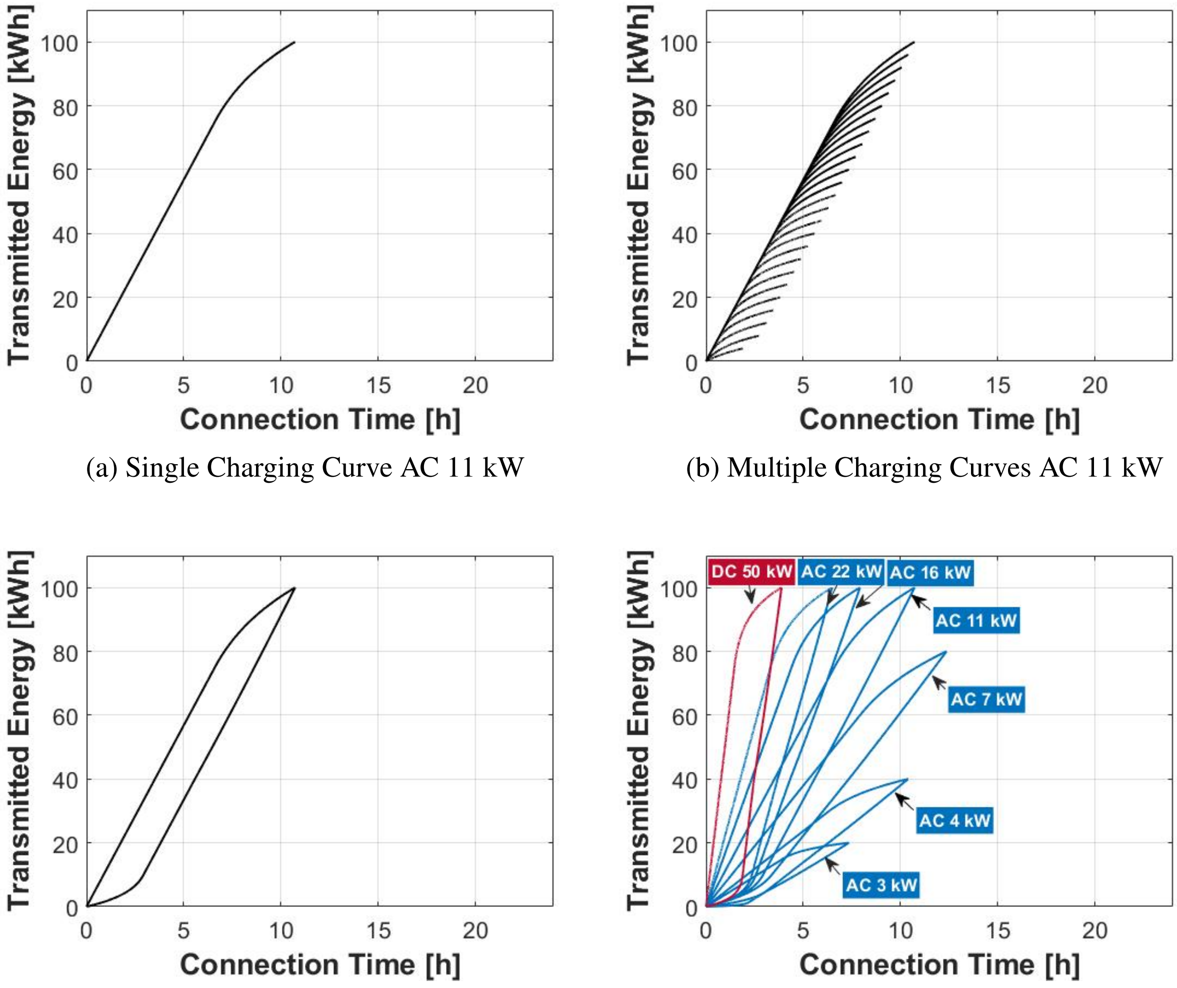
The charge correction factor C_{Charge} is formed according to Equation 4 from the charge cut-off power P_{CE}, which in turn is calculated from the nominal voltage of the battery cells U_N, the charge cut-off voltage U_{CE}, the charge cut-off current I_{CE} and the nominal energy quantity of the vehicle battery $E_{Battery}$. The charge cut-off current is used as C-rate with the unit $\frac{1}{h}$.

$$P_{CE} = \frac{U_{CE}}{U_N} \cdot I_{CE} \cdot E_{Battery} \tag{4}$$

Values for current lithium-ion cells according to (*13*) were selected as parameters for the simulations in this study. The charge cutoff voltage U_{CE} was defined as 4.2 volts, the nominal voltage of the battery cells U_N as 3.6 volts and the charge cutoff current I_{CE} as 0.03 $\frac{1}{h}$. The nominal charging power of the electric vehicle P_N and the amount of energy of the vehicle battery $E_{Battery}$ are defined according to the vehicle specific values, in this case of Figure 5 with the BMW i3 model 60 Ah a first generation battery electric vehicle with 7 kW nominal charging power P_N and a battery capacity $E_{Battery}$ of 18.8 kWh.

The basic approach of the methodology is to simulate PEV charging at public charging points to quantify the shares of charging time and idle time. For this purpose, the distribution of the individual charging sessions is combined with the charging areas based on the IU charging behavior of the Equations (2), (3) and (4). Figure (6) shows the steps involved in creating the charging areas. Figure 6a shows a single charging curve created using the IU charging method with a nominal charging power of 11 kW. The amount of energy transferred was defined as 100 kWh, since there were no series PEV with a larger usable battery capacity in the period and area of coverage. It is also important to note that the amount of energy refers to the gross amount of energy that is billed to the customer including those amounts of energy that are lost due to efficiency rather than just the net amount of energy reaching the PEV's battery. Based on the existing charging data, an efficiency loss for AC and DC charging processes of around 3% was quantified and taken into account in the creation of the charging areas. Figure 6b shows the formation of many individual charging curves. Since there is no information about the customer, the PEV used, and the SoC of the battery at the time of charging, assumptions must be made to model the charging behavior. To form the individual charging curves, the amount of energy transferred was reduced step by step and a maximum and minimum battery capacity of the PEV was taken into account according to parameter $E_{Battery}$ in Equation 4.

The maximum battery capacity defines the maximum transferred energy quantity of the respective charging processes. The maximum battery capacity is reduced step by step to the min-



(a) Single Charging Curve AC 11 kW

(b) Multiple Charging Curves AC 11 kW

(c) Charging Area AC 11 kW

(d) Multiple Charging Areas AC and DC

FIGURE 6: Building of Charging Areas

imum battery capacity. Each charge curve in the maximum battery capacity range represents a complete charge process from 0 to 100% taking into account the respective battery capacity. For charging processes with 11 kW, a battery capacity of 40 to 100 kWh was defined as the range for complete charging processes. For charging processes below the minimum battery capacity, on the other hand, partial charging of the vehicle battery was simulated. For the 11 kW charging range, for example, this means that for a transferred energy quantity of 20 kWh, a charging process from 50% to 100% has been simulated with a nominal battery capacity of 40 kWh. Table 3 gives an overview of the parameters used per charging range. The individual values were derived from an internal database for PEVs that were available on the market during the period and in the coverage area of the public charging points. The internal database is based on the database of the Allgemeine Deutsche Automobil-Club e. V. (ADAC) (*14*).

By connecting the individual charging curves, an area can be formed, which is referred to as charging area. Figure 6c shows the charging area using the example of charging processes with

11 kW. The left part of the charging area delimits the minimum charging time and the right part the maximum charging time of the charging processes. The procedure was repeated for different nominal charging powers according to Table 3. Figure 6d shows the resulting charging areas that were taken into account for the evaluation based on available PEVs and their charging power as highlighted in Table 3.

Charging area	Charging Type	Reference vehicle	Max. Battery Capacity	Min. Battery Capacity
50 kW	DC	BEV	100 kWh	40 kWh
22 kW	AC 32 Ampere 3 Phases	Renault Zoe	100 kWh	40 kWh
16 kW	AC 24 Ampere 3 Phases	Tesla Model S	100 kWh	40 kWh
11 kW	AC 16 Ampere 3 Phases	VW ID.3	100 kWh	40 kWh
7 kW	AC 16 Ampere 2 Phases	BWM i3 60 Ah	80 kWh	40 kWh
4 kW	AC 20 Ampere 1 Phase	Smart EQ	40 kWh	20 kWh
3 kW	AC 16 Ampere 1 Phase	PHEV	20 kWh	5 kWh

TABLE 3: Additional information Charging Areas

By defining the charging areas, a distinction can be made between charging processes inside and outside the charging areas. Charging processes inside or on the lines of the charging area are evaluated as charging processes without idle time, hogging or blocking time. However, for charging processes outside the charging areas, the charging process has a share of idle time. Figure 7 shows the exemplary case of an AC charging process with a connection time of 15 hours and a transferred energy quantity of 50 kWh. The charging process is marked in the diagram by the point P_{CE} and is outside of the defined charging areas. Two scenarios can be considered to quantify the charging time and idle time. In Scenario 1 according to Equation 5, the charging time is given by the horizontal intersection with the left line of the first charging range from the left P_{C1} .This is the minimum charging time, since 22 kW is the largest possible AC charging power. By calculating the difference of connection time and minimum charging time, the maximum idle time can be derived. In Scenario 2 according to Equation 6, the maximum charging time is determined by the horizontal intersection with the right line of the last relevant charging area from the right P_{C2}. The relevance of the charging range is largely determined by the defined maximum and minimum battery capacity as well as by the connection time and the transferred energy quantity of the respective charging session.

$$t_{CON\ Scenario\ 1} = t_{CHARGE\ min} + t_{IDLE\ max} \quad (5)$$

$$t_{CON\ Scenario\ 2} = t_{CHARGE\ max} + t_{IDLE\ min} \quad (6)$$

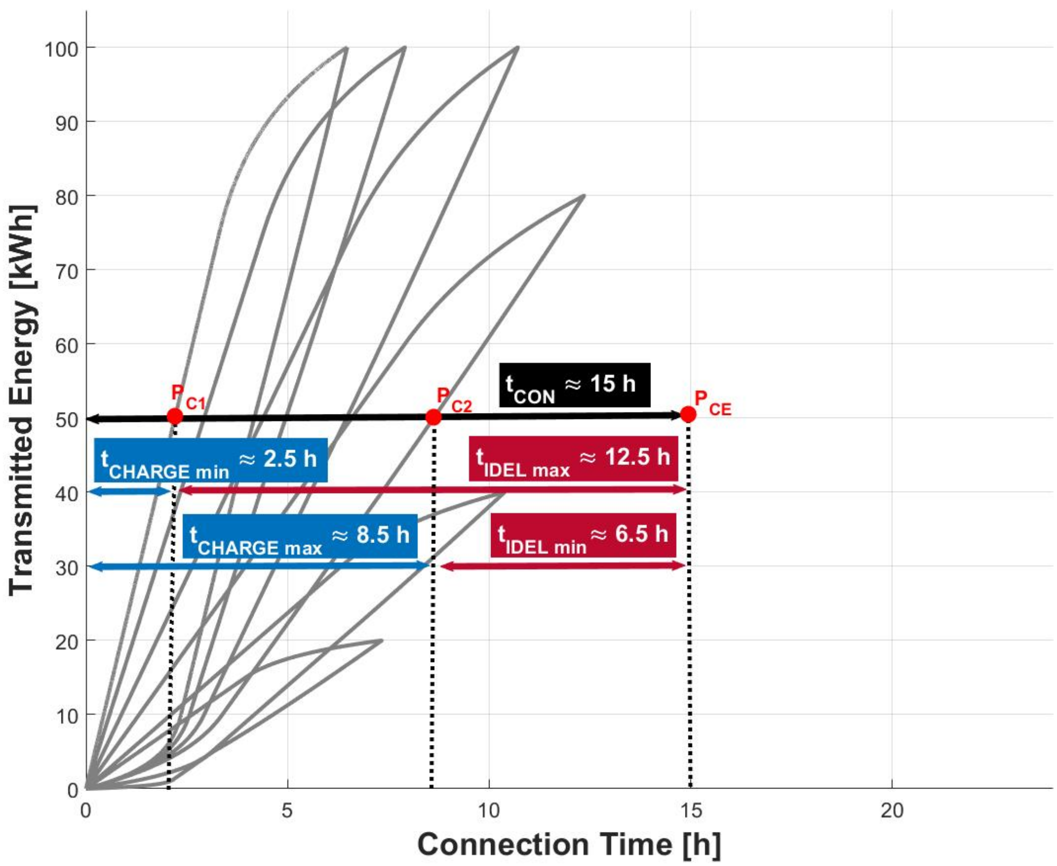


FIGURE 7: Evaluation of Charging and idle time per Charging Session

The results of the usage analysis are combined with structural data from the city of Munich in a correlation analysis to obtain relationships between charging stations with a high share of idle time and location factors. Figure 8 shows a map of Munich on the example of urban living space. The light areas indicate a high proportion of high-density living and the dark areas a low proportion. High-density urban housing was defined in this case as row houses, multifamily buildings, apartment blocks, and high-rise apartment buildings. Thus, single and duplex homes were not considered. The evaluation of location factors focuses on high-density urban residential areas, as it was hypothesized that especially public charging points close to high-density urban residential areas show overnight charging and thus a high share of idle time. This hypothesis is based on the assumption that primarily people in urban neighborhoods without access to a private parking space and private charging points rely on public charging infrastructure. The size of the defined spatial areas differs for individual areas of the city of Munich. The spatial resolution thus corresponds to the distribution of public charging points, with an accumulation of charging stations in the inner city area. For additional orientation, the public charging stations are marked as white dots on the map.

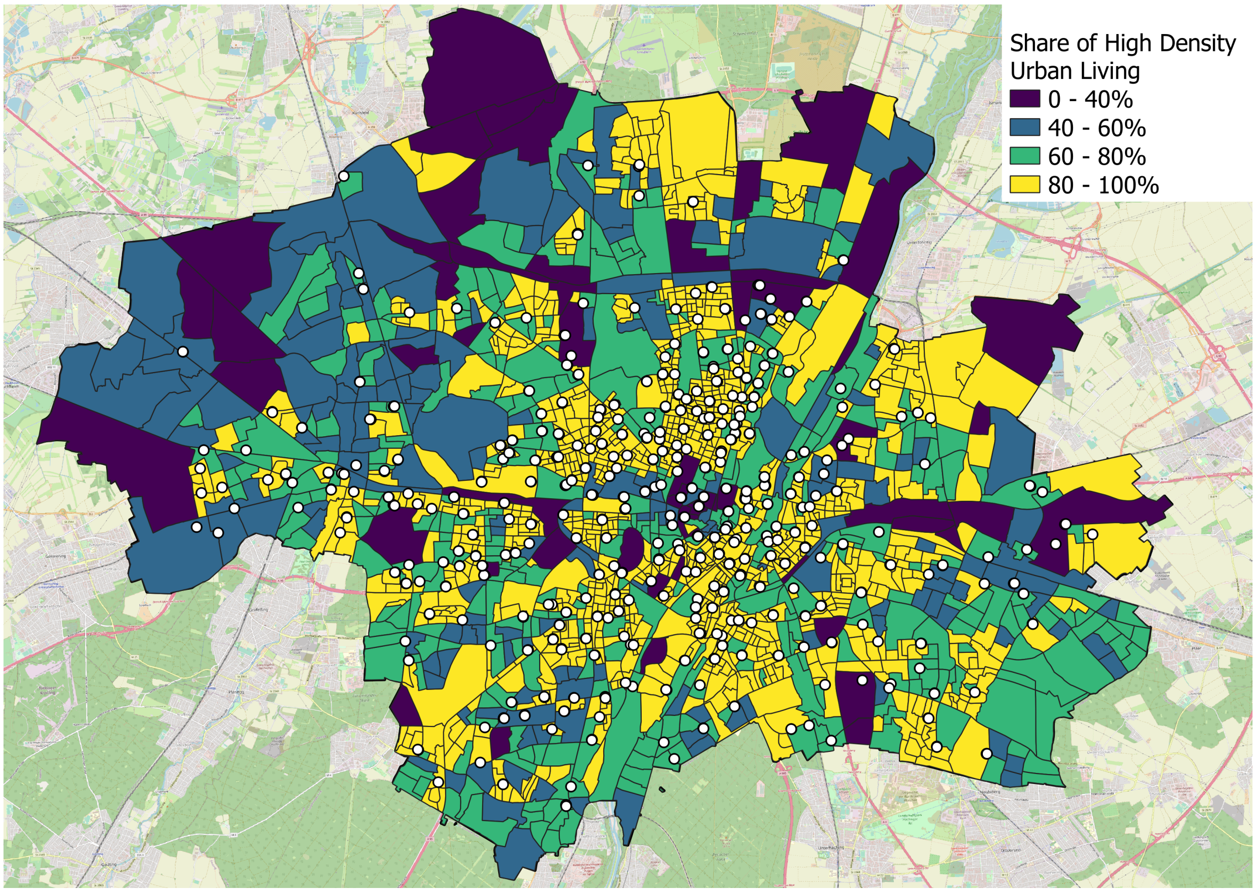
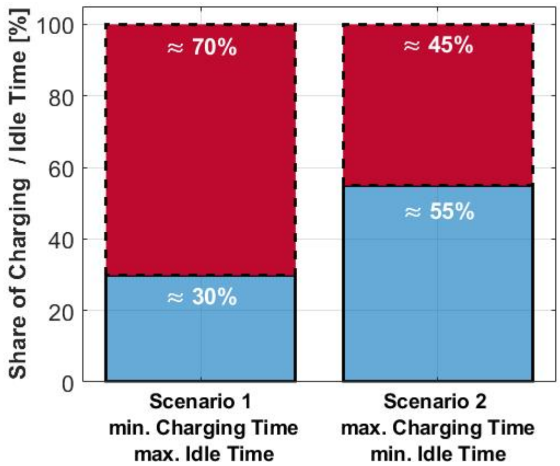


FIGURE 8: High Density Urban Living Areas in Munich

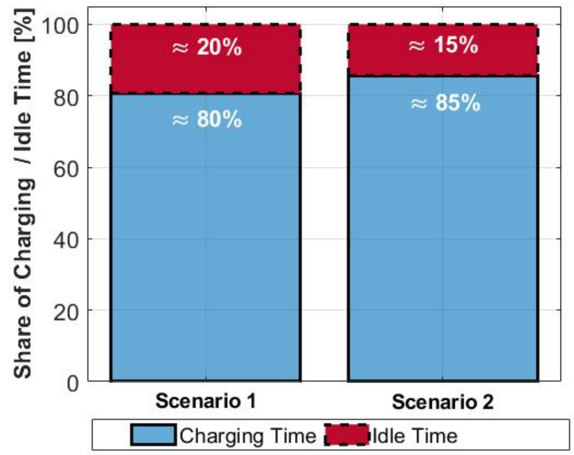
RESULTS

The following section presents the results of the investigation. In Figure 9, the charging time as well as the idle times for AC and DC charging sessions were summed up and presented in percentage ratios. The bar charts show a separate evaluation for the defined Scenarios 1 and 2 according to Equations 5 and 6. The distribution of the temporal proportions shows a significant share of idle time for AC charging sessions with about 70% and 45%, respectively. In contrast, for DC charging, both the share of idle time with 20% and 15%, respectively, and the spread between the scenarios are significantly lower. It is pointed out that the distributions shown include very long connection times in the case of AC charging. The proportion of connection times over 24 hours is about 2% of the total AC charging Sessions. If these long connections are excluded from the evaluations of the AC charging sessions, the share of idle time is 65% in Scenario 1 and 37% in Scenario 2.

Since the share of idle time is particularly high for AC charging processes, the following evaluations examine the usage behavior of AC charging stations in more detail. All AC charging



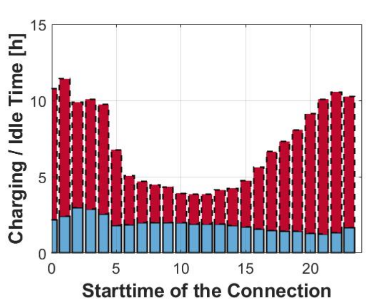
(a) AC Charging Sessions



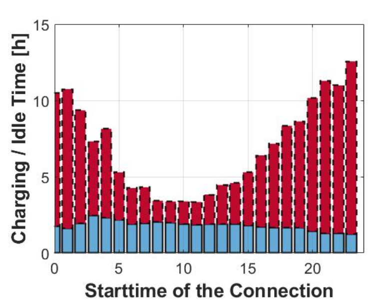
(b) DC Charging Sessions

FIGURE 9: Distribution of Charging and idle time for AC and DC Charging Sessions

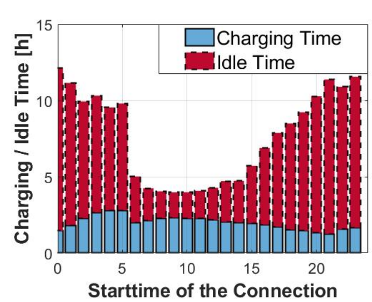
processes without excluding long connection times of more than 24 hours serve as the data basis. Figure 10 and Figure 11 shows the temporal proportions of charging time and idle time as a function of the start time of the connection. The temporal distribution of the connection time thus corresponds to the evaluations in Figure 3 from Section 3. In all types of days and in both scenarios, a high proportion of idle time can be seen for charging sessions that started at night or in the late evening. For AC charging sessions started between 0 a.m. and 5 a.m. and 5 p.m. to 11 p.m., an idle time of about 4.5 to 8 hours was found for a mean connection duration of about 10 hours. In the period from 6 a.m. to 4 p.m., the idle time of an average connection duration of about 3 hours is about 1.5 to 2.5 hours. As the evaluation reflects the average connection duration as a function of the start time of the connection, no conclusion can be drawn from the distributions regarding the frequency of the respective connections. For the recorded AC charging stations, there was a peak in connection starts on weekdays in the morning between 8 and 9 a.m. and in the evening between 5 and 7 p.m.. In total, more than 40% of the connections were started between Monday and Friday during these periods. On Saturdays and Sundays and holidays, the majority of connections are distributed between 9 a.m. and 7 p.m..



(a) AC Monday till Friday

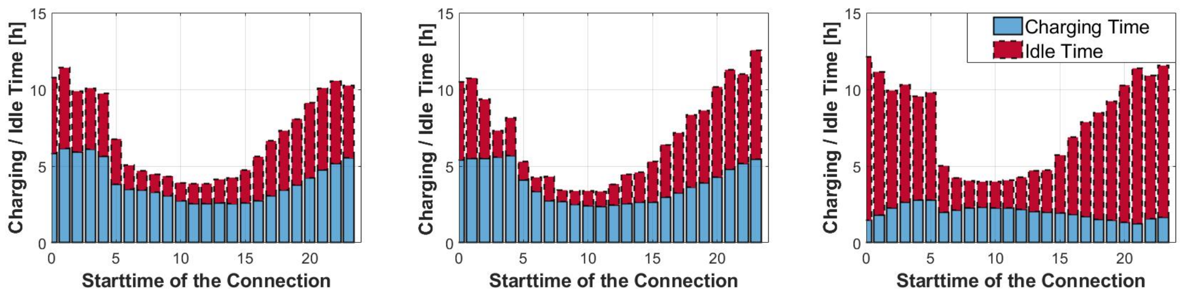


(b) AC Saturday



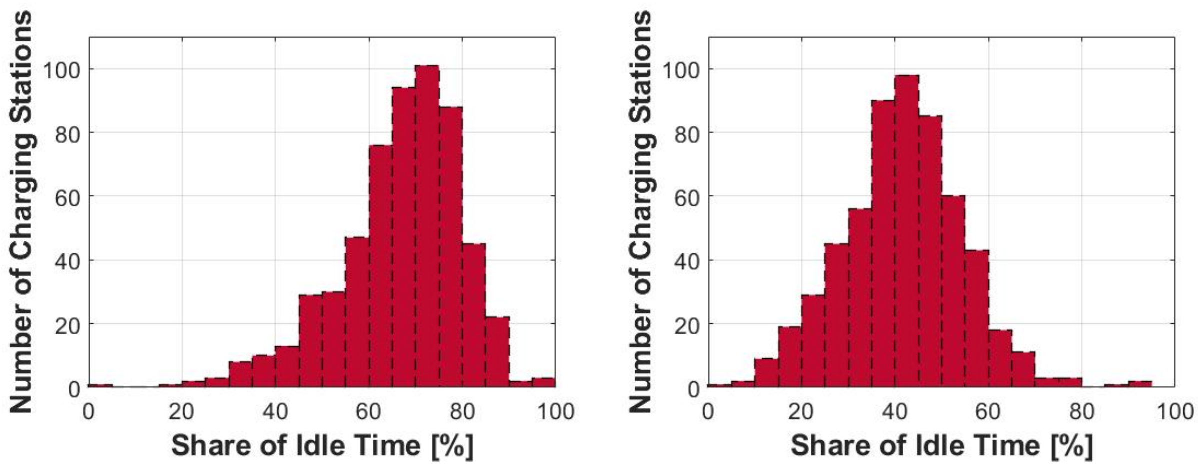
(c) AC Sunday

FIGURE 10: Scenario 1 - Distribution of Charging time and idle time on AC Charging Stations



(a) AC Monday till Friday (b) AC Saturday (c) AC Sunday

FIGURE 11: Scenario 2 - Distribution of Charging time and idle time on AC Charging Stations

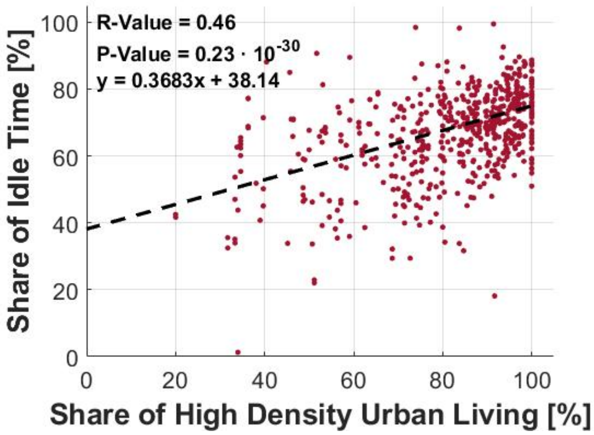


(a) Scenario 1 (b) Scenario 2

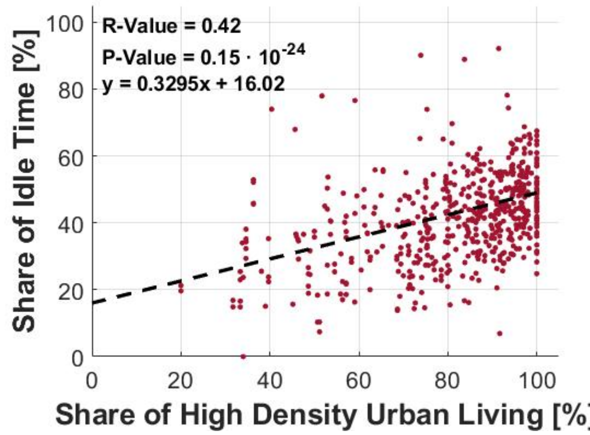
FIGURE 12: Idle time of AC Charging Stations

Figure 12 shows the number of AC charging stations by the share of idle time. The distributions were made separately for Scenarios 1 and 2 and resemble a Gaussian distribution. In a next step, the correlation of idle time to socio-demographic information on the respective charging station's location was investigated. This was carried out to be able to draw conclusion towards the reasoning behind people's charging behavior. In total, the geo-information used included about 100 attributes, such as the number of inhabitants by age group, the number of registered passenger cars, information on net income and information on building characteristics. The Correlation analysis was used based on the proportion of high-density urban living, as this resulted in the highest correlation. Pearson's correlation analysis in Figure 13 examines the relationship between the proportion of idle time and the proportion of high-density urban housing at the charging station location. With a statistically significant ($p < 0.0001$) correlation factor of 0.42 to 0.46, the correlation for both scenarios is moderate positive. Hence, we conclude that people living in high-density urban areas rely mostly on public charging infrastructure over night, when their PEV is parked.

Table 4 shows the results of the correlation analysis for further geo-information. The basis for the correlation analysis was the maximum idle connection time according to scenario 1. For the correlation analysis from Figure 13, parameters 14 to 17 were combined to the share of high density



(a) Scenario 1



(b) Scenario 2

FIGURE 13: Correlation idle time and high density Urban living Areas in Munich

TABLE 4: Results from correlation analysis for different geo-information, Scenario 1

Number	Description	R-Value	P-Value
1	Number of inhabitants per km^2	0.3575	$1.09 \cdot 10^{-18}$
2	Number of households per km^2	0.3530	$3.14 \cdot 10^{-18}$
3	Number of inhabitants per household	-0.0972	0.0201
4	Share of number of single households	0.0681	0.0104
5	Share of two-person households	-0.0301	0.4718
6	Share of households with three or more	-0.0547	0.1918
7	Share of households living in property	-0.2004	$1.34 \cdot 10^{-6}$
8	Share of households living for rent	0.2004	$1.34 \cdot 10^{-6}$
9	Purchasing power of inhabitants	-0.1602	0.0001
10	Number of passenger cars (pc) per km^2	0.3624	$3.37 \cdot 10^{-19}$
11	Number of pc per km^2, commercial	0.2513	$1.09 \cdot 10^{-9}$
12	Number of pc per km^2, private	0.3811	$3.26 \cdot 10^{-21}$
13	Share of single or duplex houses	-0.3159	$1.02 \cdot 10^{-14}$
14	Share of row houses	-0.1290	0.0020
15	Share of multifamily buildings	0.0032	0.9392
16	Share of apartment blocks	0.3595	$6.85 \cdot 10^{-19}$
17	Share of high-rise apartment buildings	-0.0667	0.1111
18	Share of office buildings	-0.3596	$6.59 \cdot 10^{-19}$
19	Share of factory and warehouse buildings	-0.1070	0.0104
20	Environmental affinity inhabitants	-0.2172	$1.55 \cdot 10^{-7}$

urban living. The results show moderate correlations, for parameters that take into account the area of the cell such as parameters 1, 2, 10, 11, and 12. The results suggest that the density of people, households, and vehicles has an impact on the usage behavior of public charging infrastructure. It is also interesting to note that there is a negative correlation for the share of office and factory and warehouse buildings. If the parameters 18 and 19 are combined, the result is a moderate negative correlation factor of about -0.35. Thus, the results show a moderate positive relationship in high-density urban residential and a moderate negative relationship in commercial land use.

CONCLUSION

The study shows a significant difference in usage behavior of public AC and DC charging stations, both in connection time as well as in the composition of charging time and idle time. DC charging stations show a usage where fast refilling of batteries is the primary target. The connection time to the DC charging point roughly corresponds to the required charging time. The connection times are on average 0.8 h and on median 0.6 h. At the same time, the share of the determined idle time is relatively low at 15% to 20%.

In contrast, AC charging shows a behavior where the PEV charging process is not the sole focus of the user and the connection times to the AC charging point tend to be longer than necessary for the charging process. The connection time of the AC charging operations is 5.9 h on average and 3.1 h on median. The proportion of idle time is significantly higher, ranging from 45% to 70%, as compared to DC charging. The share of idle times has been quantified in previous studies with 88% to 80%, where the temporal shares were directly derived from the analyzed data and due to the data collection period charging processes of electric vehicles of the first model generations with a comparably low battery capacity were collected as data basis (*3, 4*). A comparison of these results with the values from the scenarios presented here shows that the literature values tend to correspond to the values from the first scenario with minimum charging time and maximum idle time according to Equation 5, respectively.

The focus of the presented investigation is on the methodology for quantifying the individual temporal segments in the charging process. In addition, this study presents a correlation analysis of charging locations as a function of quantified idle time. The moderate positive correlation suggests that AC charging stations at locations with a high proportion of high-density urban living tend to have a high proportion of idle time. One possible reason for the high proportion of hogging time, in addition to frequent overnight charging, may be due to the increased proportion of plug-in hybrid vehicles in the study area. The share of PHEVs in electric vehicles in Munich was approximately 56% as of 12/31/2020 (*15*). In comparison, the share of PHEVs in all of Germany was 48% in the same time (*16*). If connection times remain constant, the lower energy demand per charging process could result in higher idle times.

The authors point out that a high proportion of idle time is not an immediate indicator that user behavior needs to be corrected or sanctioned, for example, by time-based tariffs. A high proportion of idle time may indicate, for example, that the offer of public charging infrastructure at the relevant locations can be adapted to user behavior. The available connection power per charging station of approximately 44 kW could, for example, be divided among more than the current two charging points to enable long connection times and at the same time ensure higher availability for customers. With 10 charging points per charging station, for example, each charging point could be supplied with a charging power of about 4 kW. As a result, energy utilization and thus income could additionally be increased through the sale of energy at the charging stations. Another approach would be to integrate the vehicles into the energy grid during the otherwise unused idle time in order to provide system services as part of vehicle-to-grid concepts. However, the analysis and discussion of causes and solutions is the subject of future investigations.

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AUTHOR CONTRIBUTIONS

The authors confirm contribution to the paper as follows:
Study conception and design: Markus Fischer, Cornelius Hardt, Klaus Bogenberger
Data collection: Markus Fischer
Analysis and interpretation of results: Markus Fischer, Cornelius Hardt, Wibke Michalk, Klaus Bogenberger
Draft manuscript preparation: Markus Fischer, Cornelius Hardt, Wibke Michalk, Klaus Bogenberger
All authors reviewed the results and approved the final version of the manuscript.

DECLARATION OF CONFLICTING INTEREST

All authors do not have any conflicts of interest to declare.

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