

LETTER • OPEN ACCESS

## Spatial and temporal patterns of electric vehicle charging station utilization: a nationwide case study of Switzerland

To cite this article: Mario Gellrich *et al* 2022 *Environ. Res.: Infrastruct. Sustain.* 2 021003

View the [article online](#) for updates and enhancements.

You may also like

- [Cost-effective electric vehicle charging infrastructure siting for Delhi](#)  
Colin J R Sheppard, Anand R Gopal, Andrew Harris et al.
- [Real-world insights on public charging demand and infrastructure use from electric vehicles](#)  
Michael Hardinghaus, Markus Löcher and John E Anderson
- [Environmental impacts of extreme fast charging](#)  
Alan Jenn, Kyle Clark-Sutton, Michael Gallaher et al.

# ENVIRONMENTAL RESEARCH INFRASTRUCTURE AND SUSTAINABILITY



## LETTER

# Spatial and temporal patterns of electric vehicle charging station utilization: a nationwide case study of Switzerland

### OPEN ACCESS

#### RECEIVED

11 February 2022

#### REVISED

8 April 2022

#### ACCEPTED FOR PUBLICATION

25 April 2022

#### PUBLISHED

7 June 2022

Mario Gellrich\* , Andreas Block and Ninja Leikert-Böhm

ZHAW School of Management and Law, Institute of Business Information Technology, Theaterstrasse 17, 8400 Winterthur, Switzerland

\* Author to whom any correspondence should be addressed.

E-mail: [mario.gellrich@zhaw.ch](mailto:mario.gellrich@zhaw.ch) and <https://orcid.org/0000-0002-7313-2368>

**Keywords:** electric vehicles, spatio-temporal patterns, public charging infrastructure, real-world data, charging demand

Original content from this work may be used under the terms of the [Creative Commons Attribution 4.0 licence](https://creativecommons.org/licenses/by/4.0/).

Any further distribution of this work must maintain attribution to the author(s) and the title of the work, journal citation and DOI.



## Abstract

The expansion of the public charging infrastructure for electric vehicles is seen as central to the development of electric mobility in many countries. Although national studies of charging infrastructure utilization based on real-world data would be a sound basis for demand planning, such studies are scarce. Using Switzerland as an example, this study examines the spatial and temporal patterns of charging infrastructure utilization. To this end, detailed, nationwide, real-time utilization data from 3086 electric vehicle supply equipment units (EVSEs) at electric vehicle charging stations were collected over a period of several months and analyzed exploratively and statistically. The maximum average utilization rate of the EVSEs surveyed during the study period is between 14% and 16%, depending on the day of the week and time of day. Most charging occurs Monday through Friday during peak working hours and on Saturday during the day. The median utilization time is higher in the largest cities than the statewide average. Charging stations along major transit routes do not have higher utilization rates than in other locations. The results suggest that public charging infrastructure is used primarily in cities and agglomeration during work hours. The findings from this study may help plan and make better use of funding to expand charging infrastructure.

## 1. Introduction

Many countries promote the expansion of electric mobility to save energy and reduce CO<sub>2</sub> emissions (Fritz *et al* 2019, International Energy Agency (IEA) 2020, März *et al* 2021). In this context, the rapid expansion of public charging infrastructure is seen as key to the development of electric mobility (Harrison and Thiel 2017). Various studies have shown that the availability of charging infrastructure can positively influence the adoption of electric vehicles (e.g., Mersky *et al* 2016, Narassimhan and Johnson 2018). Based on scenario calculations, the IEA estimates that the global number of private and public charging stations could increase from 7.3 million in 2019 to 146 million (stated policy scenario) or to 261 million (sustainable development scenario) by 2030 (IEA 2020).

The development of public charging infrastructure requires high investment costs, which should be used as efficiently as possible (Hecht *et al* 2020). Therefore, a large proportion of studies on charging infrastructure deal with the need for and planning of charging infrastructure. Reviews of such studies have been provided by Hardman *et al* (2018) and Funke *et al* (2019). A common question in these studies is how much charging infrastructure is needed in a given area and where charging infrastructure should be built. A subset of these studies examines user preferences about charging infrastructure. For example, based on a literature review of such studies, Hardman *et al* (2018) showed that the most important place for charging electric vehicles is at home, followed by the workplace and publicly accessible locations. Mathematical optimization models are frequently used to plan charging stations' optimal quantity and locations (Deb *et al* 2018).

Indirect data is often used instead of real-world data from charging stations to determine the demand for charging infrastructure. Hardinghaus *et al* (2020) identified four data sources for such studies: (1.) GPS (global position system) data from vehicles, (2.) data loggers in vehicles, (3.) non-geographic user preference surveys,

and (4.) a combination of data sources such as historical travel data, weather data, business data, and travel distances. For example, Cai *et al* (2014) used GPS data from a taxi fleet in Beijing to determine the optimal locations of charging stations. Weldon *et al* (2016) used data from vehicle data loggers and GPS data to analyze charging behavior in Ireland. Brady and O'Mahony (2016) modelled electric vehicle daily travel and charging profiles based on GPS travel data (4021 driving days) from an Irish nine-month electric vehicle demonstration project. Wood *et al* (2017) created scenarios for charging infrastructure needs in the US using data on electric vehicle registrations and travel times, and assumptions on range and the frequency of longer trips. Globisch *et al* (2019) investigated user preferences of drivers in Germany using online surveys. Pevec *et al* (2018) used business data on charging infrastructure, geographic data, and driving distances to plan charging stations in the Netherlands. Based on travel survey data in combination with electric vehicle data recorded in a UK trial in 2016, Crozier *et al* (2021) modelled charging behaviour for network capacity estimation.

Studies based on indirect data often provide only limited information on the actual charging demand. Therefore, various authors have emphasized the need for real-world data from charging stations as a basis for planning charging infrastructure. The majority of such studies exist for individual cities or regions. For example, Wolbertus *et al* (2018) analyzed the use of charging infrastructure in four Dutch cities. They evaluated extensive data from a total of six million charging events from 64 000 electric vehicle users. Yun *et al* (2019) analyzed real-time data from 90% of charging stations in Shanghai for charging infrastructure planning. Hardinghaus *et al* (2020) studied the spatial distribution of charging stations and their demand for the city of Berlin. For the usage analysis, the authors used data from 221 charging stations with 50 491 charging events. Furthermore, Siddique *et al* (2022) focused on data analysis of 189 864 charging sessions collected over 13 months from 821 ChargePoint charging stations in Illinois.

Local studies can often explain local charging patterns very well. However, it is unclear to what extent the results of these studies can be generalized to entire countries. Nationwide studies based on empirical charging data are scarce. For example, Neaimeh *et al* (2017) analyzed relationships between driving distances and fast and standard charging for the US/UK. They used nationwide data from 90 000 fast charging events and electric vehicle trip data. The results show a positive impact of fast charging events on the use of battery electric vehicles (BEVs, also known as all-electric vehicles). Flammini *et al* (2019) analyzed 400 000 charging transactions in the Netherlands. Their results show, among others, that 50% of recharges last less than four h and that usage depends on the spatial location of charging stations. Hecht *et al* (2020) analyzed data from 26 951 connectors (power connections for electric vehicle charging) of public charging stations in Germany. The results show that charging station utilization rates range from 15% to 20%, with marked variations by day of the week and time of day. They also show that charging stations are often occupied longer than necessary because they are used as parking spaces.

Other studies discuss or calculate scenarios with low utilization rates, e.g. Yi *et al* (2020), Yun *et al* (2019) or Muratori *et al* (2021), without measuring exact real-world utilization for charging stations.

Another line of research focuses on socioeconomic inequalities in access to public charging stations and rebates in California. Hsu and Fingerma (2021) find that groups with lower median incomes linked to racial and ethnic factors are significantly less likely to have access to public charging stations. Guo and Kontou (2021) examine the horizontal and vertical aspects of equity analysis associated with spatial patterns in electric vehicle rebates.

We identified a research gap from the limited number of nationwide studies on charging infrastructure usage based on real-world data. Based on real-world data on charging infrastructure usage, we wanted to address two research questions: (1.) what is the level of utilization of public charging infrastructure across Switzerland? and (2.) what spatial and temporal utilization patterns can be observed in Switzerland? By answering these questions, this study delivers relevant information for public and company decision-makers with regard to planning, deploying and managing the existing and supplementary infrastructure. This is crucial, because these decisions are associated with large investments and have a long-term influence on adapting electric mobility. When this study was conducted, no nationwide analysis of public charging infrastructure utilization was available for Switzerland. As of December 2021, 4.7 million passenger cars were registered in Switzerland, of which 2.4% were plug-in electric vehicles (PEVs) (Swiss Federal Statistical Office (SFSO 2021)). Government funding in Switzerland supports the development of charging infrastructure (Swiss Federal Department of the Environment, Transport, Energy and Communications (DETEC 2021)).

The analyses in this study were carried out using explorative and statistical methods. The results provide new insights into the use of public charging infrastructure in Switzerland. This study is structured as follows: section 2 below describes the data basis, the data preparation, and the procedure for the exploratory and statistical analyses. In section 3, we present and discuss the results. In section 4, finally, we draw conclusions and derive recommendations for action.

## 2. Data and methodology

### 2.1. Data

Following the data structure of the Open InterCharge Protocol (OICP 2018), the most widely implemented communication standard between electro mobility service providers and charge point operator (CPO) systems, this paper distinguishes between charging stations, electric vehicle supply equipment units (EVSEs), and connectors. An EVSE consists of a pillar with one or more connectors. Only one connector can be active per EVSE at any one time. A charging station has one or more EVSEs. The data used in this study comes from the Swiss platform [www.recharge-my-car.ch](http://www.recharge-my-car.ch). This platform is part of the data infrastructure electromobility (DIEMO) project and was built by different CPOs, the Swiss Platform for Energy Efficiency and Renewable Energy (EnergieSchweiz), the Swiss Federal Office of Topography (swisstopo), and the Swiss Federal Office of Energy (SFOE).

The data is freely available and provided for web applications and information purposes via a web service in two JavaScript Object Notation (JSON) files. The first file contains information about the charging stations. This information includes spatial coordinates, municipality number, postal code, street name, house number, the operator's name, the EVSEs, and information about the connectors of EVSEs (number, type, and charging capacity). The second file contains real-time information on the utilization status of the EVSEs using the categories available, occupied, out-of-service or unknown. The utilization status is reported per EVSE. A unique ID is used for each charging station and EVSE to link charging station data to utilization data.

Not all CPOs provided continuous data during the study period, from September to December 2021. Inquiries with the SFOE revealed the causes to be data transmission problems but also outages, and maintenance work. We decided not to collect a complete time series of utilization data to address this issue. Instead, data were collected for individual weeks with high availability of utilization data. Specifically, data were collected for two weeks in September (01–14.09), one week in October (18–24.10), and two weeks in December (09–22.12). Data were collected using automated server requests at five-minute intervals.

Shapefiles of the *building zones* were used to investigate the relationship between the utilization rates, utilization times and local land-use. Data on building zones were obtained from the Swiss Federal Office for Spatial Development (ARE 2017). Building zones include: *residential zones*, *mixed residential/workplace zones*, *workplace zones*, *center zones*, *other building zones* (zones for tourism, public use, recreation and traffic which were combined because of its small size) and *outside building zones*. Shapefiles of the transit road network were used to analyze the utilization rates on transit roads compared to other locations. Road data were obtained from the Swiss Federal Roads Office (FEDRO 2021).

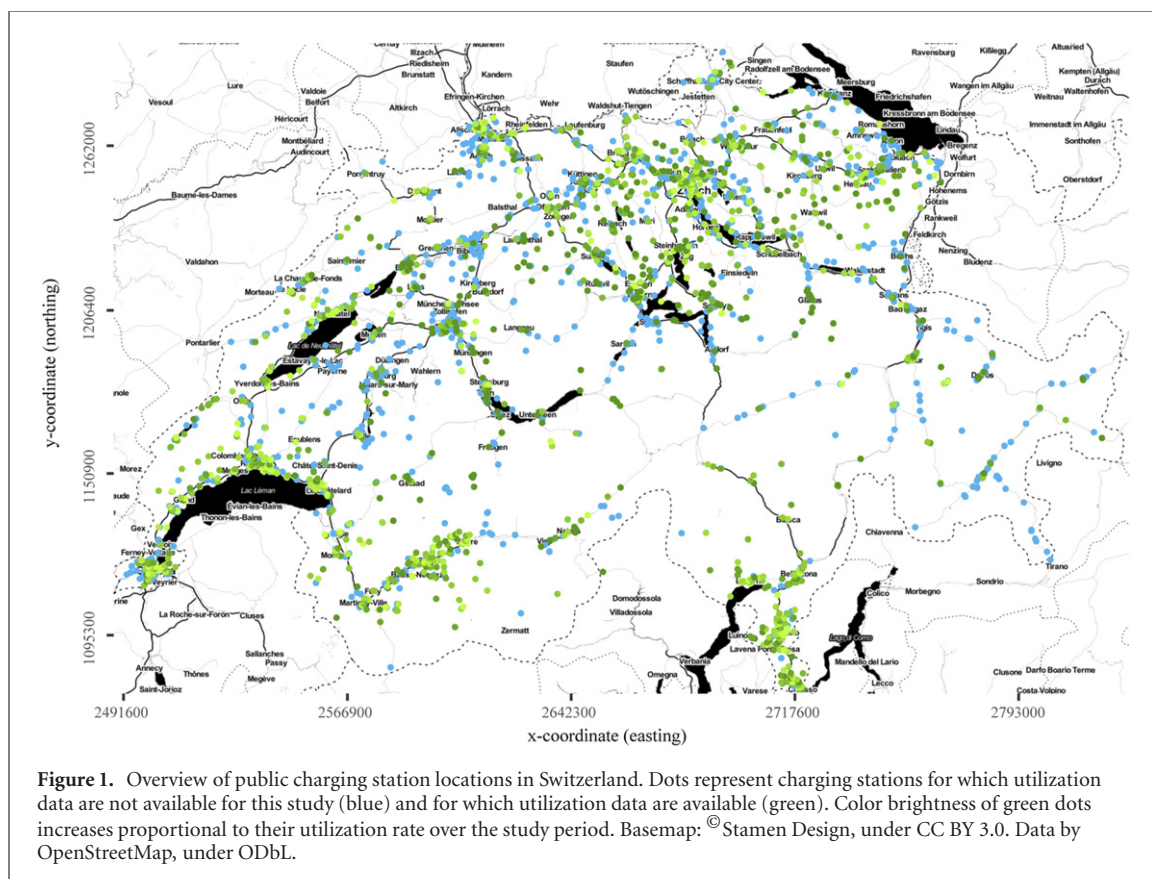
### 2.2. Methodology

The preparation and analysis of the data and the graphical representation of the results were done with the help of the statistical software R (R Core Team 2021). The data from the JSON files were first structured. Since the study focuses on the national territory of Switzerland, charging stations outside of Switzerland were excluded. At the time of the study, data from 3279 charging stations with 6615 EVSEs were available for Switzerland. The data came from various CPOs, the six largest of which operate between 250 and 2300 EVSEs. A number of 14 CPOs provided real-time data on EVSE utilization during the study period. Figure 1 shows an overview map of charging stations in Switzerland based on the data.

We considered only EVSEs with available or occupied status information, but not EVSEs with out-of-service or unknown status. In addition, we considered only EVSEs that provided complete utilization status data at all the times under investigation. For about 1% of the EVSEs, we found 100% utilization over the entire study period. These EVSEs were also excluded because we assumed they were special cases or data errors. These restrictions reduced the number of EVSEs considered for analysis to 3086. The dataset included 31 million records (3086 EVSEs  $\times$  288 status queries per day  $\times$  35 days).

Exploratory data analysis methods were used to examine the data. Exploratory analysis of spatial and temporal data focuses on analyzing patterns and relationships in the data (Andrienko and Andrienko 2006). For the analysis, we were interested in the utilization rates of the EVSEs. We defined the utilization rate of an EVSE as the proportion of status queries yielding occupied compared to the total of all status queries for that EVSE during the study period. We obtained the mean utilization rates by aggregating the status information for defined temporal and spatial units.

In the analysis of temporal patterns, we examined the differences in utilization rates by week, day of the week, hour of the day and utilization times of EVSEs. In analyzing spatial patterns, we examined the utilization rates, and utilization times at the charging station level, building zone level and municipality level. Charging stations were used instead of EVSEs for the statistical analyses because EVSEs within charging stations may show group structures, violating the assumption of independence of observations in the statistical tests (Chambers and Hastie 1992, Hollander et al 2013). Structural, socio-economic and demographic variables



were used to examine the relationships between utilization rates, utilization times and municipality characteristics. The municipality characteristics along with their collection years are shown in table 1. Municipality data were obtained from the SFSO and FEDRO. The EVSE density per municipality was calculated based on the original dataset with all EVSEs in Switzerland. The old-age-dependency ratio was calculated, according to the SFSO, as the ratio of the population aged 65 and over to the population aged 20 to 64.

The relationships between charging station utilization rates and municipality characteristics were analyzed graphically using grouped boxplots. The groups were formed from the data aggregated to the municipality-level using the deciles. ANOVA (Chambers and Hastie 1992) were performed to examine whether utilization rates differed statistically significantly (5% significance level) between groups. To gain more insights into the lower and higher utilized charging stations, *k*-means clustering (Hartigan and Wong 1979) based on the municipality-level data was used. We identified the optimal number of clusters by using the *elbow-method* (Marutho *et al* 2018). In addition, utilization rates, and times in the building zones were analysed using ANOVA.

In terms of spatial patterns, we were also interested in whether charging stations on transit roads are more heavily used than charging stations at other locations. For this purpose, we first generated a spatial buffer with a distance of 100 m on both sides around the transit roads. Subsequently, a point-in-polygon analysis was used to determine which charging stations are located within the buffer and which are located outside the buffer. It was assumed that charging stations within 100 m of the national roads are accessible from a transit road. The Wilcoxon rank-sum test for independent samples (Hollander *et al* 2013) was used to examine whether the utilization rates of the charging stations on the transit roads differed in a statistically significant manner (5% significance level) from the utilization rates of the charging stations at other locations.

For the combined spatial–temporal analysis of utilization rates, the area of Switzerland was covered with a 10 × 10 km grid. The grid cell size was chosen for the best possible visualization of the results. For each grid cell, the mean utilization rate over 24 h in a two-hour interval was calculated and displayed on a map.

### 3. Results and discussion

#### 3.1. Characteristics of charging stations and EVSEs

The characteristics of the charging stations and EVSEs were examined for the original dataset and the sample. The differences in the characteristics are shown in table 1. The sample and the original dataset have an average



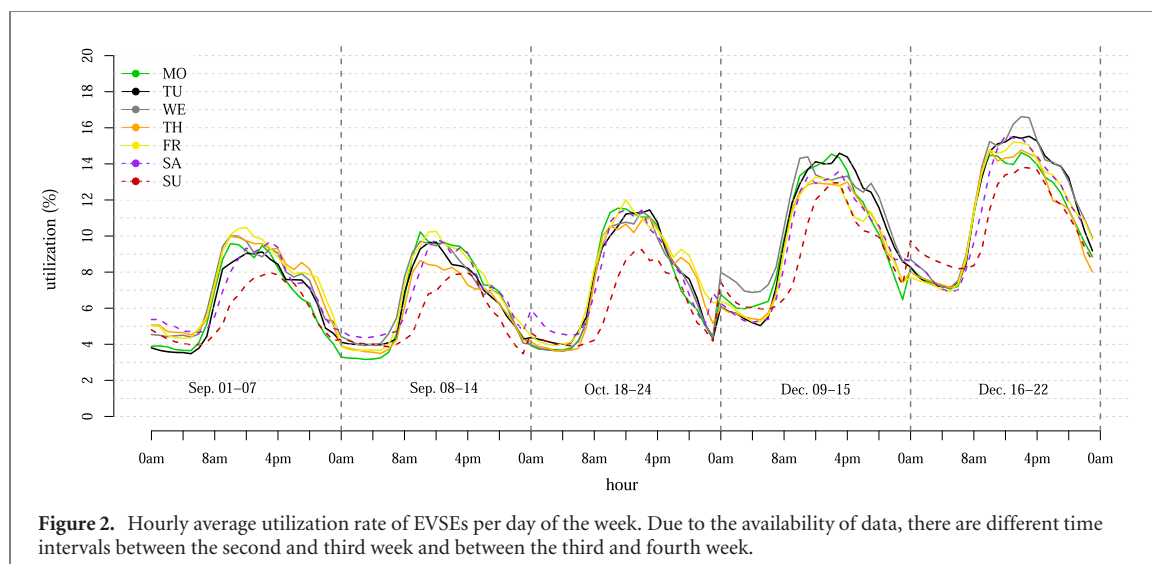
**Table 1.** Characteristics of charging stations and EVSEs.

	Analyzed sample of charging stations and EVSEs	Original number of charging stations and EVSEs
Number of charging stations	1771	3279
Number of EVSEs	3086	6615
Avg. number of EVSEs per charging station	1.7	2.0
Avg. number of connectors per EVSE	1.6	1.4
<b>Connector type of EVSEs (%)</b>		
- Domestic AC power	7.0	4.6
- Type 1	29.3	20.1
- Type 2	54.7	56.0
- CCS combo	4.9	8.0
- CHAdeMO	3.6	5.6
- Other	0.5	5.7
<b>Max. capacity of connectors for EVSEs with known capacity (%)</b>		
- <10 kW	0.4	0.5
- 10 kW–21 kW	7.2	7.9
- 21 kW–42 kW	52.6	47.9
- 42 kW–100 kW	29.2	19.3
- >100 kW	10.5	24.4
<b>Spatial locations of charging stations</b>		
- Median of <i>x</i> -coordinates (meters)	2661 981	2655 671
- Median of <i>y</i> -coordinates (meters)	1210 289	1210 561
<b>Municipality properties of charging stations (median values)</b>		
- Population density in 2020 (residents km <sup>-2</sup> )	788	745
- Passenger car density in 2020 (passenger cars/1000 residents)	590	582
- EVSE density in 2021 (EVSEs/1000 passenger cars)	1.95	1.92
- PEV share in 2020 (PEVs/100 passenger cars)	1.3	1.3
- Population development from 2010 to 2019 (%)	8.6	8.6
- Old-age dependency ratio in 2019 (%)	30.7	30.6
- Employees-to-population ratio in 2018 (%)	63.9	61.7
- Mean taxable income in 2017 (per capita and year in CHF)	31 000	31 000
<b>Share of charging stations per building zone (%)</b>		
- Residential zones	9.3	7.8
- Mixed residential/workplace zones	16.1	14.0
- Workplace zones	25.8	26.0
- Central zones	12.6	13.7
- Other building zones	22.1	23.5
- Outside building zones	14.0	15.1

of two EVSEs per charging station and one to two connectors per EVSE. Both datasets are dominated by types 1 and 2 connectors with capacities ranging from 21 kW to 42 kW. The medians of the *x* and *y* coordinates of the charging stations in the sample and the original dataset differ by only a few kilometers. This shows that there are only marginal differences in the spatial distribution of charging stations of both data sets. For each charging station, the characteristics of the municipalities described in the methodology were recorded. In addition, the share of charging stations per building zone was examined. In terms of characteristics and locations, no significant differences can be observed between the sample and the original dataset. With some caution, it can therefore be assumed that the analyzed sample is representative of Switzerland.

### 3.2. Spatial and temporal utilization patterns

Analysis of the EVSEs mean utilization rates by day of the week and hour of day shows a clear temporal pattern (see figure 2). Utilization rates increase steadily from September to December. Between October and December, a particularly sharp increase is evident. One reason for this may be that, in 2021, the October to December period alone accounts for 32.4% of new PEV registrations for the year (FEDRO 2022). Most recharges occur on weekdays during peak working hours and on Saturdays during the day. A single day of the week with the highest mean utilization rates in each case cannot be clearly identified. The day with the lowest mean utilization rate is Sunday. The highest average utilization rates, based on the day of the week, were observed in the third



week of December with 14% to 16%. One reason for the higher utilization rate in December could be the upcoming break over the holidays and the associated increased charging volume. Analysis of the quantiles of utilization rates (not tabulated) shows that 10% of the EVSEs have utilization rates of 21% and above, and 5% of EVSEs have utilization rates of 29% and above.

The mean utilization rates are similar to the utilization rates of 15% to 20% shown by Hecht *et al* (2020) for Germany. The low mean utilization rates may be explained by the fact that many CPOs expand their network ahead of time in order to secure profitable sites in anticipation of increasing demand. Compared to weekday mornings, there is a lag in the increase in utilization rates on weekend mornings. This lag is more substantial on Sunday than on Saturday and can be explained by the change in the daily rhythm of PEV owners compared to weekdays. On Friday evenings through early Saturday mornings, many PEV owners appear to be charging their vehicles in preparation for the weekend. This can be seen in the increased utilization rates from Friday night to Saturday morning.

The mean utilization rates of the charging stations differ depending on the population density in the municipalities. In more densely populated municipalities, the mean utilization rate is higher (figure 3(a)). This relationship is confirmed by the ANOVA ( $F$ -value = 3.0385,  $p$ -value = 0.0014). The result can be explained by the fact that densely populated municipalities are central commuting locations, where more charging takes place during working hours on weekdays than on the weekend. Furthermore, companies that operate public charging stations frequently offer its use to their employees during office hours. In the less densely populated municipalities, there is less charging during the day than in the centers. The mean utilization rates decrease as the density of EVSEs increases (figure 3(c)). The ANOVA shows that this relationship is statistically significant ( $F$ -value = 2.7142,  $p$ -value = 0.0042).

If public charging stations are mainly used for charging in the central commuting locations, the charging demand is derived from the number of PEVs registered in a municipality plus the PEVs of commuters. The number of PEVs registered in a municipality is, therefore, not sufficient to estimate charging demand. Another explanation is that fleets of vehicles owned by businesses are often not charged in the municipalities where they are registered. This is consistent with the finding that no statistically significant differences in utilization rates were found by car density ( $F$ -value = 0.9765,  $p$ -value = 0.4582) and by PEV share ( $F$ -value = 1.6134,  $p$ -value = 0.1077) as shown in figures 3(b) and (d). In their review of charging behavior studies, Hardman *et al* (2018) showed that 50% to 80% of charging events occur at home. Therefore, the relationship between the utilization rate of EVSEs and the density of cars and PEVs registered in the municipalities cannot be clearly shown.

As shown in figure 4(d) a statistically significant relationship exists between the utilization rates and the mean taxable income ( $F$ -value = 2.898,  $p$ -value = 0.0023). It shows that the charging demand is tendentially higher in wealthy municipalities. As shown in figures 4(a)–(c) no statistically significant relationship exists between the utilization rate and population development ( $F$ -value = 0.9319,  $p$ -value = 0.4965), old-age-dependency ratio ( $F$ -value = 0.8644,  $p$ -value = 0.557) and employees-to-population ratio ( $F$ -value = 1.3064,  $p$ -value = 0.2300).

Statically significant differences between the utilization rate of charging stations on transit roads compared to the utilization rate of charging stations at other locations could not be detected using the Wilcoxon test ( $p$ -value = 0.7362). This indicates that the use of EVSEs is not more intensive on transit roads than at

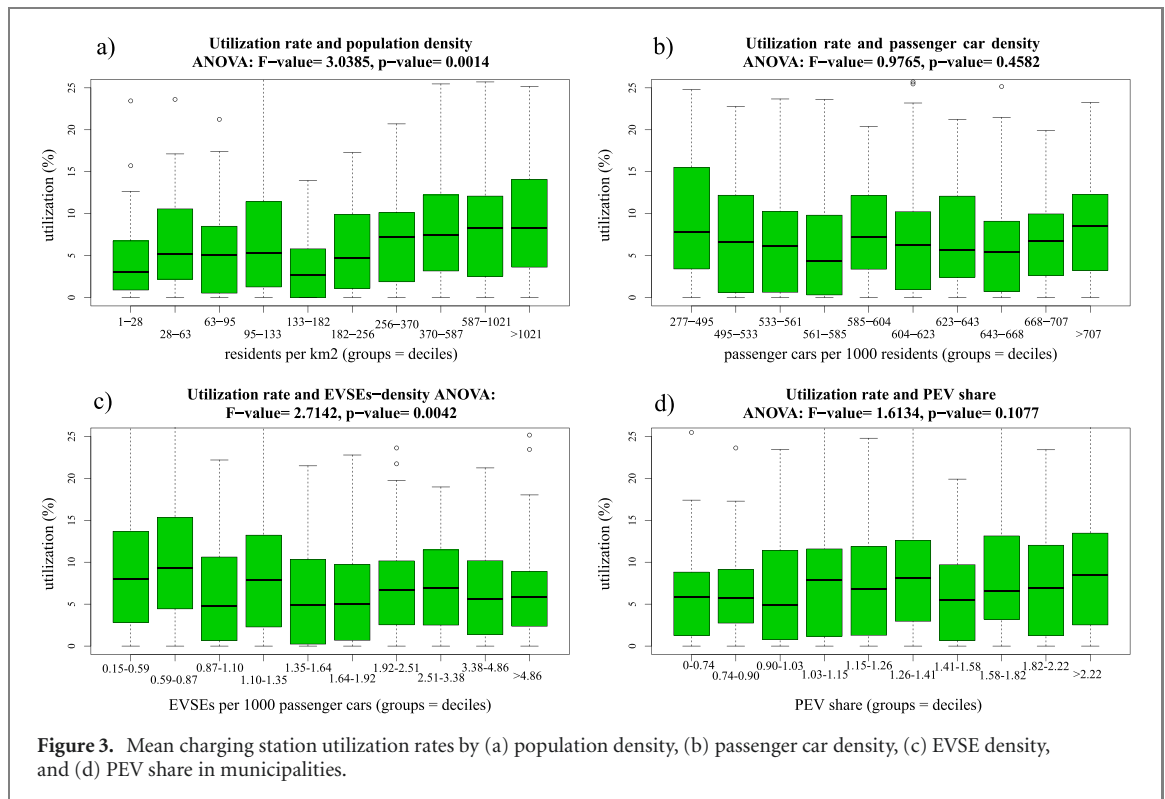


Figure 3. Mean charging station utilization rates by (a) population density, (b) passenger car density, (c) EVSE density, and (d) PEV share in municipalities.

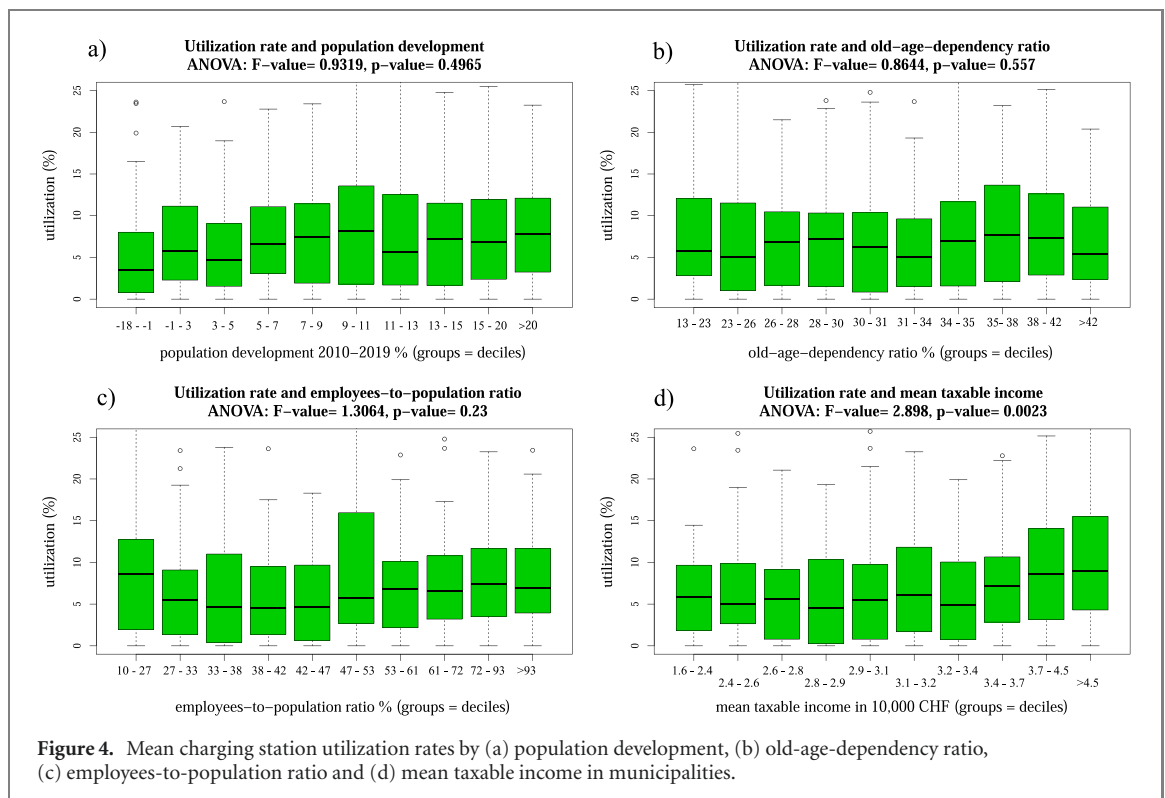
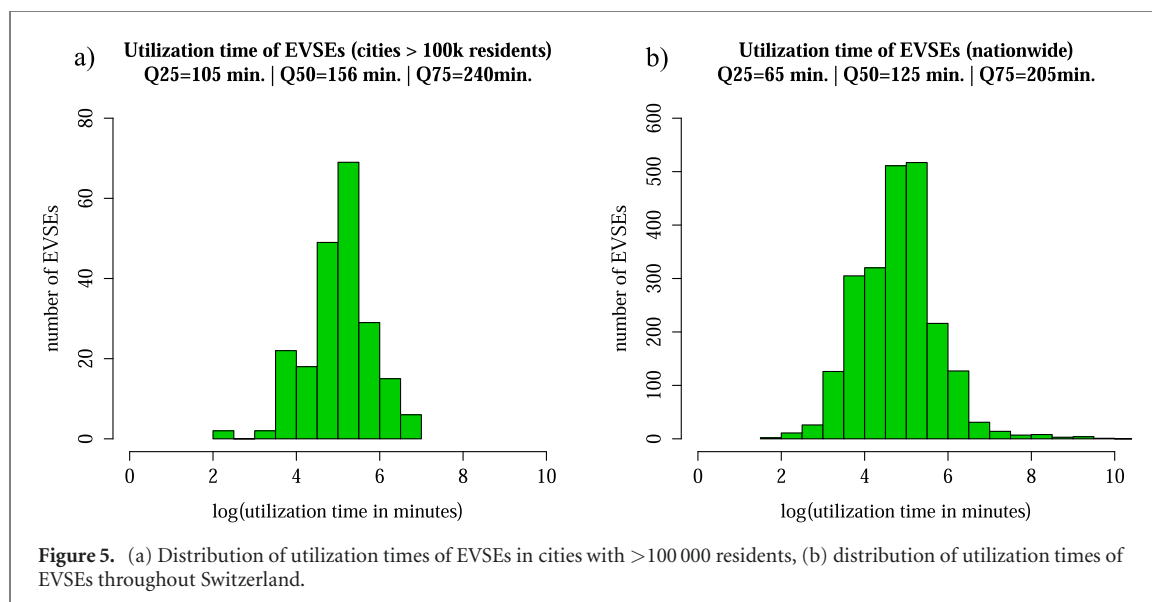


Figure 4. Mean charging station utilization rates by (a) population development, (b) old-age-dependency ratio, (c) employees-to-population ratio and (d) mean taxable income in municipalities.

other locations. This result is interesting considering that the Swiss government has declared the expansion of charging infrastructure on transit roads as one of its goals to support the development of electro mobility (DETEC 2021).

In Swiss cities with more than 100 000 residents, the data includes 231 EVSEs. Figure 5(a) shows the distribution and the lower (Q25), middle (Q50 = median), and upper quartile (Q75) of the utilization times for these 231 EVSEs. The median utilization time in the large cities is 156 min. Figure 5(b) shows the





**Table 2.** Clusters of charging stations created using  $k$ -means clustering. Values are averages of municipality-level characteristics per cluster.

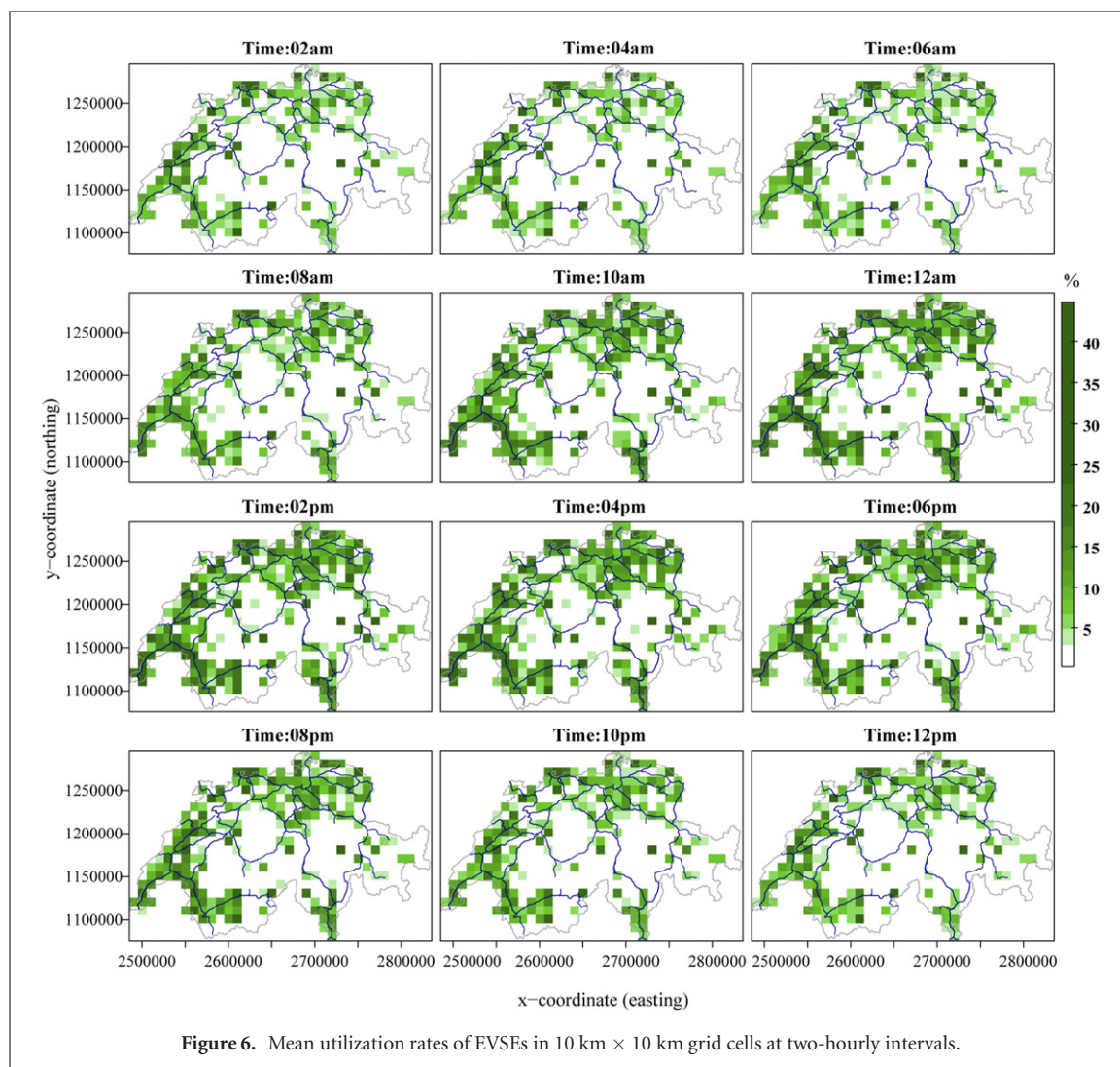
Cluster	CL_4	CL_5	CL_2	CL_1	CL_3
Number of charging stations in cluster	248	637	463	232	133
Mean utilization rate (sorted in ascending order)	3.5	4.7	5.1	10.0	30.9
Population density in 2020 (residents km <sup>-2</sup> )	1045	636	690	4031	996
Passenger car density in 2020 (passenger cars/1000 residents)	693	569	609	407	586
EVSE density in 2021 (EVSEs/1000 passenger cars)	5.1	2.8	2.2	1.9	2.0
PEV share in 2020 (PEVs/100 passenger cars)	2.5	1.2	1.2	1.6	1.4
Population development from 2010 to 2019 (%)	12.7	3.8	15.2	10.4	8.1
Old-age dependency ratio in 2019 (%)	28.1	38.1	27.3	25.6	33.0
Employees-to-population ratio in 2018 (%)	95.6	62.6	50.1	99.6	63.3
Mean taxable income in 2017 (per capita and year in CHF)	50 220	30 384	29 414	33 285	33 548

distribution of utilization times for all of Switzerland. The median utilization time is 125 min, which is shorter than in the large cities.

If charging stations are primarily used during working hours, a longer utilization time in cities is plausible. The incentive to use workplace charging infrastructure for the maximum allowed time is high. The distributions in figures 5(a) and (b) show utilization times ranging from a few minutes to more than 48 h. One reason for this range of utilization times could be the use of charging stations as short- and even long-term parking places. The phenomenon of charging stations being used in this way has also been documented in other studies (Hardinghaus *et al* 2020, Hecht *et al* 2020). The ANOVA shows a statistically significant relationship between utilization time and population density ( $F$ -value = 2.01,  $p$ -value = 0.0363). No relationships were found between utilization time and other municipality characteristics or building zones. This result supports the finding that the utilization times in densely populated locations differs from those in other locations.

It should be noted that some uncertainty in measuring utilization time in our study needs to be considered. Since we evaluated utilization data at 5 min intervals, it is theoretically possible for two vehicles charging one immediately after the other to be counted as a single charge. However, given the low utilization rates in the study period throughout Switzerland, we believe that this uncertainty can be neglected. Another factor that may have affected the utilization times measured is the limitation of the charging time by the CPOs. Often, the time restrictions are related to general parking restrictions in parking lots and parking garages.

Table 2 presents the clusters of charging stations from the  $k$ -means clustering based on the municipality characteristics. The cluster with the highest utilization rates (CL\_3) is characterized by higher population density (but much lower as in CL\_1 representing large cities), low EVSE density and a moderate employee-to-population density. These are typically small cities and agglomerations of larger cities. The cluster with the lowest utilization rates (CL\_4) is characterized by higher population density, high EVSE density, high employee-to-population ratio and higher mean taxable income. The latter are typically wealthy municipalities in the agglomeration of larger cities with a high density of charging infrastructure.



We found a strong relationship between the utilization rates and building zones ( $F$ -value = 11.6411,  $p$ -value = 0.0000). The highest utilization rates (not tabulated) could be found outside the residential and outside workplace zones. This can be explained with the lack of demand in the residential zones as PEV owners in these locations often charge at home. Furthermore, in building zones with workplaces, charging infrastructure has intensively been developed in recent years which is expressed in lower utilization rates.

The combined spatial–temporal pattern is shown as the mean utilization rate of all weekdays in a two-hour interval in a 10 km × 10 km grid (figure 6). At night and in the early morning hours, the mean utilization rates are lower, after which they increase, reaching a maximum between noon and 4.00 pm. In the late afternoon and into the night hours, utilization rates decrease more slowly than they increase in the morning. This pattern mirrors the temporal pattern shown in figure 2 and complements it with information on what regions experience changes in utilization during the day. The pattern shown in figure 6 shows larger spatial differences in the use of EVSEs. For example, individual grid cells show average utilization rates of more than 40%, but this can sometimes be attributed to a few individual EVSEs that are heavily used.

#### 4. Conclusions

Using Switzerland as an example, the present study provides new insights with regard to the spatial and temporal pattern of public charging infrastructure utilization. It shows that the maximum average EVSE utilization rate throughout Switzerland is low at 14% to 16% and that public charging stations are primarily used for charging on weekdays during peak working hours and on Saturdays during the day. Further, the results show that it is mainly densely populated locations with lower supply of charging infrastructure outside the residential and workplace zones that are highly utilized. Especially in locations with workplaces, charging infrastructure has strongly been developed during recent years which, at least in the short term, leads to a higher supply than demand. If the trend of strongly increasing numbers of PEV registrations continues, the demand of these

charging stations will increase in the future. The results furthermore suggest that public charging infrastructure is mainly used by PEV owners commuting to the cities and agglomerations during working hours. An important new finding is that charging infrastructure on transit roads is not used more frequently than at other locations. This result is interesting because one of the focal points of ongoing Swiss funding programs is the expansion of charging infrastructure on transit roads.

Limitations of this study result from the use of a sample of charging stations. The sample shows no systematic differences from the full dataset in terms of structure and location. Nevertheless, the findings from this study should be applied with some caution to the entire public charging infrastructure in Switzerland.

Based on our findings and conclusions, we have four recommendations for action with focus on the planning, deploying and managing the existing and supplementary charging infrastructure. First, the needs of commuters should be considered more consistently in promoting and planning charging infrastructure. It is important to have public charging stations in locations with high demand. Second, the impact of incentive programs should be continuously reviewed and adjusted to current charging needs. Third, the rapidly advancing expansion of public charging infrastructure necessitates additional research on its use. It is advisable to conduct continuous monitoring of the spatial–temporal use of public charging infrastructure. Fourth, the expansion of public charging stations must be coordinated with the expansion of private charging stations, as it can be assumed that many users charge their vehicles privately.

With a view to further research, the findings from this study can be of interest to various stakeholders. For CPOs, information on the spatial and temporal pattern of charging demand can help them target investments more effectively. For utilities, it is important to adapt to the additional electricity demand from PEV owners. For the state and local governments, the question is whether, where, and to what extent further expansion of public charging infrastructure should be supported. Our results can also help to adapt public funding for the expansion of charging infrastructure to local specifics and enable it to be used more effectively.

## Acknowledgments

The authors wish to thank the two anonymous reviewers for their helpful suggestions and comments. We also wish to thank Danielle Adams-Hausheer and Nathan Muehlberg for proofreading the manuscript.

## Data availability statement

The data that support the findings of this study are available upon reasonable request from the authors.

## ORCID iDs

Mario Gellrich  <https://orcid.org/0000-0002-7313-2368>

## References

- ARE (Swiss Federal Office for Spatial Development) 2017 Bauzonenstatistik Schweiz 2017—Statistik und Analysen Bundesamt für Raumentwicklung (<https://are.admin.ch/are/de/home/medien-und-publikationen/medienmitteilungen/medienmitteilungen-im-dienst.msg-id-69109.html>) Bern, 23 March 2022
- Andrienko N and Andrienko G 2006 *Exploratory Analysis of Spatial and Temporal Data: A Systematic Approach* (Berlin: Springer)
- Brady J and O'Mahony M 2016 Modelling charging profiles of electric vehicles based on real-world electric vehicle charging data *Sustain. Cities Soc.* **26** 203–16
- Chambers J M and Hastie T J (ed) 1992 *Statistical Models in S* 1st edn (New York: Routledge) p 624
- Cai H, Jia X, Chiu A S F, Hu X and Xu M 2014 Siting public electric vehicle charging stations in Beijing using big-data informed travel patterns of the taxi fleet *Transp. Res. D* **33** 39–46
- Crozier C, Morstyn T and McCulloch M 2021 Capturing diversity in electric vehicle charging behaviour for network capacity estimation *Transp. Res. D* **93** 102762
- Deb S, Tammi K, Kalita K and Mahanta P 2018 Review of recent trends in charging infrastructure planning for electric vehicles *WIREs Energy Environ.* **7** 1–26
- DETEC (Federal Department of the Environment, Transport, Energy and Communications) 2021 Gemeinsame roadmap zur Förderung der Elektromobilität unterzeichnet (<https://admin.ch/gov/de/start/dokumentation/medienmitteilungen.msg-id-73457.html>) 05 December 2021
- FEDRO (Federal Roads Office) 2021 Nationalstrassennetz (<https://astra.admin.ch/astra/de/home/themen/nationalstrassen/nationalstrassennetz.html>) 05 December 2021
- FEDRO (Federal Roads Office) 2022 FEDRO—new registrations of road vehicles (<https://bfs.admin.ch/bfs/en/home/statistics/mobility-transport/transport-infrastructure-vehicles/vehicles/road-new-registrations.html>) 05 December 2021

- Flammini M G, Prettico G, Julea A, Fulli G, Mazza A and Chicco G 2019 Statistical characterisation of the real transaction data gathered from electric vehicle charging stations *Electr. Power Syst. Res.* **166** 136–50
- Fritz M, Plötz P and Funke S A 2019 The impact of ambitious fuel economy standards on the market uptake of electric vehicles and specific CO<sub>2</sub> emissions *Energy Policy* **135** 111006
- SFSO (Swiss Federal Statistical Office) 2021 Road vehicles—stock, level of motorization (<https://bfs.admin.ch/bfs/de/home/statistiken/mobilitaet-verkehr/verkehrsinfrastruktur-fahrzeuge/fahrzeuge/strassenfahrzeuge-bestand-motorisierungsgrad.html>) 29 November 2021
- Funke S Á, Sprei F, Gnann T and Plötz P 2019 How much charging infrastructure do electric vehicles need? A review of the evidence and international comparison *Transp. Res. D* **77** 224–42
- Globisch J, Plötz P, Dütschke E and Wietschel M 2019 Consumer preferences for public charging infrastructure for electric vehicles *Transp. Policy* **81** 54–63
- Guo S and Kontou E 2021 Disparities and equity issues in electric vehicles rebate allocation *Energy Policy* **154** 112291
- Hardinghaus M, Löcher M and Anderson J E 2020 Real-world insights on public charging demand and infrastructure use from electric vehicles *Environ. Res. Lett.* **15** 104030
- Hardman S *et al* 2018 A review of consumer preferences of and interactions with electric vehicle charging infrastructure *Transp. Res. D* **62** 508–23
- Harrison G and Thiel C 2017 An exploratory policy analysis of electric vehicle sales competition and sensitivity to infrastructure in Europe *Technol. Forecast. Soc. Change* **114** 165–78
- Hartigan J A and Wong M A 1979 Algorithm as 136: a *K*-means clustering algorithm *Appl. Stat.* **28** 100
- Hecht C, Das S, Bussar C and Sauer D U 2020 Representative, empirical, real-world charging station usage characteristics and data in Germany *ETransportation* **6** 100079
- Hollander M, Wolfe D A and Chicken E 2014 *Nonparametric Statistical Methods* 3rd edn (New York: Wiley)
- Hsu C-W and Fingerman K 2021 Public electric vehicle charger access disparities across race and income in California *Transp. Policy* **100** 59–67
- IEA 2020 *Global EV Outlook 2020* IEA, Paris <https://www.iea.org/reports/global-ev-outlook-2020>
- Märtz A, Plötz P and Jochem P 2021 Global perspective on CO<sub>2</sub> emissions of electric vehicles *Environ. Res. Lett.* **16** 054043
- Marutho D, Hendra Handaka S, Wijaya E and Muljono 2018 The determination of cluster number at *k*-mean using elbow method and purity evaluation on headline news 2018 *Int. Seminar on Application for Technology of Information and Communication* pp 533–8
- Mersky A C, Sprei F, Samaras C and Qian Z 2016 Effectiveness of incentives on electric vehicle adoption in Norway *Transp. Res. D* **46** 56–68
- Muratori M *et al* 2021 The rise of electric vehicles—2020 status and future expectations *Prog. Energy* **3** 022002
- Narassimhan E and Johnson C 2018 The role of demand-side incentives and charging infrastructure on plug-in electric vehicle adoption: analysis of US states *Environ. Res. Lett.* **13** 074032
- OICP (Open interchange Protocol for Charge Point Operators) 2018 ([https://assets.website-files.com/602cf2b08109ccbc93d7f9ed/60534f2e20d0f87be17ba21b\\_oicp-cpo-2.2.pdf](https://assets.website-files.com/602cf2b08109ccbc93d7f9ed/60534f2e20d0f87be17ba21b_oicp-cpo-2.2.pdf)) 15 December 2021
- Neaimeh M, Salisbury S D, Hill G A, Blythe P T, Scofield D R and Francfort J E 2017 Analysing the usage and evidencing the importance of fast chargers for the adoption of battery electric vehicles *Energy Policy* **108** 474–86
- Pevec D, Babic J, Kayser M A, Carvalho A, Ghiassi-Farrokhfal Y and Podobnik V 2018 A data-driven statistical approach for extending electric vehicle charging infrastructure: a data-driven statistical approach for extending electric vehicle charging infrastructure *Int. J. Energy Res.* **42** 3102–20
- R Core Team 2021 R: a language and environment for statistical computing. R Foundation for Statistical Computing (<https://r-project.org/index.html>) Vienna, Austria, 29 November 2021
- Siddique C, Afifah F, Guo Z and Zhou Y 2022 Data mining of plug-in electric vehicles charging behavior using supply-side data *Energy Policy* **161** 112710
- Weldon P, Morrissey P, Brady J and O'Mahony M 2016 An investigation into usage patterns of electric vehicles in Ireland *Transp. Res. D* **43** 207–25
- Wolbertus R, Kroesen M, van den Hoed R and Chorus C 2018 Fully charged: an empirical study into the factors that influence connection times at EV-charging stations *Energy Policy* **123** 1–7
- Wood E W, Rames C L, Muratori M, Srinivasa Raghavan S and Melaina M W 2017 *National Plug-In Electric Vehicle Infrastructure Analysis* (Golden, CO (United States): National Renewable Energy Lab. (NREL))
- Yi T, Zhang C, Lin T and Liu J 2020 Research on the spatial–temporal distribution of electric vehicle charging load demand: a case study in China *J. Cleaner Prod.* **242** 118457
- Yun B, Sun D, Zhang Y, Deng S and Xiong J 2019 A charging location choice model for plug-in hybrid electric vehicle users *Sustainability* **11** 5761