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Public electric vehicle charging station utilization in the United States

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ABSTRACT

The utilization of electric vehicle (EV) charging equipment is a key driver of charging station economics, but current trends and factors related to the utilization of public charging infrastructure in the United States are not well understood. This study analyzes EV charging data from 3,705 nationwide public Level 2 (L2) and direct current fast charging (DCFC) stations over 2.5 years (2019–2022), observing utilization patterns over time. Regression analysis is used to assess the relationships between station utilization and several contextual and environmental factors. We conclude that local EV adoption is a strong indicator of utilization; L2 station utilization decreases with the size of the local charging network, while DCFC stations are less affected; and increased charging power has a greater effect on utilization for DCFC stations than L2. This study fills a critical research gap by reporting updated public charging station utilization statistics and analysis for the U.S. market.

1. Introduction

Plug-in electric vehicles (EVs) are lauded for their reduced tailpipe emissions (zero for battery EVs and plug-in hybrid EVs operating in all-electric mode), low operating costs, reduced maintenance, and high performance. In fact, EVs recently surpassed 5 % of new passenger vehicle sales in the United States, a key tipping point for mass adoption. According to *Bloomberg*, if the United States were to follow the adoption trends of the previous 18 countries to meet this threshold, a quarter of new U.S. car sales would be EVs by 2025 (Randall, 2022). Muratori et al. primarily attribute the rapid rise in EV adoption to three factors: improvements in EV battery technologies, supportive policies to reduce emissions, and new standards and regulations for reducing petroleum consumption (Muratori et al., 2021). Another factor, fuel cost savings, was shown to be a strong motivator in a recent national survey, which finds that a quarter of consumers plan to purchase an EV as their next vehicle (AAA, 2022). Despite this, many consumers remain hesitant of EVs for commonly cited reasons such as their higher purchase price, limited options for certain body styles, consumer education gaps, and a perceived lack of public charging infrastructure (AAA, 2022; Berkeley et al., 2018; Krishna, 2021; Macioszek, 2019; Wicki et al., 2022).

At the time of writing, there are 49,383 publicly accessible electric vehicle supply equipment (EVSE) stations in the United States, with 123,013 ports[1] (AFDC, 2022). These include 44,127 Level 2 (L2) stations (98,081 L2 ports)—which typically use 208-V AC electricity and deliver up to 19.2 kW of power, though most provide closer to 7 kW (roughly 25 miles of range added per hour)—and

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[1] The Open Charge Point Interface (OCPI) protocol defines an EVSE station as a site with one or more EVSE ports at the same address. Ports are capable of charging one EV at a time and may have multiple connectors. Connectors, often referred to as plugs, are plugged into an EV for charging.

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6,409 DC fast charging (DCFC) stations (24,932 DCFC ports), which convert three-phase AC electricity to DC, delivering up to 350 kW of power, though most today provide 150 kW or less (approximately 250 miles of range added per half-hour) (USDOE, 2022). As part of the Bipartisan Infrastructure Law enacted in 2021, the United States will invest $7.5 billion to meet the Biden administration's goal of establishing a national network of 500,000 EV chargers (The White House, 2022). Like with existing EVSE, many of these new stations will be installed, operated, and/or maintained by private entities under a variety of business models (APC, 2020).

Several studies have examined the current economics for operating public EVSE, citing assumed low early market utilization levels as a major impediment for profitability (Hundt et al., 2015; Lee and Clark, 2018; Nigro et al., 2015). In a recent interview, BP's head of customers and products stated that "we are nearing a place where the business fundamentals on the fast charge are better than they are on the [petroleum] fuel," while also acknowledging that the EV charging business is not expected to be profitable before 2025 (Bousso, 2022). Nigro et al. outline three major factors driving the profitability of EVSE deployments: the high upfront costs of equipment and installation, inadequate near-term utilization for stations, and the low prices consumers are willing to pay for public charging, especially those with a cheaper option (e.g., home charging) (Nigro et al., 2015). Station utilization (i.e., the amount of electricity a station delivers over time) is widely recognized as a key driver of EVSE economics (Borlaug et al., 2020; Burnham et al., 2017; Hundt et al., 2015; Muratori et al., 2019a; Nigro et al., 2015). Higher utilization enables station owners to amortize the capital costs associated with installing EVSE and mitigates the impacts of demand charges for grid-purchased electricity (Borlaug et al., 2020; Burnham et al., 2017; Muratori et al., 2019b). An understanding of current EVSE utilization patterns is critical for guiding public investments and planning future support for public EV charging infrastructure that ensures a sustainable, long-term business ecosystem with a path to profitability for EVSE operators and competitive charging prices for EV drivers (Madina et al., 2016).

The current utilization trends and factors related to increased utilization of public EVSE are not well understood. Previous studies report early market trends for distinct markets, including Germany (Hecht et al., 2022; Mortimer et al., 2021), Ireland (Morrissey et al., 2016), the Netherlands (Wolbertus and Van den Hoed, 2017; Wolbertus et al., 2016), Switzerland (Gellrich et al., 2022), China (Zhang et al., 2022), and the United States (Almaghrebi et al., 2019; Francfort, 2015a; INL, 2015; Siddique et al., 2022). Most find that current utilization levels are low, often < 1 session/port/day (Almaghrebi et al., 2019; Morrissey et al., 2016; Mortimer et al., 2021), attributed to the limited number of EVs on the road and the home-dominant charging behaviors of early EV adopters. Multiple studies identify "charge idling" (i.e., EVs remaining plugged in after a charge session is complete, blocking future customers) as an impairment to higher utilization (Desai et al., 2018; Mortimer et al., 2021; Wolbertus and van den Hoed, 2017; Wolbertus et al., 2016). Of the previous U.S.-focused studies, the U.S. Department of Energy (DOE)-sponsored EV Project is the only one that is national in scope; however, data were collected from 2011 to 2013, reflecting early-stage EVs with limited range and low-power EVSE that are fundamentally different from today (INL, 2013).

In this study, we analyze charge session data from 3,705 public L2 and DCFC stations (8,732 ports) in the United States over a 2.5-year period (2019 to 2022) to assess station utilization trends over time. We observe recent (March 2022) daily utilization patterns by charger and location type to better understand intraweek and intraday public charging demands. We quantify the real-world EV charge acceptance ratio (i.e., the average power delivered to an EV divided by an EVSE's rated power level) and charge idling frequency (i.e., the percent of time an EV is plugged in but not charging) from around 1.5 million unique charge sessions. Finally, we conduct a regression analysis to assess the relationships between public station utilization and several contextual and environmental factors. This study fills a critical research gap by reporting updated public EVSE utilization statistics and analysis for the U.S. market. These findings can be used to inform policymakers and EVSE operators around current levels of station utilization and potential influencing factors.

The remainder of this paper proceeds as follows: First, we describe the data set used for this study, comparing it with data from DOE to infer its representativeness. Next, we outline the methods used to analyze the charge session data, quantify station utilization, and perform regression analysis. We conclude by presenting results from the study and discussing their implications.

2. Data and methods

2.1. EVSE operations data

The data set used in this study was acquired through the DOE-supported EV WATTS project maintained by Energetics (Energetics, 2022). EV WATTS collects in-use data from EVs and EVSE across the United States to inform future research, development, and deployment of these technologies. The EVSE data set is derived from a nationwide network of project partners and includes port-level summaries, which contain the location, access type (public, private, or limited), venue[2] (from Francfort et al., 2015b), charger type (L2 or DCFC), rated power level, connector type, and pricing category (free or not) of ports in the data set. Ports are linked to session-level data that include charge start time, charge duration, occupation duration (i.e., the amount of time a port is occupied, even if not

[2] Primary venues correspond to those described in Francfort et al. (2015) – **Hotel**: hotel parking lots provided for patron use; **Leisure**: parks and recreation facilities, museums, sports arenas, or national parks/monuments; **Medical/Educational**: hospital campuses, medical office parks, or educational facilities such as training centers, universities, or schools; **Municipal**: city, county, state, or federal government facilities; **Office**: business offices, office parks/campuses, or industrial facilities; **Parking lot/garage**: parking lots or garages operated by private parking management companies, property management companies, or municipalities offering direct access to a variety of venues; **Retail**: retail locations both large and small, including shopping malls, strip malls, and individual stores; **Transit**: parking locations with direct pedestrian access to other forms of transportation such as airports, metro-rail stations, or ferry ports.

charging), energy delivered, and more.[3] However, information about the vehicle charging were not available for a particular session. The data were received in an anonymized "raw" format, in advance of any preprocessing or data cleansing steps employed by Energetics prior to generating their data summaries for the publicly accessible EV WATTS dashboard. These data are continuously updated on a quarterly basis dating back to October 2019. This study covers the period from October 2019 through March 2022, the most recent data vintage available at the time of writing.

2.2. Data processing

The full EVSE data set contains 39,148 ports and approximately 8.4 million sessions. However, these include ports with private or limited access types located at venues typically not associated with public access. Thus, several data filtering steps were performed to generate the data set of publicly accessible EVSE for this study.

This study follows the EVSE terminology outlined in the Open Charge Point Interface (OCPI) protocol, which classifies a charging station as a site with one or more EVSE ports at the same location. In assigning ports in the data set to stations, we assume that those with identical geographic coordinates (latitude, longitude), charger type, access type, rated power level, and venue type belong to the same station. Ports containing null values for any of these categories are filtered (27 % of total ports). Additionally, ports with "private" or "limited" access type (i.e., non-public ports) and those located at single-family homes, multiunit homes, or commercial fleet venue types are also filtered (58 % of total ports), since these locations are not typically associated with public access. Following these steps, 8,732 public ports at 3,705 stations remain for subsequent analysis.

Charging session data for each of the 8,732 public ports (3,705 stations) are compiled and subjected to several data cleansing steps to filter out erroneous session data. First, duplicated sessions (i.e., identical port and start/end times) are removed. Next, several criteria are used to filter sessions reporting infeasible delivered energy or charge duration values: (1) sessions with delivered energy > 140 kWh, since these are incompatible with the usable battery capacities of the Rivian R1T and extended-range Ford F-150 Lighting, the two mass-market EVs with the largest batteries available through March 2022; (2) sessions with a charge duration of 0 h or where no energy was delivered; and (3) sessions requiring an average charge power greater than the port's rated power level. These criteria filtered out 6 % of unique charging sessions for the 3,705 public stations, leaving 1,479,236 sessions for subsequent analysis. Table 1 summarizes the data set used for this study in detail.

2.3. Data representativeness

To assess its representativeness, we compare the EV WATTS data set used in this study to national EVSE stations reported in DOE's Alternative Fuels Data Center (AFDC) (AFDC, 2022), the most comprehensive source of station location data in the United States. We find that the share of L2 stations and ports are slightly underrepresented at 83 % (AFDC: 89 %) and 78 % (AFDC: 80 %), respectively. The average L2 station size is 2.2 ports/station, identical to the AFDC; however, the average DCFC station size is smaller, at 3.1 ports/station (AFDC: 3.9 ports/station). The majority of public L2 ports in our data set have a rated power level of 6.6 kW or less (97 %), and most public DCFC ports are 50 kW or less (97 %); however, the maximum power levels for L2 and DCFC ports are 16.6 kW and 170 kW, respectively. We do not observe a bias in rated power levels by venue type, with the average L2 port power levels ranging from 6.6 kW (leisure) to 7.2 kW (retail) and DCFC port power levels from 48.4 kW (hotel) to 52.1 kW (parking lot/garage). Since the AFDC does not include rated power levels for most of the ports in their database, a comparison could not be made; however, we note that this data set does not contain any recently deployed ultra-fast DCFC stations supplying up to 350 kW. Additionally, Tesla, the current market leader for EVs, owns/operates its own private charging stations that are not included in the EV WATTS data.

The geographic distribution of public EVSE stations in the data set reflects the distribution of data providers and partners in the EV WATTS project and thus is not nationally representative (Fig. 1). Fig. 2 explores this directly by showing the state-level shares of national public charging stations in the data set on the y-axis compared to the AFDC on the x-axis. Points above the identity line reflect states that are overrepresented in the data set, while points below are underrepresented states. We show that California, the state with the most EVSE installations, is significantly underrepresented in our data set (particularly for L2). Likewise, both Texas and Florida, states with moderately sized EVSE networks, are underrepresented. Conversely, New York, Colorado, and Massachusetts are all overrepresented. Although the two data sets are correlated ($r = 0.4$, $p = 0.004$), there is undoubtedly a geographic bias as a limitation of this study.

2.4. Station utilization

EVSE utilization is reported many ways. The simplest approach is to specify the number of charge events per day or per week (Gilleran et al., 2021; Mortimer et al., 2022). However, this is flawed because it omits the amount of energy delivered and duration of each event. These vary depending on the EV and EVSE station types, as well as the typical dwell durations for different venues. Another approach is to present utilization as the percent of time an EVSE port is "in use," which is defined as either supplying electricity (Lee and Clark, 2018) or simply plugged in to an EV (but not necessarily charging) (Gellrich et al., 2022; Hardinghaus et al., 2020; Hecht et al., 2020). Both are imperfect, the former being imprecise (EVSE ports provide electricity at a variable rate depending on multiple

[3] For a full list of data fields, see the publicly accessible Energetics EV WATTS dashboard: https://energetics.com/evwatts-station-dashboard.

Table 1
EV WATTS data set summary for publicly accessible U.S. EVSE stations (Oct. 2019 through March 2022).

Charging Venue	Station Type	Stations	Ports	Sessions	MWh Delivered
Office	L2	1,052	2,172	169,254	2,414
	DCFC	130	459	142,279	2,694
Retail	L2	208	442	64,759	511
	DCFC	332	910	255,248	5,001
Municipal	L2	564	1,115	194,506	2,309
	DCFC	72	227	82,569	1,591
Medical/educational	L2	562	1,167	204,029	2,470
	DCFC	9	41	25,367	428
Parking lot/garage	L2	282	892	157,621	2,412
	DCFC	33	106	32,750	597
Leisure	L2	225	522	78,795	823
	DCFC	31	79	12,339	225
Transit	L2	64	238	28,163	455
	DCFC	0	0	0	0
Hotel	L2	119	263	14,261	237
	DCFC	32	99	17,296	336
Total	L2	3,076	6,811	911,388	11,631
	DCFC	629	1,921	567,848	10,872

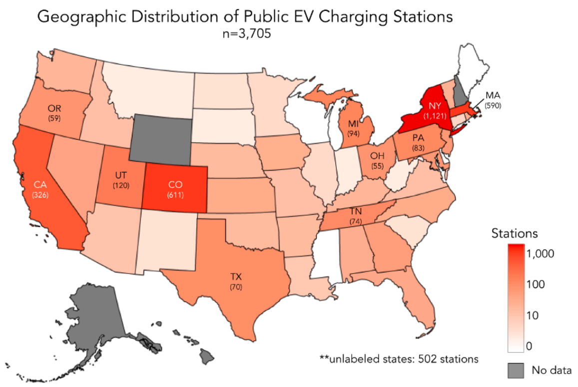

Fig. 1. Geographic distribution of publicly accessible EV charging stations in this study.

factors) and the latter being imprecise and misleading (an EV plugged in but not charging reflects a resource inefficiency that should not be embedded within utilization calculations). Here, we define station utilization as the average energy delivered by a station during a time period divided by the number of ports. This is calculated as:

$$Util_{station} = \frac{1}{p_{station}} * \frac{1}{t} \sum_{i=1}^{t} e_{station,i} \tag{1}$$

where $e_{station,i}$ is the energy delivered by a charging station during period $i \in t$, which is divided by $p_{station}$, the number of ports per station. Most often in this study, this is reported on an average daily basis in kilowatt-hours per port per day; however, it can also be calculated over alternative periods, such as hourly (kWh/port/hour). This metric is preferred for station owner-operators and utilities as it is both precise and interpretable as a measure of delivered energy for all EVSE types, power levels, EV types, and charging venues. That said, other metrics such as time-based utilization may be better suited for certain applications (e.g., determining resource availability).

2.5. Regression analysis

A multiple linear regression model was chosen for its explanatory power to assess the relationships of several contextual and environmental factors to public charging station utilization. To limit the impact of long-term trends, we isolate our sample to charge sessions beginning in March 2022 (109,689 total), using these to compute the average daily station utilization for the month. The independent variables were selected based on their availability and their previously demonstrated (Almaghrebi et al., 2019; Morrissey et al., 2016; Mortimer et al., 2021) or anticipated impacts on local charging station utilization. These include information on cost, rated port power level, and venue type from the EV WATTS data set, as well as environmental factors represented at the county level, including population density from the U.S. Census Bureau (Manson et al., 2021), the local EVSE network (AFDC, 2022), and local EV adoption (Experian, 2022). Table 2 provides descriptions for the full set of independent variables considered in this analysis.

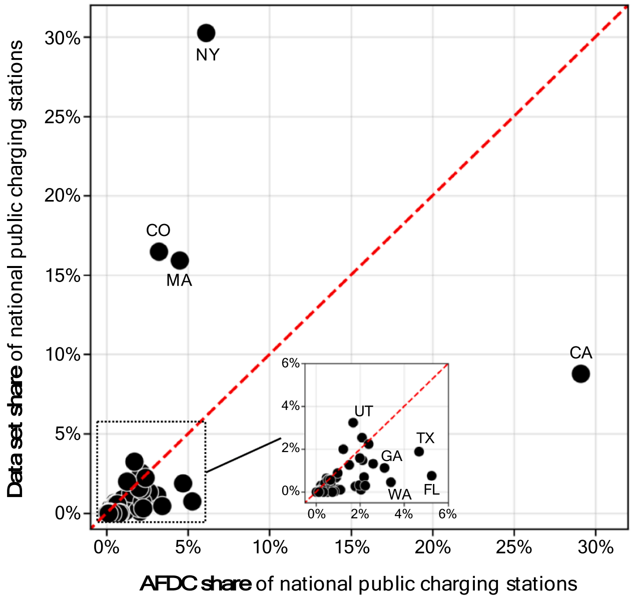

Fig. 2. Comparison of state-level shares of public charging stations in the data set (y-axis) to the AFDC (x-axis).

The following linear equation is used to understand the factors influencing public station utilization (in kWh/port/day):

$$Util_{station} = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_p X_p + error \tag{2}$$

where β_0 is the intercept and $\beta_1, \beta_2, \cdots, \beta_p$ are the regression coefficients associated with each independent variable $X_1, X_2, \cdots, X_p$. Coefficients are determined via the ordinary least squares (OLS) method (OLS regression), which minimizes the sum of the squared differences between the observed dependent variables ($Util_{station}$) and the expected values predicted by the fitted equation. The *error* term reflects the differences between the expected and observed values, representing any external factors that were not considered.

3. Results & discussion

3.1. Public EVSE utilization over time

Figs. 3 and 4 illustrate the average daily public charging station utilization over time (October 2019 through March 2022) by venue type for L2 and DCFC stations, respectively. An immediate observation is that there was a significant drop-off in both L2 and DCFC station utilization in March 2020 due to the onset of the COVID-19 pandemic in the United States and subsequent lockdowns, which caused an immediate reduction in travel and sharp decline in public charging demand. Over time, utilization gradually returned to pre-pandemic levels, achieving or surpassing parity for both L2 and DCFC stations at most venue types (though at different recovery rates) by March 2022. However, the influence of the pandemic cannot be ignored when assessing utilization over this period. Note that

Table 2
Description of independent variables used for multiple regression analysis with station utilization.

Independent Variable	Description
cost_free	Binary variable indicating if the station offers free charging
cost_paid	Binary variable indicating if the station offers paid charging
dcfc_p_pev	DCFC stations per 1,000 EVs within the county where the station is located
l2_p_pev	L2 stations per 1,000 EVs within the county where the station is located
pev_adopt	EVs per 1,000 persons within the county where the station is located
pop_dens	Population density (persons/mile^2) within the county where the station is located
port_kw	Rated power level (kW) of the EVSE ports at the station
ven_hotel	Binary variable indicating if the station venue is a hotel
ven_leisure	Binary variable indicating if the station venue is a leisure destination
ven_med_ed	Binary variable indicating if the station venue is a medical or educational campus
ven_muni	Binary variable indicating if the station venue is a municipal building
ven_office	Binary variable indicating if the station venue is an office building
ven_parking	Binary variable indicating if the station venue is a parking lot or garage
ven_retail	Binary variable indicating if the station venue is a retail location
ven_transit	Binary variable indicating if the station venue is a transit facility

station and venue types with < 30 stations in the data set are omitted to avoid small-sample bias.

In Fig. 3, the average public L2 station utilization varies from 1 kWh/port/day (hotel L2, June 2020) to 8 kWh/port/day (transit facility L2, February 2020), depending on the month and venue. In general, retail locations, municipal buildings, parking lots/garages, and transit facilities experienced the highest pre-pandemic L2 utilization. Most of these venues continue to see the highest utilization today, except for retail locations, which remain 25 % below pre-pandemic utilization levels through March 2022. Conversely, L2 utilization at medical or educational campuses is up 27 % in March 2022 compared to pre-pandemic levels.

Fig. 4 shows that the average public DCFC station utilization (i.e., delivered energy) tends to be higher than L2 utilization, varying from 2 kWh/port/day (leisure destination DCFC, June 2020) to 26 kWh/port/day (medical/educational campus DCFC, February 2020), depending on the month and venue. Like with L2 stations, most DCFC stations experienced a steep drop in utilization at the onset of the pandemic, though retail DCFC recorded the quickest bounce back of any station type, matching pre-pandemic peak utilization levels in October 2020, approximately 7 months after the initial lockdowns. We hypothesize that this could be attributed to the increase in road trips taken in fall 2020 due to a decreased willingness to fly during the pandemic (Bielecki et al., 2020; Lamb et al., 2020). DCFC stations at offices, municipal buildings, and parking lots/garages tend to experience the highest utilization (though DCFC at offices and municipal buildings might be serving a commercial fleet, providing a guaranteed source of demand). DCFC at leisure destinations experienced the slowest bounce back of any station type, with utilization in March 2022 still 37 % below pre-pandemic peak levels.

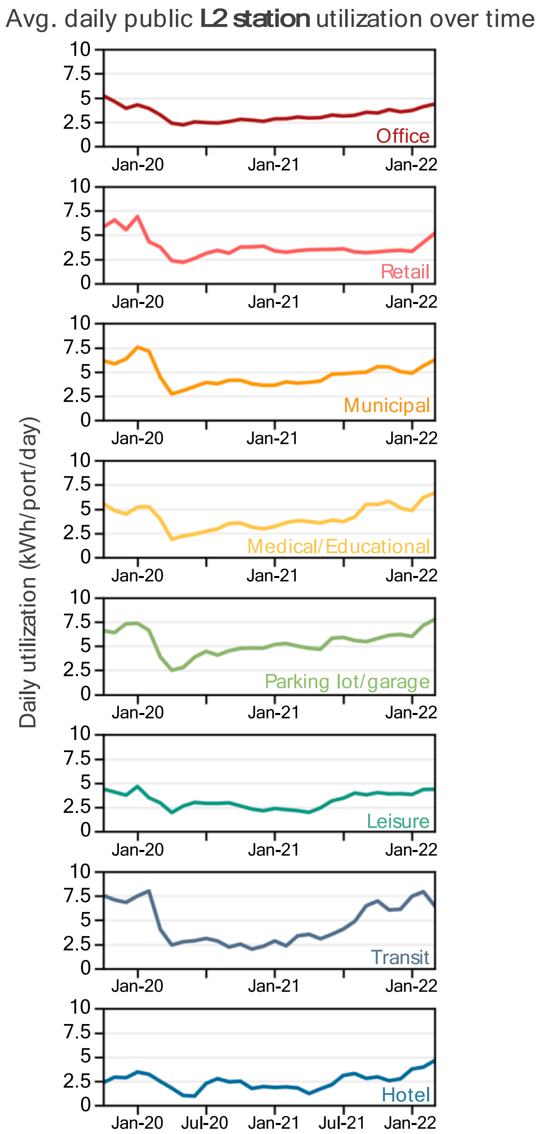

Fig. 3. Average daily public L2 charging station utilization (kWh/port/day) by venue type from October 2019 through March 2022.

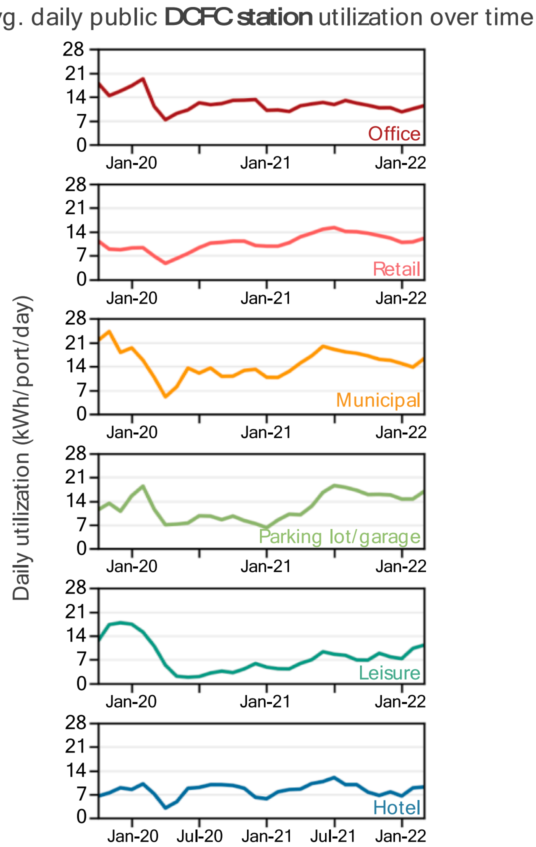

Fig. 4. Average daily public DCFC charging station utilization (kWh/port/day) by venue type from October 2019 through March 2022.

3.2. Daily public EVSE utilization

In addition to public EVSE utilization over time, intraday utilization trends are important for understanding when charging demand is likely to occur. Figs. 5 and 6 show the average hourly station utilization for different venue types in March 2022 (the most recent full month of data) split into weekdays and weekends for L2 and DCFC stations, respectively. Once again, venue types with<30 stations in the data set are omitted.

In Fig. 5, we see that weekday L2 station utilization is highest in the morning (8 a.m.–12p.m.), especially for venues experiencing a high share of workplace charging (i.e., offices, medical/educational campuses, and parking lots/garages). Retail locations, leisure destinations, and transit facilities experience weekday peak L2 utilization slightly later in the day (10 a.m.–2 p.m.) that is sustained into the evenings. Hotels, in general, experience the lowest daily L2 utilization of any venue type; however, unlike the other venues, demand peaks overnight (7–11p.m.). Average daily utilization on the weekend varies considerably depending on the venue. For instance, L2 utilization decreases on weekends (compared to weekdays) for offices and medical or educational campuses by 13 % and 15 %, respectively. Alternatively, L2 utilization increases on weekends for municipal buildings, leisure destinations, and hotels by 14 %, 26 %, and 27 %, respectively. Peak weekend L2 utilization occurs later in the day (afternoon) for all venues except hotels, which retain an overnight peak.

Fig. 6 illustrates the average hourly public DCFC station utilizations for weekdays and weekends. Unlike L2 stations, DCFC stations experience higher utilization on weekends, regardless of venue. Specifically, average weekend utilization ranges from 14 % (offices) to 54 % (hotels) higher than average weekday utilization. Additionally, peak utilization occurs later in the day (2–6p.m.) on both weekdays and weekends at all venue types, including offices, which could be due to mixed employee (or commercial) and public DCFC station use.

Overall, public station utilization in March 2022 remains low in the United States, in line with reports from other EV and EVSE markets in the literature. We find that public L2 stations average 5.6 kWh/port/day (0.42 sessions/port/day with 13.44 kWh/session). Public DCFC stations experience slightly higher utilization, averaging 13.5 kWh/port/day (0.69 sessions/port/day with 19.52 kWh/session).

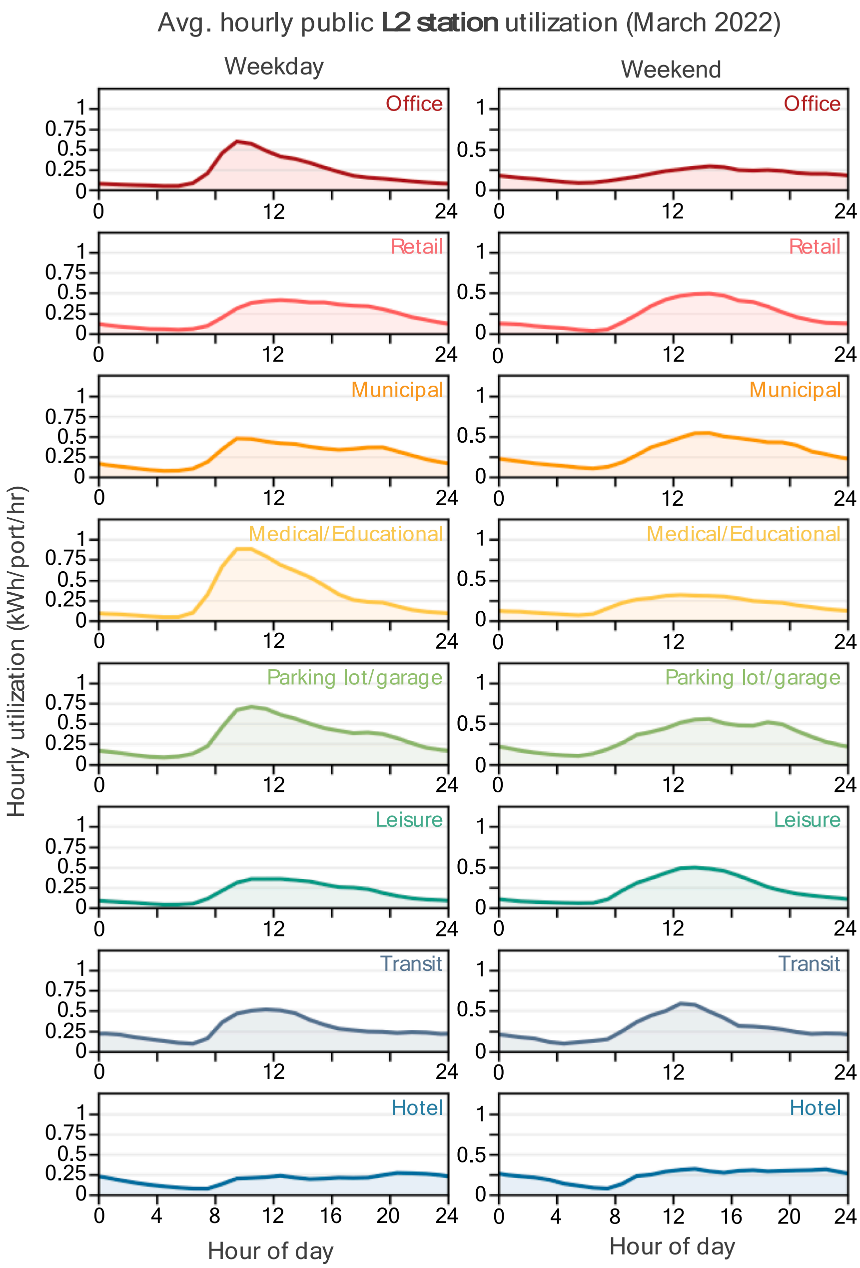

Fig. 5. Average hourly public L2 charging station utilization (kWh/port/hour) for weekdays and weekends in March 2022 by venue type.

3.3. *EV charge acceptance*

It is widely understood that an EVSE port's rated power level does not necessarily correspond to the rate at which energy is delivered (Keil and Jossen, 2016; Ucer et al., 2018). The actual rate of charging depends on multiple factors, such as ambient temperature, battery temperature, battery state of charge, and EV-specific acceptance rates. Despite this, some studies assume that EVs charge at an EVSE port's rated power level when assessing station utilization (translating percent of time charging to energy delivered under this false assumption). Fig. 7 shows the ratio of average delivered power to the port's rated power for all charging sessions in the data set, broken out by charger type (L2 and DCFC) and rated power level. We see that this ratio decreases for both L2 and DCFC ports as the rated power level increases (<50 % for L2 $\geq$ 7.2 kW and DCFC > 50 kW). This trend is explained by the current composition of EVs on the road in the United States, with a significant share incapable of charging at high power levels for an extended period (including nearly all plug-in hybrid EVs and most battery-electric vehicles before 2018) (ChargeHub, 2022; InInsideEVs, 2019). However, since new (and future) EVs have larger batteries and higher power acceptance levels, these ratios might be expected to improve over time, though EVSE power levels will also be increasing, making the outlook uncertain.

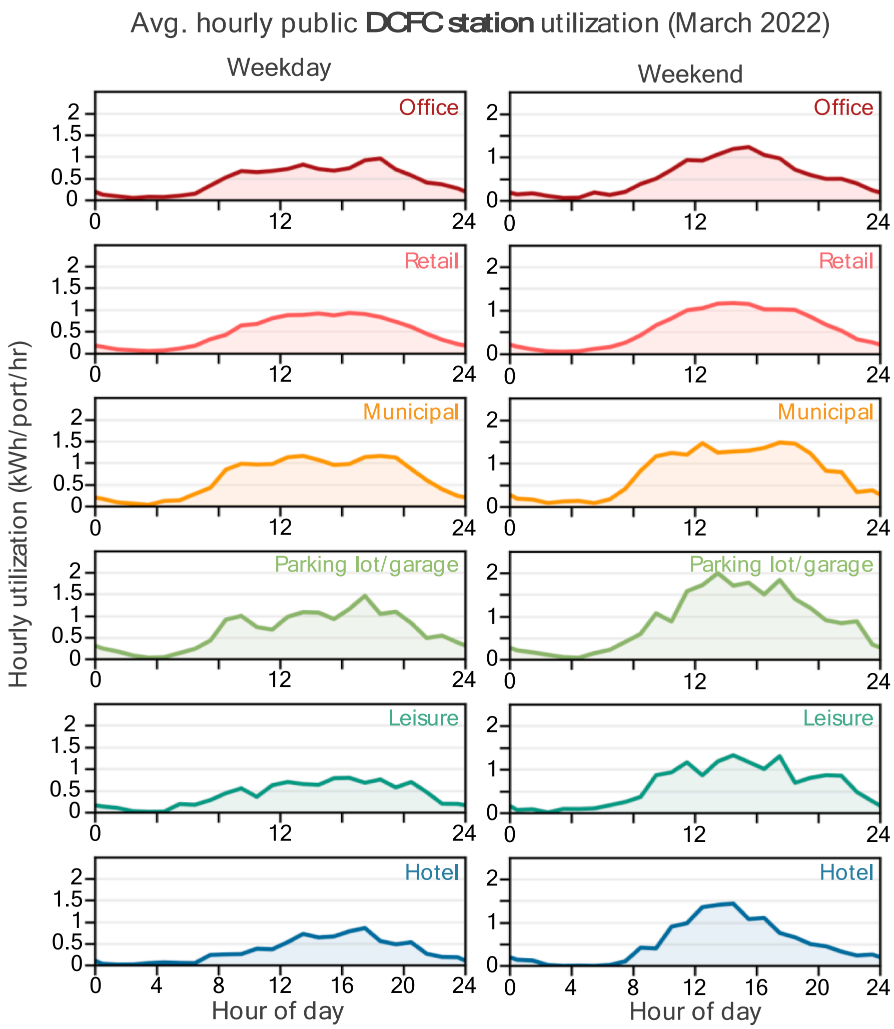

Fig. 6. Average hourly public DCFC charging station utilization (kWh/port/hour) for weekdays and weekends in March 2022 by venue type.

3.4. Charge idling

Charge idling is when an EV is plugged into an EVSE port but not charging. These behaviors reflect a system inefficiency that can be a major burden for EVSE station operators (revenue blocking) and network planners (poor use of resources). To combat these behaviors, station operators have started to implement idling fees, billing customers for time spent plugged in after a charge session ends

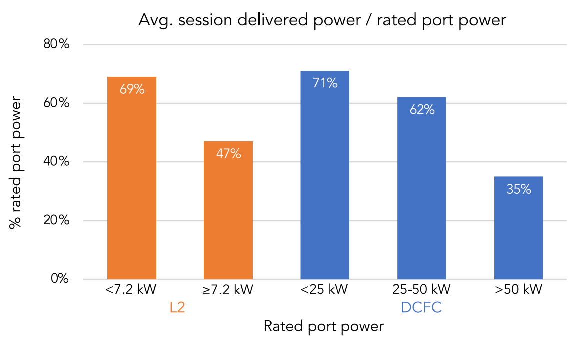

Fig. 7. Ratio of the average delivered power to the port's rated power level during charging sessions, broken out by charger type (L2 and DCFC) and rated power level.

(Tesla, 2022). In Fig. 8, we show the frequency of charge idling as a percent of total plug-in time for public L2 charging broken out by venue type (October 2019–March 2022). Higher values reflect less efficient charging etiquette (i.e., more time spent plugged in but not charging). In general, charge idling is highly prevalent at public L2 stations, ranging from 30 % (retail) to 76 % (parking lot/garage) of the time an EV is plugged in. This could be due to the nature of destination L2 charging, where activities dictate dwell durations rather than charging (LaMonaca and Ryan, 2022). Additionally, L2 stations are more likely to offer free charging (and less likely to have idle fees) than DCFC stations, which presumably contributes to more charge idling.

For DCFC stations (Fig. 9), charge idling is significantly reduced, ranging from just 5 % (hotel) to 11 % (retail) of the time an EV is plugged in. This is likely explained by the nature of DCFC charging, where the purpose is to charge the EV as quickly as possible (LaMonaca and Ryan, 2022). Current pricing strategies for DCFC stations are another likely contributor, as many are now employing idling fees to promote station throughput.

3.5. Factors affecting public EVSE utilization

We observe significant variability in the utilization of public EV charging stations, with 50 % of both L2 and DCFC stations supplying nearly 90 % of the total charging demand. Thus, linear regression analysis is conducted to better understand the factors influencing public station utilization in the United States. Separate models are developed for public L2 stations (Section 3.5.1) and DCFC stations (Section 3.5.2) to independently analyze and compare the influence of the factors presented in Table 2 for the different station types.

3.5.1. Factors affecting public L2 station utilization

We first perform correlation analysis to observe linear relationships between the various independent variables in the final regression and public L2 station utilization (l2_station_util), in kilowatt-hours per port per day (Fig. 10). We find free pricing strategies ($r = 0.23$, $p = 7e-07$) and local plug-in EV adoption rates ($r = 0.17$, $p = 3e-04$) to be most positively correlated with station utilization. Alternatively, paid pricing strategies ($r = -0.23$, $p = 7e-07$) and the size of the local L2 charging network ($r = -0.19$, $p = 5e-05$) are the most inversely related to utilization.

Results from the linear regression analysis for public L2 station utilization are presented in Table 3. An immediate observation is the low R-squared value ($R^2 = 0.138$) for the model, indicating significant variance in the dependent variable that is not explained by the independent variables. While this can be improved by including additional variables with explanatory power, models of human behavior are subject to significant inherent stochasticity, which often causes low R-squared values (Nau, 2016). This would be a severe limitation if our task were prediction; however, we are only interested in observing the associations between variables, and hence this concern is diminished. We find the following five variables to have the greatest statistically significant (0.05-level) relationship with L2 station utilization: free charging ($\beta = 2.06$, $p = 2e\text{-}03$), paid charging ($\beta = -1.19$, $p = 4e\text{-}02$), local population density ($\beta = 4e\text{-}04$, $p = 1e\text{-}02$), local L2 charging network size ($\beta = -0.02$, $p = 2e\text{-}03$), and local EV adoption ($\beta = 0.23$, $p = 1e\text{-}03$). Port power level, venue type, and local DCFC charging network size do not have a statistically significant relation to L2 station utilization.

3.5.2. Factors affecting public DCFC station utilization

For public DCFC station utilization (dcfc_station_util), Fig. 11 shows that local plug-in EV adoption rate ($r = 0.35$, $p = 9e-16$) and population density ($r = 0.23$, $p = 2e-07$) are the variables most positively correlated with station utilization. These also have moderate collinearity ($r = 0.51$), as early EV adoption tends to be greater in urban areas. However, we find the variance inflation factor (VIF) between the two, a measure of collinearity, to be 1.34—sufficiently low for multiple regression (Hair et al., 1995). The local L2 charging network size ($r = -0.18$, $p = 8e-05$) and local DCFC charging network size ($r = -0.13$, $p = 4e-03$) are the two variables most negatively correlated with utilization; however, these again are moderately collinear but acceptable for multiple regression (VIF

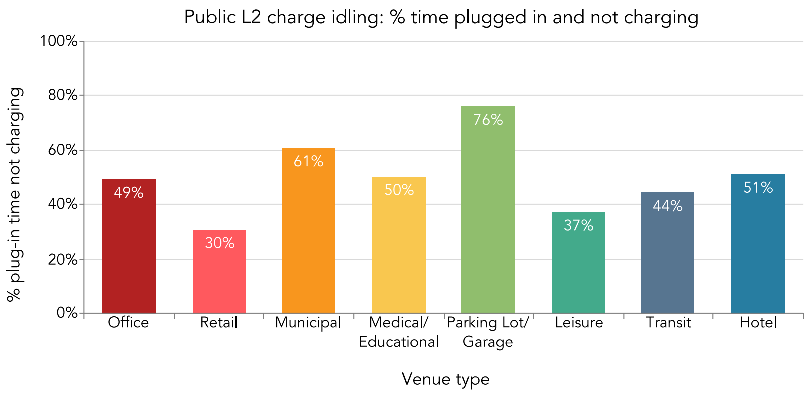

Fig. 8. Frequency of public L2 charge idling for multiple venue types.

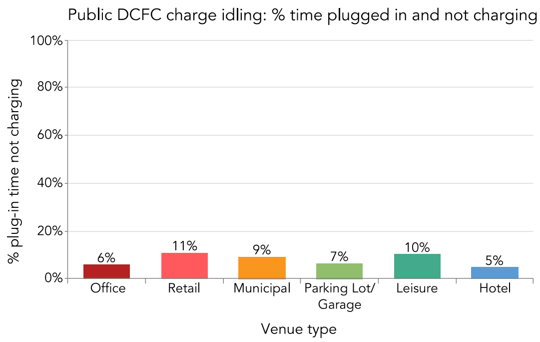

Fig. 9. Frequency of public DCFC charge idling for multiple venue types.

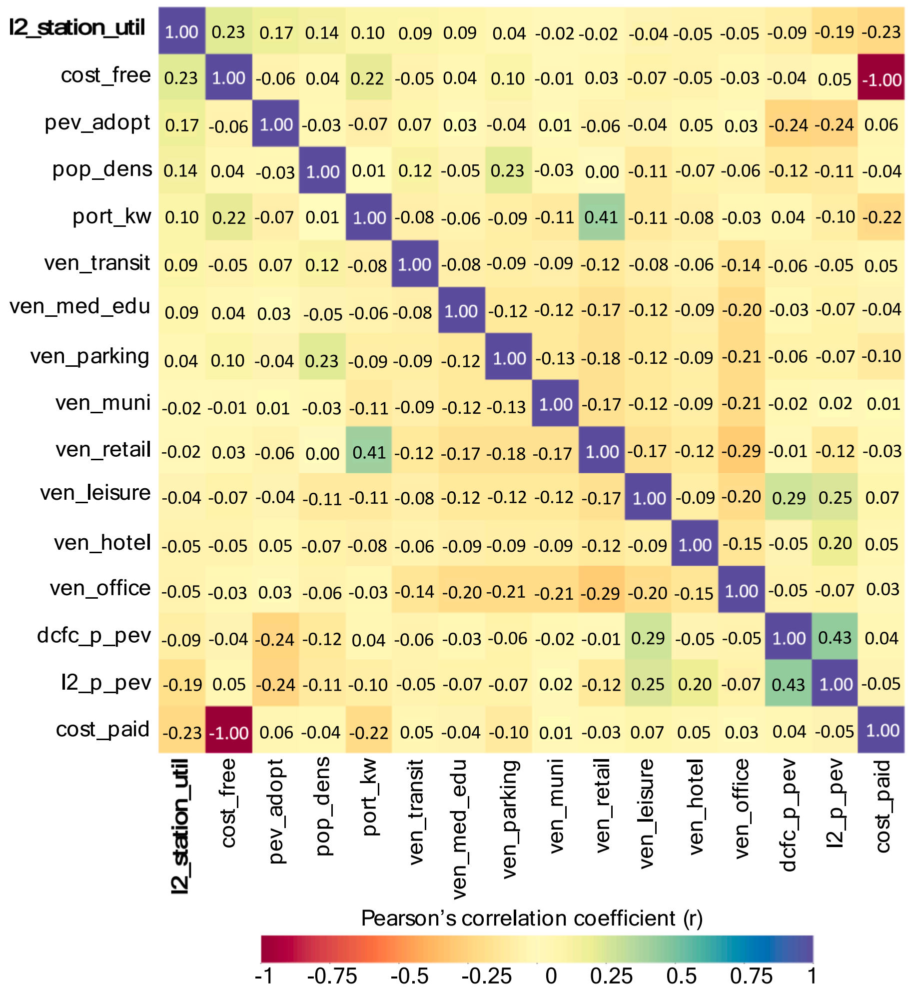

Fig. 10. Correlations between the independent variables and public L2 station utilization (kWh/port/day).

= 2.43).

Table 4 presents results from the linear regression analysis for public DCFC station utilization. The R-squared value is slightly higher for this model ($R^2 = 0.179$) than the one developed for L2 utilization, and several of the variables with statistically significant relationships are different. We find that municipal building venue type ($\beta = 5.59$, $p = 7e\text{-}03$), free charging ($\beta = 3.09$, $p = 2e\text{-}02$), rated port power level ($\beta = 0.16$, $p = 8e\text{-}03$), and local EV adoption ($\beta = 0.50$, $p = 0$) are all significant at the 0.05 level, while paid charging ($\beta = -2.47$, $p = 7e\text{-}02$) is significant at the 0.1 level.

Table 3
OLS regression results: public L2 station utilization.

Dependent Variable	l2_station_util		**R-squared**			0.138
Units	kWh/port/day		**Adjusted R-squared**			0.114
Time Period	March 2022		**F-statistic**			5.648
Number of Observations	471		**Probability (F-statistic)**			1.28E − 09
Df Residuals	457		**Log-Likelihood**			−1,543.9
Df Model	13		**AIC**			3,116
Covariance Type	nonrobust		**BIC**			3,174
	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
const	0.8720	1.050	0.830	0.407	−1.192	2.936
ven_office	−0.7777	0.625	−1.244	0.214	−2.006	0.451
ven_hotel	−0.0643	1.176	−0.055	0.956	−2.376	2.247
ven_leisure	0.5232	0.926	0.565	0.572	−1.296	2.343
ven_med_edu	1.1882	0.883	1.345	0.179	−0.548	2.924
ven_parking	−0.3366	0.878	−0.383	0.702	−2.063	1.389
ven_muni	−0.1977	0.854	−0.231	0.817	−1.877	1.481
ven_retail	−1.1795	0.796	−1.483	0.139	−2.743	0.384
ven_transit	1.7162	1.183	1.451	0.148	−0.609	4.041
cost_free	2.0609	0.663	3.109	**0.002****	0.758	3.363
cost_paid	−1.1889	0.570	−2.087	**0.037****	−2.309	−0.069
port_kw	0.3412	0.219	1.555	0.121	−0.090	0.772
pop_dens	0.0004	0.000	2.517	**0.012****	0.000	0.001
l2_p_pev	−0.0215	0.007	−3.190	**0.002****	−0.035	−0.008
dcfc_p_pev	0.0191	0.028	0.684	0.494	−0.036	0.074
pev_adopt	0.2343	0.072	3.274	**0.001****	0.094	0.375

Significance codes: * 0.1; ** 0.05.

Comparing the two models, we draw several conclusions: (1) Unsurprisingly, free charging significantly increases station utilization, especially for L2 stations; (2) venue type does not have a statistically significant relationship to utilization (with the exception of DCFC at municipal buildings, which may reflect commercial fleet charging); (3) local EV adoption is a strong indicator of both L2 and DCFC station utilization (+); (4) L2 station utilization is more sensitive than DCFC station utilization to the size of the local EV charging network (−); and (5) higher port power levels have a greater effect on DCFC station utilization (+) than L2 station utilization.

4. Conclusions

This study assesses current public EV charging station utilization trends in the United States and explores relationships between station utilization and multiple contextual and environmental factors. This section discusses several findings with relevance to policymakers and EVSE operators. First, we show that EV charging station utilization has steadily increased over time, following a steep decline in March 2020 at the onset of the COVID-19 pandemic. While much of this rise can be attributed to the slow return of pre-pandemic travel patterns, at the same time, EV adoption has increased. By March 2022, public station utilization had mostly returned to its pre-pandemic levels (two notable exceptions being retail L2 stations and DCFC at leisure destinations, where utilization remained 25 % and 37 % below pre-pandemic levels through March 2022, respectively); however, it will be interesting to observe this trend going forward as more EVs hit the road and EVSE deployments accelerate.

We observe that public L2 station utilization is highest during weekdays and in the morning (8 a.m.–12p.m.), especially for venues with a high share of workplace charging (i.e., offices, medical/educational campuses, and parking lots/garages). Retail locations, leisure destinations, and transit facilities experience weekday peak L2 utilization slightly later in the day (10 a.m.–2 p.m.) that is sustained into the evenings. Hotels, in general, experience the lowest EVSE utilization of any venue type studied; however, unlike the other venues, demand peaks overnight (7–11p.m.). Unlike L2 stations, DCFC stations experience higher utilization on weekends, regardless of venue. Specifically, average weekend utilization ranges from 14 % (offices) to 54 % (hotels) higher than average weekday utilization. Additionally, peak utilization for DCFC stations occurs later in the day on both weekdays and weekends at all venue types (2–6 p.m.).

As of March 2022, utilization in the United States remains low, in line with reporting from other EV and EVSE markets, averaging 5.6 kWh/port/day (0.42 sessions/port/day) for public L2 stations and 13.5 kWh/port/day (0.69 sessions/port/day) for public DCFC stations. Low EVSE utilization makes for challenging economics for public EV charging as a standalone business. More research is needed to assess the impacts of today's low (but possibly increasing) EVSE utilization levels on the business case and financial requirements for charging stations and the cost of charging for EV drivers.

One way to improve station utilization is to maximize the energy delivered while an EV is plugged in. To this end, we identify-two inefficiencies with charging that could be remedied. First, we find the actual rate of charging to be on average just 35 %–71 % of the port's rated power level. As the port power level increases, this ratio decreases because many older EVs are incapable of taking advantage of the higher charge rates (for both DCFC and L2). As EV adoption increases and the fleet turns over, we might expect this ratio to improve; however, it reinforces that EV charge rates are highly variable and dependent on multiple factors. Second, we show charge idling to be a common occurrence at public L2 stations (i.e., destination charging), where 30 %–76 % of the time an EV is plugged in, it is not charging. For DCFC stations, this rate is less severe (5 %–11 %) likely due to its more time-sensitive nature (e.g., en-

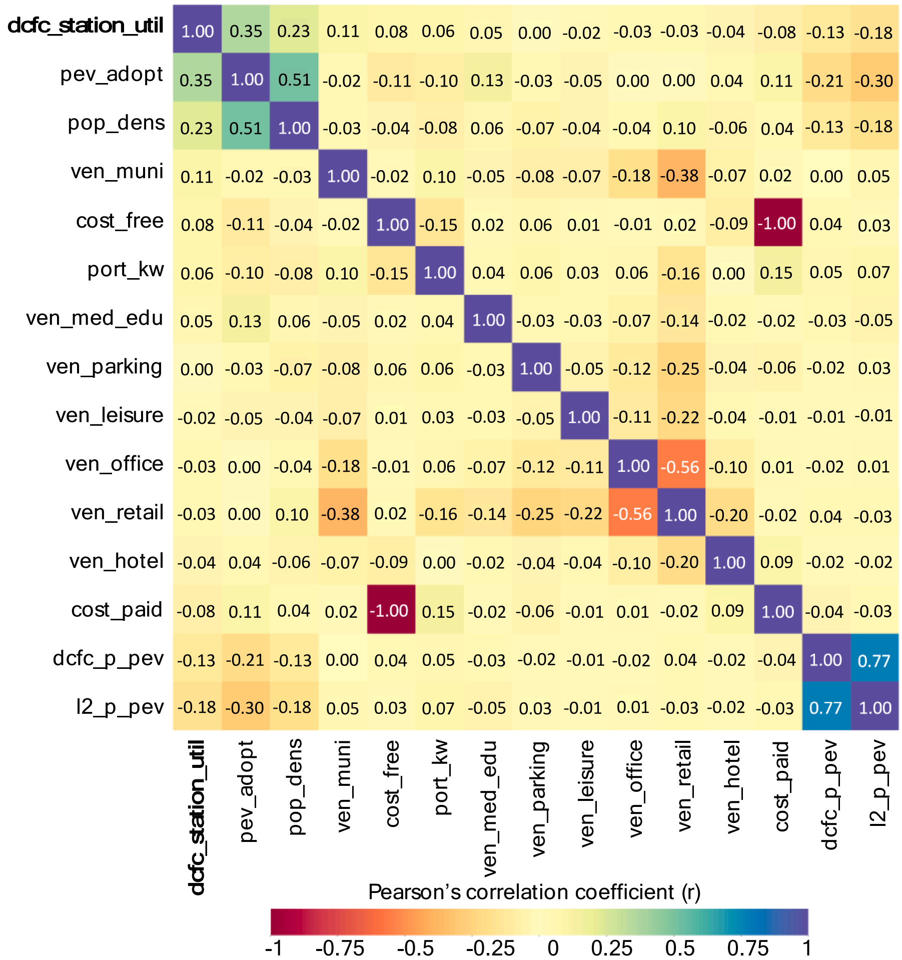

Fig. 11. Correlations between the independent variables and public DCFC station utilization (kWh/port/day).

Table 4
OLS regression results: public DCFC station utilization.

Dependent Variable	dcfc_station_util		**R-squared**			0.179
Units	kWh/port/day		**Adjusted R-squared**			0.158
Time Period	March 2022		**F-statistic**			8.546
Number of Observations	483		**Probability (F-statistic)**			9.30E − 15
Df Residuals	470		**Log-Likelihood**			−1,980.1
Df Model	12		**AIC**			3,986
Covariance Type	nonrobust		**BIC**			4,041
	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
const	0.618	2.023	0.305	0.76	−3.358	4.594
ven_office	−0.512	1.67	−0.307	0.759	−3.794	2.77
ven_hotel	−3.2069	3.386	−0.947	0.344	−9.861	3.447
ven_leisure	−0.5491	3.055	−0.18	0.857	−6.553	5.454
ven_med_edu	−0.7619	4.699	−0.162	0.871	−9.996	8.473
ven_parking	0.0517	2.797	0.018	0.985	−5.444	5.548
ven_muni	5.5894	2.074	2.694	**0.007****	1.513	9.666
ven_retail	0.0067	1.35	0.005	0.996	−2.645	2.659
cost_free	3.0904	1.345	2.297	**0.022****	0.447	5.734
cost_paid	−2.4725	1.351	−1.83	**0.068***	−5.127	0.182
port_kw	0.1587	0.06	2.651	**0.008****	0.041	0.276
pop_dens	0.0008	0.001	1.402	0.162	0	0.002
l2_p_pev	−0.0208	0.015	−1.349	0.178	−0.051	0.01
dcfc_p_pev	0.0004	0.009	0.048	0.961	−0.017	0.018
pev_adopt	0.4953	0.078	6.386	0**	0.343	0.648

Significance codes: * 0.1; ** 0.05.

route charging during long-distance travel). Some EVSE station operators implement idle fees to incentivize throughput, though we assume that these do not exist for stations with free charging, like many L2 stations in the data set. To reduce system inefficiencies, strategies for maximizing energy delivery—such as installing dual-port charging units or employing central load balancing (enabling energy orchestration across multiple ports)—should be implemented, even for stations with nonmonetized charging.

We observe significant variability in the utilization of public EV charging stations, with 50 % of L2 and DCFC stations supplying nearly 90 % of the total charging demand. Using linear regression analysis, we show that the factors influencing utilization for L2 and DCFC stations differ. L2 station utilization is more sensitive than DCFC station utilization to the size of the local EV charging network, decreasing as the market saturates. We also find that increased port power levels have a greater effect on DCFC station utilization than L2 station utilization. For both station types, the local EV adoption rate is a strong predictor of station utilization, and while L2 and DCFC station utilization are both improved by offering free charging (and diminished with paid charging), this is especially true for L2 stations. Surprisingly, venue type does not have a statistically significant relationship to utilization, however, the omission of relevant predictors may be partially responsible for obscuring these associations, as indicated by the models' low R-squared values (R^2 = 0.14–0.18). Future research should explore the sensitivity of station utilization to a more complete set of factors, including charging prices and pricing strategies (e.g., energy-based, time-based, subscriptions/memberships), station location (e.g., corridor stations), and EVSE operator. In addition, alternative EVSE business models (e.g., sources of indirect revenue) that enable low-cost or free charging are not well understood and should be further researched.

CRediT authorship contribution statement

Brennan Borlaug: Conceptualization, Methodology, Software, Validation, Formal analysis, Data curation, Visualization, Project administration, Writing – original draft. **Fan Yang:** Conceptualization, Methodology, Software, Formal analysis, Data curation, Visualization, Writing – original draft. **Ewan Pritchard:** Investigation, Resources, Data curation, Supervision, Writing – review & editing. **Eric Wood:** Funding acquisition, Writing – review & editing. **Jeff Gonder:** Supervision, Funding acquisition, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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References

Aaa, 2022. Going Electric? A Quarter of Americans want their Next Vehicle Purchase to be an EV. AAA.
AFDC, 2022. Electric vehicle charging station locations. Alternative Fuels Data Center.
Almaghrebi, A., Shom, S., Alahmad, M., 2019. Analysis of user charging behavior at public charging stations, *2019 IEEE Transportation Electrification Conference and Expo (ITEC)*. IEEE 1–6.
APC, 2020. Public EV Charging Business Models for Retail Site Hosts. Atlas Public Policy.
Berkeley, N., Jarvis, D., Jones, A., 2018. Analysing the take up of battery electric vehicles: An investigation of barriers amongst drivers in the UK. Transportation Research Part D: Transport Environment 63, 466–481.
Bielecki, M., Patel, D., Schlagenhauf, P., 2020. Reprint of: Air travel and COVID-19 prevention in the pandemic and peri-pandemic period: A narrative review. Travel medicine and infectious disease 38, 101939.
Borlaug, B., Salisbury, S., Muratori, M., 2020. Levelized cost of charging electric vehicles in the United States. Joule 4 (7), 1470–1485.
Bousso, R., 2022. For BP, car chargers to overtake pumps in profitability race. REUTERS.
Burnham, A., Dufek, E., Mohanpurkar, M., 2017. Enabling fast charging–Infrastructure and economic considerations. Journal of Power Sources 367, 237–249.
ChargeHub, 2022. Find Out the most Optimal Charging Solution for your Home According to the Electric Vehicle you Drive.
Desai, R., Chen, R., & Armington, W., 2018. A Pattern Analysis of Daily Electric Vehicle Charging Profiles: Operational Efficiency and Environmental Impacts. *Journal of Advanced Transportation* 2018, Article ID 6930932.
Energetics, 2022. EV WATTS Charging Station Dataset, Energetics.
Experian, 2022. Auto Registration Database.

Francfort, J., Bennett, B., ..., & Wishart, J., 2015b, Plug-in Electric Vehicle and Infrastructure Analysis. Idaho National Laboratory (INL), Idaho Falls, ID (United States).

Francfort, J., 2015a. What Use Patterns Were Observed for PEV Drivers at Publicly Accessible AC Level 2 EVSE Sites? Idaho National Laboratory (INL), Idaho Falls, ID (United States).

Gellrich, M., Block, A., Leikert-Böhm, N., 2022. Spatial and temporal patterns of electric vehicle charging station utilization: a nationwide case study of Switzerland. Environmental Research: Infrastructure and Sustainability.

Gilleran, M., Bonnema, E., ..., & M., Mann, M., 2021. Impact of electric vehicle charging on the power demand of retail buildings. *Advances in Applied Energy* 4, 100062.

Hair, J., Anderson, R., ..., & Black, W., 1995. *Multivariate Data Analysis (3rd ed)*. New York: Macmillan.

Hardinghaus, M., Löcher, M., Anderson, J., 2020. Real-world insights on public charging demand and infrastructure use from electric vehicles. Environmental Research Letters 15 (10), 104030.

Hecht, C., Das, S., Sauer, D., 2020. ETransportation 6, 100079.

Hecht, C., Figgener, J., & Sauer, D., 2022. Analysis of Electric Vehicle Charging Station Usage and Profitability in Germany based on Empirical Data. *arXiv preprint arXiv:.09582*.

Hundt, R., Schub, J., Galizia, M., 2015. Review of New York State Electric Vehicle Charging Station Market and Policy, Finance, and Market Development Solutions. Prepared for the New York State Energy Research and Development Authority.

InsideEVs, 2019. Let's Look At Charging Times For Some Of Today's Popular Electric Cars. InsideEVs Editorial Team, InsideEVs.

Keil, P., Jossen, A., 2016. Charging protocols for lithium-ion batteries and their impact on cycle life—An experimental study with different 18650 high-power cells. Journal of Energy Storage 6, 125–141.

Krishna, G., 2021. Understanding and identifying barriers to electric vehicle adoption through thematic analysis. Transportation Research Interdisciplinary Perspectives 10, 100364.

Idaho National Laboratory [INL], 2013. *The EV Project*. Accessed: Oct. 31, 2022. https://avt.inl.gov/project-type/ev-project.html.

Laboratory, I.N., [inl],, 2015. What Were the Use Patterns Observed at the Highly Utilized Direct Current Fast Charge Sites? Idaho National Laboratory (INL).

Lamb, T.L., Winter, S., Vaughn, A., 2020. Factors that predict passengers willingness to fly during and after the COVID-19 pandemic. Journal of air transport management 89, 101897.

LaMonaca, S., Ryan, L., 2022. The state of play in electric vehicle charging services–A review of infrastructure provision, players, and policies. Renewable and Sustainable Energy Reviews 154, 111733.

Lee, H., Clark, A., 2018. Charging the future: Challenges and opportunities for electric vehicle adoption. HKS Working Paper No. RWP18-026.

Macioszek, E., 2019. Electric Vehicles – Problems and Issues. Smart and Green Solutions for Transport Systems, pp. 169–183. TSTP 2019:

Madina, C., Zamora, I., Zabala, E., 2016. Methodology for assessing electric vehicle charging infrastructure business models. Energy Policy 89, 284–293.

Manson, S., Schroeder, J., ..., & Ruggles, S., 2021. IPUMS national historical geographic information system: Version 16.0.

Morrissey, P., Weldon, P., O'Mahony, M., 2016. Future standard and fast charging infrastructure planning: An analysis of electric vehicle charging behaviour. Energy Policy 89, 257–270.

Mortimer, B., Bach, A., De Doncker, R., 2021. Public Charging Infrastructure in Germany—A Utilization and Profitability Analysis. Journal of Modern Power Systems and Clean Energy 99, 1–10.

Mortimer, B.J., Hecht, C., De Doncker, R., 2022. Electric Vehicle Public Charging Infrastructure Planning Using Real-World Charging Data. World Electric Vehicle Journal 13 (6), 94.

Muratori, M., Elgqvist, E., Smart, J., 2019a. Technology solutions to mitigate electricity cost for electric vehicle DC fast charging. Applied Energy 242, 415–423.

Muratori, M., Kontou, E., Eichman, J., 2019b. Electricity rates for electric vehicle direct current fast charging in the United States. Renewable & Sustainable Energy Reviews 113, 109235.

Muratori, M., Alexander, M., Jenn, A., 2021. The rise of electric vehicles—2020 status and future expectations. Progress in Energy 3 (2), 022002.

Nau, R., 2016. Statistical forecasting: notes on regression and time series analysis. *Stepwise and All Possible Regressions. Available online: https://people.duke.edu/~rnau/regstep.htm (accessed on 2 May 2019)*.

Nigro, N., Welch, D., & Peace, J., 2015. Strategic planning to implement publicly available EV charging stations: A guide for businesses and policymakers. Center for Climate Energy Solutions: Arlington, VA, USA.

Randall, T., 2022. US Crosses the Electric-Car Tipping. Point for Mass Adoption, Bloomberg.

Siddique, C., Afifah, F., Zhou, Y., 2022. Data mining of plug-in electric vehicles charging behavior using supply-side data. Energy Policy 161, 112710.

Tesla, 2022. Supercharger Idle Fee.

The White House, 2022. FACT SHEET: Biden- Harris Administration Proposes New Standards for National Electric Vehicle Charging Network. The White House.

U.S. Department of Energy, 2022. Developing Infrastructure to Charge Electric Vehicles. Alternative Fuels Data Center.

Ucer, E., Kisacikoglu, M., Rames, C., 2018. Development of a DC fast charging station model for use with EV infrastructure projection tool. IEEE Transportation Electrification Conference and Expo (ITEC). IEEE 904–909.

Wicki, M., Brückmann, G., Bernauer, T., 2022. How to accelerate the uptake of electric cars? Insights from a choice experiment. Journal of Cleaner Production 355, 131774.

Wolbertus, R., Van den Hoed, R., 2017. Charging station hogging: A data-driven analysis. Electric Vehicle Symposium 1–14.

Wolbertus, R., Van den Hoed, R., Maase, S., 2016. Benchmarking charging infrastructure utilization. World Electric Vehicle Journal 8 (4), 754–771.

Zhang, Z., Chen, Z., Zhang, T., 2022. Evaluation of the multi-dimensional growth potential of China's public charging facilities for electric vehicles through 2030. Utilities Policy 75, 101344.