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Impact of electric vehicle charging on the power demand of retail buildings

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ABSTRACT

As electric vehicle penetration increases, charging is expected to have a significant impact on the grid. Electric vehicle charging stations will greatly affect a building site's power demand, especially with the onset of fast charging with power levels as high as 350 kW per charger. Here, we assess how electric vehicle charging stations would impact a retail big box grocery store, exploring numerous station sizes, charging power levels, and utilization factors in various climate zones and seasons. We measure the effect of charging by assessing changes in monthly peak power demand, electricity usage, and annual electricity bill, computed using three distinct rate structures. We find that an electric vehicle station has the potential to dwarf a big box building's power demand if behind the same meter, increasing monthly peak power demand at the site by over 250%. Cold-climate areas paired with rate structures incorporating high demand charges are most susceptible for significant changes to the annual electricity bill, with increases as high as 88%.

Introduction

Passenger electric vehicles (EVs) can improve local air quality and decarbonize the transportation sector [1,2] but currently account for less than one percent of all cars in circulation worldwide. However, this is quickly changing. In 2010, about 17,000 EVs were on the world's roads; in 2019, there were about 7.2 million [1]. Continued growth is expected: California banned the sale of new gas-powered passenger cars starting in 2035 [3] and 17 countries have announced the phase-out of gas-powered vehicles through 2050 [1]. As the adoption of EVs grows, so must that of charging stations, or electric vehicle supply equipment (EVSE). From 2016 to 2020, the number of public and private EV charging ports grew from 34,000 to over 85,000 [4].

Most charging is currently performed at owners' residences, where vehicles are parked and charged overnight [5–7], but this is expected to shift toward public options. In the European Union, the share of home charging is predicted to decline from approximately 75% in 2020 to 40% by 2030 [8] as more middle- and lower-income households without home-charging options purchase EVs. Renters, who make up an increasing percentage of the U.S. population [9,10], cannot home charge as rental-property owners have little incentive to invest in EVSE [11,12]. Inability to charge is one of the main barriers to purchasing EVs [13,14], making nonresidential EVSE development critical to not only accommodate long-distance travel [15] but also provide opportunities for those who cannot reliably charge at home [5,16].

A large proportion of nonresidential EVSE is on existing retail sites [4,7,17], particularly supermarkets [18]. Americans are already refueling traditional gas-powered vehicles at supermarkets more frequently, including Kroger, Costco, and Sam's Club [19]. Because refueling times are longer for EVs than gas-powered vehicles [16], having the opportunity to shop while refueling is particularly desirable. Charging station service providers such as Electrify America, EVgo, ChargePoint, and Tesla have already installed stations at various Walmart and Target locations, among other retail sites [4]. Incentives for retailers to develop EVSE exist, as 89% of EV drivers typically make a purchase while charging at a retail location [20].

Many anticipate extreme fast charging power levels to accommodate the desire for short dwell times while charging away from the home or workplace [21]. Research funded by the U.S. Department of Energy (DOE) aims to decrease the typical charge time to 10 min or less by increasing power levels up to 400 kW [22]. Original equipment manufacturers (OEMs) are producing vehicles that can accept higher power levels, including the Tesla Model 3 (accepting 250 kW) [23] and the Porsche Taycan (accepting 350 kW) [24]. Fast charging networks including Electrify America and EVgo have both deployed 350-kW chargers [25,26] and new ChargePoint technology can deliver up to 500 kW [27].

The majority of studies that explore the effects of EV charging on the grid focus on residential charging [2,28–34] but encourage considering the effects nonresidential charging (i.e., public direct current [DC] fast

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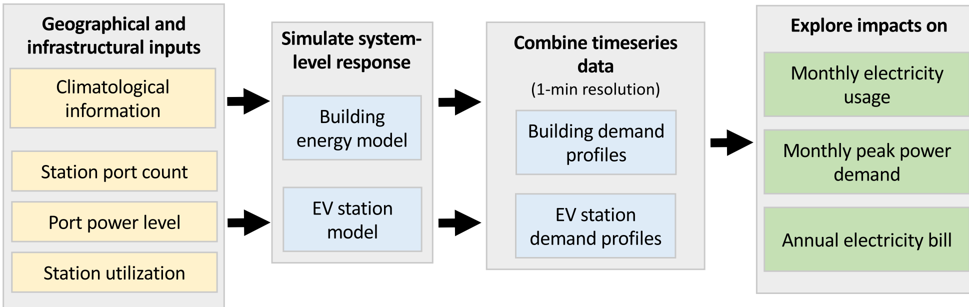

Fig. 1. Modeling method, where various building and EV parameters are altered to create numerous building and EV station demand profiles. These are then combined to explore the possible effects of EV stations on an existing building site's electricity usage, power demand, and annual electricity bill.

charging stations [2]). Current work regarding nonresidential charging evaluates the negative effects of additional loads on distribution systems (i.e., harmonic distortion and voltage quality issues [35,36]) and assesses benefits of controlled EV charging [37–39], price-based charging strategies [40–42], and vehicle-to-grid modes [43,44]. A few studies have presented characteristics of nonresidential charging for light-, medium-, and heavy-duty vehicles [18,39,45], but few also compare these to characteristics of existing building loads.

Meanwhile, many papers explore how building loads, which account for over 70% of the electricity consumption in the United States, can be shifted or shaved to improve grid operation [46–51]; however, this strongly depends on the load at the building meter, which could change significantly with the addition of DC fast charging. One relevant study analyzes the integration of EVs, retail buildings, and photovoltaics (PV) [52], but for a 50-kW two-port station in one location (Washington, D.C.). Another study demonstrates an optimization framework for a cluster of EV stations and commercial buildings in one location (San Francisco, California) [53]. In addition, whereas the location and seasonal effects of electric load profiles of commercial office buildings [54,55] and dormitories [56] have been assessed, to date, there is no adequate research in the literature considering retail big box grocery stores (big box stores). Due to this lack of data, research comparing the electricity use of big box stores and EV stations is nearly nonexistent.

Here, we show the impact that nonresidential charging of various power levels has on the electric load profile of an illustrative big box store, such as a Walmart Supercenter or Kroger Marketplace, quantifying how EV charging of customers with light-duty passenger vehicles impacts a site's monthly electricity usage, peak power demand, and electricity bill. We explore different scenarios for the EV and building load profiles. Combining these profiles, we analyze effects of charging on monthly electricity and peak power demand and apply various utility rate structures to quantify the impact of time-of-use (TOU) energy rates and demand charges on the annual electricity bill.

Synthetic demand profile generation

Fig. 1 depicts our modeling method, which combines building and EV station demand profiles to explore the impacts of charging on a building's monthly electricity use and peak power demand. We also explore impacts on a building's annual electricity bill, knowing that energy-related charges, which correspond to the total electricity consumption over a month, and demand-related charges, which correspond to the peak power demand over the course of a month, both impact an electricity bill and vary in weight based on the utility tariff.

Generating building demand profiles

To obtain realistic building demand profiles, we develop an EnergyPlus [57] building energy model of a big box store in Centennial, Colorado, according to the as-built architectural, mechanical, and electrical drawings. We then calibrate this model to 5 years of detailed submetered data, ensuring that the model accurately captures the electric power profile of each subsystem including refrigeration, heating, ventilation, air conditioning (AC), lighting, and plug loads. Inputs such as building orientation and configuration, glass-to-wall ratio, envelope constructions, external shading, internal lighting types and schedules, heating and cooling loads and schedules, and zone temperature set point and schedules were used. This model comprises 14 separate zones, including back offices, merchandise areas, receiving racks, service deli, interior pharmacy, and stockrooms. The primary EnergyPlus model characteristics can be seen in Table 1.

To verify that the model is correctly predicting the energy use of a real building, we compare our modeled electricity use to that from the actual building in Centennial, Colorado. The measurements included submetering on interior and exterior lighting, equipment, refrigeration, and AC. The model was within ±5% of the measured subsystem annual energy usage. More information on model validation can be found in Supplementary Figures 13 and 14.

We then explore how a big box store's electric load changes in both heating- and cooling-dominated climates by simulating the calibrated EnergyPlus model using typical meteorological year (TMY3) weather data for four cities: Phoenix, Arizona; Houston, Texas; Denver, Colorado; and Minneapolis, Minnesota. Heating and design conditions for these cities are summarized in Supplementary Table 1.

Monthly electricity use and peak power demand is highest in July and August for all cities studied, as seen in Fig. 2. In the summer months, the big box store simulated in Phoenix has the highest electricity usage (~630,000 kWh) and peak power demand (~1140 kW) in a month compared to other cities studied.

For each city, we analyze variances not only in monthly electricity use and peak power demand but also in the time series load profile (seen in Supplementary Figures 15–17). In winter months, the time series profiles in each city are fairly similar, because the building uses gas rather than electricity for heating. There are large demands in summer months to cool the building and provide refrigeration to groceries, especially in Phoenix and Houston due to hotter ambient temperatures [56]. There are no large electric load changes throughout the course of a week, as the building systems operate largely the same each day (this particular store operates 24/7). However, there is great variance throughout a day: during summertime in Phoenix, power demands are ~641 kW in the evening and ~1.1 MW midday. This relatively consistent diurnal trend can be attributed to the fact that business hours (e.g., the store being open vs. closed) and weather are the main contributors to electric load, rather than occupant density.

Generating electric vehicle station demand profiles

Because there is little real-world EV station demand data, we obtain synthetic but realistic EV station time series load profiles using an EV station model called the Electric Vehicle Infrastructure, Energy Estimation, and Site Optimization Tool (EVI-EnSite) [45,58]. Main inputs for EVI-EnSite can be seen in Supplementary Table 2. This tool uses an agent-based modeling approach where the vehicles and station are defined by a set of representative properties. For a vehicle, these prop-

Table 1
EnergyPlus big box store model characteristics.

Characteristic	Value (unit)
Square footage	19,500 (m^2)
Aspect ratio	1.7
Sales floor square footage	14,000 (m^2)
Floor-to-ceiling height	6.5 (m)
Wall construction	Medium-weight concrete block
Roof construction	R-20 insulation above deck with white ethylene propylene diene monomer rubber (EPDM) exterior
Lighting power density	8.3 (W/m^2)
Peak plug load density	10.8 (W/m^2)
Peak occupant density	30 (m^2/occ)
Percent conditioned	Fully heated and cooled
Rated AC efficiency	3.1–3.4 coefficient of performance (COP), depending on unit type and size*

* The range of COP values are based on the AC nameplate efficiencies, which were 3.1 COP for the three humidity control air handling units, whereas the 3- to 20-ton standard rooftop units ranged from 3.3 to 3.5 COP.

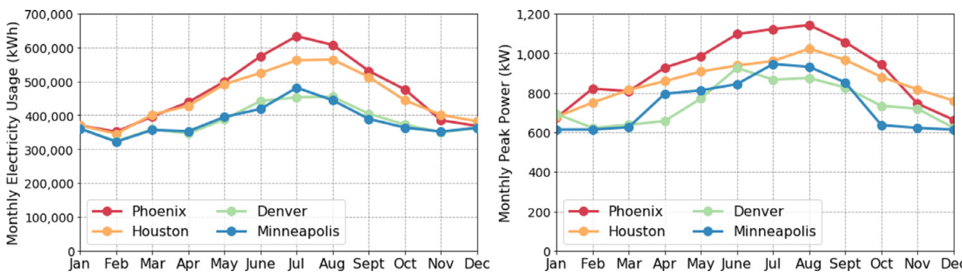

Fig. 2. Monthly (a) electric energy usage by city and (b) peak power demand by city.

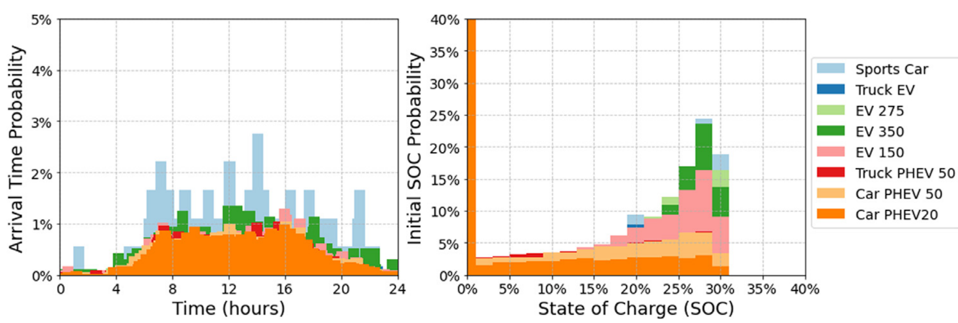

Fig. 3. Probability distribution functions of (a) arrival time and (b) initial state of charge by vehicle type.

erties include battery capacity, arrival time, and initial state of charge (SOC).

Monte Carlo simulations determine when vehicles arrive at the station, wait in the queue if there are no available ports to plug into, plug in if a port is available, charge according to their power acceptance curves, and depart the port after their energy demand needs are met. Monte Carlo simulation is an effective way of propagating the effect of stochasticity (here, probabilities of arrival time and initial SOC) through a system and investigating the stochasticity in the output. Each Monte Carlo iteration generates vehicle charging event instances that are slightly different from one another other but follow the underlying probability distributions. Such differences aggregate over the number of Monte Carlo iterations to provide the final station utilization statistics.

To obtain appropriate input probability distribution functions for arrival time and initial SOC for the Monte Carlo simulations, we process results of Minneapolis, Minnesota, conventional vehicle travel data and assume that each vehicle arrives at the station with a relatively low SOC (<15%) and leaves the station when its battery is charged to 90% SOC. This is based on a gas station theory, where the majority of vehicles arrive to fuel at a near-empty tank (low SOC) and leave with a full tank (high SOC). Charging to 100% SOC was not assumed, however, as this would increase the overall charging time at a station due to use of a constant-current, constant-voltage (CCCV) charging protocol, where charging rate declines as the battery nears full capacity [59]. The arrival time and initial SOC PDF inputs for the various vehicle types simulated is seen in Fig. 3.

Seen in the arrival time PDF in Fig. 3a, vehicle arrival peaks between 7:00 and 19:00, indicating that most charging occurs midday with bimodal peaks before and after typical working hours. Seen in the initial SOC PDF in Fig. 3b, plug-in hybrid electric vehicles (PHEVs) tend to arrive at the station with especially low, or even fully depleted, SOC because users drive the vehicle in the “electric only” mode first and then switch to gas.

We assume that big box store EV stations would predominantly be used by store customers with light-duty vehicles and design a “fleet” with a mixture of EVs and hybrids, or plug-in hybrid electric vehicles (PHEVs), that may be realistic in 2025 (Supplementary Table 3). Because the charging power of an EV is limited by either the power delivered by the port or what the EV’s onboard battery management system accepts [60], we altered each vehicle battery’s charge acceptance curve for the various power levels ran, such that the advanced battery vehicles could accept the full power level provided by the port, but the hybrids and less-advanced battery vehicles could not. To obtain this, we assume a 1.5 C-rate for the 50- and 150-kW power levels and 4 C-rate for the 350-kW power levels.

Several other EVI-EnSite model inputs are difficult to determine given the nascency of this technology, so we perform a sensitivity analysis on station design and utilization parameters to see their impact on

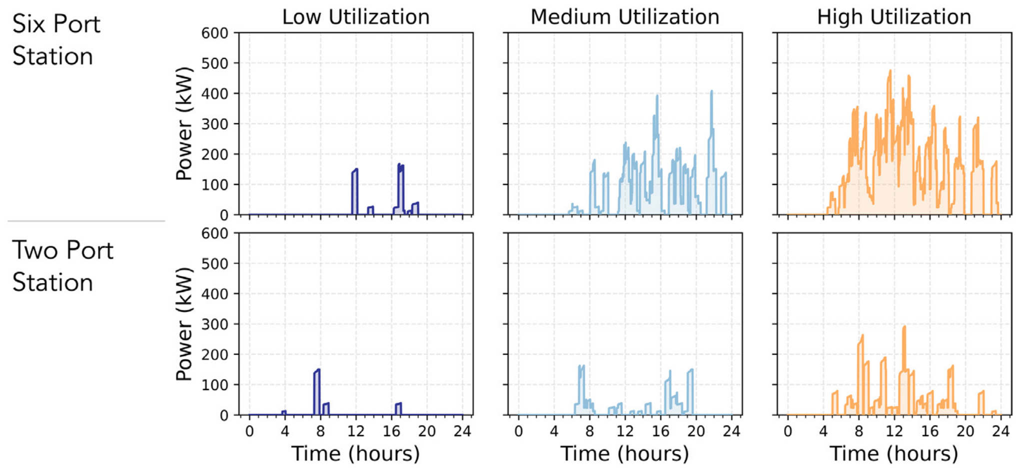

Fig. 4. Time series load profile effect of varying station size and utilization with 150-kW port charging level.

the resulting station load profile and monthly electricity usage. The two station design parameters are the number of chargers at a station and the power levels per charger. In varying the number of chargers at a station, we compare a two-port station to a six-port station as lower and upper bounds. Many EVgo fast-charging stations have two ports, and two-port stations seem to be common at grocery stores [5,17]. A Walmart gas station may have between 7 and 16 pumps [61,62], but a 6-port station was chosen for our analysis because even if EVs did penetrate a significant portion of the market, EV owners can also refuel at home or work, whereas gas-powered vehicles must refuel at gas stations [5–7].

In varying the power levels delivered by each charger, various DC fast-charging power levels were analyzed: 50 kW, 150 kW, and 350 kW. Level 2 (L2) charging was not considered, as it is most practical in homes, offices, and hotels where people regularly reside for 4 or more hours [63], rather than retail sites with shorter dwell times [21]. There are some L2 stations at grocery stores [17], but because this study specifically assesses charging from <15% SOC to 90% SOC, the average charging duration would be 3–5 h, causing unrealistic dwell and queue times. "Fairly fast" charging at 50 kW might be ideal for big box stores in addition to restaurants and bars, where dwell times are relatively long (compared to corridor charging) due to the nature of the trip. Plans for 150-kW fast charging are evident: most major charging station networks are now deploying 150-kW chargers, and OEMs including Mercedes, Jaguar, Porsche, BMW, and Tesla have announced or produced vehicles that can accept 150 kW [64,65]. Finally, 350-kW extreme fast charging [66] was considered because various EV stakeholders are targeting this rate [22,24–27].

Regarding station utilization parameters, we vary the average daily frequency of EV charging events, assessing real-world data to obtain possible bounds of the system. Assessing EVgo data, we found that the busiest station saw an average of 16 events per day per port. However, a prior study [60] saw an average of two events per day per port at some sites [5]. For DC fast charging stations throughout five European countries, one study published average station utilization between 1.1% and 13.6% in 2020, with the top 30 most-utilized stations seeing between 4% and 26% [67]. In this paper, where we assume each charging event is relatively long (using the previously described gas station theory), 15% station utilization correlates to ~16 charging events per port per day for 350 kW stations and ~3 events per port per day for 50 kW stations. As the number of charging events per day per port has high variation among sites, we considered low-, medium-, and high-utilization scenarios representing 2, 8, and 16 events per port per day, respectively. Stations may be initially oversized (or have underutilized ports) to accommodate the likely increasing demand with growing EV adoption [14].

Fig. 4 shows sample daylong time series results varying station port count and station per-port utilization for a 150-kW station. Sensitivity of port count and utilization for the 50 kW and 350 kW are found in Supplementary Figures 1 and 2, respectively. As previously mentioned, low-, medium-, and high-utilization scenarios, representing 2, 8, and 16 events per port per day, respectively, were considered. The average charging event duration is ~30 min and peak daily power demand varies from 150 kW for the low-utilization, two-port station to 474 kW for the high-utilization, six-port station. Time series load profiles for a full week, displaying the stochastic variation from Monte Carlo simulation, are found in Supplemental Figures 3–5.

Combining timeseries data

Fig. 5 shows results when combining building and EV station demand profiles. Here, we demonstrate how the additional demand introduced by on-site EV charging affects the Phoenix big box store's demand load profile during a sample day in the summer, which was the highest electricity demand for any of the cities. High demands from building AC are already straining electricity systems [56], so adding new demands from EV charging poses an even larger challenge.

A station with two 50-kW ports makes little difference to a big box store's demand profile, but a station with six 350-kW ports can have electric demands greater than the building. The six-port, 350-kW (per-port) station's peak demand depends on when the vehicles arrive to charge: if all vehicles were to charge at once, up to 2.1 MW of electricity would be required for the EV station alone. The number of ports at a station can greatly affect the peak power demand at a station, which is likely why utilities are developing rate structures to discourage installing large stations with underutilized ports and would prefer that a station owner waits to increase the port count at a station when the per-port utilization increases [68].

Impact on monthly electricity usage and peak power demand

We complete EnergyPlus simulations for each building and EV scenario, adding the EV station time series profile as an exterior equipment load to the big box store site. During each month of simulation, we record when peak electricity demand was greatest, the time at which that demand occurred, and the component breakdown of what led to that peak demand. Fig. 6 shows the highest electricity demand for each month for different big box store locations, keeping the EV station parameters constant (two ports, low utilization, 150 kW per port).

Phoenix has the highest peak power demands of all cities simulated, largely due to high cooling (>415 kW) and refrigeration (>278 kW) demands. Comparatively, Minneapolis cooling and refrigeration loads peak at 314 kW and 262 kW, respectively. Assuming the EV station and building are behind the same meter for the building simulated in

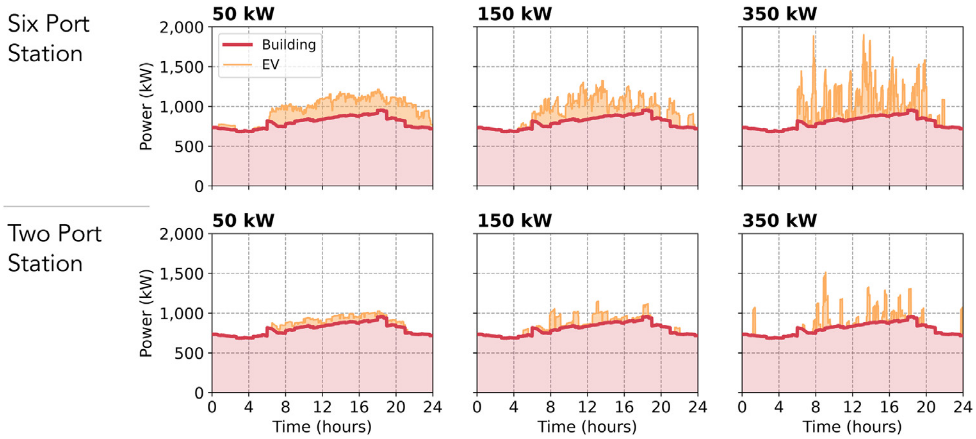

Fig. 5. Comparing Phoenix "summer" time series load profile to EV "high utilization" scenario.

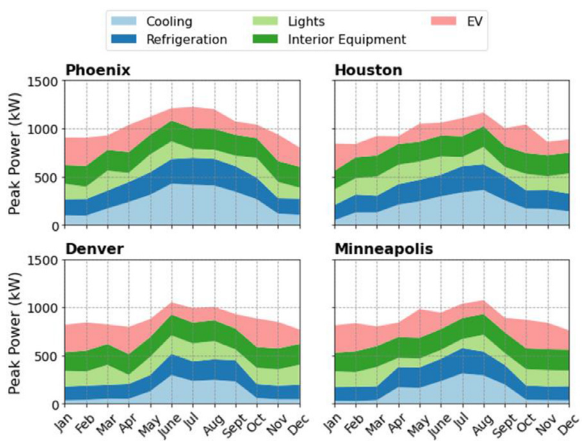

Fig. 6. Component breakdown for monthly peak power demand at 1-minute intervals for two-port, low-utilization, 150-kW-per-port station for big box store simulated in four cities (Phoenix, Houston, Denver, and Minneapolis).

Phoenix, this two-port, 150-kW-per-port station accounts for an average of 21% of monthly peak demand throughout a simulated year—as low as 10% in June and as high as 32% in February. The effects of the EV station on peak demand are exacerbated in cold climates: in Minneapolis, the EV station accounts for an average of 25% of peak demand throughout a simulated year—as low as 13% in August and as high as 35% in January. Because the building uses gas rather than electricity for heating, an EV station accounts for a similar percentage of monthly peak demand in winter regardless of city.

Fig. 7 shows the effects of changing EV station parameters, fixing the location of the building to Phoenix. We vary port power level and station utilization, comparing low- and high-utilization scenarios for a two-port station.

A two-port, 50-kW-per-port, low-utilization station does not largely contribute to the peak power demand of a big box store in Phoenix; assuming the EV station and building are on the same meter, the EV station accounts for an average of 5% of peak demand throughout a simulated year. In months when AC loads are particularly high (e.g., August), the peak demand of the month happens to occur when no EVs are charging at the station. Alternatively, a six-port, 350-kW-per-port, high-utilization station dominates demand, contributing to an average of 70% of peak demand throughout a year and a maximum of 78% in December when there are little cooling loads. Therefore, as both the utilization and power levels of an EV station increase, there is a higher probability of a significantly higher peak load.

Whether or not the monthly peak power demand correlates to when EVs are charging depends on what time the vehicles arrive to charge. Based on the input arrival time probability distribution function (Fig. 3), our simulations predict many EVs to arrive at the same time that building AC loads are the highest, between 12:00 and 20:00 (Supplementary Figure 17). There are limited public data regarding when the greatest levels of public charging at big box stores may occur, but current studies tend to suggest that peak hours of grocery stores are between 12:00 and 18:00 [69–71]. Incentives could be designed such that EVs charge more in the morning during peak solar irradiance (assuming plentiful solar photovoltaics) or in the evening when traditional building loads are lower in efforts to lower monthly peak electricity demand. For example, the power demand for a big box store in Phoenix during summer months varies from >1.1 MW midday to 641 kW at night, creating a daily delta of 481 kW (see Supplementary Figures 15 and 16). Clearly, if timed properly, this could easily supply capacity for a 350-kW port without increasing monthly peak demand. Perhaps a change in behavior (e.g., incentivizing customers to shop in the morning) could alleviate this scenario. However, the carbon intensity of the grid at midday may be low due to peak PV generation, so the timing of charging may need to also consider grid emissions in addition to power demand.

Fig. 7 breaks out how each end use, including EV charging, impacts monthly peak demand, showing that EV contributes to peak demands similar to that of interior equipment and refrigeration at lower power levels (50 and 150 kW) but exceeds all components of the building at power levels of 350 kW per port. Due to the level of detail in components causing demand (i.e., cooling, lights, refrigeration), it was difficult to demonstrate all station parameters and station utilization levels studied. Therefore, we only compare low and high utilization levels for a two-port station.

Fig. 8 compares the percentage increase in peak monthly demand with an EV charging station (including all utilization levels, station sizes, and power levels studied) to the corresponding percentage increase in monthly electricity usage for a big box store in Phoenix in summer and winter months. More detailed comparison can be seen in Supplementary Figures 6–8.

In all scenarios, the percent increase in monthly electricity demand is an order of magnitude greater than the percent increase in monthly electricity use. This effect is exacerbated in winter months, when building electricity use is lower due to lower cooling and refrigeration demands. The increase in monthly electricity demand is as low as 9% for the 50-kW, two-port, low-utilization scenario and as high as 264% for the 350-kW, six-port, high-utilization scenario. For these cases, however, the increases in monthly electricity usage are only 1% and 29%, respectively. DC fast charging, especially at 350-kW power levels, has the ability to make a significant impact on a site's peak power demand but comparatively little difference to its monthly electricity usage.

We note that this study assumes that station utilization is independent of port power level. It does not capture the fact that many more charging events are possible with extreme fast charging, especially at

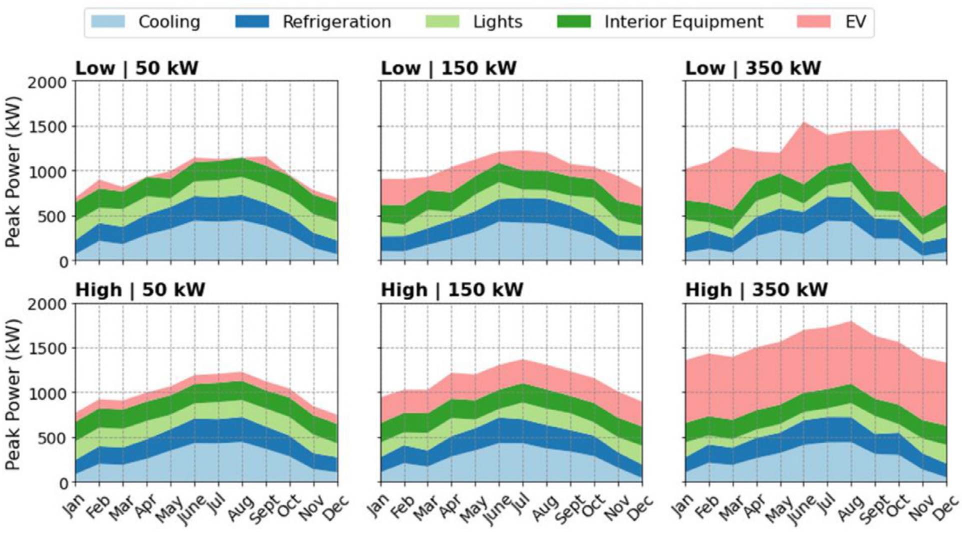

Fig. 7. Component breakdown for peak power demand at 1-minute intervals in Phoenix for a two-port station, varying utilization and power level.

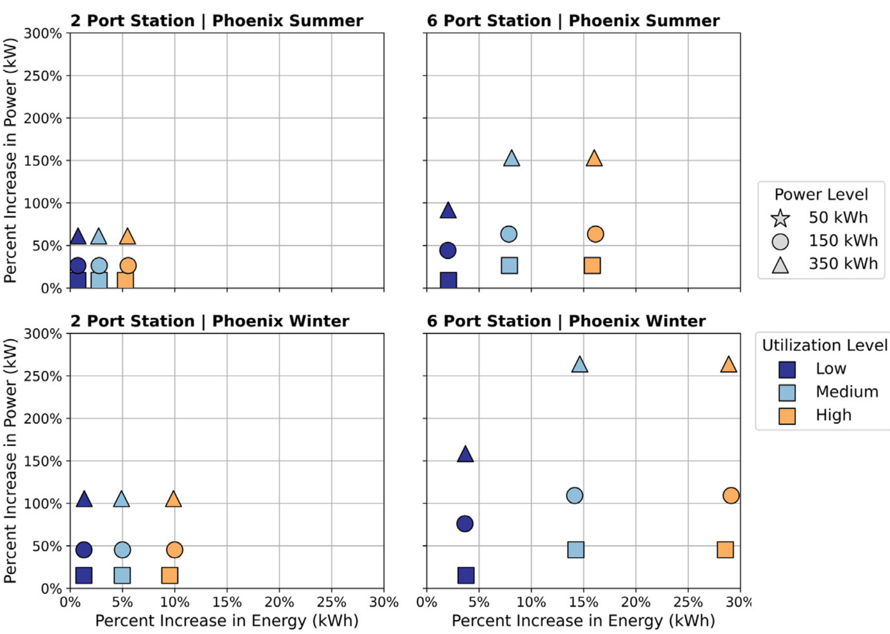

Fig. 8. Comparing percent increase in monthly demand to percent increase in electricity usage due to EV charging.

levels at or above 350 kW, where each event is around 12 min in duration (Supplementary Figure 9). This is evident in the queuing analysis explored in Supplementary Figures 10 and 11, where two-port, high-utilization stations of 50-kW, 150-kW, and 350-kW power levels experienced average queue times of 74 min, 16 min, and 1 min, respectively. Ideally, no customers would queue more than a few minutes to refuel, so based on this arrival time distribution, 16 events per port per day is only realistic for a two-port, 350-kW station. For a two-port, 150-kW station, a medium-utilization station (eight events per port per day) is more realistic, with an average wait time of 3 min to charge. For a two-port, 50-kW station, however, even a medium-utilization expectation is unrealistic due to an average queue duration of 12 min.

Impact on annual electricity bill

Both electricity use and peak power demand greatly affect electricity bills, which typically comprise fixed charges, energy-related charges (corresponding to the total electricity consumption over a month), and demand-related charges (corresponding to the peak power demand over the course of a month). To understand how EV charging can impact a big box's annual electricity bill, we calculate the bill using actual utility rate tariffs [72], selecting Denver, Colorado (Xcel Energy); Chicago, Illinois (Commonwealth Edison); and New York, New York (Consolidated Edison), as they are relatively straightforward and illustrative of three types of rate structures. Key descriptions of these tariffs are summarized in Table 2.

There are many nuances between the tariffs, such as when the on- and off-peak times occur for rates with TOU components. However, to simplify variances for the analysis, we refer to the Denver Xcel Energy rate as having "High Demand Charges," the Chicago Commonwealth Edison rate as having "Moderate Demand Charges," and the New York City Consolidated Edison rate as having "No Demand Charges." Demand charges cover the utility's cost for being able to meet a customer's highest kilowatt usage and have the greatest potential to significantly increase a customer's costs when adopting EVs [73], as EV charging events have very high power for a relatively short amount of time (especially when approaching 350-kW power levels). They are generally based on the highest level of electricity demand over a 15-minute period in a billing cycle [74]. This study analyzes and compares 1-minute time series data for both the building and EV station. However, utility demand

Table 2
Key descriptions of the three utility rates studied: Xcel Energy, Commonwealth Edison, and Consolidated Edison.

Rate	Energy Rate (¢/kWh)	Demand Charge ($/kW)
Denver (Xcel Energy)	Low TOU (4.27 on peak; 2.96 off peak)	High (16.47)
Chicago (Commonwealth Edison)	Moderate non-TOU (7.47 on and off peak)	Moderate (6.47)
New York City (Consolidated Edison)	High TOU (14.47 on peak; 1.08 off peak)	None

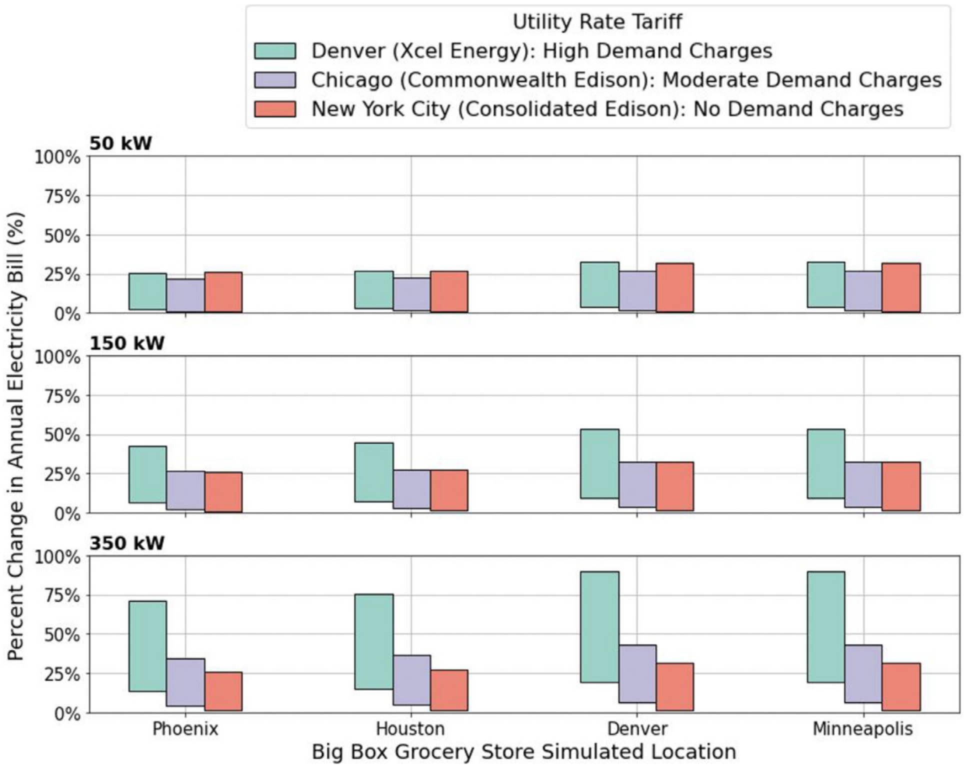

Fig. 9. Percent changes in annual electricity bill from building-only scenario to building and electric vehicle station scenario.

charges are often on a 15-minute average rolling basis. Thus, there is a difference between the peak power demand that utilities must be prepared for (1 min data) and what customers may be billed for based on current 15-minute rolling average demand charges (15-minute average data). Supplementary Figure 12 compares the results for 1-minute and 15-minute average data.

We compute the annual electricity bill for each location, utility rate tariff, and EV station port power level and compare the “base case” with no EV station to upper and lower bounds for the combined building and EV station. The upper bound correlates to a high-port, high-utilization station (6 ports/16 charging events per day per port) and the lower bound correlates to a low-port, low-utilization station (2 ports/2 charging events per day per port). For all EV scenarios that fall between these two extremes, the annual electricity bill would fall between these bounds. The percent increase in electricity bill from the base case, building-only scenario to that of a meter that includes both the building and EVSE is seen in Fig. 9, including upper and lower bounds for the impact of the EV station.

Annual electricity bills for scenarios incorporating the Xcel Energy tariff (high demand charges) vary the most with the addition of EVSE, especially at 350-kW power levels. Contrastingly, Consolidated Edison (no demand charges) sees the smallest increase in annual electricity bill when adopting EVSE. Cold-climate areas that have lower AC loads (Minneapolis) coupled with Xcel Energy’s tariff are most susceptible to significant changes in the annual electricity bill with the addition of EVSE: the annual electricity bill of a big box store could increase by as much as 88% when adding a 350-kW, six-port, high-utilization station. For context, this could occur while adding only 29% to the monthly electricity usage in months where changes are most significant (winter).

Understanding that demand charges can greatly impact an electricity bill with the addition of DC fast-charging stations, several utilities, including Xcel Energy, Pacific Gas and Electric, and Southern California Edison, are either reducing or eliminating demand charges on EV-specific utility rate tariffs. Many state that demand charges are barriers to the widespread availability of DC fast-charging stations [15,68,73]. Most of these programs are limited term; for example, Southern California Edison’s new EV rate plan offers a 5-year demand charge holiday, followed by a 5-year demand charge that is 40% below the current charge. Given the large impact of EV charging on peak demand at buildings, utilities may find it difficult to alter or eliminate demand charges without endangering their bottom lines [15].

Discussion

Future research should consider total cost of ownership of nonresidential electric vehicle charging stations. The upfront capital cost of various station-related equipment as well as costs of necessary upgrades to the distribution system should be considered alongside effects on the annual electricity bill. One should note that big box store owners may also desire longer charging dwell times to encourage customers to shop longer and spend more money. Seen in Supplementary Figure 9, average charging duration was 12 min for a 350-kW port, 32 min for a 150-kW port, and 50 min for a 50-kW port. In 2018 in the western region of the United States, the average time spent by consumers at grocery stores varied between 28 and 34 min [75]. Future research can address if 12 min charging on 350-kW ports is necessary for a big box store setting, understanding that it causes greatest increases to a site’s annual electricity bill and requires higher upfront costs for installation [76].

Additionally, the benefits of load flexibility, behind-the-meter storage and on-site generation for these sites should be assessed in greater detail. Flexible loads, on-site solar photovoltaics, energy storage, and controlled electric vehicle charging may mitigate high electricity demands and annual electricity bills caused by DC fast charging. Thermal energy storage could displace refrigeration and cooling loads whenever charging occurs, eliminating load from a chiller or air conditioner for a short amount of time. This analysis helps determine to what extent thermal energy storage could be helpful. Seen in Fig. 7, if cooling and refrigeration loads could be nonexistent while electric vehicle fast charging is occurring, all vehicle charging loads for the 50-kW and 150-kW scenarios could be displaced. However, in the 350-kW charging scenarios, this is not possible because electric vehicle station demands are even greater than all cooling and refrigeration demands. In these cases, thermal energy storage and battery storage could be superimposed, discharging simultaneously to avoid high demand charges from extreme fast charging, benefiting both the system owner and electric grid.

Conclusions

As efforts continue to promote transportation electrification, it is important to understand the possible effects of electric vehicle charging on the grid, especially as higher power levels of charging become more prevalent. Even if the total electric vehicle market share remains limited, clusters of high adoption can greatly affect specific sites, such as big box stores in urban areas. While it is important to understand the possible effects of fast charging at these retail sites, there is little adequate literature to date regarding the energy demands of nonresidential DC fast charging. Therefore, research comparing the electricity use of big box stores and nonresidential DC fast charging stations is sparse.

In this study, we explore the impacts of charging on a big box store's monthly electricity use, peak power demand, and annual electricity bill. To obtain realistic building demand profiles, we develop an EnergyPlus building energy model of a big box store in Centennial, Colorado, according to the as-built architectural, mechanical, and electrical drawings. We then calibrate this model to 5 years of detailed submetered data, ensuring that the model accurately captures the electric power profile of each subsystem, including refrigeration, heating, ventilation, AC, lighting, and plug loads. To verify that the model is correctly predicting the energy use of a real building, we compare our modeled electricity use to that from the actual building in Centennial, Colorado by submetering on interior and exterior lighting, equipment, refrigeration, and AC, finding that the model was within ±5% of the measured subsystem annual energy usage.

To produce synthetic but realistic electric vehicle station load profiles, because there is little real-world station demand data currently available, we use an electric vehicle station model called EVI-EnSite [45,58], where Monte Carlo simulations determine when vehicles arrive at the station, wait in the queue if there are no available ports to plug into, plug in if a port is available, charge according to their power acceptance curves, and depart the port after their energy demand needs are met. To obtain appropriate inputs for this model, we process results of Minneapolis, Minnesota, conventional vehicle travel data and assume that each vehicle arrives at the station with a relatively low state of charge and leaves the station when its battery is charged to 90% state of charge.

We find that fast charging can make a significant impact on a site's peak power demand (increasing monthly peak power demand at the site by over 250% in some cases) but comparatively little difference to its monthly electricity use. This effect becomes stronger as per-port power levels increase. In addition, we find that cold-climate areas (with lower AC loads) paired with rate structures incorporating high demand charges are most susceptible for significant changes to the annual electricity bill, with increases as high as 88%. Understanding that capacity issues are most likely to occur if station loads overlap with existing building demands, we also assess when building and electric vehicle loads tend to occur. Our model predicts that electric vehicles will arrive to charge at the same time building AC loads are the highest – in late afternoon between 12:00 and 18:00. Incentives for vehicles to charge between 20:00 and 6:00 (at night) when building loads are lowest could make a huge impact on monthly peak electricity demand and the need for upgrades to the distribution system. Daily power demand for a big box store in Phoenix during summer months fluctuates greatly, from >1.12 MW midday to 641 kW at night. This 481-kW delta could supply enough capacity for a one 350-kW port if controlled appropriately.

Declaration of Competing Interest

None.

CRediT authorship contribution statement

Madeline Gilleran: Conceptualization, Writing – original draft, Methodology, Software, Visualization. **Eric Bonnema:** Methodology, Validation, Formal analysis, Writing – original draft, Writing – review & editing. **Jason Woods:** Conceptualization, Methodology. **Partha Mishra:** Methodology, Software, Writing – original draft. **Ian Doebber:** Methodology, Software, Writing – original draft, Validation, Writing – review & editing. **Chad Hunter:** Writing – review & editing. **Matt Mitchell:** Writing – review & editing. **Margaret Mann:** Supervision, Funding acquisition.

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Data availability

All electric profiles that support the findings in this study are freely available for download. This includes yearlong time series profiles for the big box stores simulated in Phoenix, Houston, Denver, and Minneapolis, as well as yearlong EV charging time series profiles for the various ports, charging levels, and station utilizations studied.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.adapen.2021.100062.

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