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Electric vehicle charging behavior: An analysis of workplace charging heterogeneity to improve charging network planning.

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Capstone Project Report

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Capstone project approval

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Summary

Adoption of electric vehicles is surging across the state, country, and world, driven by government policies to reduce carbon emissions from the transportation sector. To maximally reduce emissions of EVs, however, drivers must charge their vehicles when clean electricity generation, such as solar and wind power, is abundant. In California, this means charging during the daytime when most people are at work.

Workplace charging plays a pivotal role in this context. Many EV drivers, especially those living in apartments or rented accommodations, lack access to home charging options. For these drivers, workplace charging provides a critical solution, enabling them to charge their vehicles during the day when renewable energy is most available. Moreover, workplace charging can significantly alleviate range anxiety, making EVs a more viable and attractive option for a broader segment of the population. Although the affordability of EVs has improved significantly, the challenge remains in finding reliable and accessible charging stations. Workplace charging addresses this issue, aligns with the goal of equitable access to charging infrastructure, promotes adoption, and supports the wider transition to electric mobility.

This study examines drivers' charging behavior at charging facilities at the University of California San Diego and is extensible to any workplace. The primary motivation is to analyze the heterogeneity in where and how EV drivers charge their vehicles. By mining natural variations in the data, the study aims to inform institutional policies and planning that encourage workplace charging and deliver a positive charging experience for drivers.

A. Project scope and methodology

Using datasets on drivers' preferences around charging, charging sessions, and UCSD's EV charging network, this project conducted a detailed analysis of EV drivers' charging behavior, focusing on both the spatial and temporal aspects of charging. The data for this study are derived from enrollment surveys of 806 real (anonymized) UCSD EV drivers, alongside more than 55,000 unique charging sessions retrieved from the two main charging service providers at UCSD—ChargePoint and PowerFlex. Key components of the study include:

Imbalances in the demand for charging and the supply of chargers across campus. Understanding the demand-supply imbalance in charging sessions across various campus locations is crucial. The study identifies garages with high demand but relatively few chargers, leading to significant disparities and underutilization of network efficiencies.

Driver preferences for campus charging location vs. what is revealed by their real charging behavior. The study compares drivers' stated ideal campus charging location with actual charging session data to identify discrepancies and analyze supply-demand imbalances across the campus that may cause deviations in charging location.

The depth, or size, of sessions that drivers' initiate. Analyzing whether drivers engage in deep or shallow sessions and how these behaviors are distributed spatially across campus. Frequent shallow sessions are identified as a significant factor leading to an underutilized and inefficient charging network.

Identification of driver traits that affect session depth. The study emphasizes identifying commuter traits that influence EV charging infrastructure needs at both micro and macro scales. This includes demographic factors, such as their affiliation, where they live, access to home charging, and commute distances.

The analysis of EV charging behavior at UCSD reveals critical insights into the utilization patterns, demand-supply imbalances, and session depths across different campus zones. By examining the data, several key findings have emerged that highlight the unique challenges and opportunities within the existing charging infrastructure. These findings provide a foundation for targeted improvements to enhance network efficiency, equity, and overall user satisfaction. While the study focuses on behaviors at UCSD, the lessons learned are anticipated to be generalizable to other workplaces outside the campus.

B. Key findings

Supply and demand imbalances:

There are significant disparities in the availability of charging infrastructure across different campus zones. High-demand garages such as Athena, Gilman, and Scholars experience notable supply shortages, leading drivers to frequently deviate from their preferred charging location and charge elsewhere. Six garages with high demand but few forthcoming chargers were identified – Bachman, Campus Point East, Campus Point West, Rady, School of Medicine, and Keck.

Charging session depth:

Data reveal that garages with lower demand-supply ratios have higher rates of shallow charging sessions. These shallow sessions are less efficient and can contribute to congestion at charging stations. Encouraging deeper charging sessions can improve network efficiency and parking garage utilization.

Influencing factors:

Access to home charging, commute distance, and driver demographics significantly impact charging behavior. Drivers without home charging access, particularly those from lower-income groups, face greater challenges in finding available charging spots and have higher deviation sessions. Temporal patterns show peak usage times coinciding with typical work hours, stressing the need for optimal charger placement and availability.

C. Conclusion and recommendations

This study on workplace EV charging behavior at UCSD provides crucial insights into the significant disparities and heterogeneity in the demand for charging and supply of charging infrastructure across different campus zones. The findings reveal prevalent shallow charging sessions and high demand-supply imbalances in specific garages, leading to network inefficiencies and driver inconveniences. To address these issues, the following strategies are recommended:

Prioritize installing new charging stations where supply-demand imbalances are greatest:

Prioritizing the installation of new charging stations in garages with high demand-supply imbalances, such as Athena, Gilman, and Scholars, to address current imbalances is crucial for mitigating deviation sessions and encouraging deeper sessions. It is important to focus on maximizing kWh sales, EV throughput, and charger cost recovery while also considering goals of access and equity.

Encourage deeper charging sessions:

Implementing incentives such as kWh-based pricing may encourage deeper charging sessions, reducing the frequency of shallow sessions and optimizing charger usage. Additionally, developing targeted support programs for drivers lacking home charging options, including dedicated charging slots for long-hour charging.

Optimize charging schedules:

Introducing a reservation system or time-based access to manage peak usage times, distributing the charging load more evenly and reducing congestion during peak hours may influence behavior heterogeneity.

Continuous monitoring and adaptation:

Establishing a continuous monitoring system to assess the performance and utilization of the charging infrastructure will inform decisions on future expansions and improvements. Preferably, focus on those parking garages where actions are most required. The enrollment survey-led incentive mechanism already exists as an effective method to communicate behavioral benefits directly to users.

Expand public awareness and education:

Awareness campaigns to inform drivers about the benefits of optimal charging practices and the impact of their behavior on network efficiency may increase emphasis on deeper charging sessions, including improved commute efficiency and potential incentives.

By adopting these recommendations, UCSD can enhance the performance and user satisfaction of its charging network, supporting the broader adoption of electric vehicles and contributing to sustainable transportation initiatives on campus.

Content

Figure

Table

Abbreviation

Arbor	Arbor Hillcrest Parking Structure
Athena	Athena Parking Structure
Bachman	Bachman Hillcrest Parking Structure
BEV	Battery electric vehicle
Birch	Birch Aquarium SIO
CARB	California Air Resources Board
CASIO	California Independent System Operator
CO2	Carbon Dioxide
CP East	Campus Point East Parking Structure
CP West	Campus Point West Parking Structure
CPO	ChargePoint operator
CSC	Campus Services Complex
CSP	Climate Science and Policy
CUP	Central Utilities Plant
DCFC	Direct Current Fast Charging
DOE	Department of Energy
ECUP	East Campus Utilities Plant
EIA	US Energy Information Administration
EV	Electric vehicle
EVSE	Electric Vehicle Supply Equipment
GHG	Greenhouse gas
Gilman	Gilman Parking Structure
HFCV	Hydrogen fuel cell vehicle
Hopkins	Hopkins Parking Structure
Hubbs	Hubbs Hall Parking SIO
Keck	Keck Oceanographic and Atmospheric Research SIO
kWh	Kilowatt-hour
L2	Level 2 (refers to Level 2 chargers)
LSTM	Long-Short Term Memory
Marine CTF	Marine Conservation Technology Facility SIO

MAS	Master of Advanced Studies
Med Centre	Medical Centre Parking Structure
Mesa Nuevo	Mesa Nueva Parking Structure
MESOM	Marine Ecosystem Sensing, Observation and Modelling SIO
MSE	Mean Squared Error
N	Number of unique drivers (used in the context of transition matrix)
NREL	National Renewable Energy Laboratory
Nuevo East	Nuevo East Parking Structure
Nuevo West	Nuevo West Parking Structure
OEM	Original Equipment Manufacturer
OMS	One Miramar Street
Pangea	Pangea Parking Structure
PHEV	Plug-in hybrid electric vehicle
PwC	Price Waterhouse Coopers
Rady	Rady School of Management Parking Structure
Ritter	Ritters Hall Parking SIO
RNN	Recurrent Neural Network
Scholars	Scholars Parking Structure
Seaside Forum	Scripps Seaside Forum SIO
SIO	Scripps Institution of Oceanography
SOC	State of Charge
SOM	School of Medicine
South	South Parking Structure
South Mesa	Mesa Canyon Parking Structure
Theatre Dist.	Theater District Parking
Torrey Pines	Torrey Pines Center South Parking Structure
UCSD	University of California San Diego
V2G	Vehicle-to-Grid
ZEV	Zero Emission Vehicle

I. Introduction

The transportation sector accounts for roughly 16% of total GHG emissions, with road transportation contributing around 11% (2022) of the total global share.[1,2] In the United States (US) it accounts for 29%, while more than half, i.e. about 58% of road transportation emissions stemming from light-duty vehicles, referred to as passenger cars.[3] To address this issue, the transportation sector is undergoing a massive transition to cleaner and more affordable means of mobility options. Electrification of mobility is a crucial component of this transition. Among the variety of alternatives, the adoption of BEVs, PHEVs, and HFCVs is widely promoted and accepted. Both government and private players have leveraged a range of subsidies and technological advancements to drive these changes, resulting in significant strides toward sectoral decarbonization. The impact of these efforts is evident in the reduction of direct air pollution and overall GHG emissions. A study suggests that BEVs emit significantly lower lifecycle GHG emissions compared to conventional gasoline cars, even when considering the emissions from electricity generation.[4] In California, cities with high EV adoption rates, such as Los Angeles and San Francisco, have reported substantial improvements in air quality, benefiting public health.

Governments worldwide are implementing policies to encourage the adoption of BEVs. For instance, the US government has implemented several policies to encourage the adoption of electric vehicles. Federal tax credits of up to $7,500 for new and up to $4,000 for eligible used EV purchases are available, which has significantly boosted consumer interest and sales.[5] Additionally, many states offer incentives, such as California's Clean Vehicle Rebate Project, which provides rebates for the purchase or lease of qualifying EVs.[6] Similarly, private sector initiatives are also playing a pivotal role. Light-duty EV manufacturers like Tesla, Rivian, and Lucid Motors are at the forefront of producing advanced BEVs with longer ranges and shorter charging durations, making EVs more appealing to the end consumers.[7] Technological advancements are further accelerating the shift to electric mobility.

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[1] Our World Database, (2022). Greenhouse Gas Emissions by Sector. <https://ourworldindata.org/ghg-emissions-by-sector>

[2] The Climate Watch Data, (2021). Historical GHG Emissions. <https://www.climatewatchdata.org/ghg-emissions?end_year=2020&source=US&start_year=1990>

[3] U.S. Environment Protection Agency, (2023). < https://www.epa.gov/greenvehicles/fast-facts-transportation-greenhouse-gas-emissions>

[4] International Council on Clean Transportation, (2022). The lifecycle emissions of electric vehicles. <https://theicct.org/publication/ghg-benefits-incentives-ev-mar22/>

[5] U.S. Department of Energy, (2023). Federal Tax Credits for New All-Electric and Plug-in Hybrid Vehicles. <https://www.energy.gov/save/electric-vehicles>

[6] California Air Resources Board, (2023). Clean Vehicle Rebate Project. <https://ww2.arb.ca.gov/resources/fact-sheets/clean-vehicle-rebate-project>

[7] U.S. Department of Energy, (2023). Federal Tax Credits for New All-Electric and Plug-in Hybrid Vehicles. <https://fueleconomy.gov/feg/tax2023.shtml>

Improvements in battery technology have increased energy density and reduced the cost of batteries, making BEVs more competitive with traditional internal combustion engine vehicles.[8] The development of fast-changing technologies is also enhancing the convenience of driving EVs, reducing charging anxiety significantly.

The future of light-duty transportation is electric mobility. EVs are now growing rapidly, with over 14 million global sales in 2023, which is a 35% increase from the 2022 trend globally.[9] The global number of EVs has reached an all-time high at 40 million in 2023. Although global sales of BEVs are on the rise, they are largely concentrated in China, Europe, and the US. By 2023, nearly 60% of new electric cars were registered in China, almost 25% in Europe, and only 10% in the US, which collectively accounts for about 95% of global EVs on the road. This means that, out of all new cars registered, more than one-third are EVs in China, one-fifth in Europe, and one in ten in the US. In terms of the US, EV sales reached a record high with over 1.4 million in 2023, i.e. 40% year-over-year growth compared to the 2022 trend in this segment.[10] As shown in figure 1, the US EV transportation sector is projected to undergo a 10 times growth by 2030, and will consistently grow thereafter.

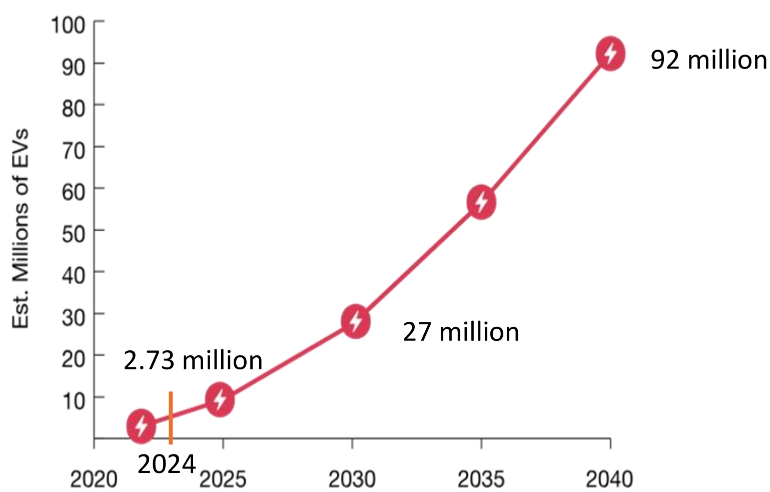

Fig 1. Projected growth trend of EV sales in the US market.
Source: PwC Analysis (Akshay Singh, A. M. (2021).

According to the PwC analysis of the US EV growth market, the infrastructure to support such a growth segment is projected to grow over $100 billion by 2040. Being among the early

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[8] BloombergNEF, (2023). Electric Vehicle Outlook 2023. <https://assets.bbhub.io/professional/sites/24/2431510_BNEFElectricVehicleOutlook2023_ExecSummary.pdf>

[9] Global EV Outlook, International Energy Agency, (2024). <https://www.iea.org/reports/global-ev-outlook-2024>

[10] Trend in Electric Cars, Global EV Outlook, International Energy Agency, (2024). <https://www.iea.org/reports/global-ev-outlook-2024/trends-in-electric-cars#abstract>

starters and widely spread across the nation, ChargePoint, a prominent charging service provider in the US EV charging market, has a chance of generating most of the revenue. As shown in figure 2, growth is expected in the service and maintenance of charging infrastructure. The largest growth is assumed to be in the advanced hardware solutions that will drive over 20 billion market by 2030. Operations and maintenance-related software will grow but contribute a smaller portion of the market. What this indicates is the thriving state of the EV market ecosystem, both presently and in the future, which is a positive sign for continuum investments in research and innovation.

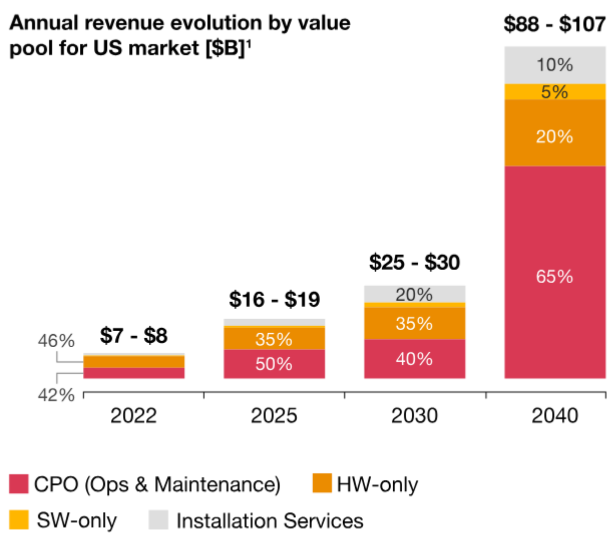

Fig 2. Growth projection of EV infrastructure in the US by 2040. The upper range of revenue is assumed to be full adoption by 2040, and the lower range is assumed by 2045. CPO refers to ChargePoint operators, HW is hardware, and SW is software.
Source: PwC Analysis.[11]

California state emerged as a frontrunner in adoption, accounting for a 37% increase in light-duty EVs in 2022.[12] From 2016 to 2022, the number of registered EVs in California quadrupled, from 0.24 million to 1.1 million.[13] According to some estimates, there could be 12 million EVs on California roads by 2035.[14] As EV adoption accelerates, the demand for suitable charging infrastructure becomes increasingly critical. Currently, in the US there are approximately 0.18 million public and private charging ports available, which is insufficient

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[11] The US electric vehicle charging market could grow nearly tenfold by 2030: How will we get there. PwC Analysis. <https://www.pwc.com/us/en/industries/industrial-products/library/electric-vehicle-charging-market-growth.html>

[12] U.S. Energy Information Administration. <https://www.eia.gov/state/seds/seds-data-fuel.php?sid=US#OtherIndicators>

[13] Alternative Fuel Data Centre. <https://afdc.energy.gov/stations/#/find/nearest?show_about=true>

[14] California Energy Commission. <https://www.energy.ca.gov/data-reports/energy-almanac/zero-emission-vehicle-and-infrastructure-statistics/light-duty-vehicle>

to support the growing EV population on the road.[15] In California, there are 75 EVs per charging location, the second highest in the nation, which is insufficient for the emerging demand.[16,17] California alone needs to expand the charging network significantly, aiming to reach 0.25 million charging stations by 2025 to meet the state's ambitious EV goals.[18] It is projected that approximately 1.01 million public and shared private chargers will be needed to support 7.1 million light-duty EVs by 2030. By 2035, this number is expected to rise to 2.11 million chargers to accommodate 15.2 million passenger EVs. Additionally, around 0.11 million chargers will be required to support 0.15 million medium- and heavy-duty EVs by 2030.[19] According to California's government Executive Order N-79-20, it has intermediate-term goals of including 5 million zero-emissions vehicles on roads by 2030 and 250,000 public and shared charging stations by 2025.[20]

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[15] U.S. Department of Energy, (2023). Electric Vehicle Charging Infrastructure Trends. <https://afdc.energy.gov/fuels/electricity-infrastructure-trends>

[16] Review Report, U.S. Energy Information Administration <https://www.eia.gov/totalenergy/data/monthly/>

[17] New ZEV Sales in California. <https://www.energy.ca.gov/data-reports/energy-almanac/zero-emission-vehicle-and-infrastructure-statistics/new-zev-sales>

[18] California Energy Commission, (2023). Charging Infrastructure for Electric Vehicles in California. <https://www.energy.ca.gov/data-reports/reports/electric-vehicle-charging-infrastructure-assessment-ab-2127>

[19] California Energy Commission, (2023). Assembly Bill 2127. <https://www.energy.ca.gov/publications/2024/assembly-bill-2127-second-electric-vehicle-charging-infrastructure-assessment>

[20] Governor Brown Takes Action to Increase Zero-Emission Vehicles, Fund New Climate Investments, Governors' Office. (2018). <https://archive.gov.ca.gov/archive/gov39/2018/01/26/governor-brown-takes-action-to-increase-zero-emission-vehicles-fund-new-climate-investments/index.html>

II. Background

The rapid adoption of EVs has highlighted the need for extensive charging infrastructure to support the growing EV usage. Despite the facilitation of several governments and private sector incentives for EV adoption, adequate charging infrastructure remains the key factor for miles-driving uptake. A major reason for this uptake is due to EVs' competitive pricing and improved driving efficiencies that cover long-range in a single charge. Public and private charging infrastructures are expanding, and workplace charging emerges as a crucial component for equitable and affordable access for low to middle-income families or first-generation commuters. In the context of US government regulations, 'workplace charging' refers to the dedicated provisions made of EV charging stations at the workplace to support and encourage their employees to drive electric vehicles.[21] The US Department of Energy identifies workplace charging as a critical strategy to support the growing demand for EVs.[22, 23]

A. Why is workplace charging infrastructure important?

Access to home charging is not universal, for example, for those living in apartments, rented accommodations, or multi-unit dwellings where installing personal charging infrastructure is often not feasible. Lack of home charging creates a significant barrier for new potential EV adopters. Charging infrastructure at workplaces is therefore expected to play a pivotal role in making EVs a more viable and attractive option for all segments of the population.

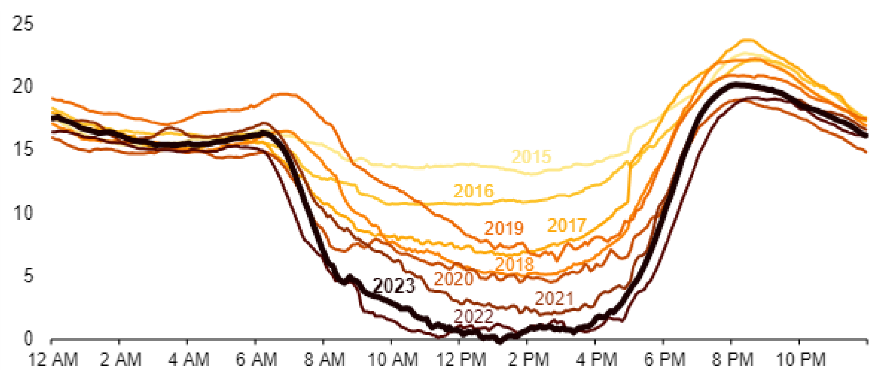

Fig 3. California state "duck curve", indicating net electric load after considering variable renewable energy generation, in GW. Data shown are for March-May, 2015-2023.
Source: California Independent System Operator (CASIO) Today's Outlook and EIA.[24]

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[21] Implementing Workplace Charging within Federal Agencies, Margaret Smith, Energetics Incorporated. U.S. Department of Energy Vehicle Technologies Office. (2017). <https://afdc.energy.gov/files/u/publication/federal_wpc_case_study.pdf>

[22] Workplace Charging for Electric Vehicles. Alternative Fuels Data Center. <https://afdc.energy.gov/fuels/electricity-charging-workplace>

[23] How to Guide: Starting an electric vehicle workplace charging program. City of Boston Transportation. (2020). <https://www.boston.gov/sites/default/files/file/2020/03/1527-03%20-%20Workplace%20Charging.pdf>

[24] Today in Energy, EIA (2023). <https://www.eia.gov/todayinenergy/detail.php?id=56880>

As California continues to increase its renewable energy capacity, a significant drop in net load is becoming more apparent during the middle of the day when solar generation peaks. This phenomenon, often referred to as the "duck curve" (illustrated in figure 3), represents the net load curve, which sharply rises in the evening as people return home and consume more electricity for different house purposes. This evening surge in demand occurs because most of the workforce follows a similar daily pattern—leaving home in the morning and returning in the evening. As a result, there is a widespread pattern of energy consumption that leads to a sudden and substantial increase in electricity demand during the late afternoon and early evening hours. This predictable surge puts significant stress on grid suppliers, as they must quickly ramp up production from non-renewable sources, such as natural gas or nuclear, to meet the heightened demand, often at a time when solar energy is tapering off. This strain on the grid underscores the need for better demand management strategies, such as encouraging daytime energy use through workplace EV charging, to alleviate the evening peak and make better use of abundant daytime solar power.

From figure 4, it is evident that in California, renewable energy sources are insufficient for rapid ramping and can stress the grid, hence adding a load of charging does not make economic and environmental sense.

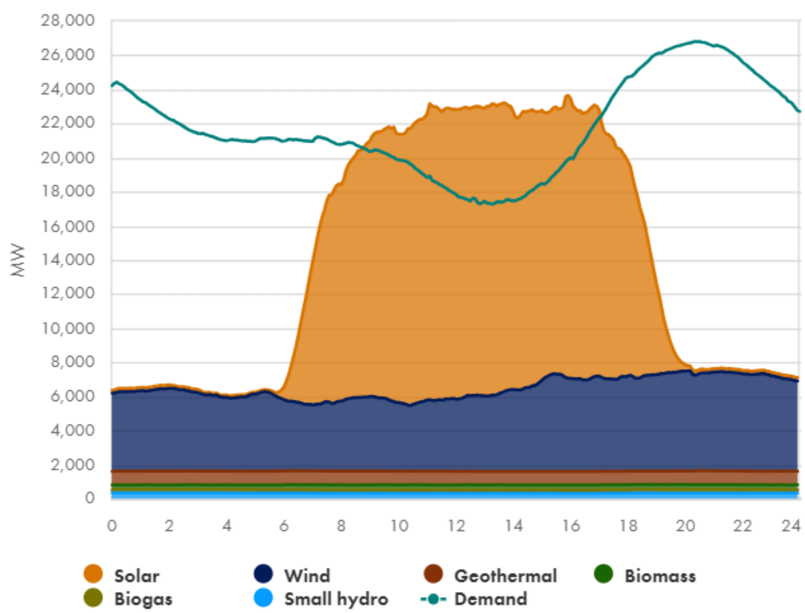

Fig 4. California's renewable energy supply and demand (in megawatts) over 24 hours, with every 5-minute daily increment data, on June 1, 2024.
Source: California Independent System Operator (CASIO) Today's Outlook.[25]

[25] California ISO. <caiso.com/todays-outlook/supply>

Charging should be emphasized in hours when supply is adequate and environmentally sustainable. From a decarbonization perspective, it is the way future adoption needs to be planned as it has a significant impact on environmental outcomes throughout their lifecycle. As shown in figure 4 and 5, nighttime charging causes more emissions due to drawing energy from other than renewable sources. In contrast, daytime charging can leverage cheap renewable electricity that might have been sourced from solar power, which is more readily available during daylight hours. Adoption of such behavior has better possibilities of reducing reliance on fossil fuels and decreasing the overall CO2 emissions associated with EV charging.

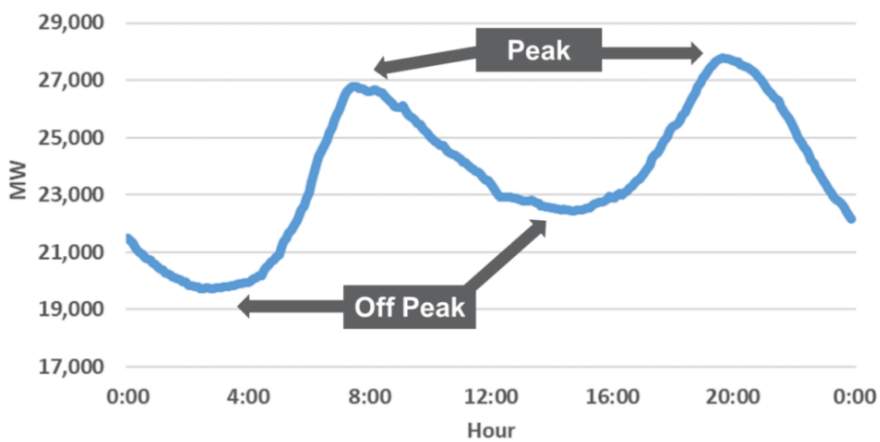

Fig 5. California electricity demand, March 12, 2019.
Source: Scottmadden Management Consultants, White Paper 2019.[26]

Adequate workplace charging infrastructure not only offers a convenient solution for emission reduction and helps to distribute the charging load throughout the day or reduce the strain on the power grid during peak hours but also encourages EV ownership, especially early adopters to consider as most reliable mobility for work. Allowing EV drivers to charge during their routine commute is more likely to access dependable and clean-sourced electricity, thus alleviating range anxiety and supporting their transportation needs.[27] Workplace charging offers multiple benefits to both employers and employees. For employers, it can add to an attractive employee benefit and address companies'

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[26] Charging Up: A Review of Electric Vehicle Workplace Charging, Scottmadden. (2019). <https://www.scottmadden.com/content/uploads/2019/04/ScottMadden_A_Review_of_EV_Workplace_Charging_2019_0401.pdf >

[27] Institute for Economic Policy Research, Stanford University, (2024). Overcoming roadblocks to California's public EV charging infrastructure. <https://siepr.stanford.edu/publications/policy-brief/overcoming-roadblocks-californias-public-ev-charging-infrastructure>

sustainability commitments by reducing scope 3 emissions associated with employee commutes. For employees, they benefit from the convenience of charging while at work, potentially reducing the need for separate charging trips, and thus increasing workhour productivity.

As shown in figure 6, the ideal workplace parking garage should be provided with adequate space available for EV charging stations along with space for non-EVs to park. The goal should be to provide charging spots when commuters need them and optimize the operating costs of a well-planned charging station network (with the right charging capacity per kilowatt delivered and number) distribution within the parking infrastructure. Any long charging queues or higher costs of kWh delivery may lead to drivers' anxiety, and hence discourage EVs from workplace commutes.

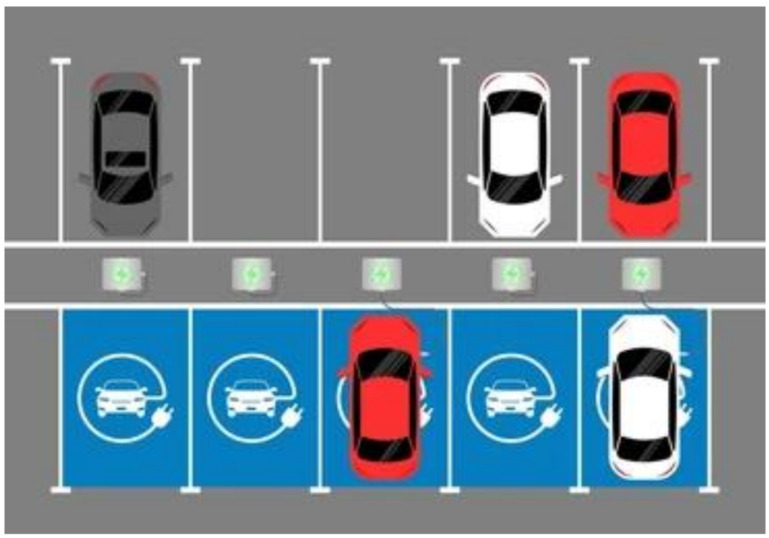

Fig 6. Schematic of an ideal workplace parking garage with adequate EV charging stations (blue) along with non-charging parking spaces (gray).
Source: Shutterstock.com – 2367860679

As the EV market is evolving as along with users' perspectives on driving, better understanding is required to explain the complexity of users' behavior and their synchronous responses to the infrastructure developed either by the private employer or by the public sector for charging-enabled parking. For this study, the aim is to establish a causal relationship between BEV drivers' behavior? number? and the functional model of workplace charging infrastructure. This means, that establishing the positive and negative relationship between increasing BEV drivers has direct implications on energy consumption and plug-in parking congestion and has indirect implications on drivers' deviation from desired charging location and lesser charging or battery replenishment cycle. It is assumed that there are fewer insights available to take decisive action on factors affecting the charging infrastructure optimization and usability maximization, especially among those drivers with no home charging access and who prefer driving BEV for work.

B. UCSD campus charging infrastructure

As an expansion of the Scripps Institution of Oceanography established in 1904, UCSD is founded as a public university in 1960. It is a locus of eminent research scholars and practitioners from multidisciplinary fields. As one of the top 20 research universities in the world, the campus is located near the Pacific Ocean on approximately 2178 acres of coastal woodland in La Jolla, California. The campus sits on the ancestral homelands of the Kumeyaay Nation. Its rich academic portfolio includes 12 academic, professional, and graduate schools and over 200-degree programs, considered a public Ivy for academic research and practice.[28]

The primary focus of this study is to identify a workplace parking structure which has a significant attribution of EV drivers, vehicle type, and charging network. Adequate demographic diversity and charging service utilization are assumed to be the key elements to explain the workplace charging heterogeneity and driver's response to it. For this purpose, the University of California San Diego (UCSD) campus is found to be the most adequate location. Being one of the prominent educational institutions in the Western Hemisphere, it attracts more than 73,000 academic scholars and above 170,000 non-academic professionals every year. [29, 30]

With such large footfall every year, the campus is grappling with increasing EV influx and demand for public charging access, distributed for the proximity needs of professors, students, staff, and other affiliates along with visitors who prefer parking within campus premises. Due to its scale and diversity, it stands among the largest educational workplace charging networks in the world. Furthermore, since the campus is committed to its decarbonizing goals, with the support of the National Science Foundation, the California Energy Commission, and other key stakeholders from San Diego County, it has installed one of the largest public charging networks. As shown in figure 7, its installed capacity is 439 Level 2 and 13 DCFC charging stations.[31, 32] The future expansion is anticipated to add over 762 Level 2 and 22 DCFCs by the end of 2025.[33] Although the current charging network is

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[28] Carnegie Classification of Institutions of Higher Education. 2020. <https://carnegieclassifications.acenet.edu/institutions/?basic2021__du%5B%5D=15>

[29] UCSD Campus Profile. 2023. <https://univcomms.ucsd.edu/about/campus-profile/#about-students>

[30] UCSD at Glance. 2024. <https://www.universityofcalifornia.edu/about-us/information-center/uc-employee-headcount>

[31] Direct Current Fast Charging (DCFC) are made for rapid charging, preferably used around heavy-traffic and long-range transportation corridors. DCFCs can charge a BEV up to 80 percent in just 20 minutes to 1 hour, however these are not compatible with most of the PHEVs in the market. <https://www.transportation.gov/rural/ev/toolkit/ev-basics/charging-speeds >

[32] Level 2 charging are typical and most common charging ports, supplies higher-rate AC charging through 240V (in residential applications) or 208V (in commercial applications) electrical service. Level 2 chargers can charge a BEV to 80 percent from empty in 4-10 hours and a PHEV in 1-2 hours. <https://www.transportation.gov/rural/ev/toolkit/ev-basics/charging-speeds >

[33] EV Project. <https://transportation.ucsd.edu/commute/drive-electric/projects.html >

half of the future expansion, it is distributed based on the vehicle influx within major parking garages on the campus. For instance, as shown in figure 7 the intensity of color on the heatmap indicates the frequency or density of charging sessions at each location, with brighter or more intense colors (reds and yellows) representing higher usage, and cooler colors (blues and greens) indicating lower usage. It is assumed that the east campus and graduate housing parking garages are frequently engaged by visitors of the medical centers and/or graduate residents.

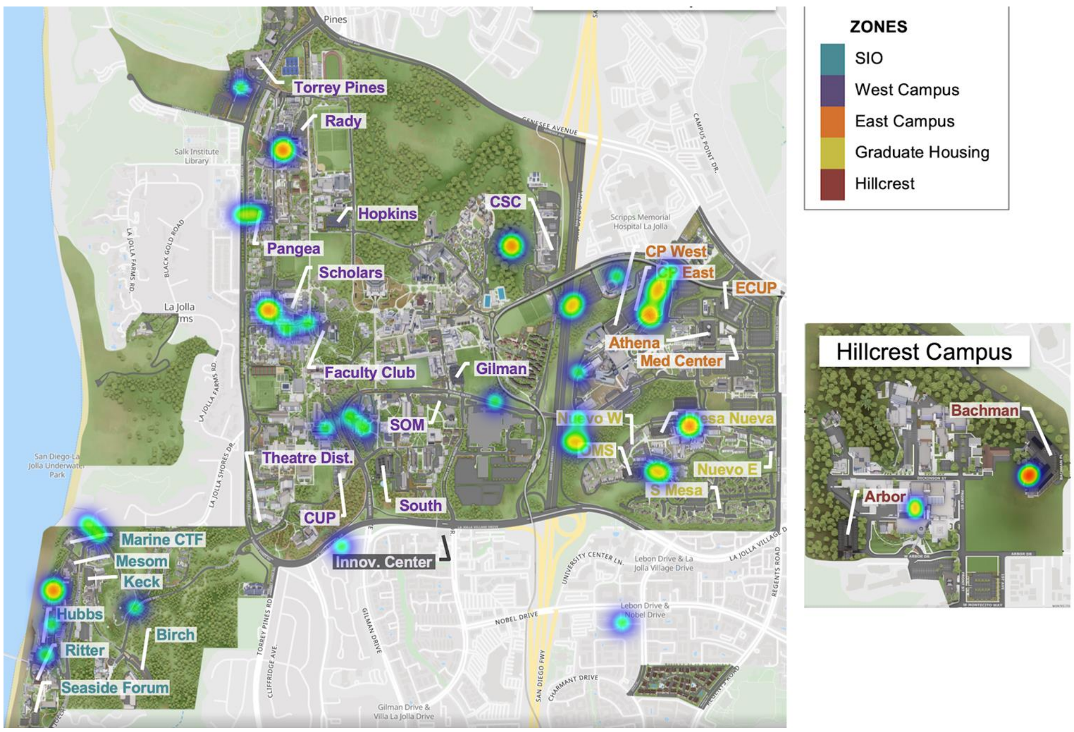

Fig 7. EV charging network of UCSD campus, described in zones and garages. The parking garages are segregated within five zones, that are illustrated in test word with different color code. The color density is reflecting the number of charging stations in different garages. Source: UCSD's transportation services.[34]

C. Research questions and hypotheses

Findings from this study are expected to provide drivers' behavior patterns and plausible interventions for campus charging network optimization strategies. This study focuses on two distinct sets of data sources. The individual drivers' response (N=806) has been recorded over a year through a voluntary incentive-led program, i.e., Triton EV Charging Club survey. Another set of data has been retrieved from charging sessions (n=53572), recorded over two seasons by charging service providers. The objective is to assess demand-supply heterogeneity among charging sessions and drivers' behavior-attributed responses from the

[34] UCSD's transportation services. <maps.ucsd.edu/map/Default.htm>

enrollment survey. It is assumed the findings will be useful in influencing new EV policies and infrastructure development planning on campus.

This study is focused on two research questions and associated hypotheses.

- First, does charging infrastructure distributed across the campus sufficiently meet the demand for charging services by commuters? There is substantial spatial heterogeneity across campus chargers, parking garages, and drivers' working location. While chargers are installed in salient locations with anticipated high demand, no retrospective analysis of supply and demand has ever been done to calculate potential demand-supply gaps and associated attribution heterogeneity. With the campus EV network set to expand threefold over the coming years, this analysis looks to the network's future to understand whether new chargers are being allocated in areas of highest demand for charging, thereby encouraging network optimization and cost recovery for the campus.
- Second, once commuters arrive at campus, how do they charge their vehicles? Commuters might prefer to plug in frequently (e.g., every time they arrive at campus) independent of the charge in their battery. But charging with frequent, shallow sessions decreases network utilization because it blocks EV stalls for others who would otherwise use them. Fewer deeper sessions, rather than frequent shallower sessions, would improve network utilization and cost recovery. Encouraging drivers to charge via less frequent longer sessions would allow for overall more charging sessions within the existing infrastructure. One hypothesis is that drivers who commute long distances do primarily deep charging, while those who reside closer to campus more commonly do shallow charging.

This research aims to explore driver behavior heterogeneity in the following manner:

Supply and demand heterogeneity

- Are EV chargers at UCSD supplied (properly sited) across parking garages to meet demand for charging?
- Is the expansion of UCSD's EV charging network occurring in parking garages with the highest demand-supply imbalances (where demand most exceeds supply)?

Session depth heterogeneity

- What is the nature of charging session depth across UCSD parking garages?
- What explains variation in session depth?

D. Driving and charging behavior

Any individual using a motorized means of transportation medium and taking specific movement actions such as acceleration is referred to as driving (Higgs and Abbas, 2014). The advantage of such acceleration provokes the capacity of mile coverage, which tends drivers' driving ability in different situations and circumstances (Guangchuan et al., 2016). Services and infrastructure are essential elements of addressing driving anxiety. Especially, in the emerging driving culture with EVs, it emerges as a major concern. Well-distributed and reliable charging stations are crucial for preferring EVs for medium to long-range mobility (Giuseppe et al., 2023).

Drivers' charging demand is influenced by several factors, including access to private charging, driving range, and commute requirements (Myers and Hanna, 2023). This demand is shaped by individual charging behaviors such as the preferred plug-in time, choice of garage, and the depth of charging sessions. Research indicates that human stress or anxiety often arises when individuals perceive that the resources needed to meet a situation or circumstance are unavailable or insufficient (Lazarus and Folkman, 1984). The decision to adopt EVs for commuting, along with the associated charging behaviors, is governed by a complex interplay of social, environmental, economic, and psychological factors. In this context, access to workplace charging becomes particularly vital. Providing a convenient charging solution at the workplace, especially for those without access to home charging, significantly enhances EV usability and mitigates range and cost anxieties, making electric vehicles a more practical and appealing choice for daily commutes.[35]

[35] Alternative Fuels Data Center, U.S Department of Energy. <https://afdc.energy.gov/fuels/electricity-charging-workplace>

III. Methodology and approach

This study analyzes drivers' charging behavior to guide the UCSD's transportation and infrastructure policy. In-depth understanding of driver behavior is assumed to be important to encourage the adoption of EVs, particularly among drivers who prefer EVs for commuting to work. The first phase of analysis emphasizes establishing causal inferences of demand-supply imbalance and charging session deviation. The second phase focuses on estimating drivers' engagement with the charging infrastructure campus provides, estimating the charging session depth per driver and garage. Session depth is critical for drivers' charging experience and cost recovery on investment.

A. The challenge with estimating workplace charging behavior

Decreasing prices, modified technological advantage, and increased attraction within the middle- and low-income classes have significantly increased EV adoption and hence demand for the charging infrastructure. Simultaneously, due to stringent government regulation and incentives for achieving decarbonization targets, more and more employers are providing charging infrastructure to encourage EV adoption. Adequate availability of charging stations like pots and parking spaces, incentives like free or minimum charging costs, parking time limits, etc., at a workplace may influence usage patterns. For instance, limited availability of parking slots and charging ports might lead to charging congestion, thus influencing EV regular usage (especially among BEVs and PHEVs users) for workplace commute.[36]

The biggest challenge with estimating workplace charging behavior or usage pattern is due to variability in the employee and employer understanding (Shariatzadeh et al., 2024). Employees coming from different socio-economic backgrounds vary greatly regarding the type of car that they drive, the car usage, and the demand for charging during their working schedule (Lihore et al., 2023). Another challenge is the availability of reliable and accessible databases. The concept of workplace charging is relatively new, hence, there are few databases available to guide research on historical trends and compare usage patterns in practice.

Being progressive to address workplace charging infrastructure design and adoption challenges, UCSDs transportation and planning departments have ensured routine and exhaustive database generation in collaboration with respective service providers and qualified researchers. To support this with primary data, the university has also ensured regular collection of drivers' responses through a charging enrollment survey.

[36]Charging Up: A Review of Electric Vehicle Workplace Charging. White Paper, Scottmadden Management Consultants, (2019).
<https://www.scottmadden.com/content/uploads/2019/04/ScottMadden_A_Review_of_EV_Workplace_Charging_2019_0401.pdf/>

B. Study methodology

In the first phase, drivers' stated preferences, i.e., preferred plug-in time and location, are considered to quantify charging demand. Here the drivers' charging preferences based on the garage and hours derived from their responses to the enrollment survey. It is subject to their proximity to work or commute distance from the garages. For each campus garage, the ratio of the number of drivers who stated their preference of charging at a particular garage to the number of charging ports available in that garage is calculated and used to derive insights regarding the demand-supply gap. Here the demand is defined as the unique driver (as per their unique random identification number) plugged in per parking garage. Whereas the supply is defined as the number of charging ports available per parking garage.

Thereafter, drivers' garage preference over deviation due to congestion is calculated to explain the deviation session per garage. Here deviation session is considered a crucial component of the analysis, as it will guide the drivers' motivation for utilizing the charging infrastructure facilitated by the campus and most importantly, the battery replenishment. It is assumed that a higher driver deviation leads to lesser charging session depth. The session depth is the percentage of battery replenishment per charging session. Two other factors are also considered to be crucial for explaining drivers' behaviors: the miles travelled to campus, and the availability of home charging.

Drivers' revealed preferences are quantified to build the causal inferences on behavioral attribution to the demand and supply gap. For each driver, I identified their full set of campus charging sessions and calculated the fraction of the total sessions they initiate at each garage. This helped in explaining the pattern of drivers' engagement with the charging infrastructure. Given stated preferences for each preferred garage, I generated an N-by-N matrix that describes the frequency with which drivers deviate from their preferred garage when charging. Here, the N rows and N columns are distinct garages, and the matrix values are the mean frequencies with which drivers charge at both their preferred and non-preferred (i.e., deviations) garages. This matrix also quantifies the probability with which a driver charges at any garage in reference to their chances of getting at preferred or deviate among other garages.

Basic data clearing, analysis, statistical tests, and plotting is performed using the R library packages such as tidyverse, readr, dplyr (Sanguesa, 2021), grid, and ggplot2 (Alrubaie, 2023). Key analysis objective it served as in to identify the charging demand-supply gaps are different garages, deviation sessions per garage, and therefore overall garage utilization. The analysis of garage utilization is also important to explain whether the drivers' travel distance and access to home chargers play a causal role in their deviation. Whereas Python library packages such as numpy, panda, mapplotlib, seaburn, tenderflow (Abadi, 2016), sklearn is used to perform deep learning predictive model, i.e., random forest model (Y. Lu, 2018) and long-short term memory model (Shahriar S, 2020) which is important to train the model for predicting the future behavior responses.

The second emphasis is on calculating the depth of drivers' charging sessions. The depth is determined by the median and mode from the full set of camping charging sessions per garage, complemented with information on their model type and battery size. For each session, I calculated the fraction of the battery replenished over the size of the battery. The mean and standard deviation of the depth of campus charging sessions is used to explain the deviation of the driver by their session depth. Furthermore, session depth was discretized into three categories: shallow, intermediate, and deep charging (see further details below).

C. Data analysis and inference building

Data on drivers' demographic diversity, type of EV, preference of charging session as a function of time of plug-in and plug-out, parking garage as the location of charging, duration of charging or sitting idle, session depth, distance travelled, access to home charging, university affiliation type, and many more variables were collected from the drivers' survey response and charging sessions data from the service provider. Some of these variables, including commute distance, university affiliation, vehicle type, income, and access to home network utilization and sufficiency, as well as on driver attributes and behaviors that explain charging outcomes.[37] This study focuses on two primary analysis approaches:

- Analysis of charging session depth adopted by drivers on any day of their plug-in preference and their spatial distribution relative to existing and future charging infrastructure facilitated.
- Statistical tests to analyze drivers' attribution to the category of charging session engaged in. This is to quantify the causal association between commuter type defined by a subset of key attributes, and their charging behavior.

This study used three data sources, i.e., a) driver-stated preference collected from the charging club survey response, b) driver-revealed preference collected from the charging session data from the two service providers—ChargePoint and PowerFlex, and 3) charging network data collected from the UCSD's transportation planning. The data attributes for this study are classified as drivers' attribution and charging network as illustrated in Table 1 and Table 2.

Table 1. Driver and charging session attributes.

Data points	Attributes
Demographic	Age, gender, education, income, home ownership
Affiliation	Faculty, student, staff

[37] An optimal coordinated planning strategy for distributed energy stations based on characteristics of electric vehicle charging behavior under carbon trading mechanism. <https://www.sciencedirect.com/science/article/pii/S0142061522008808>, <https://ieeexplore.ieee.org/document/9194702>

Commute distance	Distance from home zip code to central UCSD campus
Living arrangement	Campus residence, own house, or rental apartment
Charging access	Home charging, public charging, and other charging options.
EV type	Year, make, model, type (BEV or PHEV)
Charging session	Plug-in and plug-out time, charging and idling durations, energy consumed, session depth, and preferred and deviation sessions.

Table 2. Attribution of charging network to drivers' demand and supply and service utilization.

Data points	Attributes
Spatial distribution	Zones and charging garages, proximity to the work location, residential, and other engagement priorities.
Charging utilization	Charging garage preference and deviation, charging durations by parking garages and zones.

D. Data sources and analysis objective

Primary analysis is performed on a dataset comprising 66,346 individual charging sessions collected between September 2023 and February 2024. The data is sourced from two major charging service providers to the UCSD campus – ChargePoint and PowerFlex. The data is collected online while signing up for the charging session, and the feed lives on the cloud server. Key data outputs from this source are shown in Table 3. To avoid errors, the data set was cleaned of missing data, irrelevant information, and duplicate data. Individual drivers have a unique random number, which is followed by their attributes. After the data was sanitized, a total of 16,023 individual drivers charging attributions, i.e. network, driver, and vehicle, were considered for heterogeneity analysis.

Table 3. Example of key session outputs, as generated by the service providers when a driver initiates a session.

Attributes	Output
Driver unique ID	2649
Garage	Arbor
Zone	Hillcrest
EVSID	779181
Session starts date	11/21/2023
Session starts time	18:10:00
Session starts minute	117730
Session end date	11/21/2023

Session end time	18:40:00
Session end minute	117760
Session duration	30
Charging duration	22
Session idle	8
kWh delivered	1.812999964
Success charge	1
Charging port type	Level 2
Port number	1
Plug type	J1772
Session cost to the driver	0.54
Lower kW at the initial	3.751034498

To quantify the significance of network attributes on the driver's charging behavior, the entire charging network of thirty-one parking garages is divided into five geographic zones (as shown in Table 4). Garages can be supplied by either ChargePoint (consisting of dual-port stations), PowerFlex (consisting of single-port stations), or both. It is assumed that the driver who plugs in has the intention of battery replenishment, and therefore that parking garage cannot be occupied and uncharged. To analyze the charging supply, the session start time is considered to quantify day-to-night charging cycle and peak and non-peak charging hours. Likewise, session duration is the sum of actual energy consumed by the battery per charging session, with the remaining being session idle, which means the vehicle is not consuming any energy but occupying the parking space. A larger session idle duration indicates a larger deviation from the driver's preferred garage.

Table 4. Distribution of charging ports across the UCSD campus by zone and parking garage.

Zone	Garage	Vendor	Ports
East campus	Athena	ChargePoint	10
	Athena	PowerFlex	27
	CP East	ChargePoint	2
	CP West	ChargePoint	2
	Med Center	ChargePoint	10
Graduate housing	Mesa Nuevo	ChargePoint	10
	Nuevo East	ChargePoint	4
	Nuevo West	ChargePoint	30
	OMS	ChargePoint	2
	South Mesa	ChargePoint	2
Hillcrest	Arbor	ChargePoint	12
	Bachman	ChargePoint	6

Seaside forum	Birch	ChargePoint	2
	Hubbs	ChargePoint	4
	Keck	ChargePoint	2
	MESOM	ChargePoint	2
	Ritter	ChargePoint	2
	Seaside Forum	ChargePoint	4
West Campus	CSC	ChargePoint	12
	CUP	ChargePoint	2
	Faculty Club	ChargePoint	2
	Gilman	ChargePoint	8
	Gilman	PowerFlex	25
	Hopkins	PowerFlex	20
	Pangea	ChargePoint	12
	Pangea	PowerFlex	4
	Rady	ChargePoint	10
	Som	ChargePoint	10
	Scholars	ChargePoint	28
	South	ChargePoint	26
	Torrey Pines	ChargePoint	14

The analysis is complemented by a second dataset comprised of 804 individual charging enrollment survey responses gathered over a year from April 2023 to March 2024. Since it is an incentive-driven voluntary enrollment, the feed gathered is random and diverse. The survey captured more than fifty responses which vary across basic demographic information to specific stated preferences like garage preferences, vehicle type, distance travelled, home charging access, residence, etc., (see Table 5). Selective attributions are considered to quantify their implication of charging behavior.

Table 5. Example of key stated preferences as collected by the enrollment survey.

Prompt	Response
Start date and time	1/28/2024 3:12
End date and time	1/28/2024 3:27
Charging duration	933
UCSD affiliation	Staff
Work location	UC San Diego Health-Sulpizio Cardiovascular Center
Home location zip	92128
Home type	Owned
Living on-campus	Off-campus
Home charging access	No

Home charger type	Unsure
Vehicle make	Hyundai
Vehicle category	Hyundai Ioniq BEV
Vehicle make year	2022
Vehicle model	2022 Ioniq 5 AWD (Long Range)
vehicle operating type	BEV
battery size	88 kWh
PowerFlex ID	NA
ChargePoint ID	31929381
Garage preference	East Campus (Athena, Medical Center, Skaggs)
Garage preference others	NA
Household income	$150,000 or more
Age	36-45
Gender	Female
Qualification	Bachelor's degree
Charging operator	No
Modal charging time	06 to12

IV. Results and discussion

The analysis was focused on a new method of appraising supply and demand imbalance by looking at the driver's preference for garages, their deviation sessions from said preference, and the session depth, especially among those who have no access to home charging.

A. Demand-supply imbalances

From the enrollment survey response, stated preference is considered to quantify the user's demand. Based on a unique identification number, autogenerated during enrollment, each respondent is considered a unique EV driver. Their stated preference for garages is considered as demand for charging. Likewise, supply is considered as the number of ports available per installed charging station. The fraction of supply and demand is estimated as shown in figure 8.

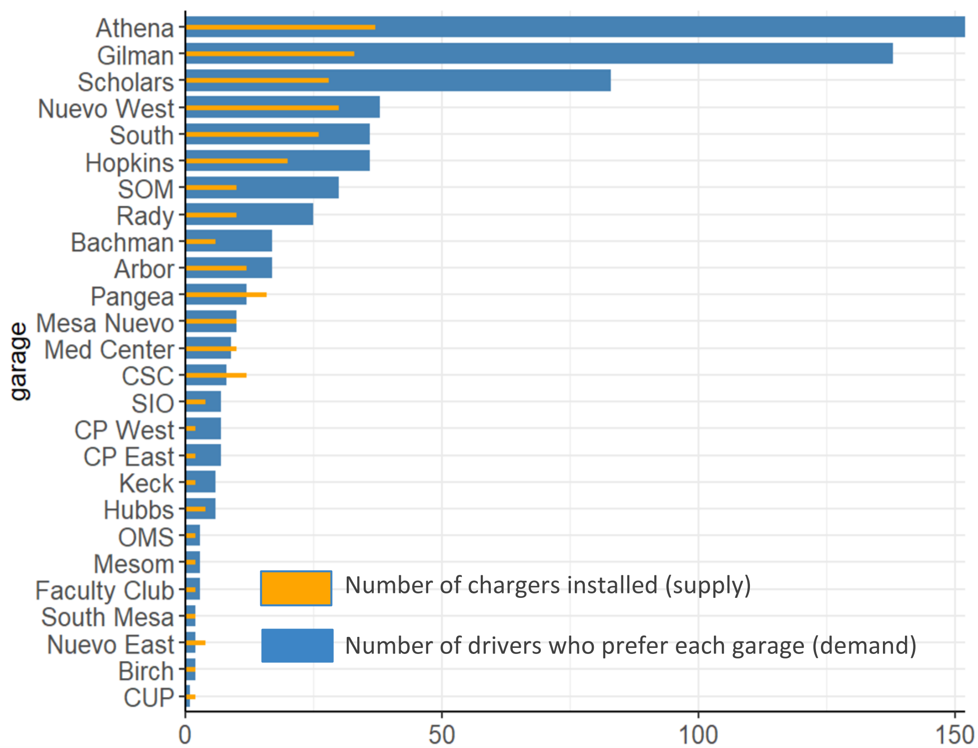

Fig 8. Numbers of charging stations and drivers, by garage. The demand-supply ratio is the ratio of charging stations to number of drivers who "prefer" that garage.

Here, the distribution of the charging stations indicates that the usability of the parking garages closer to prominent working locations within campus is likely high. This means that the higher the gap is, the more demanded the garage like Athena, Gilman, and Scholars, all of which are located at the center of major engagement locations, are highly demanded. As demand is high and charging stations are insufficient, drivers likely tend to deviate from their preferred garages to the nearest available garages. On the contrary, garages like Pangea, which is in the center of major colleges, are in less demand. It is likely that a multimodal parking facility available nearby which allows access to parking space even for long hours is driving this pattern. CSC, Mesa Nuevo, Nuevo East, and CUP all exhibit low demand-supply gaps, which could be due to either fewer people driving EVs who work or live there, or to less deviation and deeper session charging. From figure 9, it is evident that there is a wide variation in demand-supply balance across garages. Some places are heavily engaged, and some are less. This also indicates a potential challenge with fulfilling the gap across the network.

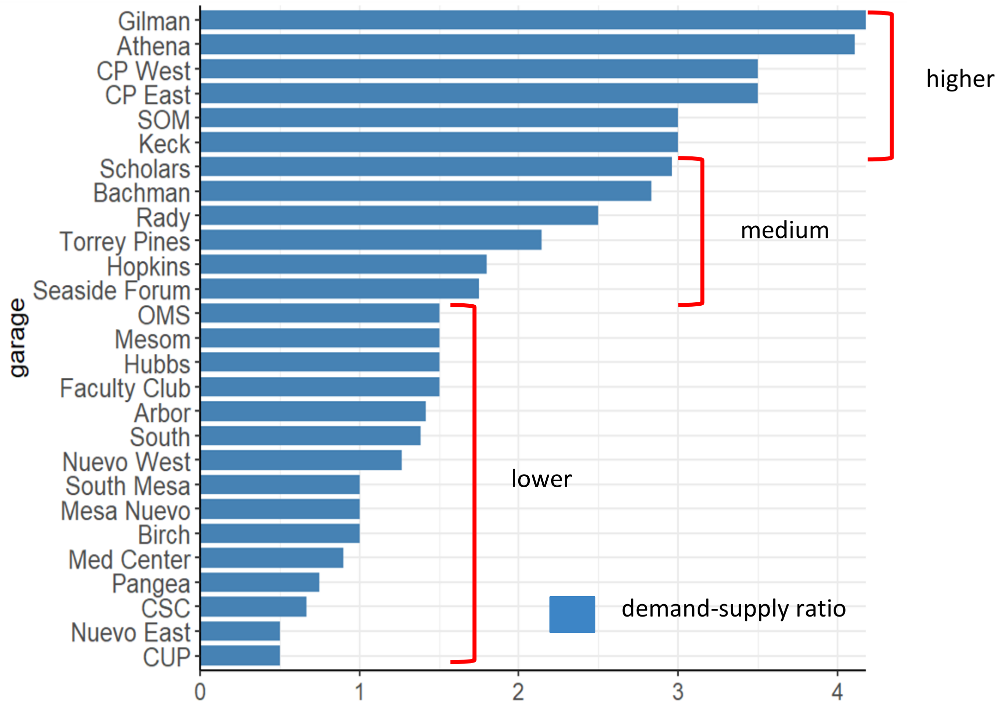

Fig 9. Charging demand-supply gap by high, medium, and low ratio.

The question arises, are new chargers being installed in high-demand garages? Future charging stations, shown in figure 10, are unlikely to close the current demand-supply gap. While some forthcoming stations are planned for garages that show a large gap, their planned distribution does not always match current needs. For example, garages such as CP East and West, Keck, and Rady are all facing high to medium gaps and are not considered in future planning. The uneven distribution of forthcoming stations is clearly shown in figure 11. A subset of garages that have high demand relative to existing chargers have relatively few new chargers scheduled for installation. Such a scenario will result in fewer charging sessions at preferred garages, producing congestion and leading to deviation sessions at adjacent garages. Therefore, current growth plans will not improve equity.

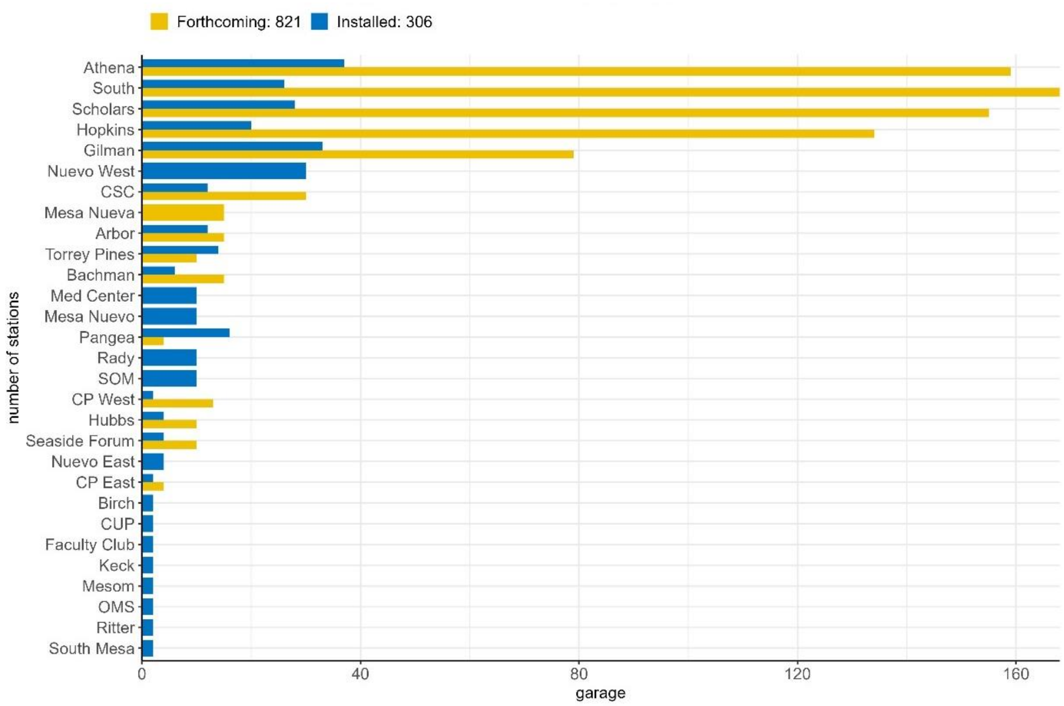

Fig 10. The number of installed and forthcoming charging stations.

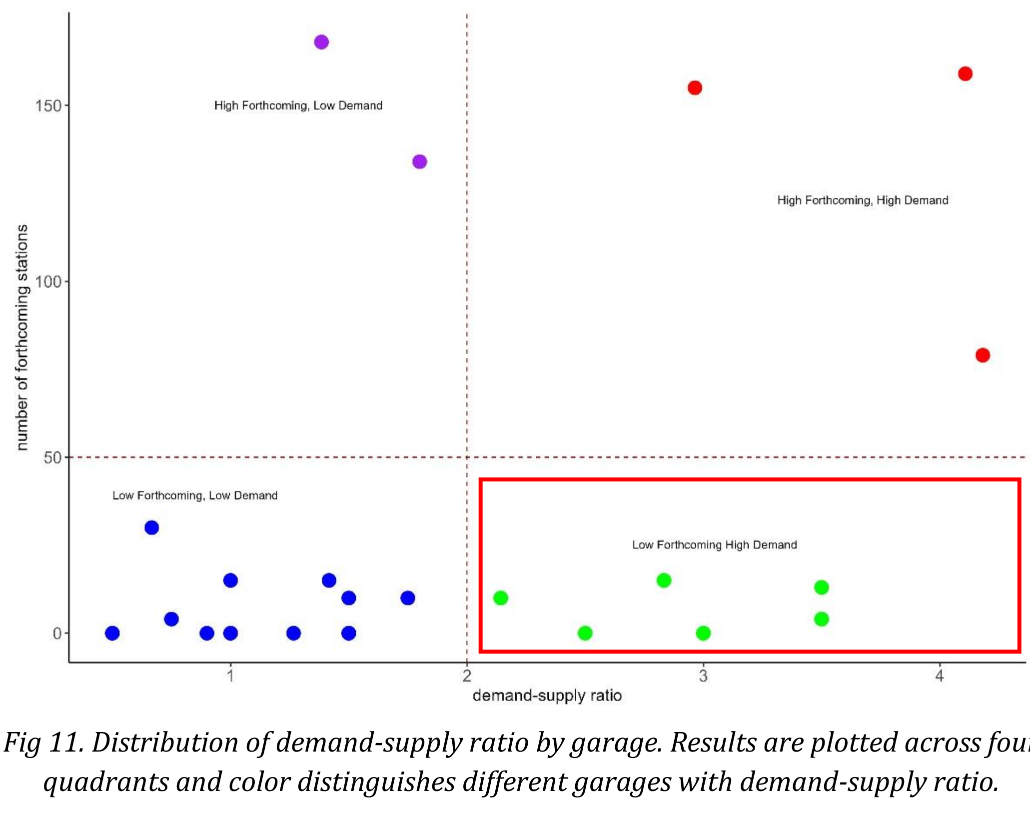

Fig 11. Distribution of demand-supply ratio by garage. Results are plotted across four quadrants and color distinguishes different garages with demand-supply ratio.

B. "Preferred" and "Deviation" charging sessions

Drivers who look for charging stations at the campus either drive fully battery electric vehicles or plug-in hybrid electric vehicles that partially need battery as backup to improve driving milage efficiencies. Figure 12 illustrates the distribution of vehicle charging sessions at garage by plug-in time, BEV, and PHEV. The most significant charging sessions occur between 6:00am and 8:00am, with a sharp peak around 7:00am. This peak indicates a high demand for charging in the early morning hours, likely due to drivers plugging in their vehicles as they arrive at their destination. Another smaller peak is observed around 6:00pm, which might correspond to drivers plugging in their vehicles after their workday, might be those who either live in the campus housing or leave their service vehicles at the campus. Most of the charging sessions are by BEV across almost all hours, particularly during the peak morning hours. Also, it shows that BEVs are plugged in much more frequently than PHEVs, especially during the peak hours, suggesting that BEV drivers are more reliant on these sessions at the campus. Whereas, PHEVs show a more dispersed distribution of sessions throughout the day, with a noticeable presence during the early morning hours but significantly fewer sessions compared to BEVs during the peak times that might be an indication of least reliance on battery over gas as alternative sources.

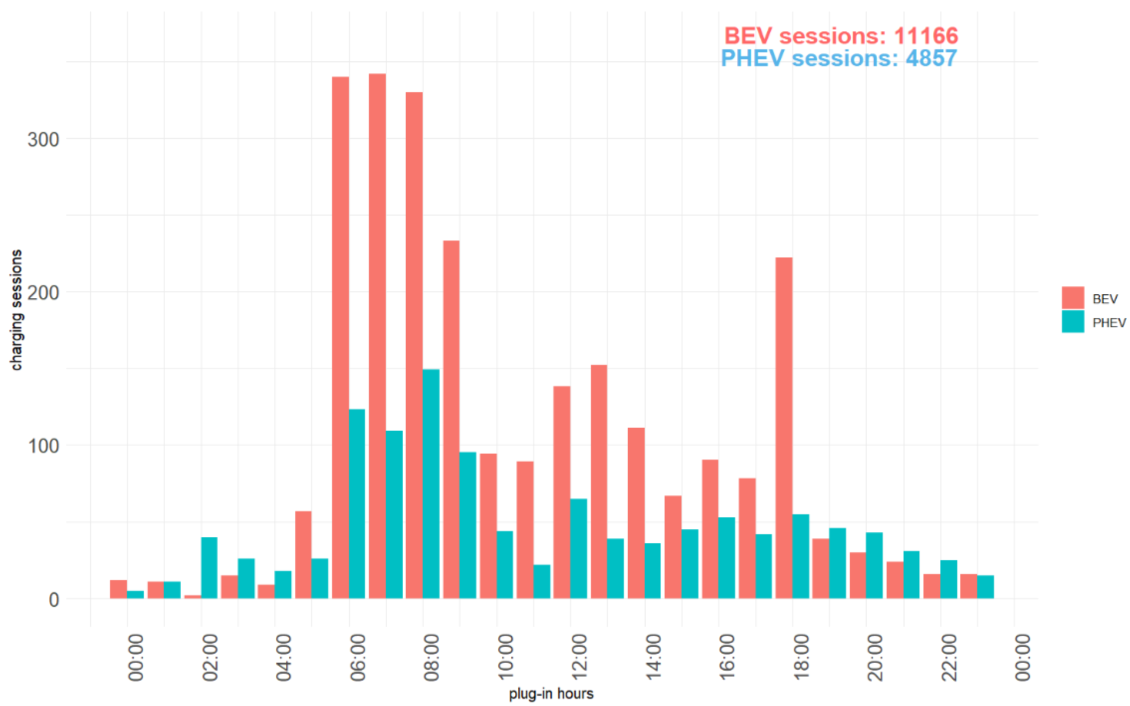

Fig 12. Average vehicle charging sessions by plug-in time and vechile type.

Session deviation means drivers deviating from their preferred garages in search of charging space close to their work location. As shown in figure 13, about 23% of all charging sessions are deviation sessions. This is one of the consequences of a demand-supply imbalance. Deviation sessions are important to notice as there is a dollar value attached to the drivers who deviate more and waste their time in finding an available parking garage with a charger.

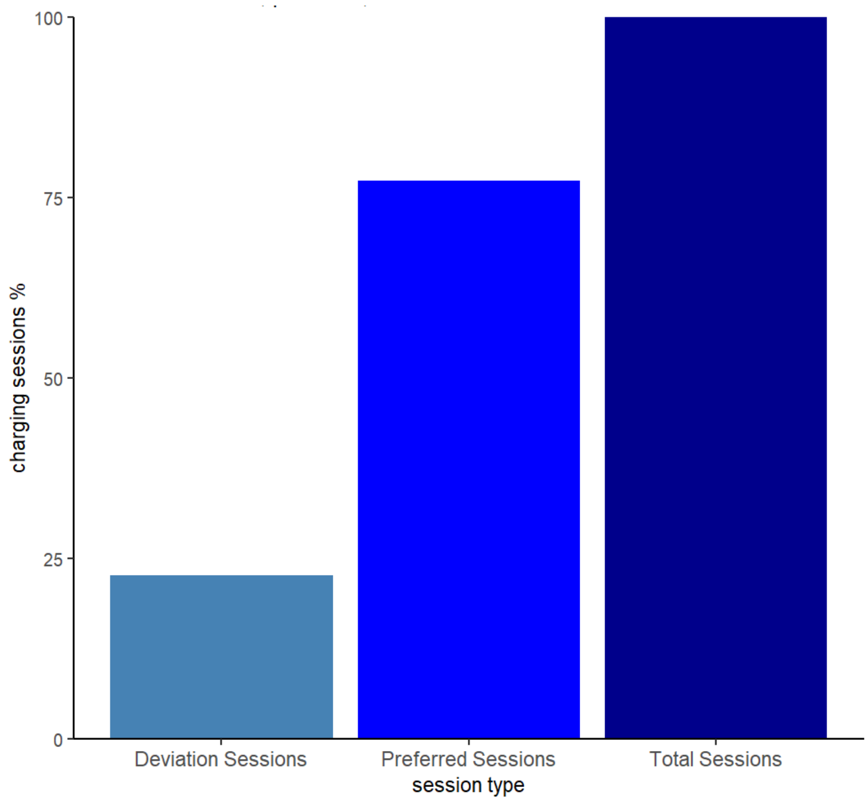

Fig 13. Percentage of deviation and preferred sessions.

Figure 14 illustrates the relationship between the number of charging sessions and the frequency of deviations from preferred charging garages among drivers with home charging access. It differentiates between BEV and PHEV sessions, with BEV sessions shown in red and PHEV sessions in blue. The positive linear relationship observed in the trend lines for both vehicle types indicates that as the number of charging sessions increases, the frequency of deviations also rises. Notably, BEV drivers tend to deviate more frequently from their preferred garages as their total number of sessions increases, which is reflected in the steeper slope of the BEV trend line compared to the PHEV line.

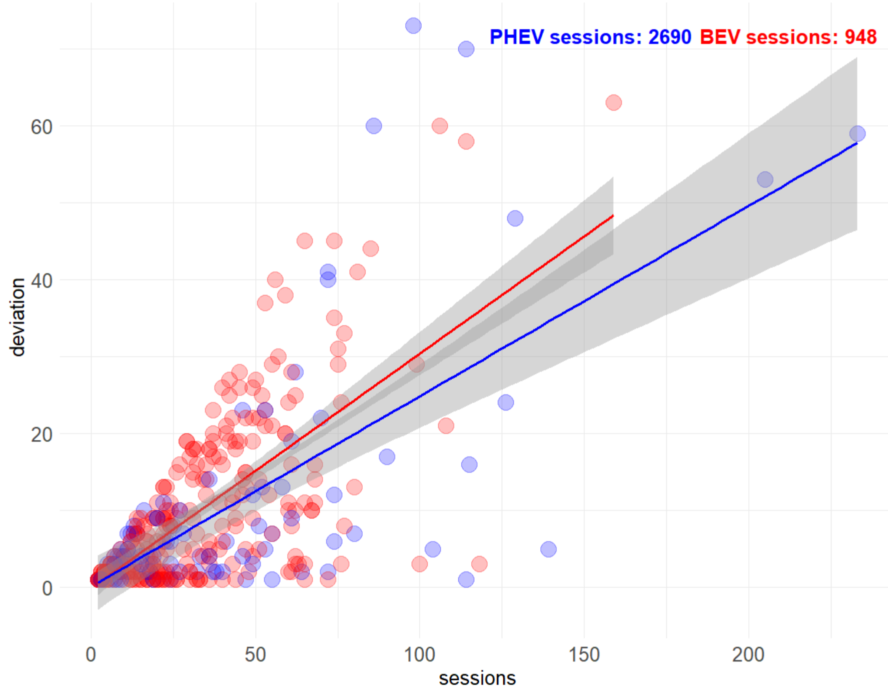

Fig 14. Average frequency of charging sessions deviation of BEV and PHEV drivers who have access to home charging.

The plot also reveals that most deviations occur among drivers with fewer sessions, suggesting that those who charge less frequently might have less consistent charging routines, leading to more deviations. Additionally, the presence of outliers, particularly among BEV drivers, indicates that some individuals exhibit high deviation frequencies even with relatively few sessions, possibly due to the greater flexibility or unpredictability in their charging patterns. The confidence intervals around the trend lines suggest greater variability in deviations for drivers with many sessions, particularly in the BEV group. It highlights that BEV drivers, who rely more heavily on charging infrastructure, may face more frequent deviations, underscoring the potential need for more dependable or increased charging options at their preferred garages to better accommodate their charging behaviors.

Now, the question is, does deviation sessions of BEV occur more with no or less access to home charging? If an association exists between the two, this can be considered an issue of equity. As shown in figure 15, BEV drivers who have no access to home charging have more deviation sessions compared to those who have access. More than 2000 drivers have no access to home charging. These tended to deviate more frequently from their preferred garage, although comparatively they participated less in charging sessions. Drivers who have access participate more in charging sessions and are less likely to deviate from their preferred garage. Assuming that the lack of a home charger is to some extent indicative of the overall household income, this difference means that less affluent drivers who do not have home charges are suffering the most from the lack of adequate charging supply. This supports the idea that this can be considered an equity issue that could affect the adoption of EV vehicles for a subset of the campus community.

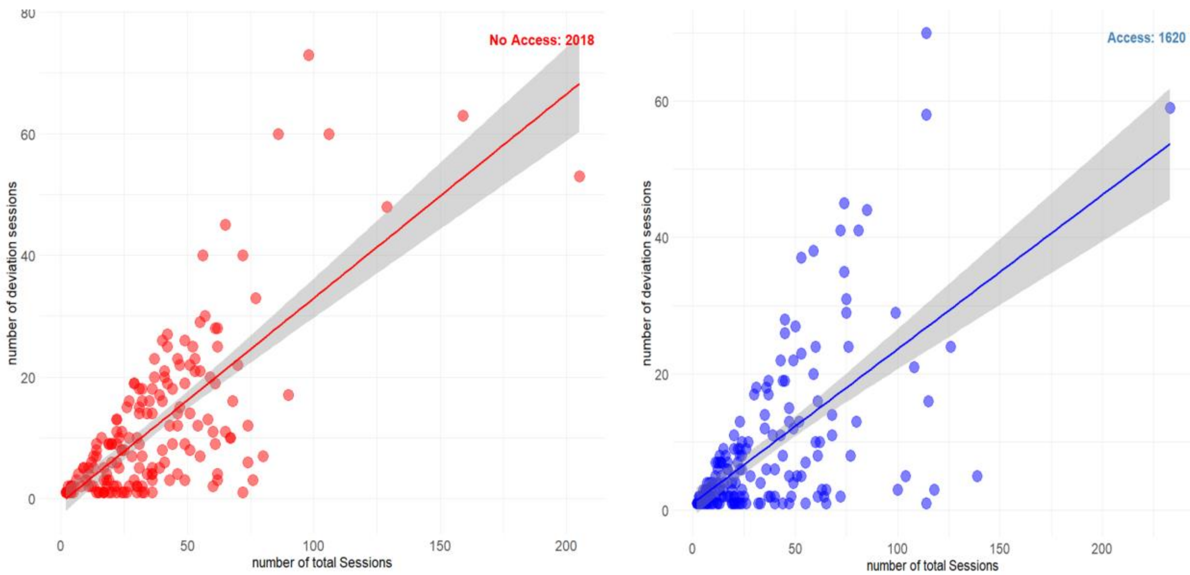

Fig 15. The trend in deviation sessions for BEV drivers who have (right, blue) and don't have (left, red) access to home charging. The red and blue dots are charging sessions adopted.

When looking at the deviation sessions by the commute distance, a relationship between the two is evident (figure 16). Travel distance is estimated as the number of miles separating the UCSD campus from the zip code of their residence. This might not be the actual travelled distance between the drivers' home and their preferred parking garage, but it still provided a fair understanding of overall commuting distance. The distance is binned into five categories: drivers living on-campus housing (<1 mile), off-campus but within the county (<=10 miles), short (>10, <=25 miles), medium (>25, <=50 miles), and long (>=50 miles).

The results reveal an unexpected pattern – deviation sessions are most prevalent among drivers who commute short distances, particularly those living on-campus or in near proximity to the campus. This pattern suggests that individuals who are closer to their preferred charging locations may be experiencing the most difficulty in securing a charging spot. This is likely because these drivers might rely heavily on the convenience of nearby charging stations, and when these stations are fully occupied or unavailable, they are forced to deviate to less convenient locations.

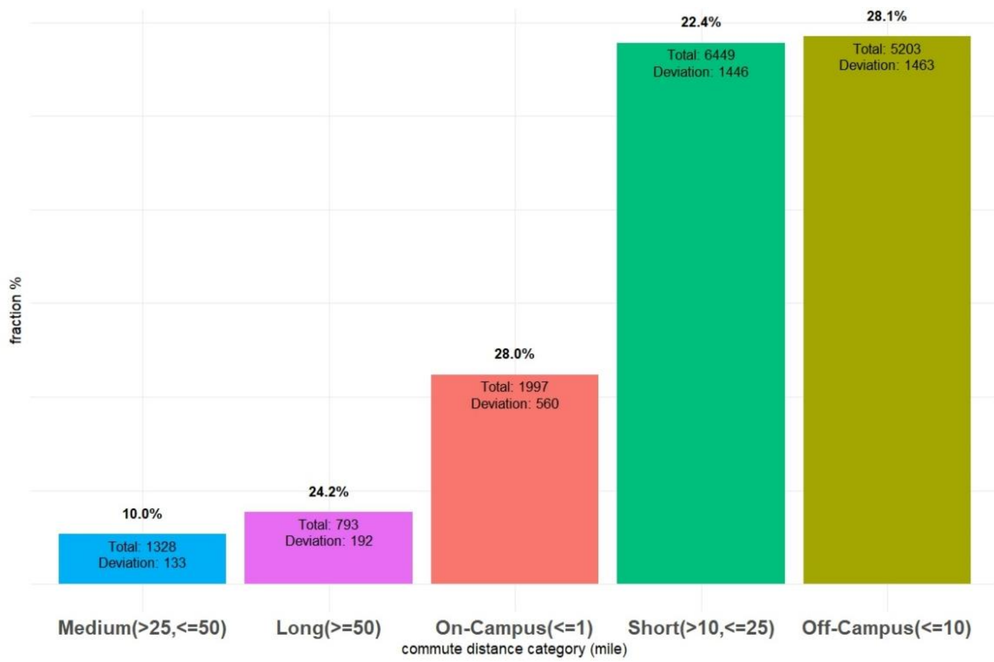

Fig 16. Fraction of deviation sessions by drivers' commuting distance to the main campus.

One potential reason for this trend could be the timing of charging sessions. Early morning arrivals, typically staff and faculty, likely occupy the charging stations first, leaving fewer options for those arriving later in the day, such as students. Additionally, the concentration of lecture hours starting after 9 am may further contribute to this deviation, as a surge in campus arrivals during this time could exacerbate the competition for available charging spots. This pattern underscores the importance of strategic planning in the distribution and availability of charging stations to ensure that those who need them most—particularly those with less flexibility in their schedules—can access them without undue inconvenience.

Although the data available does not clearly support this claim, it seems like most of the charging stations plug-in early in the morning, from 6 to 8, as shown in figure 17. The highest concentration of charging sessions occurs between 7:00am and 10:00am, with a sharp peak around 8:00am. It is evident that the bulk of the charging peaks in the morning and then towards noon onward as second slot, which are 4hrs charging slots, mostly preferred by the drivers. Whereas other available charging slots offer 1hr and 12hrs slots which are least preferred at the campus. This indicates that many users plug in their vehicles early in the morning, corresponding to when most employees arrive at work. This suggests that as demand increases, the availability of preferred charging spots decreases, forcing many drivers to use alternative locations. After 10:00 AM, there is a gradual decline in the number of charging sessions throughout the day. This drop-off indicates that most users plug in early in the day and that the availability of charging stations likely improves as the day progresses, resulting in fewer deviation sessions later in the day. There are very few charging sessions between midnight and 5:00am, which is expected as most users are not on campus during these hours. The probability of deviation during these hours is also minimal.

From the average sum of probability distribution, it evident that a larger proportion of sessions occur at preferred garages, however quite significant drivers have to move at non-preferred ones. The total number of sessions shown at the top is 539 sessions at preferred garages and 359 at non-preferred garages, suggesting a stronger tendency for drivers to willingness to stick to their preferred garages.

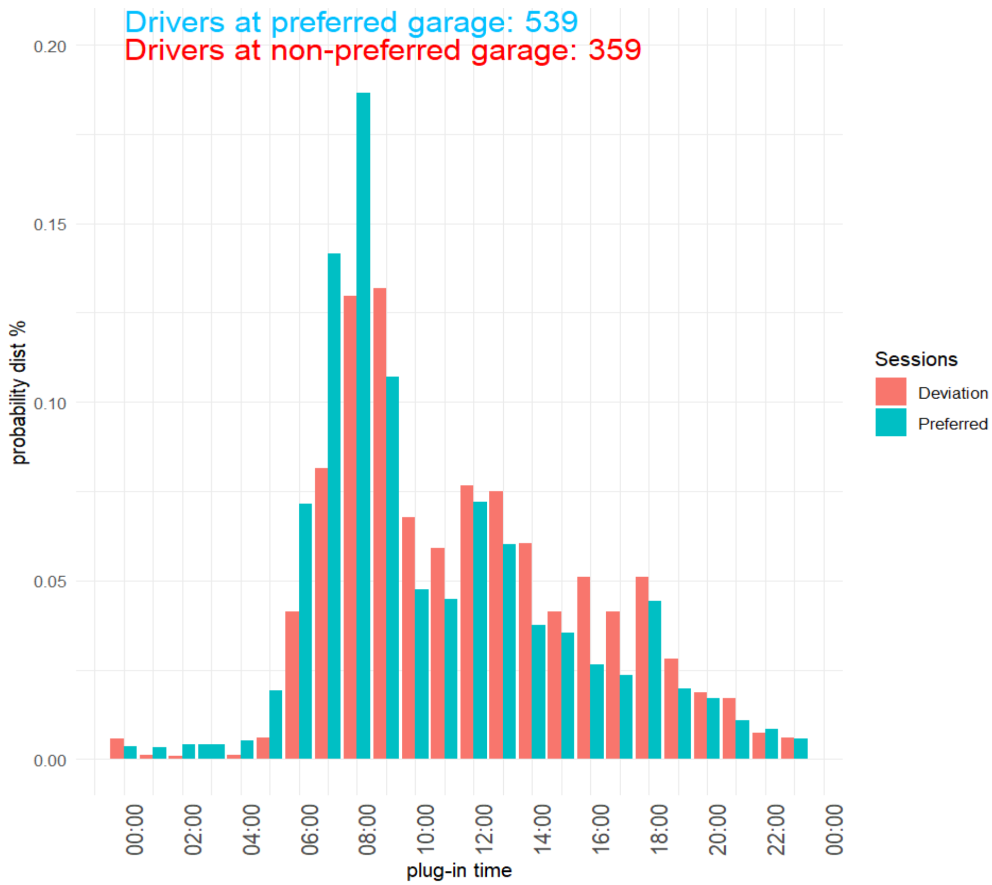

Fig 17. Preferred and deviation sessions by plug-in time.

When looked to the gender and affiliation distribution of charging sessions across the garages, as illustrated in figure 18, the distribution is even across diverse groups of people categorized by gender and working affiliation, i.e., female faculty, students, and staff, likewise for male and others. It is interesting to observe that most charging sessions is being practiced by female drivers and staff, the latter of which includes a wide array of working groups excluding faculty. For instance, Athena has a remarkably high count of female staff (depicted as pink bar) and a lesser count of male staff (depicted as light green), indicating that these two groups are the predominant users of this garage, which is surrounded by medical/ health care facilities. Bachman garage, which is also surrounded by health care facilities, shows a similar trend.

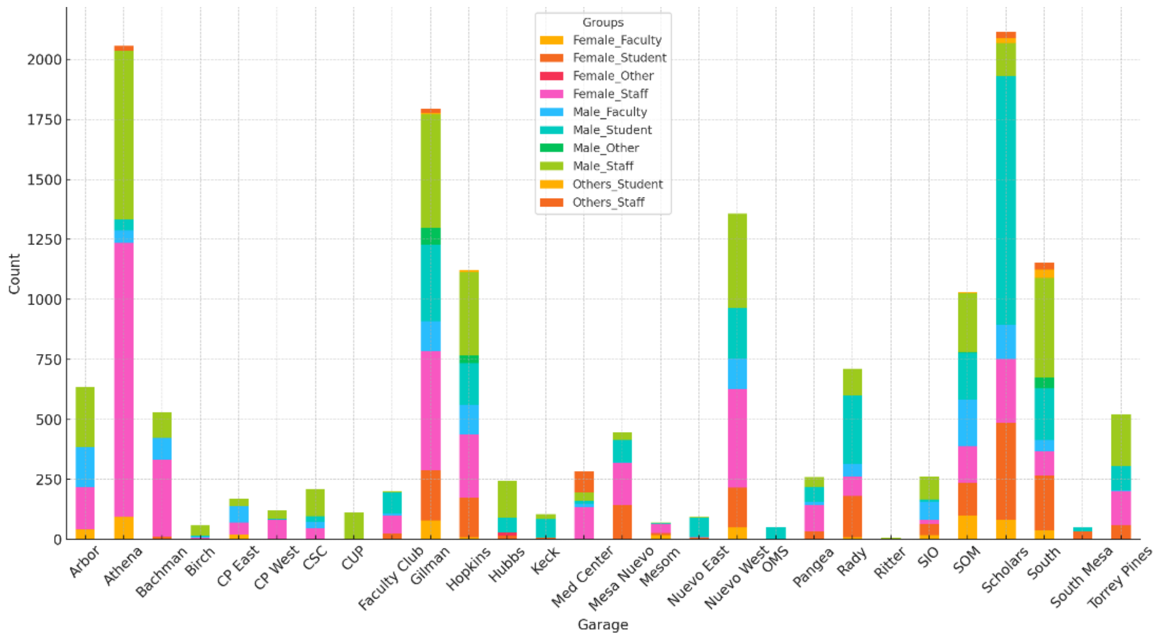

Fig 18. Distribution of charging session utilization by gender and their affiliation to the UCSD.

To identify which garages, have the most frequent transitions or deviation, either within the same garage or among different garages, the garage-by-garage transition matrix is plotted as shown in figure 19. This is important to understand charging sessions depth which simply explains the total energy drawn within a particular charging duration adopted by a driver. Therefore, the dependent variable for session depth is the battery recharging needs and availability of the charging spot. For instance, the more the empty battery, the more the need for finding longer hours charging spot, which simply means more energy drawn and time spent. Since finding charging spot is time and location dependent, often driver deviate or engage with lesser battery charging session. The transition matrix as illustrated is crucial to determine the charging pattern in terms of driver's deviation from their stated preference to non-preferred garages. Each cell in the matrix represents the frequency with which drivers charge at garages other than their preferred one. The color intensity of each cell represents the frequency. Garages such as Gilman and Scholars have high frequencies of deviation sessions, and are often interchanged by drivers, indicating that deviation sessions often occur among garages that are geographically closer. The overall pattern can also be interpreted to depict some garages being more central to the transition compared to others, and thus peripheral garages face congestion. For instance, garages like Athena, Gilman, and Scholars are central hubs with high charging frequencies, both by preferred drivers and by drivers from other garages who are deviated. On the other hand, garages like OMS, Ritter, and South Mesa have low deviation frequencies, indicating they are less centrally located or less frequently used. There are clear patterns of transitions, with certain garages being more popular destinations or points of origin for transitions than others, which is also an indication of heterogeneity within charging stations at different garages.

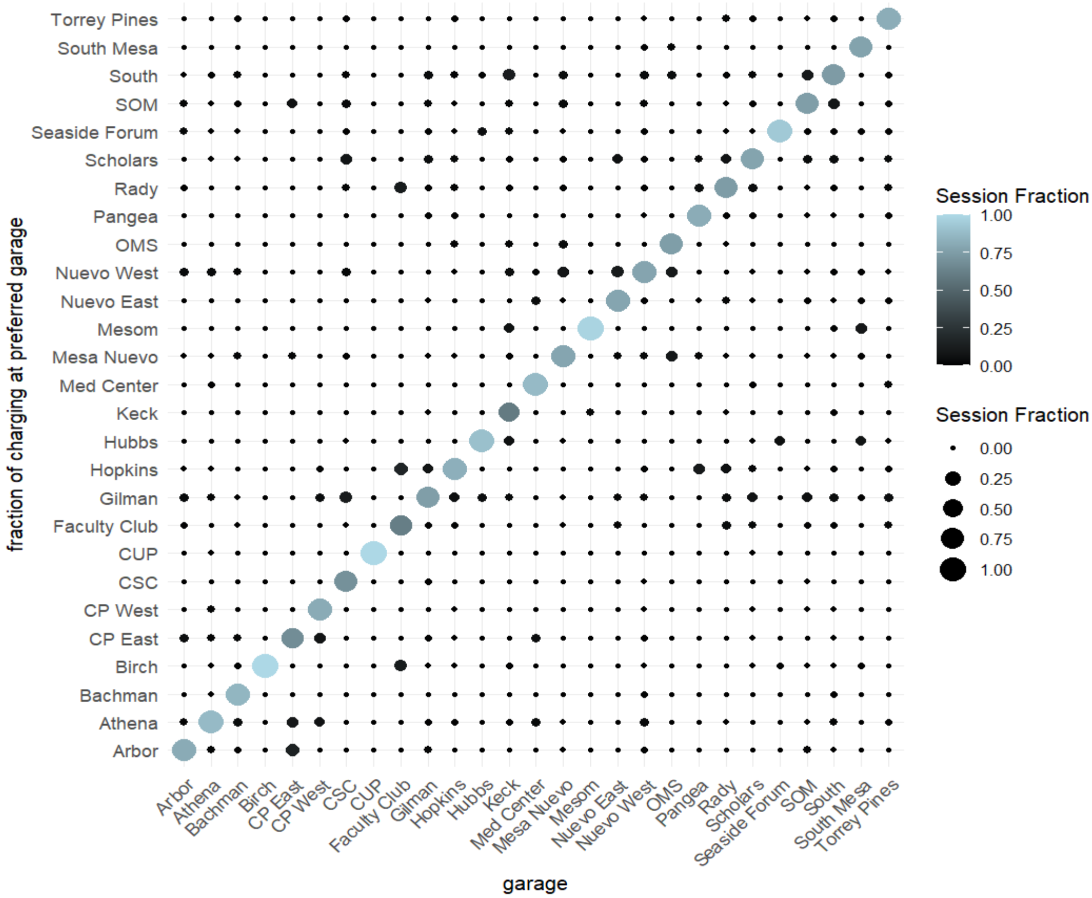

Fig 19. A garage "transition" matrix, indicating the garages that drivers charge in and when they do not charge in at their preferred garages. Color density and size indicate average charging fraction.

C. Charging session depth

When focusing on the charging behavior of the completely battery-operated cars, the drivers' revealed preference indicated that they participate less in deeper sessions compared to shallow sessions. Figure 20 shows that less than 20% of BEV drivers engaged in deeper sessions, while over 50% engaged in shallow sessions. The depth of the session is defined as the kWh delivered during a charging session. If an EV replenishes more than 50% of their battery, they were considered to have engaged in a deeper session, likewise, charging below 25% was considered a shallow session; values in between are intermediate sessions. The predominance of shallow sessions might be due to the lower availability of charging stations for deeper or might be an issue of proximity of charging stations to the workplace. Such a large fraction of sessions that are shallow is alarming. These sessions are problematic because they put additional stress on network efficiency to deliver adequate electricity throughout the day, and thus worsen the demand-supply gap. A charging behavior where most drivers are engaging in lower kWh delivery can be a main driver of congestion at parking garages.

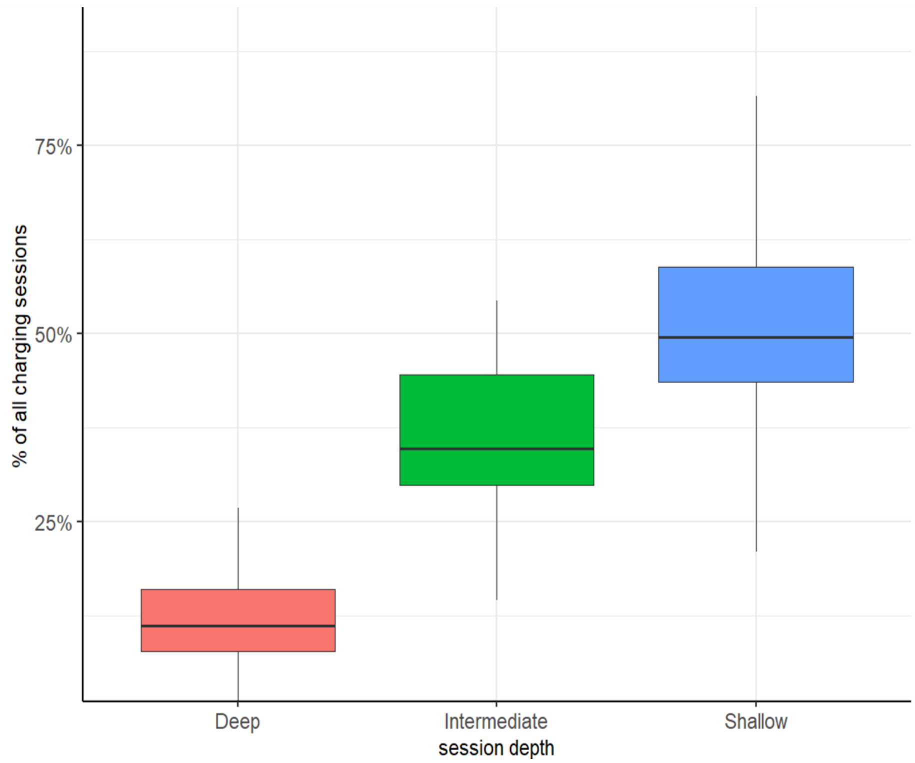

Fig 20. Depth of charging sessions by BEV drivers. Depth categories are defined as Deep: ≥50%, Intermediate: <50% - >25%, and Shallow: ≤25%

It is important to understand how categorization of the session's depth is defined, as it cannot just rely on the responses gathered from drivers. To get such a category range, the session data is analyzed, and the probability distribution curve is plotted. As shown in figure 21, probability distribution modes occur at two values, 25% and 84%. In some cases, due to varied information about battery size which is collected through the enrollment survey the replenishment percentages are inflated to values above 100%. However, it helped in defining the range of charging session depth, from deep to shallow.

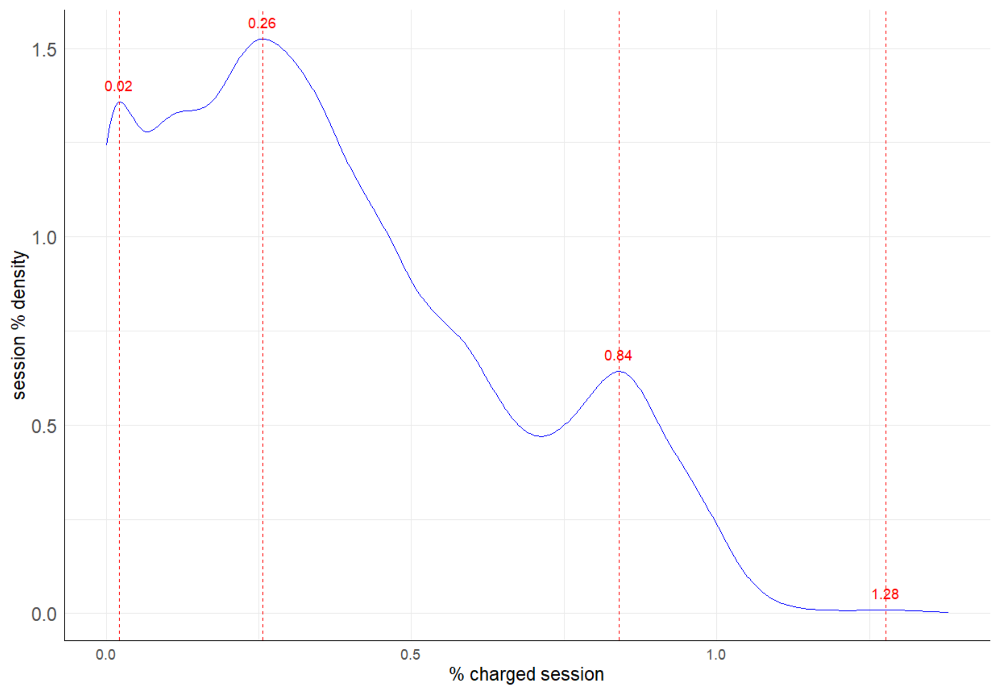

Fig 21. Probability distribution function of session depth, or the kWh delivered to the vehicle with respect to the vehicle's battery size.

This brings us to a question, is the behavior of choosing shallow sessions influenced or correlated with demand-supply imbalance? The results from the analysis reveal a strong correlation. As shown in figure 22, session depth has high variability across garages. Especially at garages with high demand-supply imbalance. This plot illustrates the distribution of charging sessions by BEV drivers across various campus parking garages, categorized into three session depths – Deep, Intermediate, and Shallow.

The separate bar charts for each session type reveal distinct charging patterns across the garages. Garages like Ritter, CUP, and Keck have a high fraction of deep sessions, indicating that drivers tend to charge their vehicles for longer durations at these locations. In contrast, garages such as Nuevo East, Pangea, and Birch have higher fractions of shallow sessions, suggesting that drivers often engage in shorter, quick top-up charging sessions. The intermediate sessions are more evenly distributed, reflecting moderate charging behavior across multiple garages. This variability is more at garages where driver's diversity is more. This analysis highlights specific garages favored for different charging needs, providing valuable insights for optimizing the placement and management of charging infrastructure to cater to the varying demands of EV drivers.

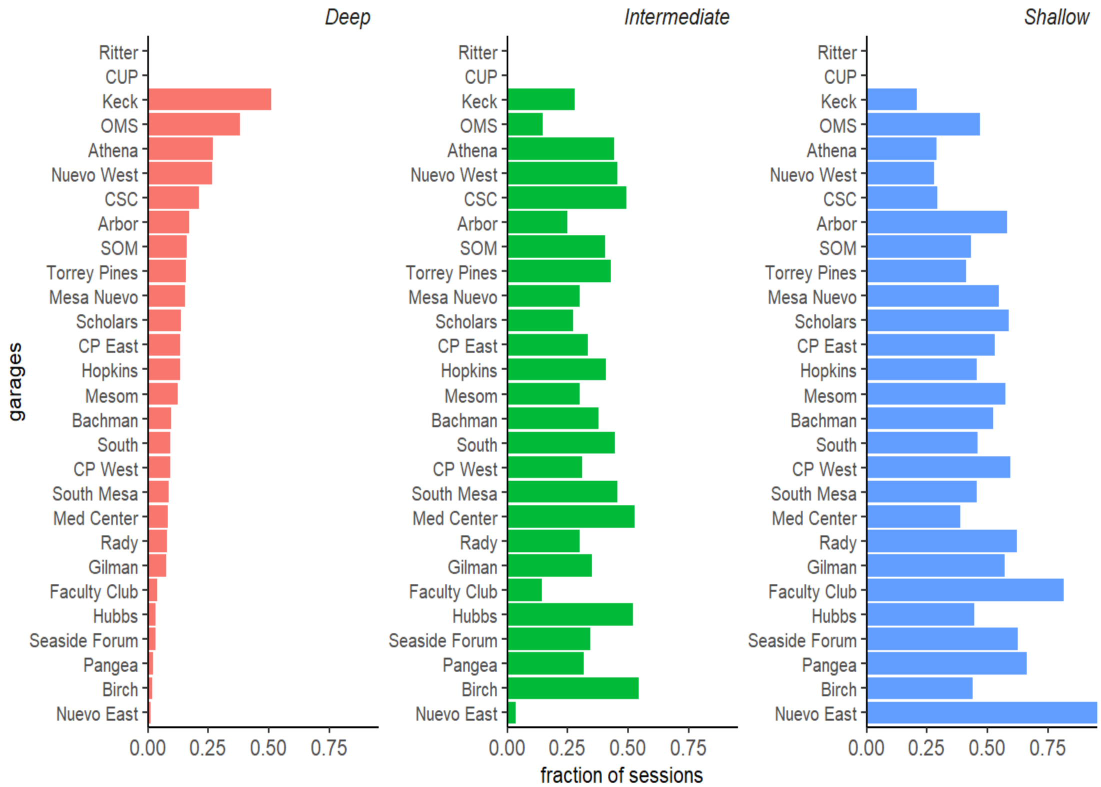

Fig 22. The fraction of BEV charging sessions that are "deep," "intermediate," and "shallow," by parking garage.

Since shallow sessions are a commonly adopted behavior across garages, it is worth exploring how these charging demand-supply imbalances affect shallow sessions. Interestingly, the analysis suggests that the garages with higher demand are associated with fewer shallow sessions. The scatter plot shown in figure 23 displays the indicative relationship with some mild trend between the demand-supply gap ratio on the x-axis and the fraction of shallow charging sessions on y-axis. Each blue dot represents an observation point, i.e., a garage. The slope represents a linear regression fit to the data, indicating the overall trend in the relationship between the demand-supply ratio and the fraction of shallow sessions. This explains that the fraction of charging sessions is more where the demand-supply gap is high and likewise session is less where the gap is low. The number of data points is low, and there is quite some spread around the trend line, indicating a considerable amount of variability in the fraction of shallow sessions for given demand-supply ratios. This suggests that while there may be a general trend, other factors are also influencing the adoption of shallow session behavior.

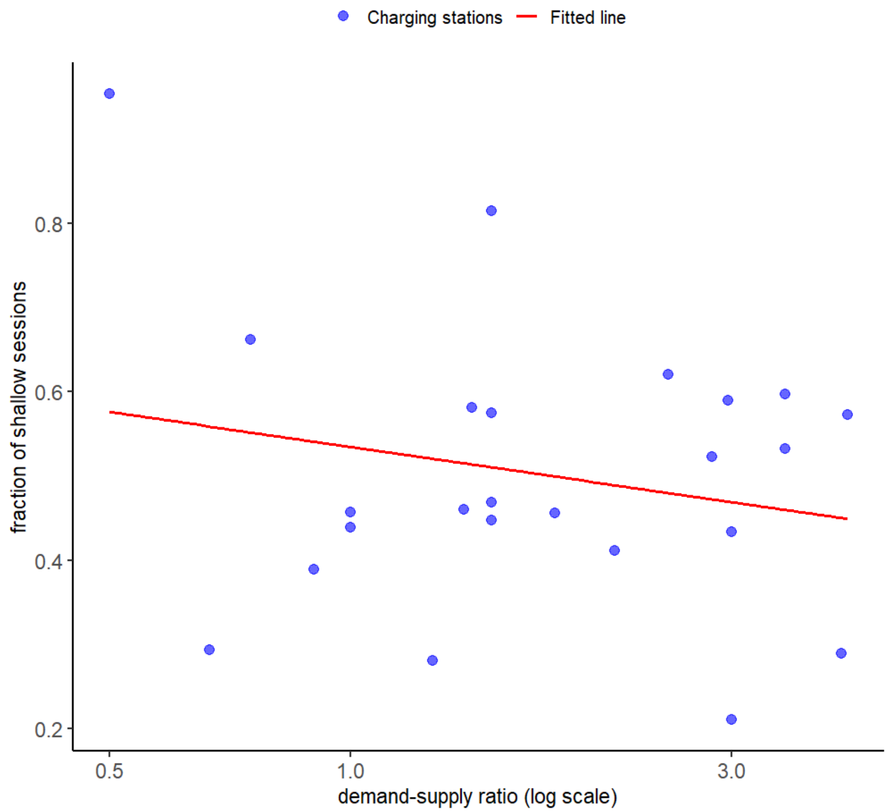

Fig 23. The fraction of shallow sessions by garage as a function of the demand-supply ratio of the garage. The blue dots are individual garages with charging stations, and red line is trend of demand-supply gap.

To further evaluate the session distribution, a k-mean cluster is plotted. As illustrated in figure 24, the scatter plot has EV battery charged percent per session in the x-axis and kilowatt-hours of charging delivered during that session in the y-axis. The points are colored based on their allocated cluster. Orange and blue clusters represent a group of charging sessions where they replenish up to 25 kWh of charging and are thus located primarily at the lower end of the y-axis. This charging behavior could be typical of drivers who regularly replenish their batteries rather than performing full charging at once. On the contrary, the green cluster has a comparatively wide range of charged percentage but tends to have higher kWh energy delivered. These indicate medium to long charging sessions that delivered a substantial amount of energy. These clusters help in understanding the depth of the session, as well as where optimization of charging infrastructure is needed the most. For instance, locations with more users from cluster two might need higher capacity chargers or more charging stations to accommodate deeper sessions.

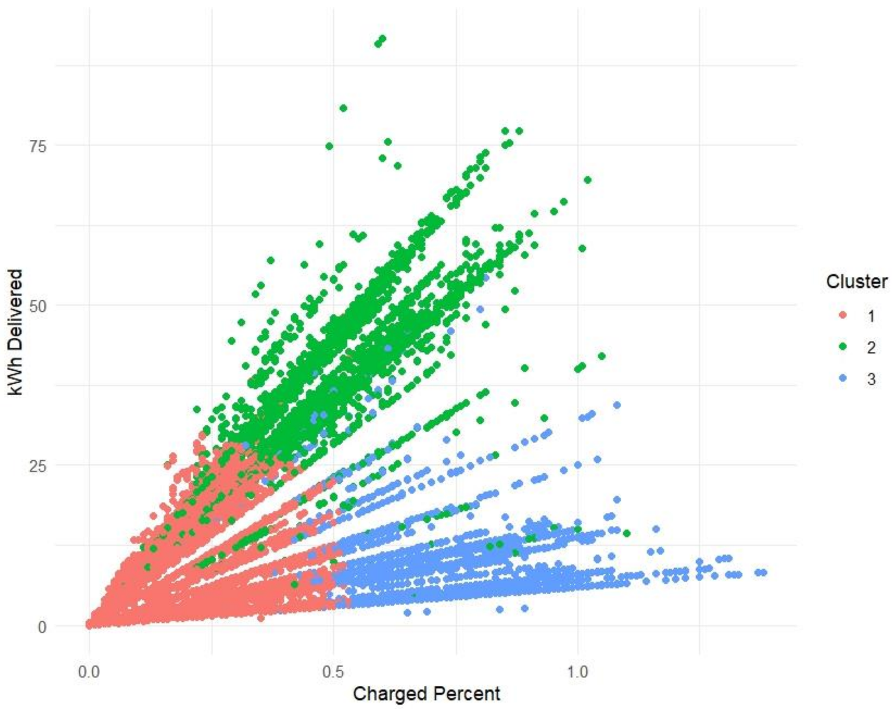

Fig 24. K-mean clustering for percent of charging session by kWh charge delivered.

As the campus network expands, a higher supply of chargers might lead drivers to charge more frequently with shallower sessions, a behavior that should be discouraged when possible.

V. Future work

Training LSTM learning model to better predict future workplace charging behavioral patterns from the revealed and stated preference of identified drivers. Based on the current scope, for training the model, the task involves building and evaluating a deep learning model to predict EV charging behavior, which is crucial for optimizing the charging network or infrastructure.

A. Dataset preparation

A similar dataset is used for this purpose, with a focus on attributes such as date, day, time, garage, vehicle type, charged percent, and session depth. Data preparation involved filtering for BEVs, converting date and time formats, normalizing features, and creating sequences for the LSTM model.

B. Baseline model - LSTM

Model architecture

A linear regression model is implemented as a sample baseline to provide a reference regression line for evaluating the performance of the LSTM model prediction. Linear regression is straightforward and offers a quick way to assess the predictive power of basic statistical methods.

Data preparation

The dataset is normalized, and sequences are created for the LSTM model. For the linear regression model, the sequences are flattened to fit the model requirements.

Training and evaluation

The linear regression model is trained on the flattened training data. Predictions are made using the linear regression model on the test data, and the MSE is calculated to evaluate its performance.

C. Deep learning - LSTM

Model architecture

An LSTM-based *Neural Network* is adopted due to its ability to capture temporal dependencies in sequential data. It consists of two LSTM layers with 150 units each, followed by dropout layers for regularization, and a dense output layer.

Model training

The model is trained using the *Adam Optimizer* with a learning rate of 0.001, batch size of 64, and early stopping based on validation loss to prevent overfitting. The training is conducted over 100 epochs with a validation split of 20%.

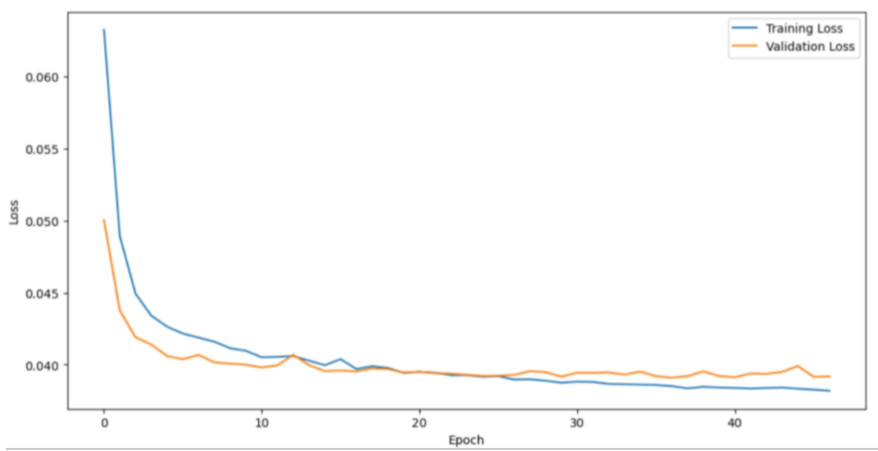

Fig 25. Training and validation loss curve with 40 epoch

Model implementation

The dataset is split into training and test sets, sequences are created, and the model is trained on the processed data. The training included plotting the loss curves for analysis as shown in figures 25 and 26. Initially, the model is trained for 40 epochs to prevent overfitting, which is expected to occur when the model is closely aligned to the training data, capturing noise instead of general patterns, leading to poor performance. By stopping the training early (at

40 epochs), it prevented model's overfitting. After the training run, it is noticed that the model could smooth with additional training, therefore, run for another 10 epochs. This additional step is to fine-tune the model to achieve the best possible outcomes, specifically to check how the loss (error) evolves over time.

D. Analysis and result

Comparison of Models

The linear regression model is adopted for the baseline comparison. The MSE used for the baseline model is calculated to gauge its performance. The LSTM model's effectiveness is also analysed by the MSE on the test set. The comparison showed that the LSTM model provided a more accurate prediction of the charged percent compared to the baseline linear regression model. The results of the simulation are–baseline model MSE is 0.0339, and LSTM model MSE is 0.0328.

Fig 26. Training and validation loss curve with 50 epoch

Effectiveness of adjustments

Key adjustments in the LSTM model included the use of dropout layers to prevent overfitting and the implementation of early stopping to halt training when the validation loss stopped improving. These adjustments are crucial in stabilizing the training process and improving the generalization of the LSTM model.

The plot shown in figure 27 and 28 is for a subset of predictions that demonstrate the model's ability to capture temporal patterns effectively. Figure 29 illustrates the predicted vs. actual charging percent for both the baseline and LSTM models, providing a visual comparison of their performance across different feature classes.

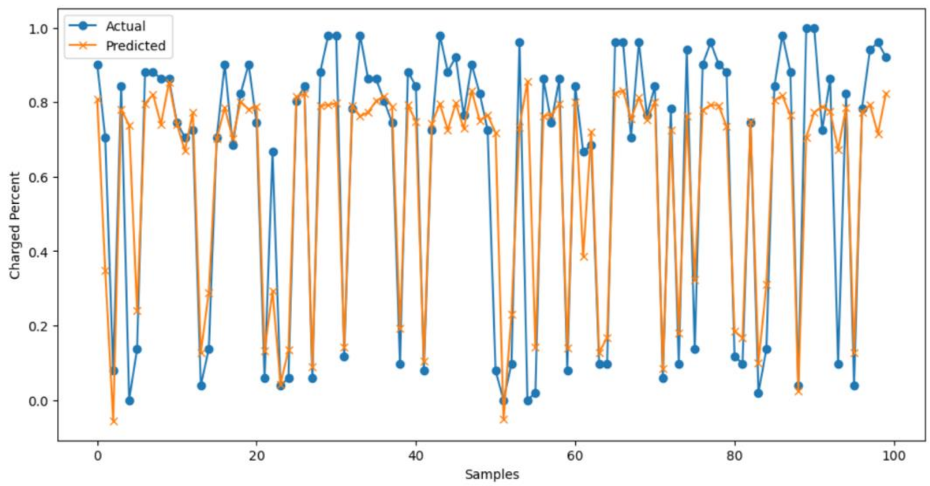

Fig 27. LSTM model performance with a subset of actual and predicted charging percentage data simulation at 100 epoch

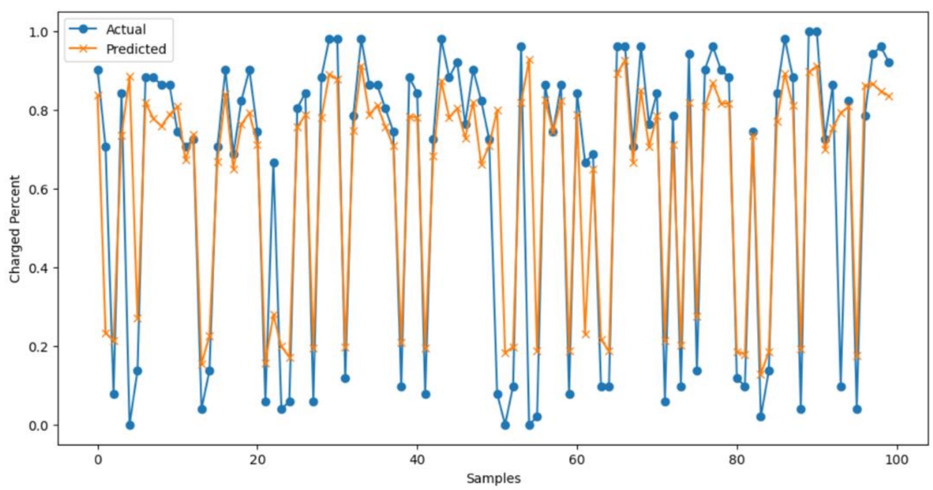

Fig 28. Baseline model performance with a subset of actual and predicted charging data simulation at 100 epoch

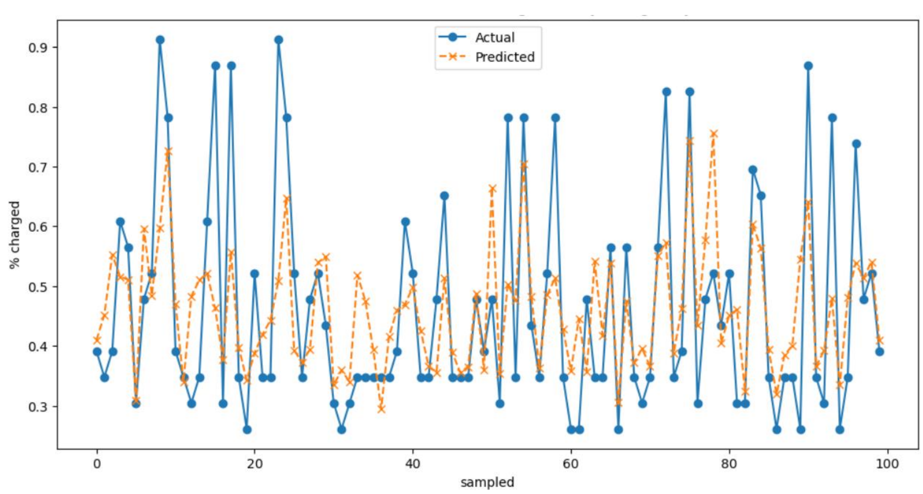

Fig 29. Prediction of percentage battery charged with both baseline and LSTM performance on feature classes.

E. Early findings

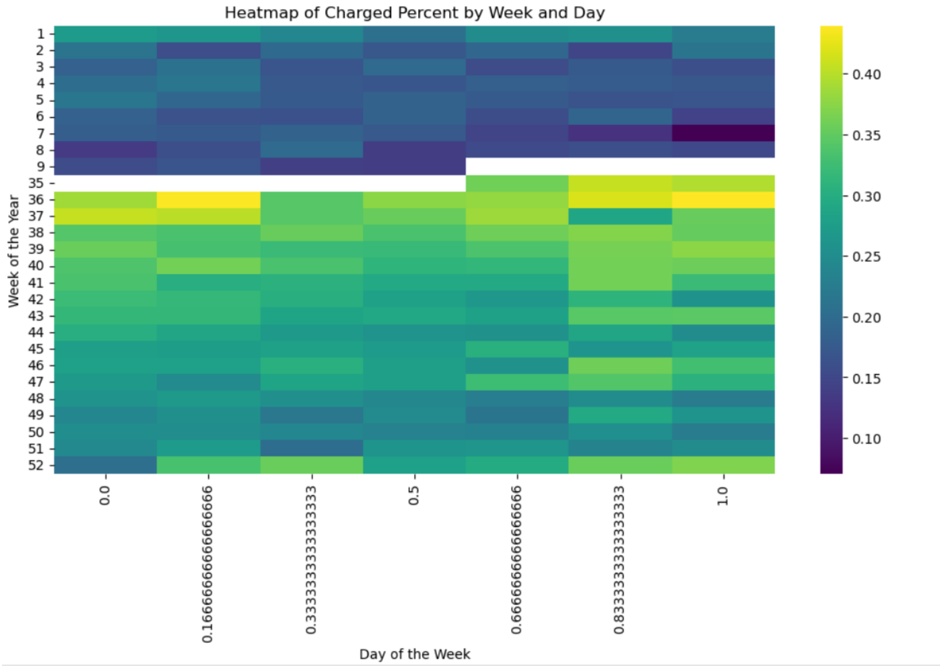

Fig 30. Heatmap of predicted charging percentage by week and day of the recorded year.

The heatmap shown in figure 30 is an illustration of how charging behavior varies temporally. Here, the x-axis is the days of the week, from Monday, i.e., zero to Sunday, i.e., 1, and the y-axis is the weeks of the year, from 1 to 52. In terms of weekly trend, the yellow sheds indicate higher average charging percentages around weeks of 36 to 40 and 48 to 50, whereas lower average charging percentages are observed around weeks 1 to 9 and week 52, indicated with blue shades. In terms of seasonal variation, week 1 to 9 indicates lower less intensive use or different charging behavior, and by weeks 36 to 50 more consistent average charging percentages behavior. This could be due to seasonal factors, increased EV usage, or other external factors influencing charging behavior which is a matter of further investigation.

The heatmap reveals clear temporal patterns in charging behavior, with distinct periods of high and low charging activity. Consistency in certain weeks suggests predictable charging behavior, which can be useful for planning and optimizing charging garage utilization. In terms of seasonal variation, the higher average activity is in the mid to late year and might be influenced by academic calendar or seasonal factors such as weather, long-off due to summer break, or changes in commuting patterns due to work priority.

Figure 31 illustrates the predicted charging percent of EVs over the weeks of the year, compared with the actual charging percentage predictions. This prediction is made by the baseline linear regression model about the results retrieved from the LSTM model. The x-axis represents weeks of the year and the y-axis charging percentage, is normalized to a scale from 0 to 1. Here, the blue line is the actual charging percentage, whereas the orange represents the predicted charging percentage by the baseline linear regression model and the green line is the predicted charging percentage by the LSTM model. The shades represent uncertainty in this prediction.

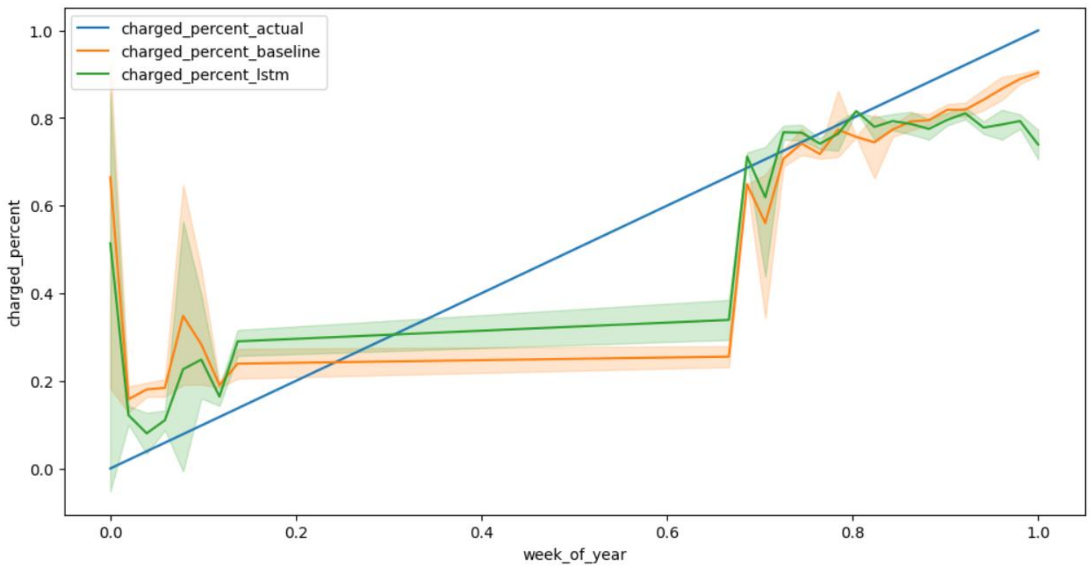

Fig 31. Predicted charging percent of EVs over the weeks of the year

In the early weeks of the year, i.e., represented as 0.0 to 0.1, both the baseline and LSTM models could not capture the high variance in the actual charging percentages. The predictions show significant deviation from the actual values, indicated by the wider shaded areas. Whereas towards the mid-year, i.e., represented from 0.1 to 0.6, explains that as the weeks progress, both models begin to stabilize. The LSTM model shows better alignment with the actual values compared to the baseline model, although some deviations still exist. In the remaining part of the year, the LSTM model closely follows the trend of the actual charging percentages, indicated by the narrower shaded areas, revealing lower variance and higher confidence in predictions.

What this means is the actual charging percentage shows a general increasing trend over the weeks, which is better captured by the LSTM model than the baseline model. This indicates that the LSTM model is more effective in capturing the temporal patterns in the data. While both models show improvement over time, the LSTM model's performance is consistently better, highlighting the advantage of using a more complex model for time-series data.

The LSTM model, with its ability to capture temporal dependencies of stated preferences, provides a more accurate and confident prediction of EV charging percentages over time compared to the baseline linear regression model. This enhanced understanding can significantly benefit planning strategies for charging session optimization in several ways as elaborated in the recommendation.

F. Future work

Future work could be to explore incorporating additional features such as deviation patterns, energy consumption, travel distance, and user demographics to further refine predictions. Additionally, experimenting with different model architectures and hyperparameter tuning could yield further improvements. Investigating other types of models such as RNNs and ensemble methods could also provide valuable insights and potentially enhance prediction accuracy to aid the strategic planning of workplace charging infrastructure.

VI. Conclusion and recommendations

This study on workplace EV charging behavior at UCSD provides crucial insights into the heterogeneity of charging practices among diverse EV drivers. The findings emphasize the significant disparities in the supply of charging infrastructure across campus parking garages relative to demand for charging at those garages. Some garages experience high demand-supply imbalances, leading to frequent deviations from preferred charging locations and underutilization of the network. It also highlights the predominance of shallow charging sessions, which are less efficient and contribute to congestion at charging stations.

The study identifies key factors influencing charging behavior, including access to home charging, commute distance, and drivers' demographics. Drivers without home charging access, particularly those with no-access to home charging face greater challenges in finding available charging spots, resulting in higher deviation rates. The temporal patterns of charging sessions indicate peak usage times that coincide with typical work hours, further stressing the importance of optimal charger placement and availability. To optimize the effectiveness of the EV charging infrastructure provided at the workplace, the following recommendations are proposed:

I. Enhancing the charging network by targeted distribution.

Prioritize the installation of new charging stations in high-demand garages identified in the study to address current imbalances. Focus on areas such as Athena, Gilman, and Scholars, where the demand-supply gap is most pronounced. While other goals such as access and equity are important, prioritizing charger placement in these high-demand areas will maximize kWh sales, EV throughput, and charger cost recovery. The analysis identified six garages with high demand but few forthcoming chargers: Bachman, Campus Point East, Campus Point West, Rady, School of Medicine, and Keck. Strategically increasing the number of chargers in such garages will address the current imbalances and improve overall network efficiency.

II. Encouraging deeper charging sessions over shallow and intermediate sessions.

Currently, garages with lower demand-supply gap ratios have higher rates of shallow charging sessions, leading to underutilization of the charging infrastructure. To mitigate this, there should be consideration for implementing 'driving more incentives' such as kWh-based pricing to encourage drivers to engage in deeper charging sessions. This approach will enhance the efficiency of the charging network by reducing the frequency of shallow sessions and optimizing charger usage.

By adopting these recommendations, the workplaces can enhance the performance and user satisfaction of its EV charging network, supporting the broader adoption of EVs, and contributing to sustainable transportation initiatives on campus. Implement policies and incentives to encourage deeper charging sessions over shallow ones. This could include providing discounted rates for longer charging durations or offering priority access to charging stations for drivers who have a considerable trend of engaging in deeper charging.

III. Improving equity among drivers with no access to home charging.

Develop targeted support programs for drivers who lack home charging options. This could involve providing dedicated charging slots or offering financial assistance for home charger installations, particularly for lower-income employees.

Introducing a reservation system or time-based access for EV charging can significantly enhance the efficiency and fairness of charging infrastructure utilization. Such systems can help manage peak usage times, ensuring that charging opportunities are distributed more evenly throughout the day. Key aspects and benefits of this approach could be:

a. Allowing drivers to reserve charging slots in advance, ensuring they have access to charging when and where they need it. This can reduce uncertainty and stress for drivers, especially those who perform deep charging sessions. This may discourage randomness by choosing multiple shallow or intermediate sessions.

b. Introducing penalties for no-shows or delayed cancellations to ensure that reserved slots are utilized efficiently. This can include fines or non-rebated costs of charging privileges. Charging club members who avail discounted changing costs might get discouraged for the next plug-in session.

c. Providing real-time updates on available charging slots would allow drivers to make informed decisions about when and where to charge.

d. Introducing variable pricing based on peak and off-peak hours charging. Charging during off-peak hours could be cheaper, incentivizing users to charge during times when the grid is less stressed.

IV. Expanding public awareness and education about workplace charging, plug-in hours, and depth of charging sessions.

Conducting educational campaigns to inform charging infrastructure users about the benefits of optimal charging practices and the impact of their charging behavior on the overall efficiency of the network. Raising awareness about the advantages of deeper charging sessions, including improved commute efficiency and potential incentives, should be prioritized. These campaigns will help drivers understand how their charging habits affect both their own experience and the broader charging infrastructure.

V. Continuous monitoring of access and garage utilization.

Establish a robust monitoring system to continuously assess the performance and utilization of the charging infrastructure. Using this data to conduct a similar kind of analysis at regular intervals could help inform decisions on future expansions and required improvements.

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VIII. Annexure

Table 6. Count of drivers' affiliation by their gender engaged in charging sessions over different garages.

Garage	Female_Faculty	Female_Student	Female_Other	Female_Staff	Male_Faculty	Male_Student	Male_Other	Male_Staff	Others_Student	Others_Staff
Arbor	41	2	0	175	166	0	0	252	0	0
Athena	94	0	0	1141	53	45	0	702	0	21
Bachman	0	13	0	320	89	0	0	109	0	0
Birch	1	3	0	1	6	3	0	44	0	0
CP East	19	0	0	51	68	1	0	31	0	0
CP West	1	3	0	78	0	4	0	36	0	0
CSC	0	0	0	47	25	25	0	113	0	0
CUP	2	0	0	1	0	0	0	109	0	0
Faculty Club	3	22	0	75	7	87	0	7	0	0
Gilman	80	209	0	495	126	318	70	472	8	16
Hopkins	10	163	0	266	122	173	32	349	7	0
Hubbs	1	14	13	2	1	61	0	151	0	0
Keck	1	6	0	1	0	76	0	21	0	0
Med Center	0	1	0	135	14	9	0	37	0	87
Mesa Nuevo	0	142	0	177	1	94	0	33	0	0
Mesom	18	9	0	36	0	4	0	3	0	0
Nuevo East	0	6	0	4	0	79	0	4	0	0
Nuevo West	49	166	0	411	128	209	0	394	0	0
OMS	0	0	0	0	0	51	0	0	0	0
Pangea	1	33	0	110	12	64	0	39	1	0
Rady	10	170	0	81	53	287	0	110	1	0
Ritter	0	0	0	0	0	0	0	5	0	0
Seaside Forum	18	45	0	20	74	9	0	96	0	0
SOM	98	139	0	151	196	194	3	246	3	0
Scholars	82	404	0	266	144	1034	0	139	19	26
South	39	225	0	102	47	216	46	415	34	29
South Mesa	0	33	0	0	0	17	0	0	0	0
Torrey Pines	1	58	0	142	4	100	0	218	0	0

Table 7. Count of charging sessions occurred by relevant garages and their zone.

Garage	Zone	Sessions
CUP	West Campus	13
Ritter	SIO	13
South Mesa	Graduate Housing	21
OMS	Graduate Housing	44
Mesom	SIO	49
CSC	West Campus	60
Keck	SIO	68
Hubbs	SIO	107
Nuevo East	Graduate Housing	107
Bachman	Hillcrest	142
CP East	East Campus	144
Pangea	West Campus	161
Med Center	East Campus	163
Torrey Pines	West Campus	175
Faculty Club	West Campus	202
CP West	East Campus	237
Mesa Nuevo	Graduate Housing	239
Seaside Forum	SIO	241
Arbor	Hillcrest	263
Rady	West Campus	429
SOM	West Campus	429
Hopkins	West Campus	448
Nuevo West	Graduate Housing	481
Birch	SIO	558
South	West Campus	615
Athena	East Campus	866
Scholars	West Campus	932
Gilman	West Campus	1335

Table 8. Count of charging ports installed in different garages and zones by their coordinates and service providers.

Zone	Garage	Vendor	Port	Latitude	Longitude
East Campus	Athena	Charge Point	10	32.87959	-117.222
East Campus	Athena	Power Flex	27	32.87961	-117.222
East Campus	CP East	Charge Point	2	32.88022	-117.226
East Campus	CP West	Charge Point	2	32.87972	-117.226
East Campus	Med Center	Charge Point	10	32.88089	-117.221
Graduate Housing	Mesa Nuevo	Charge Point	10	32.8755	-117.224
Graduate Housing	Nuevo East	Charge Point	4	32.87462	-117.219
Graduate Housing	Nuevo West	Charge Point	30	32.8763	-117.222
Graduate Housing	OMS	Charge Point	2	32.87387	-117.226
Graduate Housing	South Mesa	Charge Point	2	32.87242	-117.221
Hillcrest	Arbor	Charge Point	12	32.7542	-117.168
Hillcrest	Bachman	Charge Point	6	32.75517	-117.163
Seaside Forum	Birch	Charge Point	2	32.86626	-117.249
Seaside Forum	Hubbs	Charge Point	4	32.86707	-117.254
Seaside Forum	Keck	Charge Point	2	32.86955	-117.251
Seaside Forum	Mesom	Charge Point	2	32.87012	-117.252
Seaside Forum	Ritter	Charge Point	2	32.86549	-117.254
Seaside Forum	Seaside Forum	Charge Point	4	32.86438	-117.254
West Campus	CSC	Charge Point	12	32.86408	-117.254
West Campus	CUP	Charge Point	2	32.87445	-117.239
West Campus	Faculty Club	Charge Point	2	32.8793	-117.24
West Campus	Gilman	Charge Point	8	32.87749	-117.234
West Campus	Gilman	Power Flex	25	32.87812	-117.234
West Campus	Hopkins	Power Flex	20	32.88381	-117.239
West Campus	Pangea	Charge Point	12	32.88409	-117.243
West Campus	Pangea	Power Flex	4	32.88441	-117.243
West Campus	Rady	Charge Point	10	32.88718	-117.241
West Campus	SOM	Charge Point	10	32.87504	-117.238
West Campus	Scholars	Charge Point	28	32.87986	-117.242
West Campus	South	Charge Point	26	32.87986	-117.242
West Campus	Torrey Pines	Charge Point	14	32.89002	-117.243

Table 9. Charging session matrix by garages.

Garage	Torrey Pines	Pangea	Hopkins	Gilman	South	Faculty Club	Bachman	CP East	CP West	Mesa Nuevo	Nuevo East	Nuevo West	CSC	CUP	Birch	Athena	Arbor	Keck	Mesom	Med Center	Ritter	South Mesa	OMS	SOM	Hubbs
Arbor	9	0	0	393	342	23	299	743	2	90	43	7499	0	0	0	1247	0	0	0	0	0	0	0	299	0
Athena	35	0	237	816	666	7	658	206	1253	176	5	4563	95	3	41	0	1247	57	1	916	0	0	0	170	2
Bachman	90	0	0	52	343	43	0	481	12	12	6	539	0	0	7	658	299	0	0	0	0	0	0	41	0
Birch	0	0	0	3	29	1	7	1	1	2	2	20	0	0	0	41	0	21	10	0	0	33	0	14	15
CP East	0	0	0	31	91	15	481	0	410	6	6	1631	0	0	1	206	743	0	0	117	0	0	0	125	0
CP West	0	0	0	7	70	30	12	410	0	4	2	483	0	1	1	1253	2	3	0	4	0	0	0	71	0
CSC	6	0	0	1118	279	50	0	0	0	128	0	1162	0	0	0	95	0	0	0	9	0	0	0	586	89
CUP	0	0	0	0	0	0	0	0	1	0	0	1	0	0	0	3	0	0	0	0	0	0	0	0	0
Faculty Club	249	0	0	891	554	0	43	15	30	188	113	19	50	0	1	7	23	0	0	3	0	0	0	1005	3
Gilman	578	93	6153	0	2571	891	52	31	7	729	183	948	1118	0	3	816	393	50	2	7	0	0	0	4568	32
Hopkins	0	2681	0	6153	0	0	0	0	0	0	0	0	0	0	0	237	0	0	0	0	0	0	0	0	0
Hubbs	15	0	0	32	45	3	0	0	0	186	9	11	89	0	15	2	0	37	67	1	670	189	0	61	0
Keck	4	0	0	50	164	0	0	0	3	92	0	920	0	0	21	57	0	0	85	0	0	0	322	79	37
Med Center	15	0	0	7	0	3	0	117	4	0	4	406	9	0	0	916	0	0	0	0	0	0	0	12	1
Mesa Nuevo	0	0	0	729	2302	188	12	6	4	0	469	3127	128	0	2	176	90	92	9	0	0	47	195	6153	186
Mesom	0	0	0	2	13	0	0	0	0	9	9	9	0	0	10	1	0	85	0	0	0	243	0	4	67
Nuevo East	9	0	0	183	45	113	6	6	2	469	0	724	0	0	2	5	43	0	9	4	0	33	0	108	9
Nuevo West	118	0	0	948	1045	19	539	1631	483	3127	724	0	1162	1	20	4563	7499	920	9	406	0	89	335	372	11
OMS	0	0	0	0	75	0	0	0	0	195	0	335	0	0	0	0	0	322	0	0	0	30	0	0	0
Pangea	0	0	2681	93	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Ritter	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	670
SOM	136	0	0	4568	9681	1005	41	125	71	6153	108	372	586	0	14	170	299	79	4	12	0	0	0	0	61
South	509	0	0	2571	0	554	343	91	70	2302	45	1045	279	0	29	666	342	164	13	0	0	10	75	9681	45
South Mesa	0	0	0	0	10	0	0	0	0	47	33	89	0	0	33	0	0	0	243	0	0	0	30	0	189
Torrey Pines	0	0	0	578	509	249	90	0	0	0	9	118	6	0	0	35	9	4	0	15	0	0	0	136	15
Rady	1879	0	0	1652	681	601	0	11	13	169	95	255	321	0	4	105	202	65	1	0	0	0	140	672	12
Seaside Forum	66	0	0	122	164	14	39	16	0	188	3	247	192	0	205	275	25	40	11	18	0	27	0	222	144
Scholars	1549	0	0	8038	4964	2841	43	37	49	367	29	376	121	32	37	213	16	37	1	175	0	0	0	2144	20