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Title:
Design of workplace and destination-based EV charging networks considering driver behavior, habits, and preferences

Potential alternatives:
- Integrating human behavior into planning models for workplace EV charging networks
- Impacts of drivers' commuting and charging behaviors, habits, and preferences on the design of workplace EV charging networks
- A driver behavior-centric approach to designing workplace EV charging networks
- Designing workplace EV charging networks around human behavior
- Behavior-based design for destination-based EV charging networks

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Abstract (217 words; aim: ~200)
Many workplaces and other institutions are grappling with how to support their employees and other constituents who drive electric vehicles (EVs) by providing local charging services. We develop a novel driver-centric approach for designing workplace EV charging networks that estimates constituents' charging needs based on their driving and charging habits and determines the optimal number and type of chargers to meet these charging needs. Unlike most prior

literature, our approach explicitly incorporates the behavior of an institution's commuters to guide institutional strategy for deploying and expanding real-world workplace charging services. We demonstrate our approach at the University of California San Diego (UCSD) EV network of 439 charging ports using behavioral data derived from surveys of 800 EV drivers. We find that driver behaviors significantly affect network usage and optimal design. For example, using the data of UCSD drivers instead of regionally-averaged data (a common approach) increases the number of workplace sessions initiated by drivers fivefold and EV network size threefold. Among driver behaviors, drivers' tendency to recharge at relatively high state-of-charge dominates, increasing network size by 50% alone—while also implying less need for high-capacity chargers. In addition to driver behavior, we find that an institution's goals for supporting drivers, which are important for equity, also have a large effect on commuters' network usage and network design.

1. Introduction

Societal shifts from gasoline to electric vehicles (EVs), already well underway in numerous countries (Hanna and Victor, 2021), are pivotal to cutting greenhouse gas (GHG) emissions from transportation (Jaramillo et al., 2022). Although the shift to EVs has occurred in tandem with home charging (LaMonaca and Ryan, 2022), workplace charging remains crucially important for at least two reasons (Bauer et al., 2021). First, whereas early EV adopters tend to be wealthier homeowners (Tal et al., 2020), later mass adopters will likely have less access to private home charging (Pierce and Slowik, 2023; Chakraborty et al., 2019) and thus rely more on alternatives like workplace networks. Second, to minimize vehicle emissions, EVs must charge when renewable energy generation is abundant. In California and other solar-dominant grids, that means daytime when most drivers are at work (Coignard et al., 2018).

Meanwhile, a growing number of institutions (corporations, public entities, universities) have committed to net-zero carbon goals (Erb et al., 2021). To reduce GHG emissions associated with commuting (known as "Scope 3" emissions—perhaps 17% of emissions at U.S. universities; Klein-Banai and Theis, 2013), they are encouraging a switch to EVs by installing workplace charging facilities.

Despite a desire to support workplace charging, institutions are struggling with how to set goals for supporting EV drivers and implement charging policy to cost-effectively meet those goals. At such motivated institutions, decision-makers must grapple with several strategic planning questions: how much charging do constituents need? How many parking stalls should be "electrified," i.e. converted to EV stalls or EV-ready stubouts, to meet these needs? Which kinds of chargers should be installed? What is the optimal charger "dwell time," which limits charging session duration but may increase overall utilization of the network?

These questions form the essence of the workplace EV network planning problem (Section 2) that most EV-supporting institutions will likely face—and our focus in this paper. The aim is to design an EV charger network that reliably meets drivers' charging needs at minimal cost.

The literature on the design of EV charging infrastructure is extremely rich. It includes studies focused on the supply side, e.g. on designing networks to achieve technical goals, such as integrating renewable energy (Fachrizal et al., 2022; Hassan et al., 2023), alleviating grid congestion (Gonzalez-Garrido et al., 2024), and integrating chargers in microgrids (Hafez and Bhattacharya, 2017), as well as on charging strategies that achieve similar goals (Gong et al., 2020). It also includes studies on the demand side, e.g. understanding drivers' charging patterns (Helmus, Lees, & van den Hoed, 2020) as well as preferences (Delmonte et al., 2020) and motivations (Sun et al., 2021) for charging. This paper is unique in that it integrates supply and demand by building a new optimization algorithm for workplace-wide network design based on bottom-up calculations of drivers' demand for workplace charging.

In our framing, answers to the workplace EV network planning problem depend pivotally on the behaviors, habits, and preferences of drivers who commute regularly and would use the workplace EV network. We focus on human behavior because it shapes infrastructure needs, yet existing planning models for workplace EV networks have ignored it (Erdogan et al., 2021), bypassed it by using idealized or average behavior (Huang and Zhou, 2015; Li et al., 2020; Erdogan, Kucuksari, and Murphy, 2022; Wu, Aziz, and Haque, 2023), or otherwise neglected commuters' driving and charging habits (Ferguson et al., 2018). As noted in a recent review of infrastructure planning (Patil, Kazemzadeh, and Bansal, 2022), supply-side studies still tend to make simplistic assumptions about driver charging behavior.

Moreover, studies of human behavior and EV charging have focused primarily on home (Bailey et al., 2023) and public charging (Rempel et al., 2022) where policy support has been stronger; comparatively less is known about systematic charging behaviors in the workplace and therefore about strategies for optimally designing workplace networks.[1]

In this context, we propose a modeling framework for the optimal design of workplace EV networks (Section 3) that advances the literature in two key ways. First, while networks could be designed by prioritizing any number of criteria, we prioritize human behavior that existing models have neglected and create data collection systems to obtain a broad cross-section of behaviors, habits, and preferences of real drivers (Section 4). We collect these data through surveys of a new EV club (*N=800*) at UCSD that we created to support this research.[2] The data characterize, for example, how far and frequently people commute to the workplace, how far they drive between charging sessions, whether they have access to home charging, and the type of EV they drive, among many other attributes.

Second, because these new data empirically resolve human behavioral parameters for driving and charging, they allow for building models that improve the representation of drivers' charging needs. We integrate these behavioral data into a new EV network planning framework

[1] We observe that seemingly similar institutions are pursuing markedly different strategies for providing charging services: the University of California Los Angeles has installed 406 Level-1 charging ports (96% of the network total; UCLA Transportation, 2024), whereas the University of California San Diego has installed 439 Level-2 ports (97% of the network total; UCSD Transportation Services, 2024b).

[2] Setting up data collection systems through an institution-wide EV club has been relatively inexpensive but required deep engagement with the university's transportation and facilities offices that oversee EV chargers and parking. To encourage drivers to sign up and share (anonymized) data, we implemented financial rewards including discounts on charging as well as raffles for membership and responding to surveys. Institutions that charge for parking could similarly offer discounts; where parking is free, institutions could use gift cards, lotteries, or games (e.g., competition across departments) to incent employee participation.

built explicitly on behavioral parameters that implicate network design. Embedding real human behavior into network planning models can significantly improve model outputs for network usage and design (as we will show); moreover, it enables analysis of how driver behaviors affect network planning, and how planned charger investments and parking rules affect drivers' use of the network.

We demonstrate the model using UCSD's EV club (*N=800*) and charging network (Section 5) to two ends. First, we investigate the significance of obtaining and using individual driver data where previous models have used idealized or average data. We find that use of local driver data has a profound effect—affecting model outcomes for network usage fivefold. Second, we analyze previously unstudied effects of human behavioral parameters, which models have struggled to integrate, relative to technological variables that are standard in network design models, like charger throughput. We find that behavioral parameters dominate. In addition, we quantify network usage (how drivers use the network to meet their charging needs) and the levels of stall electrification required to supply these usage patterns.

2. Parking stall electrification

We consider the decision problem of an institution (businesses, universities, other public institutions) with regular commuters, parking facilities, and a commitment to support the charging needs of its EV-driving constituents. The goal is to build (or expand) a network of EV chargers that meets drivers' charging needs while minimizing investment and maintenance costs. We refer to this as the problem of *parking stall electrification*: a selection problem that requires choosing a portfolio of chargers from a set of candidate portfolios. While this applies to charging networks generally (installed anywhere in society), we focus on the workplace because evidence suggests it will repeat at innumerable institutions motivated to support drivers for reasons of environmental stewardship, reputation, or competitiveness (i.e., to attract top employee talent), among others.

In its simplest form at a workplace, the stall electrification problem asks: for an institution, what number and type of EV chargers should be installed to meet drivers' charging needs? The challenge is that the ecosystem of chargers and capabilities is diverse and advancing constantly, while drivers too are diverse and have unique needs (as we elaborate in Sections 3-4).

Underinvesting in chargers could lead to frustration among drivers who find it difficult to reliably find an open charger, which in turn could undercut the workplace charging business model (and the EV transition generally). Overinvesting can be expensive, potentially wasteful, and lead to stranded assets as old chargers are eclipsed by new needs and capabilities.

More complex forms of the stall electrification problem could consider other institutional choices, such as parking rules, differential pricing to incentivize certain behaviors, and options for building EV-ready stubouts instead of chargers; or the potential for time-varying investments given exogenous factors that similarly change over time, like EV adoption rates, technological performance, and markets.

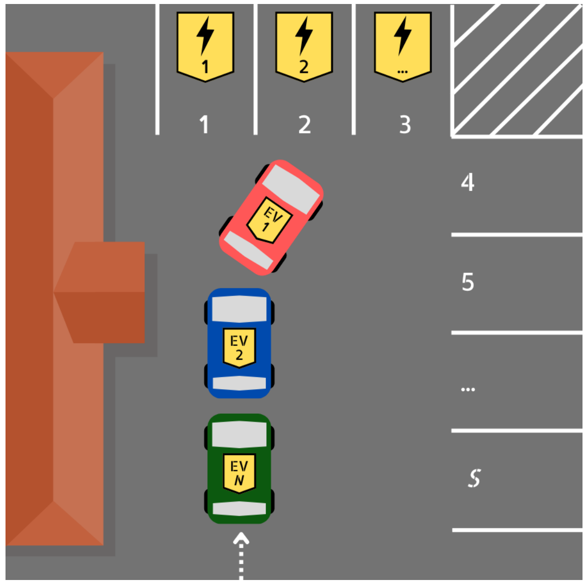

Fig. 1. Schematic of the workplace parking stall electrification problem. A subset of an institution's constituents commute to the workplace in an EV and, with each commute, may park in either an EV or non-EV parking stall. The goal of the stall electrification problem is to determine the optimal (cost-minimizing) number and type of chargers to install that meet the charging needs of the institution's constituents. While the number of parking stalls at the institution is fixed {1,...,S}, the institution seeks to determine the number of chargers to install within the set of parking stalls to support their {1,...,N} EV-driving constituents.

3. Problem formulation

Herein, subscript i indexes N EV drivers (commuters) at an institution, i.e. $i \in \{1, \ldots, N\}$. Each commuter drives a unique EV, so i similarly indexes EVs. EVs are either a battery EV (BEV) or plug-in hybrid EV (PHEV). Subscript c indexes the types of chargers that an institution could invest in (e.g., level-1, level-2, and DC fast chargers) as well as the parking rules (e.g., allowable session dwell time) they might enforce.

To optimally design a workplace EV network that meets drivers' charging needs, institutions must first know four things: its policy goals for supporting drivers; the driving and charging behaviors of its EV-driving constituents; constituents' EVs; and, if applicable, the institution's existing portfolio of chargers and parking rules (Fig. 2). What emerges from these is a unique picture of each driver's interaction with the workplace network: how frequently they "plug in" to the network (relative to total commutes) and the number of weekly sessions they initiate. In our modeling approach, the workplace network must be sized to fulfill these needs.

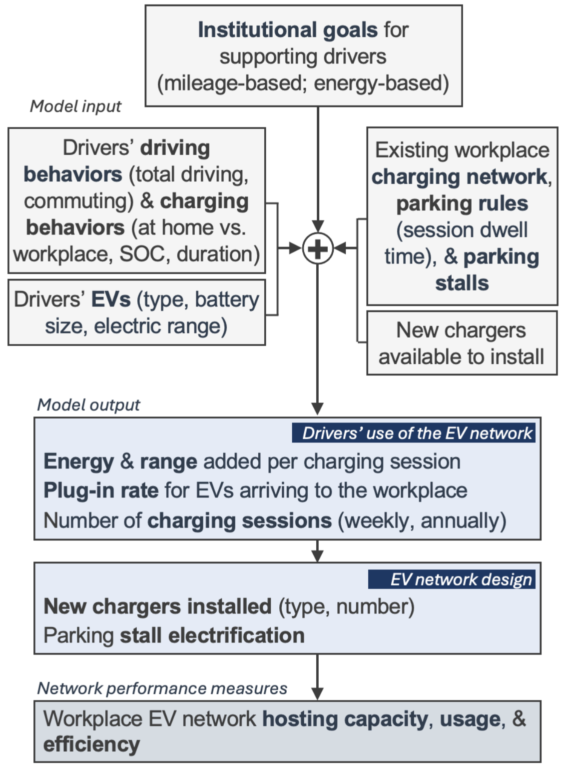

Fig. 2. Model structure: input data, outputs, and EV network performance measures. Our approach to the stall electrification problem is rooted in real driver behavior collected through charging session records and surveys that solicit information about drivers' EVs, demographics, habits, and preferences for driving, charging, and commuting in their EV.

Table 1. Nomenclature. SOC–state-of-charge; BEV–battery electric vehicle; PHEV–plug-in hybrid electric vehicle; occ–occurrences; LCC–lifecycle cost.

Parameter / Variable	Description	Units
Indices and sets		
$i \in \mathscr{D}$	EV drivers at the institution; EVs	–
$c \in \mathscr{C}$	EV charger types installed and available to invest in; charger dwell time limit	–
EV drivers		
N	Number of regular EV commuters at the institution	–
d_i	Commute distance (residence-to-workplace roundtrip) of driver i	mi
f_i	Commute frequency of driver i	occ/week
M_i^{total}	Annual total driving (commuting plus non-commuting) by driver i	mi
M_i^{commute}	Annual commuting mileage by driver i	mi
M_i^{other}	Annual other (non-commute) mileage by driver i	mi
C_i^{home}	Fraction of charging done at residence (i.e., home charging) by driver i	–

C_i^{work}	Fraction of charging done at the workplace by driver *i*	–
T_i	Mean duration of workplace charging sessions by driver *i*	h
$\underline{\mathrm{SOC}}_i$	Mean battery SOC minimum ("floor") maintained by driver *i* (i.e., by which they plug in to charge)	–
EVs		
V_i	EV type (BEV or PHEV)	–
B_i	Nominal battery size	kWh
R_i	Nominal electric range	mi
ϵ_i	Fraction of miles driven on electricity (for PHEVs)	–
B_i^{eff}	Effective battery size (respecting the driver's SOC floor)	kWh
R_i^{eff}	Effective electric range (respecting the driver's SOC floor)	mi
Institutional policy for supporting constituents' charging needs		
M_i^+	The subset of driving mileage to supply workplace charging for	mi
EV chargers and parking stalls		
S	Number of parking stalls at the institution	–
K	Number of charger types installed and available to invest in	–
n^{CD}	Number of "charging days" per week at the institution ()	
U_c	Number of existing EV chargers type *c* at the institution	–
P_c	Power delivery ("throughput") for EV charger type *c*	kW
$\overline{E}_c$	Maximum energy that charger type *c* can deliver during a charging session of τ_c duration	kWh
Δ_c	Number of charging sessions per workday that charger type *c* can provide	–
Decision variables		
υ_c	Number of chargers of type *c*	–
τ_c	Permissible session dwell time for EV charger type *c*	h
Driver and workplace network measures		
$E_{i,c}^{session}$	Energy delivered to EV *i* during a charging session at charger type *c*	kWh
$R_{i,c}^{session}$	Electric range added to EV *i* during a charging session at charger type *c*	mi
$\pi_{i,c}$	Plug-in rate of driver *i* (i.e., fraction of workplace commutes that end at an EV charger) when using charger type *c*	–
$\sigma_{i,c}^{annual}$	Annual charging sessions required by driver *i* when using charger type *c*	occ/yr
$\sigma_{i,c}^{weekly}$	Weekly charging sessions required by driver *i* when using charger type *c*	occ/week

σ^{network}	Network hosting capacity for weekly charging sessions	–
E^{network}	Network hosting capacity for weekly energy delivered	kWh
LCC	Lifecycle cost of the EV charging network	USD$

3.1 Institutional support for EV drivers

The optimal design of a workplace charging network depends on an institution's policy for supporting its EV-driving constituents. While institutions could support drivers in numerous ways, we study two strategies that plausibly bookend levels of support they might provide. In one strategy, an institution invests in chargers to meet some or all of affiliates' driving mileage needs, e.g. total driving M^{total} or commuting M^{commute}. A second strategy meets some or all of affiliates' charging needs, e.g. 100% of charging or the portion of charging not already done at home $1–C^{\text{home}}$.

These support strategies recognize (and plan for) the fact that drivers have different habits, needs, and opportunities (e.g., some have access to home charging while others, such as renters, rely on charging outside the home) (CPUC, 2022). Moreover, they implicate ideals of fairness and access, since newer EV adopters tend to have less access to home charging than early adopters and hence depend more on charging outside the home (Pierce and Slowik, 2023; Chakraborty et al., 2019).

In all cases, institutional support manifests in the model as a requirement to supply some mileage driven by constituents, denoted M^{+}. As we show in Section 5, institutional choices for supporting drivers can significantly affect drivers' network usage and can determine model outcomes.

3.2 Driver behavior and charging needs

Drivers' charging needs are a function of their driving and charging behaviors, such as the amount of driving and commuting they do, how often and deeply they charge, the EV they drive, and whether they have access to home charging. These affect, for example, the energy needed for commuting and the effective size of a driver's battery. Charging needs also depend on institutional choices such as the type of chargers installed at the workplace and parking rules that govern their use.

3.2.1 Driving and commuting

Driving behaviors include home-to-workplace roundtrip commute distance d (mi), commute frequency f (per week), and annual mileage for total driving M^{total} (mi), commuting M^{commute}, and other driving (non-commuting) M^{other}. To protect personal information (including address), d_i is estimated as the driving distance between the institution and the centroid of the driver's home zip code. At UCSD, drivers report f_i and home zip code in the EV club enrollment survey. M_i^{total} could be obtained in several ways; we have EV drivers report vehicle odometer readings through recurring surveys (Section 4.3). A driver's unique annual commuting profile is therefore given by

$$M_i^{\text{commute}} = 52 f_i d_i \ , \ i = 1,\dots,N \ , \tag{1}$$

and $M_i^{\text{other}} = M_i^{\text{total}} - M_i^{\text{commute}}$.

3.2.2 Charging

Charging habits include the fraction of charging done at home C^{home} and the workplace C^{work}, measured on an energy (kWh) basis; the duration T of workplace charging sessions that drivers initiate when unrestricted by policy; and the typical SOC by which they plug in to charge, $\underline{\text{SOC}}$. $C^{(\cdot)}$ are self-reported in the enrollment survey. T and $\underline{\text{SOC}}$ are revealed through charging session data.

3.2.3 EVs

EVs are characterized by their type (BEV or PHEV), battery size B (kWh), electric range R (mi), and fraction of total driving using electricity ε (for PHEVs). EV type matters because BEVs and PHEVs can have markedly different charging patterns: relative to BEVs, PHEVs could be high-frequency chargers (Venegas, Petit, & Perez, 2021) because they have smaller batteries and electric ranges commensurate to commute distances; or they could be low-frequency chargers if they drive predominantly on gasoline.

Drivers report their EV (year, make, model, and type) in the club enrollment survey. B and R are then obtained from manufacturers through DOE (Department of Energy, 2024). ε depends on driver behavior, but we cannot measure it directly. Instead, we consider it as a function of vehicle range R, following the empirical relationship defined in Isenstadt et al. (2022) and given by

$$\epsilon_i = \begin{cases} 1 & , \text{ if BEV} \\ 1 - \exp\left(-\sum_{j=1}^{10} \left(\frac{R_i}{\text{ND}} \right)^j c_j \right) & , \text{ if PHEV} \end{cases} , \quad i = 1,\dots,N \tag{2}$$

where ND = 700 mi is normalized distance (and reflects proposed updates to codified EPA analysis) and c = [13.1, –18.7, 5.22, 8.15, 3.53, –1.34, –4.01, –3.9, –1.15, 3.88] is a weighting coefficient. Given the variation in R among EVs, mean values are 0.2–0.7. For BEVs, $\varepsilon = 1$.

An EV's effective battery size B^{eff}, given in Eq. (3), is the portion of the battery that the driver regularly uses, respecting that they typically plug in with ample remaining SOC. An EV's effective range R^{eff}, given in Eq. (4), is the distance it typically travels between plug-ins, similarly respecting how human behavior affects $\underline{\text{SOC}}$ and ε. Since $\underline{\text{SOC}} \in [0,1]$, BEVs have

$B^{\text{eff}} \leq B$ and $R^{\text{eff}} \leq R$. For PHEVs, we set $\underline{\text{SOC}} = 0$ and instead capture variation in R^{eff} through variation in ϵ; with ϵ typically 0.2–0.7 for PHEVs, $R^{\text{eff}} > R$.

$B_i^{\text{eff}} = B_i\left(1 - \underline{\text{SOC}}_i\right), \quad i = 1,\ldots,N$	(3)
$R_i^{\text{eff}} = R_i\left(1 - \underline{\text{SOC}}_i\right)\epsilon_i^{-1}, \quad i = 1,\ldots,N$	(4)

3.2.4 EV chargers and parking rules

Chargers are defined by their power delivery or "throughput" P (kW), while parking rules cap the session dwell time τ (h) over which drivers can charge. EV chargers can therefore deliver maximum session energy (kWh) given by

$\overline{E}_c = P_c\tau_c, \quad c = 1,\ldots,K$	(5)

Chargers and parking rules affect network design because they determine $\overline{E}$ and in turn the range that drivers could recoup per session.

3.2.5 Use of workplace charging

Notwithstanding permissible dwell time τ_c, driver behavior reveals the typical duration T_i for which they actually charge, which may be larger or smaller than τ_c. When unrestricted by dwell time limits, drivers receive session energy given by

$E_{i,c}^{*} = P_c T_i, \quad i = 1,\ldots,N, c = 1,\ldots,K$	(6)

Ultimately, when plugging into a charger of type c, driver i recoups energy equivalent to $E_{i,c}^{\text{session}}$, given in Eq. (7). The energy delivered $E_{i,c}^{\text{session}}$ could be as large as $\overline{E}_c$ but is usually smaller and constrained by the driver's behavior—either their typical session duration T_i (which affects $E_{i,c}^{*}$) or the SOC with which they typically plug in, $\underline{\text{SOC}}_i$ (which affects B_i^{eff}). Delivered energy $E_{i,c}^{\text{session}}$ begets an increase in range $R_{i,c}^{\text{session}}$, given in Eq. (8), that is proportional to the fraction of battery replenished $E_{i,c}^{\text{session}}/B_i^{\text{eff}}$.

$E_{i,c}^{\text{session}} = \min\left\{\overline{E}_c,\ E_{i,c}^{*},\ B_i^{\text{eff}}\right\}, \quad i = 1,\ldots,N, \ c = 1,\ldots,K$	(7)
$R_{i,c}^{\text{session}} = \dfrac{E_{i,c}^{\text{session}}}{B_i^{\text{eff}}}\mathrm{R}_{\mathrm{i}}^{\text{eff}}, \quad i = 1,\ldots,N, \ c = 1,\ldots,K$	(8)

To recoup energy equivalent to M^{+} annual driving miles, driver i requires $\sigma_{i,c}^{\text{annual}}$ annual charging sessions at charger c, given in Eq. (9). σ^{annual} considers that PHEVs drive only a fraction ϵ of total miles on electricity, will drive farther than R before charging, and hence require fewer charging sessions than implied by R alone.

$$\sigma_{i,c}^{\text{annual}} = \frac{M^{+}}{R_{i,c}^{\text{session}}}\epsilon_i\,, \quad i = 1,\ldots,N\,,\ c = 1,\ldots,K \tag{9}$$

The number of *implied* weekly sessions is given by $\frac{1}{52}\sigma_{i,c}^{\text{annual}}$. However, this is constrained by the driver's commute frequency f_i: in our model, drivers do not make additional commutes just to charge; if the number of required weekly charging sessions exceeds commutes (i.e., if $\frac{1}{52}\sigma_{i,c}^{\text{annual}} > f_i$), we assume drivers charge outside the workplace and initiate only f_i weekly workplace sessions.

It follows that the driver's plug-in rate $\pi_{i,c}$, or fraction of workplace commutes that end at an EV charger, is given by Eq. (10); and the number of *actual* weekly charging sessions that driver i initiates, $\sigma_{i,c}^{\text{weekly}}$, is given by Eq. (11).

$$\pi_{i,c} = \min\left\{\frac{\frac{1}{52}\sigma_{i,c}^{\text{annual}}}{f_i}, 1\right\}\,, \quad i = 1,\ldots,N\,,\ c = 1,\ldots,K \tag{10}$$

$$\sigma_{i,c}^{\text{weekly}} = \pi_{i,c} f_i\,, \quad i = 1,\ldots,N\,,\ c = 1,\ldots,K \tag{11}$$

Notationally, $\sigma_{i,c}^{(\cdot)}$ gives the number of sessions required by driver i when plugging in at charger type c. We note that the number of weekly sessions drivers initiate is a function of the portfolio of chargers $\{v_c, \tau_c\}\ \forall c \in \{1,\ldots,K\}$ that the institution chooses to install.

3.3 Algorithm for selecting EV chargers

The goal of workplace EV network planning (Section 2) is to invest in a cost-minimizing portfolio of EV chargers that meets the charging needs of drivers. To determine optimal investment of chargers, we formulate a constrained optimization problem:

$$\underset{v_c,\ \tau_c}{\text{minimize}}\ \text{LCC}\,, \tag{12}$$

such that $\upsilon_c,\ \tau_c \in \mathbb{Z}$ (are integers), $\upsilon_c,\ \tau_c \geq 0,\ \sum_c \upsilon_c \leq S$, and $\tau_c \leq 24 \quad \forall c \in \{1,\ldots,K\}$,

where LCC is the lifecycle cost of the EV network (inclusive of upfront and operating costs), υ_c is the number of chargers of type c, τ_c is the allowable session dwell time at charger type c, and S is the total number of parking stalls at the institution that can host chargers.

In general, the constraint to meet drivers' charging needs is nonlinear: the institution seeks to install υ_c chargers with dwell time τ_c, yet drivers' charging needs, given by $\sigma_{i,c}^{(\cdot)}$ and $\pi_{i,c}$ in Eq. (9)–(11), are a function of the institution's decisions for υ_c and τ_c.

We therefore propose a heuristic algorithm to solve the optimization problem in Eq. (12) using particle swarm optimization (PSO) (Poli, Kennedy, & Blackwell, 2007), a commonly used heuristic method that requires few assumptions about problem continuity and differentiability (Eberhart and Shi, 2001). With PSO, n_{part} particles search an n_{dim}-dimension solution space, solve the problem in Eq. (12) for a location in the space (a candidate solution), and store and share the solution value, or "fitness." Each dimension corresponds to a single decision variable. Particles interact and exploit areas around better solutions.

Following prior work, we adapt the PSO routine specified in Hanna et al. (2019) (and direct the reader there for details), with two main updates. One, dimensions in the solution space correspond to υ_c and τ_c and are constrained by S and 24 h, respectively; hence candidate solutions are portfolios of chargers and their permissible dwell time. Two, solution fitness is defined as LCC.

3.4 Heuristic for determining whether charging needs are met

The algorithm in Section 3.3 generates a portfolio of chargers—a candidate EV network—given by $\{\upsilon_c, \tau_c\}\ \forall c \in \{1,\ldots,K\}$. To determine whether a candidate network meets drivers' charging needs, we need criteria that appraise supply and demand for charging. While many criteria are possible, we use weekly charging sessions and energy because they are the most granular discrete measures that our data collection systems generate. A network can support a weekly maximum number of sessions σ^{network} and can deliver energy E^{network}, given by

$$\sigma^{\text{network}} = n^{\text{CD}} \sum_c \upsilon_c \Delta_c \tag{13}$$

$$E^{\text{network}} = n^{\text{CD}} \sum_c \upsilon_c \Delta_c P_c \tau_c \tag{14}$$

where n^{CD} is the number of "charging days" per week (i.e., number of weekly workdays over which drivers can reasonably be assumed to commute and charge) and Δ_c is the number of daily sessions that charger type c can host and a function of human behavior in response to τ_c. Based on our observations of UCSD drivers, we define $n^{\text{CD}} = 5$ and Δ_c as

$$\Delta_c = \begin{cases} 3\,, & \tau_c \leq 2 \\ 2\,, & 2 < \tau_c \leq 4 \\ 1\,, & \tau_c > 4 \end{cases} \tag{15}$$

While the upper potential for supplying sessions and energy is a deterministic feature of the network (and therefore known), we cannot know which drivers $i = 1,\ldots,N$ will charge at which of the potentially many types of chargers $c = 1,\ldots,K$. Drivers could self-allocate efficiently (e.g., wherein high-need drivers use high-kW-throughput chargers) or inefficiently. We therefore propose an allocation algorithm (Algorithm 1) that randomly assigns drivers to chargers (lines 4–7), calculates the number of sessions and energy the network delivers per that allocation (lines 8–9), and determines whether drivers' aggregate need for sessions and energy are met by the network (lines 12–14).

The process of random allocation in Algorithm 1 can be embedded within a Monte Carlo routine and repeated until driver assignments to chargers $\{\mathscr{A}_c\}$, supply of sessions X, and supply of energy Y converge. The network is deemed to meet drivers' charging needs (i.e., Z = true) when the probability of meeting demand from a random allocation of drivers and chargers exceeds some threshold, say 0.95 (95th percentile), meaning we would expect network supply to meet demand during 49.4 weeks of the year.

We note that Algorithm 1 omits human behavior and could be improved in future work by integrating observations of human responses. For example, driver behaviors may tend toward efficient network outcomes, e.g. if drivers seek opportunities to charge when network utilization is low, thereby distributing demand and increasing usage. Alternatively, drivers may flout rules on session dwell time, thereby decreasing network supply. This motivates the need to investigate the potential flexibilities in human behavior that can, all else equal, reduce investments in charging infrastructure without sacrificing service quality.

Algorithm 1. Determines the number of weekly sessions X and energy Y delivered by a workplace EV charging network, and whether that meets aggregate driver demand for sessions and energy, denoted Z. [a]

Input: $N, \sigma_{i,c}^{\text{weekly}}, E_{i,c}^{\text{session}}, \sigma^{\text{network}}, E^{\text{network}}$. **Output:** X, Y, Z

1 Set initial conditions[b]: $X_j = Y_j = 10^6 \ \ \forall j \in \{1,\ldots,N\}, Z =$ false

2 Unassigned drivers $\mathscr{U} = \{1,\ldots,N\}$

3 **for** charger type $c \in \{1,\ldots,K\}$ **do**

4   Randomly assign $\sigma_c^{\text{network}}$ drivers $\mathscr{A}_c \in_R \mathscr{U}$

5   **if** $\sigma_c^{\text{network}} > |\mathscr{U}|$ **then**

6         $\mathscr{A}_c = \mathscr{U}$

7   **end if**

8 Supply sessions $X_j = \sigma_{j,c}^{\text{weekly}} \quad \forall j \in \mathscr{A}_c$

9 Supply energy $Y_j = E_{j,c}^{\text{session}} \quad \forall j \in \mathscr{A}_c$

10 Set unassigned drivers $\mathscr{U} = \mathscr{U} \backslash \mathscr{A}_c$

11 **end for**

12 **if** $\sum_j X_j \leq \sigma^{\text{network}}$ **and** $\sum_j X_j Y_j \leq E^{\text{network}}$ **then**

13 Z = true

14 **end if**

[a] $\in_R$ denotes random allocation; $|\cdot|$ denotes set cardinality (number of set elements).
[b] Elements in X and Y are set to arbitrarily high numbers and overwritten (lines 8–9) only when the network is sufficiently sized to meet demand. Insufficiently-sized networks thus fail the conditions in line 12.

3.5 Stall electrification

The stall electrification rate is given by $\frac{1}{S}\sum_c \upsilon_c \in [0,1]$. This is the fraction of parking stalls at the institution that must be "electrified," i.e. converted to an EV charging stall, to meet the aggregate charging needs of the institution's EV drivers.

3.6 EV network performance metrics

We define three categories of metrics to quantify network performance, or how efficiently drivers use the workplace network:

- *Network hosting capacity* is the quantity of charging activity the network *could* accommodate, assuming perfectly efficient use of the network. The upper potentials for sessions and energy delivery are given by σ^{network} and E^{network}, respectively.
- *Network usage* is a measure of drivers' actual use of the network. We define network usage via the number of weekly sessions initiated and energy delivered.
- *Network efficiency* is the ratio of actual usage to hosting capacity.

4. Driver behavioral data

In this section, we elaborate the three data collection systems we implemented at UCSD to generate human behavioral data: records of campus charging sessions (obtained from the EV charger vendors operating on campus); an intake survey that drivers complete upon joining UCSD's EV club; and recurring odometer surveys sent about monthly to club members (Table 2). These data, which provide a unique profile of how each driver interacts with the workplace network, enable new planning models based explicitly on human behavior.

Institutions without the ability to set up data collection systems can configure the model in Section 3 using stylized averages for human behavior parameters; however, use of behavioral inputs that reflect the local driver population can vastly improve data quality and model outputs (as we show in Section 5.3).

Table 2. Data collection systems we have implemented at UCSD to generate human behavioral data, and the model parameters it defines. For completeness, we include key external data sources as well.

Data collection system	Driver attribute	Units
Club enrollment survey	Commute distance (roundtrip)	mi commute^{-1}
	Commute frequency	week^{-1}
	Commuting mileage	mi year^{-1}
EV reported in club enrollment survey; EV specs obtained from DOE (2024)	EV type	BEV or PHEV
	EV battery size	kWh
	EV battery range	mi
Club enrollment survey; updated per recurring odometer surveys and campus charging sessions	Fraction of total charging done at home	–
	Fraction of total charging done at the workplace	–
Recurring odometer surveys	Total driving mileage	mi year^{-1}
Campus charging sessions	Typical charging session duration	h
	Typical battery SOC when initiating a charging session	–
Isenstadt et al. (2022)	Fraction of driving on electricity (for PHEVs)	–

4.1 Workplace charging sessions

UCSD contracts with EVSE vendors who install and manage EV chargers throughout campus. From these vendors we receive charging session-level data on every instance of an EV connecting to the campus network, including the time an EV plugs in, stops charging, and unplugs from each charger, along with the energy delivered and driver who initiated the session (through an anonymized ID number). Drivers who opt to enroll in the UCSD EV club consent to our matching their information to these IDs, allowing analysis of their sessions. In this work, we draw on 3,218 distinct charging sessions at 113 charging ports since June 2023.[3]

Local charging session data is important because it defines two key human behavioral parameters. First is the duration for which drivers plug in when unconstrained by limits on

[3] In total, our level-2 session data span 66,000 distinct sessions over 7 years at 386 charging ports. The majority of these have been generated since May 2023 from new drivers and chargers.

session dwell time, *T*. While workplaces might assume 8–9 h of plug-in time (reflecting a 9–5 pm schedule), we observe wide variation among UCSD drivers and a mean of 7.3 h (Fig. 3a).[4]

The second parameter is the typical SOC to which drivers let their batteries fall before plugging in, $\underline{SOC}$. While automakers and analysts recommend 20% of capacity as a floor (Kostopoulos Spyropoulos, & Kaldellis, 2020), we observe that UCSD's BEV drivers typically use only 36% of their battery; i.e., they recharge when $\underline{SOC}$ = 0.64, on average. For PHEV drivers, the numbers are 73% and $\underline{SOC}$ = 0.27 (Fig. 3b). Planners who assume drivers plug in only upon reaching a low SOC may significantly underestimate the number of sessions that will be initiated on a workplace EV network. Such assumptions may also overestimate energy delivered per session, and hence overvalue higher-throughput chargers.

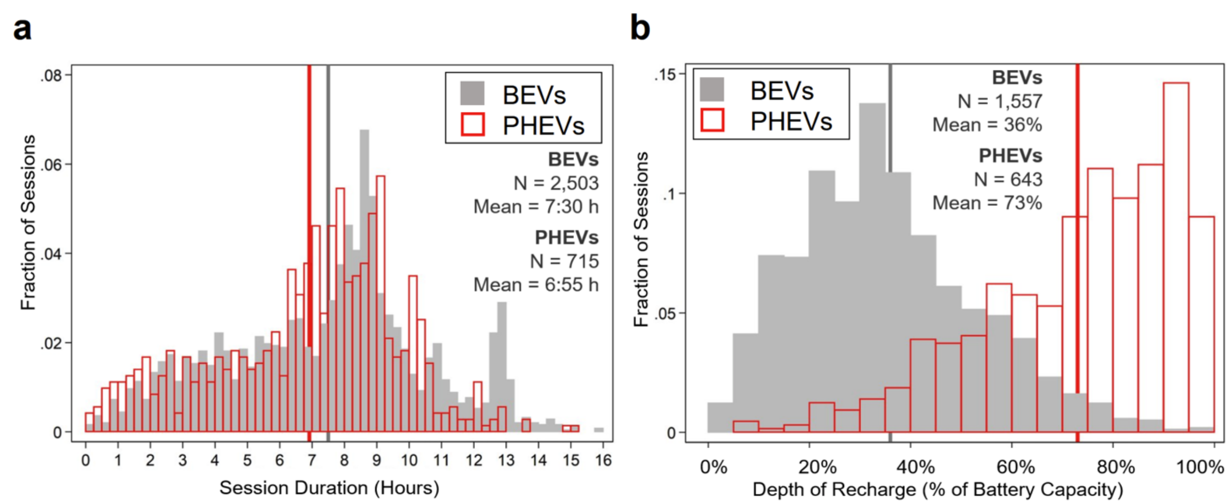

Fig. 3. Key human behavior model inputs collected from charging session records of UCSD's EV club. **a,** Session duration is the duration drivers leave their EV plugged in and indicates the length of time drivers occupy the stall when unrestricted by parking rules. **b,** Depth of recharge is the energy delivered to the EV as a percentage of the battery capacity and indicates the SOC drivers let their battery fall to before recharging. BEV and PHEV drivers charge in markedly different ways: although PHEV sessions last about as long as those of BEVs (lasting only 0.5 h shorter, on average), they recharge their smaller batteries quickly, spending only half as much time actively charging, and hence "block" (i.e., occupy without charging) parking stalls for about two hours longer, on average, than

4.2 Enrollment survey: Charging and commuting habits

Upon joining the UCSD EV club, drivers complete an intake survey about their EV, charging habits, driving behaviors, and demographics.

EV information includes EV make, model, and year, which we cross-reference with manufacturer databases (Department of Energy, 2024) to obtain specifications such as battery size and range. The type of EV that drivers use shapes their interactions with the workplace network, including how much energy they require and how many sessions they initiate to procure it. There are large differences, for example, between BEVs and PHEVs (Fig. 3b)—due to large

[4] At UCSD, drivers can park at level-2 chargers for up to 4 or 12 h (depending on the type of charger) and at DC fast chargers for up to 1 h. The campus is moving toward 12-h dwell-time stations.

differences in battery size (Fig. 4a; 77 vs. 12 kWh mean among UCSD EV club members). At UCSD, we observe that PHEV drivers tend to be either high-frequency chargers (charging with nearly every commute) or low-frequency chargers (instead driving regularly on gas). The type of EVs drivers use significantly affects workplace network design.

Commuting and charging information includes commute frequency f and home zip code, which together enable calculations of commute distance d and total annual commuting mileage $M^{commute}$ (Fig. 4b); and the share of charging done at home C^{home} (Fig. 4c). UCSD drivers self-report charging 41% at campus and 39% at home, on average (on an energy basis), while charging session data reveal 47% charging at campus (with the remaining 53% done off-campus). These are much lower than U.S. Department of Energy estimates, which put the national home charging average at 80% (Office of EERE, 2020). A recent meta-analysis suggests the share of residential charging exceeds 90% (Yang, Fulton, and Kendall, 2024). For institutions that support EV-driving constituents based on their driving and charging habits (as envisioned in Section 5.1), assuming higher levels of home charging than actually occur could significantly underestimate the needed size of a workplace charging network.

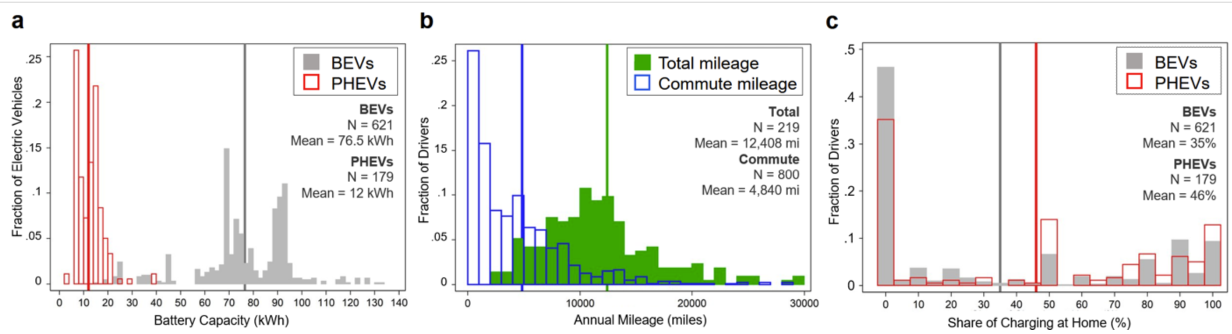

Fig. 4. Key human behavior model inputs collected from enrollment surveys and odometer surveys of UCSD's EV club. **a,** What people drive—EV battery size. **b,** How far people drive—annual total and commuting mileage. **c,** Where people charge—the self-reported fraction of charging done at home (we also obtain the fraction charged at the workplace). Wide variation in behaviors and preferences underscore the importance of building EV network design models around personalized driver data: drivers have different EVs (a), may live proximate to or distant from the workplace (b), and tend to be either primarily home chargers (e.g., >75% home charging) or defined by utter lack of access to home charging (0%) (c)—all of which lead drivers to interact with the workplace network in unique ways.

4.3 Odometer surveys: Total driving

We ask UCSD's EV club drivers monthly to report their odometer reading. Multiple readings allow for calculations of total driving mileage M^{total}, which implicates the total charging that drivers need (Fig. 4b).[5] We observe that EV club members average 35 mi/day, or 12,775 mi/year—similar to national and statewide estimates of 12,500–14,000 mi (Federal Highway Administration, 2019; Federal Highway Administration, 2022) but 48% higher than the citywide

[5] Odometer surveys are also useful as a conduit to ask additional questions of high value, e.g. about changes over time in EV ownership or home residence.

estimate of 8,650 mi (Comen, 2016). Plausible variation in estimates of driving mileage greatly affects network usage and design. As we show in Section 5.2, assuming UCSD's club members drive the smaller San Diego-derived distance of 8,650 mi would decrease workplace charging sessions by 23%.

Odometer surveys include a free-response field in which drivers enter their mileage, as well as a field for uploading a photo of the odometer, allowing us to verify readings. We observe that 17% of readings that include a photo are reported with errors (e.g., due to excessive rounding, typos, or guessing). For drivers who have not submitted verifiable odometer readings, we construct a profile of their annual mileage using the data of drivers who have submitted readings, as shown in Fig. 5.

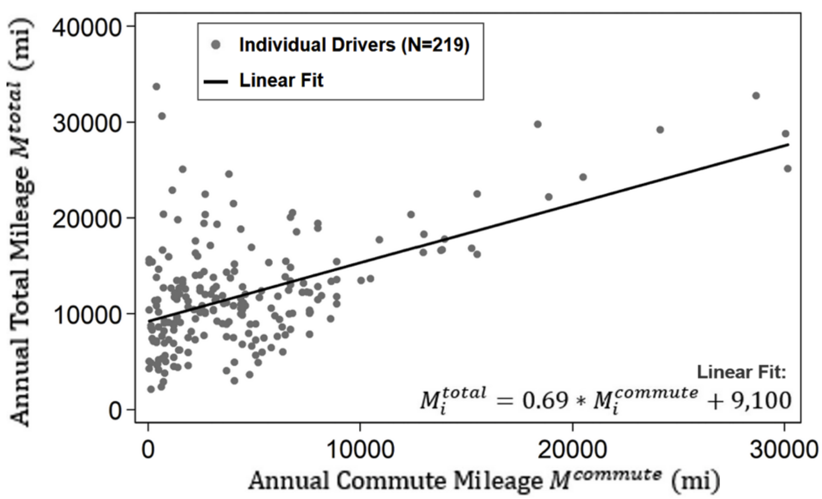

Fig. 5. Total driving and commuting for the subset of UCSD's EV club members (*n=219*) who have responded to sufficiently many (2+) odometer surveys to estimate their total driving. For the subset of drivers without 2+ readings, we estimate total driving from their self-reported commuting mileage, which is known, and the total driving–commuting relationship shown in the figure. Total driving mileage increases linearly with commuting mileage, given by $M_i^{total} = 0.69\ M_i^{commute} + 9100$.

5. Case study and results

In this section we animate the model using UCSD's EV network and 800 drivers enrolled in the UCSD EV club. UCSD is a large institution with 75,000 affiliates (students, staff, faculty), approximately 20,000 parking spaces, and an EV network of 439 level-2 (6.25 kW) charging ports (UCSD Transportation Services, 2024a; Bayram et al., 2016).[6]

Our model for network design in Section 3 requires that institutions first know how they will support drivers. In what follows, we analyze four plausible levels of support (Section 5.1), then perform general sensitivity analysis on model parameters (Section 5.2), and follow this with deeper analysis on what we find to be the most determinant model inputs: configuring

[6] UCSD's network is currently undergoing expansion: an additional 762 level-2 ports are anticipated by year-end 2025. The campus also hosts 13 DC fast chargers, with 22 more planned. About 3,000 unique drivers have used the network multiple (>1) times.

parameters with local behavioral driver data instead of regional average data (Section 5.3), the effective battery range that drivers actually use (Section 5.4), the synergy between EV charger capability and permissible dwell time (Section 5.5), and potential behavioral rebound effects in which drivers bring some fraction home charging to the workplace (Section 5.6).

5.1 Institutional strategies for supporting drivers

While institutions could supply charging needs in numerous ways, we investigate two systems of support that generate plausible bookends on driving mileage (and hence volume of charging) that might be supported: one based on affiliates' driving (e.g., total driving or commuting only), and another based on charging needs (e.g., all charging or only the portion of charging not already done at home). Numerically, support manifests as the total electric range M_i^+, in miles, that the workplace EV network should be capable of delivering to drivers. We analyze all four combinations of these goals, with M_i^+ set to M_i^{total}, M_i^{total} $(1–C_i^{home})$, $M_i^{commute}$, and $M_i^{commute}$ $(1–C_i^{home})$ (Table 3).

Table 3. Four strategies (goals) for supporting EV drivers with workplace charging.

Case	**Institutional support for…**		**Range (mileage) to supply M_i^+**	**Logic behind support**
	Driving	**Charging**		
1	Total driving	All charging	M_i^{total}	Upper bound of institutional support
2	Total driving	Charging not met at home	M_i^{total} $(1–C_i^{home})$	Develop workplace charging around the home chargers that affiliates have already invested in and use
3	Commuting only	All charging	$M_i^{commute}$	An ethos that workplace networks support commuting, while other networks (destination, highway) support other driving
4	Commuting only	Charging not met at home	$M_i^{commute}$ $(1–C_i^{home})$	Combination of case 2 and 3

Fig. 6 shows drivers' use of the workplace charging network under the four scenarios in Table 3. Numerical results are reported in Table 4.

Three important observations emerge from Fig. 6. First, network usage varies widely across scenarios, from 0.6 to 2.3 sessions per week per driver (Fig. 6b), indicating that institutional choices about supporting EV drivers profoundly affect network usage and size. For example, supporting all charging needs associated with commuting (scenario 3) would require a portfolio of EV chargers that supports 1 session per week per driver, on average; while a commitment to supporting all charging needs and all driving (scenario 1) would require a network that supports 2.3 sessions per week per driver. Given that these policies implicate supporting many additional sessions, institutions should exercise caution when establishing goals and in choosing the criteria by which they support commuters. There is high value in iterative planning that begins with modest ambition, evaluates progress over time, and adjusts goals accordingly.

Second, for UCSD, the decision of whether to support total driving or commuting only (scenarios 1–2 vs. 3–4) is more important than the decision of whether to support all charging or only non-home charging (scenarios 1, 3 vs. 2, 4). Increasing support from commuting to total driving triples the mean plug-in rate, from 17% to 51%; while increasing support from non-home charging to all charging increases the mean plug-in rate 55%, from 51% to 79%.

Third, BEVs and PHEVs have similar network usage when non-home charging is supported (scenarios 2, 4) because PHEV drivers report higher reliance on home charging, on average. When all charging is supported (scenarios 1, 3), PHEV usage is higher because the smaller batteries in PHEVs require more frequent charging and cannot draw as much energy per session as those of BEVs.

For the 800 UCSD club drivers, scenarios 1–4 envision supporting 0.6–2.3 weekly charging sessions per driver. This would require 96–368 chargers with 6.25 kW throughput and 12-h maximum dwell time (the current UCSD standard), assuming uniform distribution of sessions across the 5-day workweek. With 20,000 parking spaces, that equates to a 0.5–1.8% stall electrification rate. (We report these calculations only for illustration; UCSD's 439 level-2 charging ports are sufficient to meet this demand but are used by other (non-EV club) drivers at UCSD and often highly congested. Our focus herein is how human behavior affects drivers' use of the network; in future work we plan deep analysis of network design.)

Table 4. Drivers' use of the campus charging network: plug-in rate and anticipated number of charging sessions per week per driver. Results are the mean by EV type.

Case	**1**	**2**	**3**	**4**
Support for driving	**Total driving**	**Total driving**	**Commuting only**	**Commuting only**
Support for charging	**All charging**	**Charging not met at home**	**All charging**	**Charging not met at home**
Plug-in rate (%)				
All EVs	79%	51%	30%	17%
BEVs	76%	51%	28%	17%
PHEVs	87%	51%	35%	17%
Sessions per week per driver				
All EVs	2.3	1.5	1	0.6
BEVs	2.2	1.5	1	0.6
PHEVs	2.5	1.5	1.1	0.6

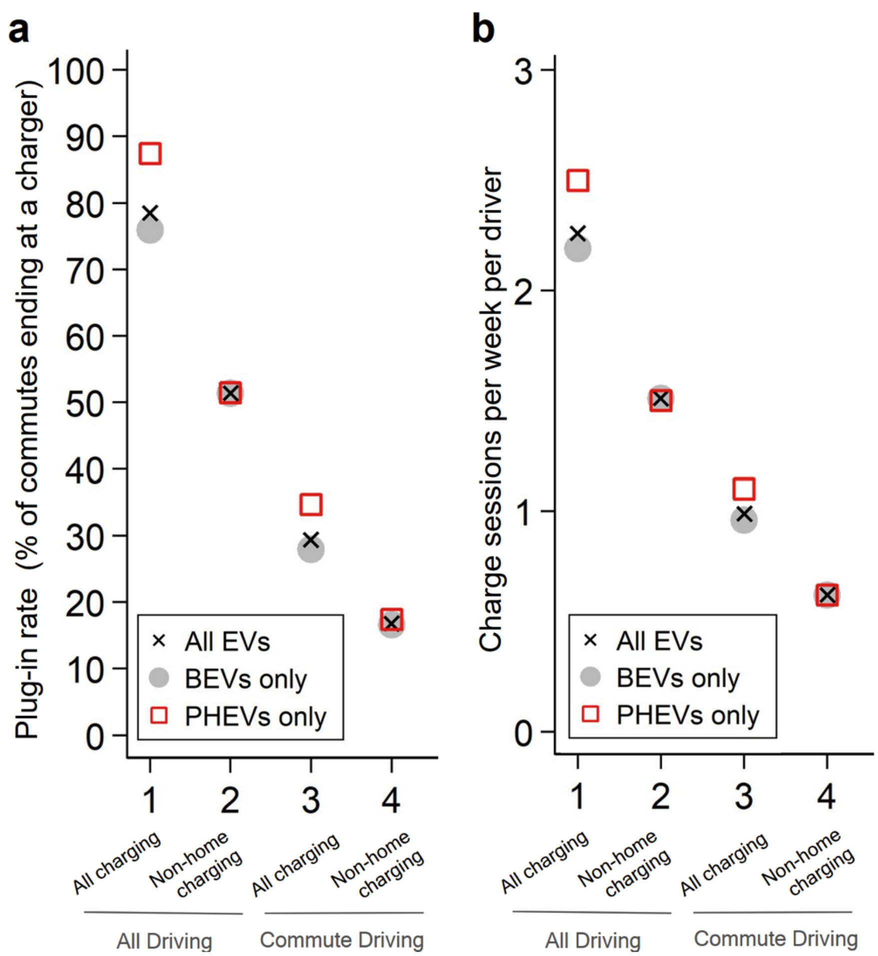

Fig. 6. Drivers' network usage for 4 scenarios of institutional support: support for total driving (scenarios 1–2) or only commuting driving (scenarios 3–4), alongside support for all drivers' charging need (1, 3) or only charging not already done at home (2, 4). **a,** Plug-in rate (i.e., the percentage of commutes to campus that must end in an EV stall for drivers to recoup mileage). **b,** The number of charging sessions per week per driver. Markers denote the mean across 800 UCSD EV club members (621 BEVs, 179 PHEVs).

5.2 Simple sensitivity analysis

In this section we vary all seven of the significant parameters in the model within ranges specified in Table 5. In each sensitivity analysis, we vary the single parameter noted while holding constant all other model parameters, using scenario 3 as a baseline. In Sections 5.3–5.6 we investigate the most important parameters for charging network design and explore wider parametric variation to show deeper implications for decision-making.

The seven sensitivities span two major clusters of factors that affect network planning: those that implicate human behavior, which institutions may have little control over; and decisions about network design, which institutions plausibly control. Fig. 7 shows results for the simple sensitivity analysis: how drivers' use of the network changes following variation in a single model parameter. While results are nuanced, several trends emerge:

- Among the two clusters of parameters, sensitivity is greater for institutional choices—especially the level of institutional support.
- After institutional goal-setting, SOC floor is the most important parameter for workplace network usage. The SOC floor sensitivity is high because drivers typically plug in with high SOC (mean BEV: 64%) yet park for a duration (mean BEV: 7.5 h) that could yield significantly deeper sessions. With deeper sessions, drivers need fewer sessions (and hence an overall smaller workplace network) to recoup the energy they need.
- Sensitivities to dwell time policy are small in our baseline because 4–8.5 h dwell times, when combined with 6.25 kW chargers, are commensurate with the energy drivers need to recoup. This also explains the lack of any benefit from switching to higher 8.6 kW chargers. Dwell time has a larger impact in cases where the institution's chargers have lower throughput capability (e.g., level-1), as we show in Section 5.5.
- Sensitivity to the fraction that PHEVs drive on electricity is small because they comprise a small share of the fleet (22%) and most must already plug in with each commute to campus for an assumed fraction of electric driving. However, we observe that PHEV drivers tend to be either electricity-maximizing or gas-dependent drivers. What could matter more (but remains beyond our data collection) is the ratio between these PHEV driver archetypes at the institution.

Two takeaways emerge from these sensitivities. First, institutions should be mindful about their ambition and the chargers they plan to install. While higher-throughput chargers may allow for deeper sessions, they may not reduce usage (plug-in rates, the number of sessions) unless drivers also adapt their behavior (e.g., SOC floor). Second, to that end, institutions should strive to know their constituents' driving and charging patterns. Two behaviors—SOC floor and total driving mileage—greatly effect network usage. Institutions cannot control drivers' SOC floor (which relates to range anxiety), but may be able to shape it, e.g. through workplace charging incentives that encourage deeper (greater kWh) sessions. Credible estimates for total driving span 8,650–14,000 mi, which imply 7–29% additional or fewer weekly charging sessions that a workplace network would be designed to support. Drivers' driving and charging profiles can be understood through surveys and odometer readings like those we have created at UCSD.

Table 5. Parametric variation of 7 parameters in the simple sensitivity analysis. Sensitivity analysis is done with respect to scenario 3 in Table 3.

Parameter	Baseline value	Sensitivity value (low, high)	Justification
Institutional support	Total driving, non-home charging (Scenario 2)	Commuting; non-home charging (Scenario 4)	Institutional workplace network intended to support commuting needs unmet at home (see Section 5.1)
		Total driving, all charging (Scenario 1)	Upper bound of institutional ambition for supporting drivers through workplace charging (see Section 5.1)
EV charger kW		2 kW	Typical level-1 charger throughput

EV charger kW throughput	6.25 kW	8.6 kW	Anticipated future modal level-2 charger at UCSD
EV charger dwell time	7 h [a]	4 h	Institutional policy focused on access (aimed at providing 2 sessions per workday per charger)
		8.5 h	Institutional policy focused on convenience (intended to allow drivers to park for the full workday, inclusive of a break)
Battery $\underline{SOC}$ (for BEVs) [b]	64%	44%	SOC floor associated with the 85th percentile session depth (per UCSD driver session data; see Fig. 3b)
		83%	SOC floor associated with the 15th percentile session depth (per UCSD driver session data; see Fig. 3b)
Percentage of home charging brought to campus [c]	0	–25%	Potential feedback in charging behavior in which drivers migrate some workplace charging outside the workplace, e.g. due to expensive rates
		25%	Potential feedback in charging behavior in which drivers migrate some home charging to the workplace, e.g. due to competitive rates
Average annual total driving	12,775 mi	8,650 mi	San Diego regional average (Comen, 2016)
		14,000 mi	Upper bound estimate reflecting working-age U.S. population (Federal Highway Administration, 2019; Federal Highway Administration, 2022)
Mean PHEV fraction of driving on electricity	41%	33%	Mean value using 2022 industry updates to EPA's methodology (Isenstadt et al., 2022)
		58%	EPA's codified methodology (Isenstadt et al., 2022)

[a] Level-2 chargers at UCSD are installed in parking stalls with 4-h and 12-h dwell time limits. The baseline value of 7 h reflects observed behavior of UCSD EV club drivers when unconstrained by dwell time limits.

[b] For PHEVs, we set $\underline{SOC} = 0$, as explained in Section 3.2.3.

[c] The negative sensitivity value is applicable only to projects to expand an existing EV network.

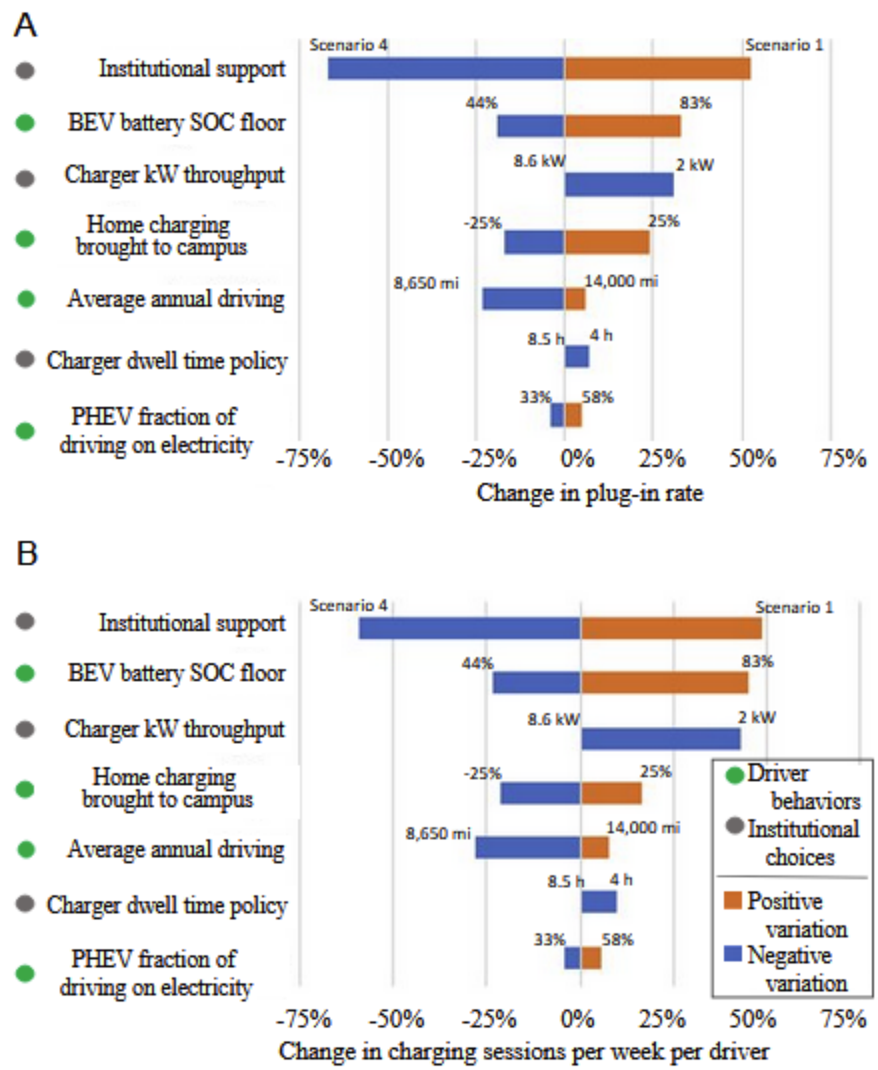

Fig. 7. Change in drivers' network usage due to variation in select model parameters. We report network usage as: **a,** plug-in rate; and **b,** charging sessions per week per driver. Variation is noted next to each parameter and reported in Table 5.

5.3 The value of local driver behavioral data

Institutions may lack the resources to deploy the kinds of data collection systems (Section 4) that we implement and use in our approach to EV network design (Section 3). Instead, institutions might turn to national or regional average data instead of calibrating the model with local driver data.

Here, we quantify the differences in drivers' workplace network usage derived from two types of data inputs: external estimates (e.g., national or regional averages that disregard the institution's local drivers) and individual driver estimates derived from the institution's affiliated EV drivers, as detailed in Table 6. At UCSD, local driver data reveal a smaller fraction of home charging, greater total driving, shorter-duration sessions, and smaller (fewer kWh) sessions—all of which push model outcomes toward greater electrification.

Fig. 8 shows results for the two model specifications. We find that obtaining and parameterizing our model with locally collected data from UCSD's real drivers has a massive effect on workplace charging activity. With local data, plug-in rates and weekly sessions are threefold higher than those derived from external estimates, underscoring the value of calibrating the model with local human behavioral data. Using externally sourced estimates is likely better than guessing blindly, but in our case, it still significantly underestimates the need for workplace chargers.

Table 6. Model parameterizations for two model runs: one derived from "external estimates" (which know nothing of local driver data); and a second derived from individual data obtained from UCSD's EV drivers.

Parameter	Parameter basis (source)	
	External estimates (e.g., national average)[a]	**Driver-derived estimates (from the institution's EV drivers)**
Percentage of charging done at home	80%	38%[b]
Total annual driving	11,000 mi	12,775 mi[c]
Permissible (or effective) charger dwell-time	8 h	7 h[d]
SOC floor (for BEVs)	20%	64%[d]

[a] External estimates are: 80% home charging (Office of EERE, 2020), 11,000 mi annual total driving (Steinbach and Tefft, 2022), and 20% SOC floor per manufacturer guidance; an 8-h dwell time reflects a standard workday.
[b] Calculated from driver responses to the UCSD EV club intake survey.
[c] Calculated from driver responses to the UCSD EV club intake survey and odometer surveys.
[d] Calculated from driver charging session records at UCSD. Driver behavior reveals that sessions are typically shorter than the permissible dwell time implied by an 8-h workday.

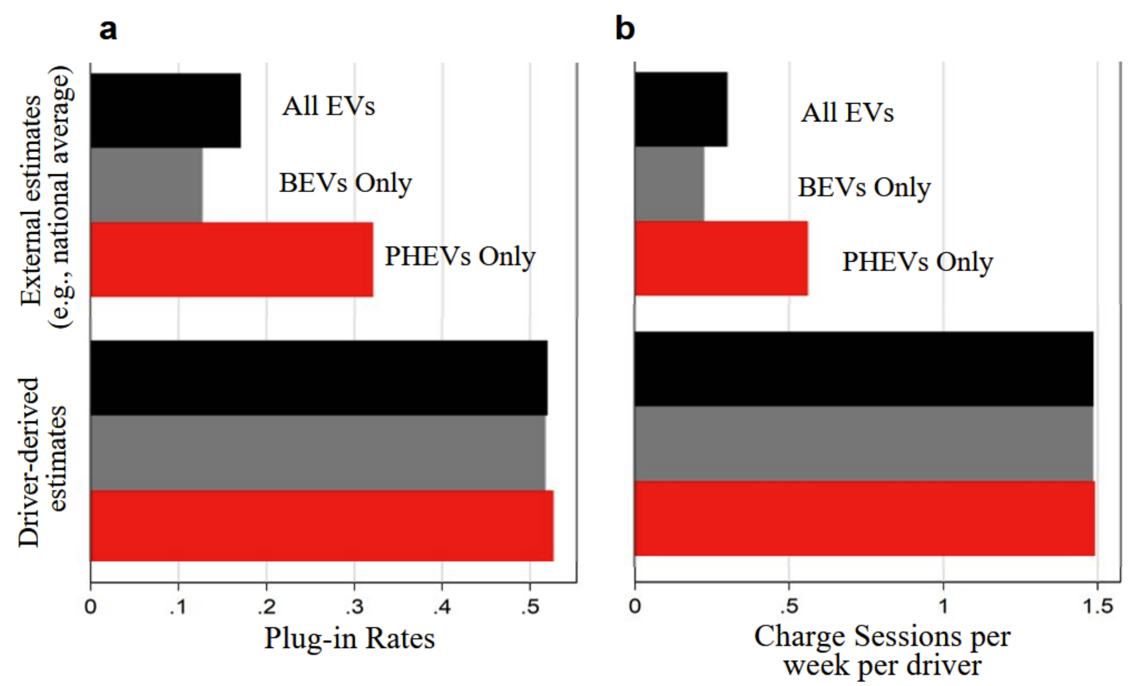

Fig. 8. Workplace network usage—**a,** plug-in rate and **b,** charging sessions per week per driver—for two model specifications that use either (at top) stylized national or regional estimates (without reference to locally known data, which in our study is derived from UCSD EV drivers); or (at bottom) known behavioral data from the institution's EV drivers (in our study, UCSD EV drivers) that has been used to generate unique individual profiles of network usage.

5.4 EV driver behavior: a key uncertainty

As we showed in Section 5.2, floor SOC is the model parameter that most affects workplace network usage. Here we investigate the full range of plausible behavior, from 0 to 0.9 (Fig. 9). $\underline{\mathrm{SOC}}$ = 0 represents ideal driver behavior, in which drivers use the full available battery capacity before charging; at the other extreme, $\underline{\mathrm{SOC}}$ = 0.9 indicates very conservative driving, in which drivers use only 10% of the available battery capacity before charging. We hold the workplace network constant, with 6.25 kW chargers and 7-h dwell time, while varying $\underline{\mathrm{SOC}}$. (The 7-h dwell time reflects the observed behavior of UCSD EV club drivers when unconstrained by dwell time limits; UCSD policy typically allows 12 h of dwell time.)

We observe two patterns in how $\underline{\mathrm{SOC}}$ affects network usage. First, decreasing $\underline{\mathrm{SOC}}$ from 0.9 to 0.5 has a sharp effect on drivers' network usage: plug-in rates decrease 38 percentage points (from 80% to 42%) and weekly sessions per driver fall from 2.7 to 1.2. Second, decreasing $\underline{\mathrm{SOC}}$ further, from 0.5 to 0.1, yields additional but shallower declines in plug-in rate of 15 percentage points (from 42% to 27%), and in weekly sessions, from 1.2 to 0.7. Network operators can achieve steep declines in network usage (and hence in the number of workplace chargers needed to support drivers) by encouraging drivers to charge at lower SOC, with the greatest impact achieved by pushing down relatively high SOC floor values to 50%; diminishing returns accompany further behavioral change. These benefits hinge upon combinations of EV charger throughput and dwell time that sufficiently charge the larger empty portion of the battery.

Encouraging BEV drivers to run down their batteries more deeply is a substantial point of leverage to improve network utilization and reduce stall electrification requirements. Indeed, $\underline{\text{SOC}}$ may be suited to behavioral intervention, e.g. financial incentives that encourage deeper charging sessions. If institutional policy can encourage drivers to travel farther between charging sessions (in effect reducing $\underline{\text{SOC}}$), that can reduce the number of chargers the institution must otherwise install to meet drivers' needs.

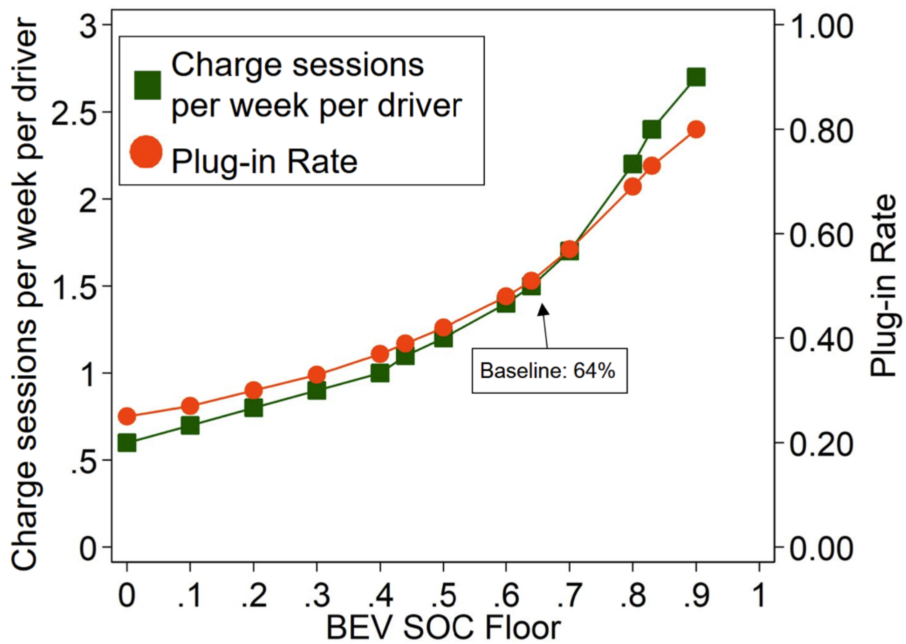

Fig. 9. The effect of $\underline{\text{SOC}}$ (the SOC to which drivers allow their batteries to fall before charging) on **a,** plug-in rate and **b,** charging sessions per week per driver. $\underline{\text{SOC}}$ varies widely among UCSD EV drivers and is the most important human behavioral parameter in the model. $\underline{\text{SOC}}$ for PHEVs is set to 0. $\underline{\text{SOC}}$ = 0.64 is the baseline value observed among BEV drivers in UCSD's EV club; $\underline{\text{SOC}}$ = 44% and 83% indicate the sensitivity values in Section 5.2.

5.5 EV chargers and parking rules: a key synergy

Charger capabilities (kW throughput) and session dwell time rules (h) interact to affect the maximum energy (kWh) that drivers recoup per session—and hence the number of workplace sessions drivers require. They are the two variables that institutions likely have the most control over.

We vary dwell time from 2 h to 12 h, indicating policies that prioritize access (a workday plausibly permits four 2-h sessions) or convenience (a 12-h dwell time allows a driver to plug in and disregard their EV for the entire workday). In tandem, we vary charger kW-throughput from

2 kW to 18 kW, indicating level-1 chargers compatible with 120 V outlets and higher-end level-2 charger that are common in workplace settings.[7]

Fig. 10 shows the change in network usage for each combination of charger type and dwell time limit. Two observations stand out. First, an institution's dwell time policy has a larger effect on drivers' network usage when the institution uses lower-kW-throughput chargers. At lower kW throughput, the dwell time constraint becomes increasingly binding, limiting the energy drivers can recoup and driving up the number of sessions they need. Second, higher products of kW-throughput and dwell time reduce network usage but eventually see diminishing returns. For UCSD's drivers, returns plateau at 40–50 kWh per session. For example, with a 8-h dwell time policy, little is gained with respect to reducing network usage by installing chargers with >6.25 kW capacity.

As a corollary, with sufficiently high kW-throughput (≥12 kW), dwell time ceases to meaningfully affect network usage (except for the 2-h dwell time); while with sufficiently high dwell time (12 h), kW-throughput ceases to have a meaningful effect on usage (except for 2 kW chargers).

In making decisions about the types of chargers to install (and the dwell time rules that accompany them), institutions must be mindful of drivers' SOC floor. Institutions could install higher-kW-throughput chargers, allowing drivers to receive more energy per session. But if drivers use them opportunistically rather than by necessity (i.e., plug in with relatively high SOC; Helmus, Lees, & van den Hoed, 2020), they recharge quickly to 100% SOC and block the stall, causing congestion (Nicholas and Tal, 2015) and low charger utilization rates. In response, institutions could implement new rules to improve stall sharing—e.g. shorter dwell times that beget higher station utilization (but potentially burden employees by requiring them to charge more often and re-park their EV during the workday).

[7] Though level-2 chargers are common, some institutions are electrifying parking by strategically prioritizing level-1 chargers (UCLA Transportation, 2024). We suspect workplaces will not emphasize DC fast chargers, due to high capital costs and demand charges.

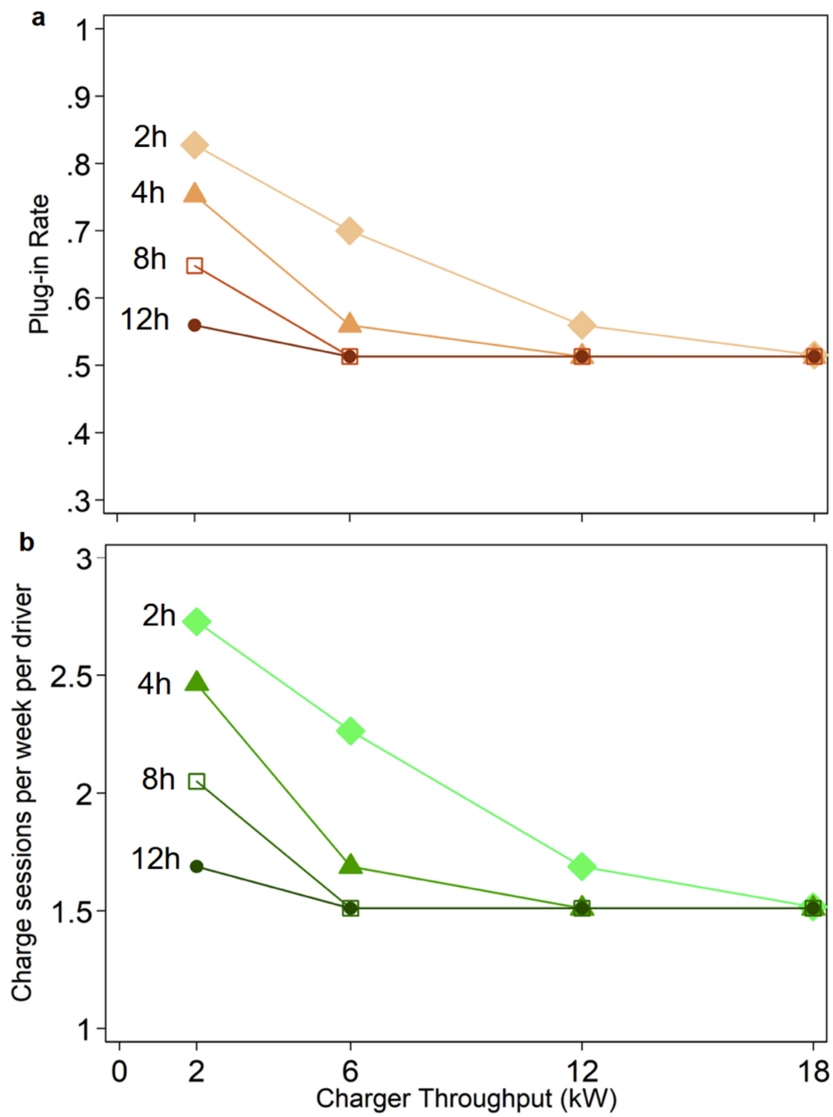

Fig. 10. The effect of institutional choices for installing EV chargers that differ in kW throughput and implementing parking rules for session dwell time on **a,** plug-in rate and **b,** weekly charging sessions. Variation in charger throughput (dwell time) is plotted on the x-axis (by data series). In our baseline scenarios, chargers have 6.25 kW throughput and stalls have a 7 h dwell time.

5.6 Home share of charging brought to campus

Building or expanding workplace EV networks may lead drivers to adjust their charging habits. We investigate one effect we suspect is likely in response to a network expansion: drivers migrating some share of charging done at home to the workplace. We vary this share from 0% (the baseline) to 50% of home charging. (A value of 50% indicates that drivers who charge at home for, say, 60% of their energy would shift half, or 30%, to campus.)

Fig. 11 shows the resulting change in network usage. Experimental evidence at UCSD suggests drivers might have the flexibility to shift about 20% of their charging to the workplace

(Garg et al., 2024). Such a shift would increase plug-in rates by 11 percentage points, from 51% to 62%.

These relatively small effects reflect at least two factors. First, of UCSD drivers who do any charging on campus, many already report doing 100% of charging there (and thus cannot increase their charging on campus). Second, there is headroom to increase the amount of energy delivered per session without driving up the number of sessions (since drivers park for 7 h per session, on average, but do not charge the entire time to reach 100% SOC).

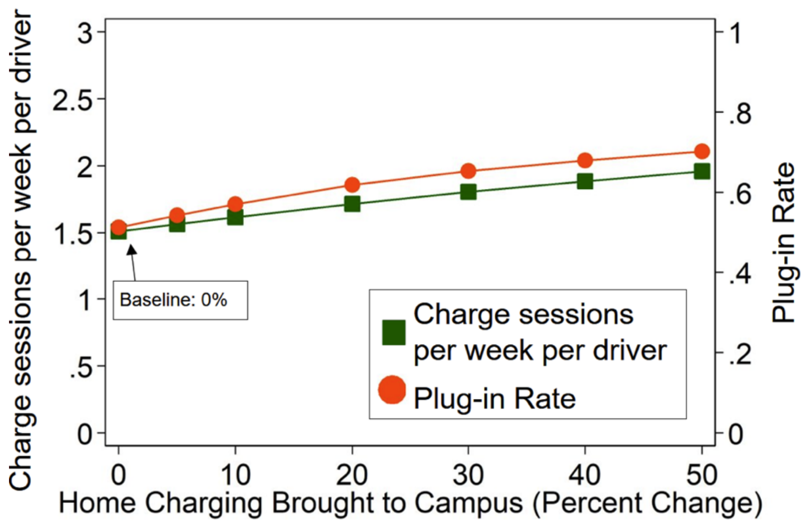

Fig. 11. The effect of coaxing charging done at home to the institution's workplace network on network usage (plug-in rate, charging sessions per week per driver).

6. Conclusion

This paper presented a new model for designing workplace EV charging networks at institutions (e.g., public entities, corporations) with regular commuters, parking facilities, and a commitment to support the charging needs of EV-driving constituents. The novelty of our approach is that it is built centrally around the real behavior, habits, and preferences of drivers that would use the network. We obtained these data from 800 EV drivers at UCSD and demonstrated the approach using UCSD's EV network.

We find that driver behavioral data have a significant effect on network usage. For example, use of individual driver data, instead of regional averages that are commonly used when local estimates are unobtainable, increases network drivers' network usage threefold. In addition, the goals for supporting drivers that an institution could plausibly set for itself have a similarly large impact—also affecting network usage threefold.

Institutions should exercise caution about the level of charging they commit to supporting. Our results suggest there is value in beginning with modest support, evaluating network usage and driver satisfaction, and increasing ambition over time. While an institution could ensure needs are met (at very high cost) by electrifying every parking stall, we find that drivers plug in to the workplace EV network on 51% of their commutes, on average. That translates to about 1.5 sessions per week per driver, on average.

The EV chargers that institutions install, the parking rules they implement to govern them, and driver behavior interact in complex ways that affect charging needs, network usage, and network design. Our model helps not only to answer questions around network design, but also to *identify* the key unknowns in human behavior that most affect network design. Particularly important is the minimum SOC with which drivers typically plug in to charge (equivalently, the distance they drive, or the percentage of their battery they use, between charges).

A major unknown, which our model does not currently treat, is how human behavior may change as a workplace network forms or expands. Future work is needed to understand these feedback effects. For example, although institutions cannot directly control drivers' minimum SOC, it may be malleable or amenable to shaping, e.g. through pricing and incentives that encourage "deeper" sessions. Ongoing work by our team includes controlled trials and natural experiments aimed at understanding human behavioral responses to incentives, price changes, and expansions in the number of workplace chargers.

Finally, while we have focused our effort here on how driver behaviors and habits shape their workplace charging needs, understanding how those needs in turn shape optimal network design requires further work. We have framed an optimization routine and simulation algorithm that determine network design as a function of drivers' needs, but what is needed next is systematic analysis that applies them to emergent networks in the real world. In future work, we intend to analyze the performance of these algorithms and the factors that most shape network design.

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