Integrating human behavior into planning models for workplace EV charging networks

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***Abstract*—Many institutions are grappling with how to support their employees and other constituents who drive electric vehicles (EVs) by providing local charging services. We formulate a novel "parking stall electrification" model that estimates constituents' charging needs and can guide institutional strategy for deploying and expanding workplace charging. Unlike most prior literature, our model explicitly incorporates commuter behavior—pivotal for any network built to operate under real-world commuter conditions—derived from recurring surveys of EV drivers (N=626) at the University of California San Diego (UCSD). We demonstrate the model at UCSD using these behavioral data and find that institutional goals and choice of chargers have a profound effect on commuters' network usage and stall electrification requirements. To support practitioners, we have made the full model and a sample dataset available to the public at https://tinyurl.com/2v262znh.**

***Index Terms*—Commuting, decarbonization, electric vehicle, electrification, transportation**

I. Introduction

Societal shifts from gasoline to electric vehicles (EVs), already well underway in numerous countries [1], are pivotal to cutting greenhouse gas (GHG) emissions from transportation. Although such shifts have occurred in tandem with home charging [2], workplace charging remains crucially important for at least two reasons: 1) whereas most early EV adopters tend to be wealthier homeowners [3], later mass adopters will likely have less access to private home charging [4]; 2) as electric grids transition to greater shares of renewables, cutting vehicle emissions requires that EVs charge when renewable energy generation is abundant (in California, daytime) [5].

At the same time, many institutions (corporations, public entities, universities) have committed to net-zero carbon goals. To reduce Scope 3 GHG emissions associated with commuting (perhaps 17% of university GHG emissions [6]), they are encouraging a switch to EVs while installing workplace chargers.

At such motivated institutions, decision-makers must grapple with numerous strategic planning decisions: 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 parking rules change?

Answers to these questions depend centrally on the institution's EV drivers and their behaviors, habits, and needs. While human behavior has been studied extensively for home charging [7], little is known about workplace charging behaviors. Indeed, prior research on planning models for workplace charging networks has largely ignored human behavior [8], bypassed it by using idealized behavior [9, 10], or otherwise neglected the driving and charging habits of the drivers that workplace networks are intended to serve [11].

This paper addresses these gaps by focusing on how human behavior affects institutions' plans for supporting EV-driving constituents. We develop a new planning model for workplace stall electrification built centrally on the real behaviors and habits of an institution's constituents. These new data, obtained from driver surveys, explicitly resolve human behavioral parameters for driving and charging. The model can be used to quantify network usage and sufficiency, plan for future stall electrification, and analyze the effects of institutional policies aimed at supporting EV commuters. We demonstrate the model using a large set (N=626) of EV driver data collected as part of a new EV club at the University of California San Diego (UCSD)—one of the world's largest institutional charging hubs [12].

In what follows, Section II introduces our analytical model; Section III demonstrates the model using real driver data; and Section IV concludes with remarks on ongoing work.

II. Model Description

Our model—for "parking stall electrification"—frames the decision problem of an institution with regular commuters, parking facilities, and a commitment to support the charging needs of EV-driving constituents. It generates fundamental information about network usage (how commuters use the network to meet their needs), "hosting capacity" (the number of commuters the network *could* accommodate given driver behavior and parking rules); and sufficiency (whether hosting capacity fulfills commuters' needs). It is also an analytical tool and can be used to analyze, e.g., how parking rules, driver behavior, planned charger investments, and institutional goals interact to affect commuters' network usage and needs.

The model also points toward questions of network expansion: given EV adoption rates, how should planners invest over time to support a growing EV population? How do technology and market forecasts affect this need? What are the risks of investing too quickly, possibly leading to stranded assets as old chargers and stubout capabilities are eclipsed by new needs and capabilities?

For now, we set aside these and other important questions around pricing, business models, and minimizing EV charging emissions. Our focus here is network sufficiency and usage—both the number of charge sessions commuters initiate to maintain charge in their EVs and their plug-in rates (i.e., the share of commutes that end in a workplace EV stall). To calculate these, institutions must know four things: the driving and charging habits of their EV-driving constituents; constituents' EVs; the institution's parking rules and charging network; and its goals for meeting drivers' charging needs (Fig. 1). We discuss each in turn.

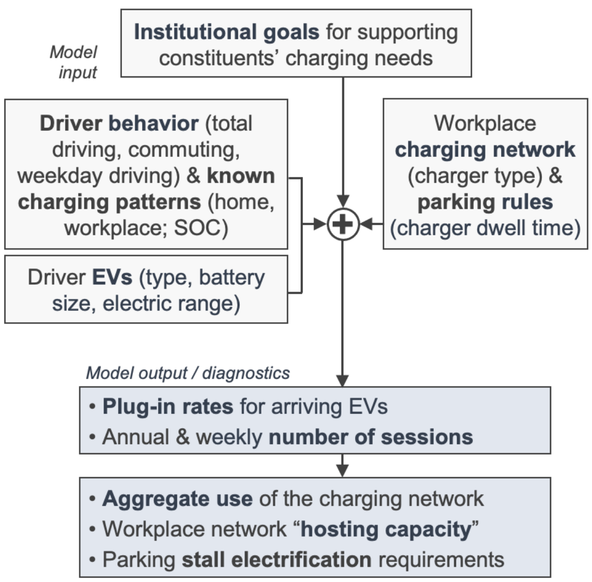

Fig. 1. Model structure: input data and outputs.

A. Model input

EV drivers and behavior. In our model, drivers are characterized by their driving and charging habits. Driving habits include home-to-workplace commute distance d (mi), commute frequency f (per week), and annual driving totals for total mileage M^{total} (mi), commuting mileage M^{commute}, other (non-commuting) mileage M^{other}, and weekday mileage M^{weekday}. For each driver $i \in \{1, ..., N\}$, we calculate a unique driving profile: $M_i^{\text{commute}} = 52 f_i d_i$, where d_i is estimated per the institution's address and driver's zip code, and f_i and d_i are reported via survey; M_i^{total} is obtained and updated through periodic odometer reading surveys; and $M_i^{\text{other}} = M_i^{\text{total}} - M_i^{\text{commute}}$. Because our odometer surveys are monthly, we estimate weekday driving as $M_i^{\text{weekday}} = \alpha M_i^{\text{total}}$, where α is the fraction of total driving that occurs on weekdays, per regional or national statistics. For this paper, we apply a simpler model that uses a regional average for M^{total}, α, and the fraction of total driving that is commuting β. In this rendering, $M^{\text{weekday}} = \alpha M^{\text{total}}$, $M^{\text{commute}} = \beta M^{\text{total}}$, and $M^{\text{other}} = M^{\text{total}} - M^{\text{commute}}$.

Charging habits include the fraction of charging done at home C^{home} and the workplace C^{work}, measured on an energy (kWh) basis (both reported via survey); the state-of-charge (SOC) drivers maintain as a minimum (i.e., by which they plug in to charge), $\underline{\text{SOC}}$; and the fraction of total driving done on electricity ϵ (applicable to plug-in hybrid EVs—PHEVs).

EVs. EVs are characterized by their type (BEV—battery EV, or PHEV), battery size B (kWh), and electric range R^{elec} (mi). EV type matters because BEVs and PHEVs have different charging patterns: PHEVs could be high-frequency chargers [13] because they have smaller batteries and electric ranges commensurate to commute distances, or low-frequency chargers if they commonly drive on gasoline. We consider ϵ, given in Eq. (1), per [14], where ND = 700 mi is normalized distance 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. While ϵ depends on driver behavior, mean values (given variation in R^{elec}) are 0.2–0.7. For BEVs, ϵ = 1.

$$\epsilon_i = \begin{cases} 1, & \text{if BEV} \\ 1 - \exp\left(-\sum_j (R_i^{\text{elec}})^j \, \text{ND}^{-j} \, c_j\right), & \text{if PHEV} \end{cases} . \tag{1}$$

To calculate an EV's charging need, we first calculate its effective battery size B^{eff} and effective range R^{eff}. Effective battery size, given by $B_i^{\text{eff}} = B_i(1 - \underline{\text{SOC}}_i)$, is the regularly used portion of the battery and respects that drivers often plug in with ample remaining battery charge. For BEVs, standard practice is to maintain SOC above 20% (i.e., $\underline{\text{SOC}}$ = 0.2). BEVs thus have $B^{\text{eff}} < B$. For PHEVs, we set $\underline{\text{SOC}}$ = 0. R^{eff}, given in Eq. (2), is the distance an EV can travel between plug-ins, respecting how human behavior affects $\underline{\text{SOC}}$ and ϵ. R^{eff} is $< R^{\text{elec}}$ for BEVs and $> R^{\text{elec}}$ for PHEVs.

$$R_i^{\text{eff}} = R_i^{\text{elec}} \, (1 - \underline{\text{SOC}}_i) \, \epsilon_i^{-1} \quad \forall i = 1, \ldots, N \tag{2}$$

EV chargers and parking rules. Chargers are defined by their power delivery P (kW throughput), while parking rules cap the dwell time or session duration τ (hours). EV chargers can thus deliver maximum session energy $E^{\text{charger}} = P\tau$ (kWh). Chargers and parking rules matter because they affect E^{charger} and, in turn, mileage recouped per session. With higher-kW-throughput chargers, drivers can receive more energy per session. But if drivers use them opportunistically rather than by necessity (i.e., plug in with relatively high SOC) [15], they recharge quickly and block the stall, causing congestion [16] and low charger utilization rates. In response, institutions could implement new rules to improve stall sharing, e.g. shorter dwell times that permit higher station utilization (but burden employees by requiring them to charge more often and re-park their EVs during the workday). Alternatively, they could install a greater number of long-dwell chargers with lower, variable power delivery and automated load management.

Institutional policy for meeting drivers' charging needs. Not all EV drivers have access to home charging; some rely primarily on workplace charging. Institutions that wish to support EV-driving constituents with charging services must first define the extent of that "support," since stall electrification requirements follow directly from it.

Institutions could aim for different levels of support. They could meet a subset of constituents' driving miles (e.g., commuting mileage M^{commute} or total mileage M^{total}) or some fraction of constituents' charging needs (e.g., 100% of charging or only the portion of charging not already done at home $1 - C^{\text{home}}$), or they could combine these aims, among potential other options. Support manifests as an institutional goal for meeting some annual mileage, denoted M^{+}. As we will show, institutional goals matter: they are strategic decisions that the institution has direct control over, they implicate ideals of fairness and access, and they are often the determinant variables in the model—i.e., those that most affect model outputs.

B. Model output

Idealized charge session. For each driver *i*, we calculate the energy delivered E_i, in Eq. (3), and range added R_i, in Eq. (4), during an idealized charge session—i.e. one that draws maximal energy. An EV charger can deliver up to E^{charger} kWh but no more than the effective battery capacity B_i^{eff}. Delivered energy E_i begets an increase in range R_i that is proportional to the fraction of battery replenished, E_i/B_i^{eff}.

$$E_i = \min\left\{E^{\text{charger}}, B_i^{\text{eff}}\right\} \quad \forall i = 1, ..., N \tag{3}$$

$$R_i = \frac{E_i}{B_i^{\text{eff}}} R_i^{\text{eff}} \quad \forall i = 1, ..., N \tag{4}$$

Total charge sessions and plug-in rates. To recoup energy equivalent to M^{+} annual miles, driver *i* requires σ_i^{annual} annual charge sessions, given in Eq. (5). σ^{annual} considers that PHEVs drive only a fraction ϵ of total miles on electricity, will drive farther than R^{elec} before charging, and hence require fewer charge sessions than implied by R^{elec} alone.

Given a driver's required number of weekly charge sessions, given by 1/52 σ_i^{annual}, and their weekly commute frequency f_i, we can calculate the fraction of workplace commutes that must end in an EV stall, ϕ_i, given in Eq. (6)—what we call the "plug-in rate." In our model, drivers do not make additional commutes just to charge; if required charges exceed commutes (i.e., if $1/52\,\sigma_i^{\text{annual}} f_i^{-1} > 1$), we assume they charge outside the workplace and initiate f_i weekly workplace sessions.

The number of weekly charge sessions that driver *i* initiates is σ_i^{weekly}, given in Eq. (7); and the total weekly sessions (defined by E_i) that the institution must accommodate is $\Sigma_i \sigma_i^{\text{weekly}}$.

$$\sigma_i^{\text{annual}} = \frac{M^{+}}{R_i} \epsilon_i \quad \forall i = 1, ..., N \tag{5}$$

$$\phi_i = \min\left\{\frac{1}{52}\,\sigma_i^{\text{annual}}\, f_i^{-1}, 1\right\} \quad \forall i = 1, ..., N \tag{6}$$

$$\sigma_i^{\text{weekly}} = \phi_i f_i \quad \forall i = 1, ..., N \tag{7}$$

III. Case study at UC San Diego

A. Input data and scenarios

To demonstrate the model, we apply real data from a subset of UCSD—a large institution with 75,000 affiliates (students, staff, faculty), 3.1 MW of distributed solar PV [17], 14,000 parking spaces, and a growing EV network [18] of 331 level-2 chargers, 13 direct-current fast chargers (DCFC), and >2,000 unique EV drivers. An additional 760 level-2 chargers and 35 DCFCs are anticipated by year-end 2025. Most chargers have a 4-h dwell time and throughput of 6.25 kW . (For simplicity, we neglect the smaller but growing share of 12-h dwell stations and 1-h dwell DCFCs.)

EV driver behavior is central to our model and the campus's EV planning efforts. To gather behavioral data, we created a campus club for EV-driving affiliates (N=626 and is growing). Drivers who opt in receive discounts on campus charging and, in return, respond to recurring surveys about their EV, commuting and driving, and charging habits. Averages for annual mileage, commute mileage, roundtrip commute distance, and commute frequency are 11,000 mi, 4,867 mi, 28 mi, and 3.3 commutes/week. (For now, we use a regional average for total driving, but future modeling will use odometer reading data obtained via surveys.) Mean home and campus charging fractions are 39% and 42%, respectively. BEVs comprise 76% of the EV population.

What remains unknown—and what we investigate here—are how the goals that the campus could set for itself shape network needs and usage. We frame four scenarios that differ in goals for 1) meeting drivers' mileages (we investigate all driving mileage and weekday mileage); and 2) meeting drivers' charging needs (we investigate all charging need and all charging less that already done at home). In these four scenarios, M_i^{+} is set to M_i^{weekday}, $M_i^{\text{weekday}}(1 - C_i^{\text{home}})$, M_i^{total}, and $M_i^{\text{total}}(1 - C_i^{\text{home}})$.

B. Weekly charge sessions and plug-in rates

Fig. 2 reports drivers' use of the campus charging network (plug-in rate; anticipated number of weekly charge sessions per driver) for the four scenarios. The wide variation in outcomes across scenarios indicates that campus policy for supporting charging has a profound effect on plug-in rates and charge sessions. Scenario 2, for example, has a plug-in rate of 33%—the lowest among the four and less than half that of Scenario 3 (78%). In other words, a campus commitment to supply energy for commuters' full charging and driving needs (Scenario 3) would more than double campus network usage compared to a commitment to meet only their non-home charging and weekday driving (Scenario 2).

EV type can lead to moderate differences in outcomes. In Scenarios 1 and 3, for example (wherein the campus meets all charging needs), PHEVs plug in 26% more often than BEVs because they drive less between charge sessions (75 mi vs. 86 mi). In Scenarios 2 and 4, these differences become negligible because PHEV drivers do more home charging (45%) than BEV drivers (37%) and hence rely less on workplace sessions.

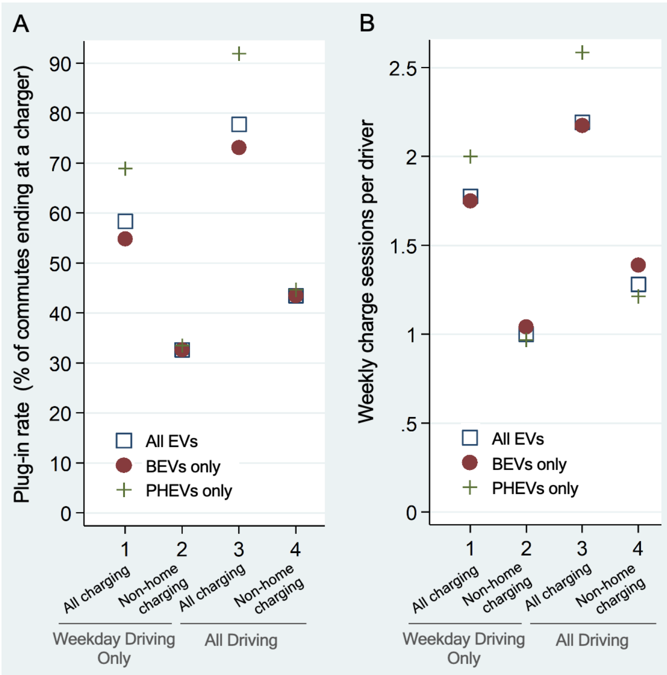

Fig. 2. Plug-in rate (i.e., the percentage of commutes to campus that must end in an EV stall for drivers to recoup mileage) (A) and weekly charge sessions per driver (B) for four scenarios in which the campus supports weekday-only driving (scenarios 1–2) or all driving (scenarios 3–4) alongside all of drivers' charging need (1, 3) or only charging not already done at home (2, 4). Markers denote the median across all 626 drivers, 475 BEVs, and 151 PHEVs).

C. Sensitivity analysis

Fig. 3 shows how drivers' use of the campus network changes following variation in particular model parameters. The baseline is Scenario 2, which represents an incipient (minimum) level of ambition among our four scenarios that we suspect institutions might trial initially.

Among all parameters, we find that institutional policy for supporting charging matters most for plug-in rates, weekly charge sessions, and hence stall electrification requirements. Support for "All mileage, all charging" (the top bar in Fig. 3), which is equivalent to Scenario 3, envisions that drivers charge entirely on campus (bringing the 39% of charging currently done at home to campus)—leading to a doubling of workplace charge sessions. Given that such policies implicate a huge number of additional sessions to support, institutions should exercise care when establishing goals.

Institutions should also be mindful about the chargers they install. Charger type (specifically power delivery; "EV charger kW throughput") and rules on session duration ("EV charger dwell time") have a large effect on outcomes. Compared to a workplace network built exclusively on 6.25-kW stations (as our baseline envisions), higher 39-kW-throughout stations (equivalent to a DCFC) reduce the plug-in rate and weekly charge sessions by about 45%. Doubling the dwell time from 4 to 8 h (a standard workday) yields a reduction of about 35% in both outcomes. Using 3.12-kW chargers or a 2-h dwell time, meanwhile, would increase the number of sessions by 60%.

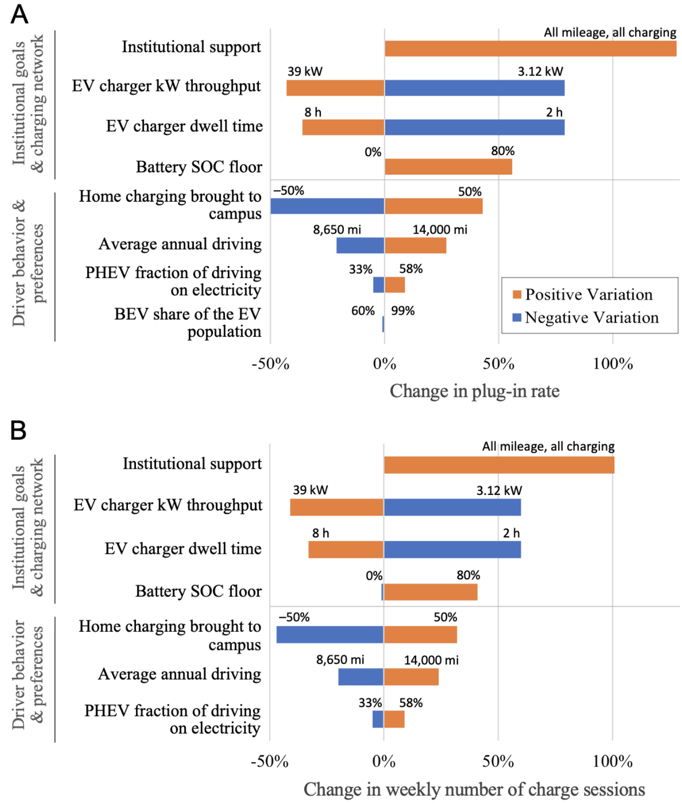

Fig. 3. Change in plug-in rate (A) and total weekly charge sessions (B) given variation in select model parameters. Variation is noted next to each parameter: "Support all mileage, all charging" indicates Scenario 3; 3.12 kW and 39 kW charger throughput indicate a shared 6.25 kW charger and DCFC; a 2 h and 8 h dwell time are the median session at UCSD and full workday; an 80% SOC floor represents high range-anxiety charging; +/–50% home charging is half that supported in Scenario 3; 8,650–14,000 mi annual driving are low and high literature estimates; 33–58% of PHEV driving on electricity captures underlying methodological differences in [14]; and 60–99% BEV share is per industry forecasts plus a possible high-BEV future.

Driver behavior also plays a big role. A switch to higher-throughput chargers and longer dwell times means EVs can recoup miles in fewer sessions. But that strategy depends pivotally on driver decisions to delay charging until the EV has a low battery SOC. If drivers maintain SOC above 0.8, rather than 0.2, weekly charge sessions increase by about 40%. Institutions must know their constituents' driving patterns: credible estimates for total annual driving span 8,650–14,000 mi—variation which leads to 20–25% additional or fewer weekly charge sessions. Such variation suggests extremely high value in knowing commuters' driving and charging profiles, for example through surveys and odometer readings.

EV features matter the least. Longer BEV ranges, for example, would have effectively no impact on plug-in rates, since plug-in rates are constrained by the energy that chargers can deliver, E^{charger}, rather than EV range or battery size. This suggests that there is value, in our example, in opting for charger-dwell-time combinations that deliver >25 kWh (6.25 kW $\times$ 4 h).

In theory, PHEVs could have a big effect on a charging network's hosting capacity because they have smaller batteries and electric ranges commensurate to commute distances. In our study, however, the BEV-to-PHEV ratio has negligible impact because both have similar needs, on average (with 4-h 6.25-kW stations, BEVs add 86 mi of range, while PHEVs travel 75 mi between plug-ins). Different station dynamics, however (higher kW throughput or dwell time), would change this; for example, increasing dwell time to 8 h reduces BEV plug-in rates by 47%, while PHEVs plug in just as often.

Institutional policy and driver behavior dominate in our model, while plausible variations in policy and behavior also have big effects. This has two key implications. One, institutions should exercise caution in choosing the criteria by which they support commuters. There is high value in iterative planning that evaluates progress over time and adjusts. Two, there is also high value in understanding the behavior of an institution's EV-driving constituents, such as through surveys and EV clubs like the one we have created at UCSD that generate vital information about the population.

IV. Conclusion

This paper presented a new planning model for workplace EV charging networks at institutions (e.g., public entities, corporations) with regular commuters, parking facilities, and a commitment to support constituents' charging needs. The full model and a sample dataset are available for public use at https://tinyurl.com/2v262znh. We demonstrated the model using UCSD network and driver data from the campus's $>$330 chargers and $>$2,000 EV-driving affiliates. Unlike prior literature, our model is built centrally upon driver behavior, habits, and preferences obtained via a new UCSD club of 626 EV drivers who respond to recurring surveys.

The EV chargers that institutions install, the parking rules that govern them, and driver behavior interact in complex ways that affect charging needs and stall electrification requirements. Our model not only helps answer questions around stall electrification, but also helps *identify* the key unknowns that need to be answered about human behavior. Our ongoing work includes a series of human behavioral experiments to better understand these unknowns—e.g., how drivers respond to rules and incentives. We are also integrating forecasts into the model so that it can inform long-term planning.

References

[1] R. Hanna and D. G. Victor, "Marking the decarbonization revolutions," *Nat. Energy* 6, 568–571, 2021.

[2] S. LaMonaca and L. Ryan, "The state of play in electric vehicle charging services–a review of infrastructure provision, players, and policies," *Renew. Sustain. Energy Rev.*, vol. 154, p. 111733, 2022.

[3] G. Tal, K. Kurani, A. Jenn, D. Chakraborty, S. Hardman, and D. Garas, "Electric cars in California: Policy and behavior perspectives," in *Contestabile, M., Tal, G., Turrentine, T. (eds) Who's Driving Electric Cars. Lecture Notes in Mobility. Springer, Cham.*, 2020.

[4] D. Chakraborty, D. Bunch, J. Lee, and G. Tal, "Demand drivers for charging infrastructure—charging behavior of plug-in electric vehicle commuters," *Transp. Res. Part D: Transport and Environment*, vol. 76, pp. 255–272, 2019.

[5] J. Coignard, S. Saxena, J. Greenblatt, and D. Wang, "Clean vehicles as an enabler for a clean electricity grid," *Environ. Res. Lett.*, vol. 13, p. 054031, 2018.

[6] C. Klein-Banai and T. Theis, "Quantitative analysis of factors affecting greenhouse gas emissions at institutions of higher education," *J. Clean. Prod.* 48, 29–38, 2013.

[7] M. Bailey, D. Brown, B. Shaffer, and F. Wolak, "Show me the money! Incentives and nudges to shift electric vehicle charge timing," *National Bureau of Economic Research*, p. w31630, 2023.

[8] N. Erdogan, D. Pamucar, S. Kucuksari, and M. Deveci, "An integrated multi-objective optimization and multi-criteria decision-making model for optimal planning of workplace charging stations," *Appl. Energ.* 304, 117866, 2021.

[9] Y. Huang and Y. Zhou, "An optimization framework for workplace charging strategies," *Transp. Res. Part C: Emerging Technologies*, vol. 52, pp. 144–155, 2015.

[10] S. Li, F. Xie, Y. Huang, Z. Lin, and C. Liu, "Optimizing workplace charging facility deployment and smart charging strategies," *Transp. Res. Part D: Transport and Environment*, vol. 87, p. 102481, 2020.

[11] B. Ferguson, V. Nagaraj, E. Kara, and M. Alizadeh, "Optimal planning of workplace electric vehicle charging infrastructure with smart charging opportunities," in *2018 IEEE 21st International Conference on Intelligent Transportation Systems (ITSC)*, 2018.

[12] "Electric Vehicle Charging Stations at UC San Diego," (available at https://transportation.ucsd.edu/commute/ev-stations.html; accessed October 31, 2023).

[13] F. Venegas, M. Petit, and Y. Perez, "Plug-in behavior of electric vehicles users: Insights from a large-scale trial and impacts for grid integration studies," *ETransportation*, vol. 10, p. 100131, 2021.

[14] A. Isenstadt, Z. Yang, S. Searle, and J. German, "Real world usage of plug-in hybrid vehicles in the United States," (ICCT, 2022).

[15] J. R. Helmus, M. H. Lees, and R. van den Hoed, "A data driven typology of electric vehicle user types and charging sessions," *Transp. Res. Part C: Emerging Technologies*, 115, 102637, 2020.

[16] M. Nicholas and G. Tal, "Charging for charging at work: Increasing the availability of charging through pricing," in *Transp. Research Board 94th Annual Meeting*, 2015.

[17] S. Silwal, C. Mullican, Y. Chen, A. Ghosh, J. Dilliott, and J. Kleissl, "Open-source multi-year power generation, consumption, and storage data in a microgrid," *J. Renew. Sustain. Energy* 13, 025301, 2021.

[18] I. Bayram, V. Zamani, R. Hanna, and J. Kleissl, "On the evaluation of plug-in electric vehicle data of a campus charging network," in *2016 IEEE International Energy Conference (EnergyCon), Leuven, Belgium*, 2016.