Increases in electric vehicle load flexibility attributable to changes in EV charging policy

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***Abstract*—Electric vehicle charging is a promising source of load flexibility that could support power grid operators and other societal goals. Although it's recognized that charging polices could enhance flexibility by shaping driver behavior, there is a persistent need for field evidence on how policies affect behavior and flexibility in the real world. Here we report on and analyze two policies—a minimum session fee and increase in charger dwell-time, or the maximum duration a vehicle can park at a charger, from 4 to 12 h—implemented at the University of California San Diego in 2023–2024 across 304 chargers in 11 parking lots collectively used by 4,538 drivers. We present evidence on how these policy changes have affected the timing of drivers' plug-ins, charging, and idling and led, in turn, to gains in flexibility. We then quantify how gains in flexibility, if exploited, help reduce grid congestion and emissions from charging. While flexibility-exploiting smart charging algorithms alone reduce congestion and emissions, their benefits are amplified when combined with policy.**

***Index Terms*—Electric vehicle, electrification, EV charging network, transportation, workplace EV charging**

I. INTRODUCTION

As societies increasingly shift to electric vehicles (EVs) [1], many are grappling with how to make EV charging more flexible. Greater flexibility, i.e. capacity to shift electric load in space or time [2], could generate benefits for EV drivers, charging network operators, grid operators, and society, such as lower costs, emissions, and risks to reliability [3].

EV charging flexibility is a function, broadly, of two factors: driver plug-in behaviors, i.e. decisions about where, when, and how to charge, and the charging process delivered by the charger [4]. Plug-ins depend on drivers' travel patterns and habits [5]; charging processes are largely automated and require little or no driver engagement once initiated. Flexibility can thus be increased by improving the charging process, reshaping driver behavior, or both.

There are substantial but distinct literatures on shaping plug-in behaviors and the charging process. To improve charging, researchers have developed numerous smart charging algorithms [6], [7] with an array of unique features, e.g. time-based setpoints [8], power setpoints [9], interruptible charging [10], and grid constraints [11], among many others. These algorithms, in effect, use the flexibility that drivers inherently provide through their plug-in behaviors to achieve a specified goal. Goals vary and include minimizing cost [12], avoiding grid congestion [13], integrating renewable energy [14], and maximizing user convenience [15], among others.

While algorithms shape the charging process, policy shapes plug-in behavior. Numerous policies have been proposed and studied, such as time-varying rates [16], incentives to charge during off-peak hours [17] and avoid charging during on-peak hours [18], temporary price discounts [19], financial payments [20], [21], discounts [22], informational nudges [23], and whole smart charging paradigms [24], among many others. These policy analyses aim to uncover interactions between policy, behavior, and flexibility. Some aim to increase flexibility as an end; others aim more broadly at generating grid benefits.

The motivation of this work is to better understand the efficacy of charging policy in the real world. While many policies have been proposed, there is a persistent need for empirical evidence on how policies affect behavior and flexibility under real world conditions where policy alongside other exogenous and unforeseen factors shape behavior.

While no single paper can fill this gap, we contribute by presenting new field data from the real-world implementation of two policies at the University of California San Diego (UCSD) charging network [24]. In 2023–2024 UCSD introduced a 10 kWh-equivalent minimum session fee and increased charger "dwell-time," or the maximum duration a vehicle can park at a charger, from 4 to 12 h. Although policies were changed to improve resource allocation and driver convenience, we assess how the pair has affected driver behavior. We analyze changes in behavior as a quasi-natural experiment [25], where the experimental "treatment" is exposure to the two policy changes. With (anonymized) data on drivers' individual sessions, including location, we can isolate and compare charging activity at affected chargers pre- and post-policy changes.[1]

We find and report changes in plug-in, charging, and idling behavior, as well as the effect of these behavioral changes on flexibility and opportunities for avoiding grid congestion and emissions from charging. Results indicate that policies have increased charging and flexibility and could contribute

[1]This study used de-identified charging data that is collected by the campus for operational purposes, contains time-stamped charger-level telemetry, and does not contain personally identifiable information. Our work nevertheless has IRB approval at UCSD (#805222)

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greater reductions in congestion and emissions. Policies have also increased idling, which in turn points to an array of complementary charging policies that could boost energy sales. This study, to our knowledge, is the first-ever analysis of how workplace EV charging policy in the real world has shaped behavior and EV load flexibility.

In what follows, Sec. II presents methods and the structure of our analysis; Sec. III presents key findings; and Sec. IV concludes with implications for future research.

II. Methodology

Setting and policy changes. UCSD operates an EV charging network of >600 Level 2 chargers (as of writing). Over 8 months in 2023–2024, it replaced 150 old chargers across 11 parking lots with new chargers[2] and, in these lots, increased the allowable dwell-time from 4 to 12 h; shortly thereafter it introduced a 10 kWh-equivalent minimum session fee.[3] We refer to these 31 weeks in which policy was in flux as the *policy period*. During the 21 and 37 weeks before and after the policy period—what we call the *pre* and *post* periods—infrastructure and policy were stable. In all periods we consider only non-holiday weekdays (66% of days in the data set), since this day-type has distinct plug-in patterns.

Quasi-experiment and interrupted time series analysis. We assess drivers' charging behavior in the pre- and post-policy periods and compare differences between the two. From the standpoint of analysis, then, the policies were implemented simultaneously. We analyze changes in behavior as a quasi-natural experiment [26]. Quasi-experiments are common and used to study naturally occurring phenomena, like policy, where random assignment is not possible [25]. We use single-group interrupted time series analysis, wherein sessions are *treated* if they occurred in affected parking lots in the post-period. Policy effects are calculated as the difference between treated sessions and pre-period sessions in the same lots.

The key assumption in interrupted time series analysis is that treated behavior (in the post period) would have otherwise resembled pre period behavior in absence of the policy changes. While it is impossible to confirm this counterfactual, our setting does meet key validity criteria for quasi-experiments that strengthen claims of causality: treatment was exogenous because the policy changes followed engineering and logistical constraints, not demand patterns; drivers (and hence sessions) did not select into treatment, as we observe that drivers do most of their charging in a single lot irrespective of policy; and drivers were not informed of treatment ahead of time in a way that could bias treatment.

Our dataset contains minute-level session data on every instance of a vehicle connecting to the UCSD charging network, including the (anonymized) driver, location, energy received, and the time it plugged in, stopped charging, and unplugged from the charger. Our focus here is the timing of drivers' plug-ins, charging, and idling, and the effect of changes in these on flexibility. In total, our analysis comprises 304 chargers, 58 weeks, 4,538 unique drivers, and 21,948 and 17,992 sessions in the pre- and post-policy periods, respectively.

Structure of the analysis. EV charging load and flexibility depend broadly on drivers' plug in behaviors (e.g., plug-in time, battery state-of-charge, session duration), which are mediated by policy, and the charging process, which can be shaped with managed charging algorithms. We therefore structure our analysis along these two dimensions, shown in Fig. 1, to disentangle the impacts of each.

Along the first dimension we assume immediate charging and characterize driver behavior in the pre- and post-policy periods (quadrants I and II). If policies shape behavior and flexibility, these would manifest as differences in outcomes between quadrants I and II.

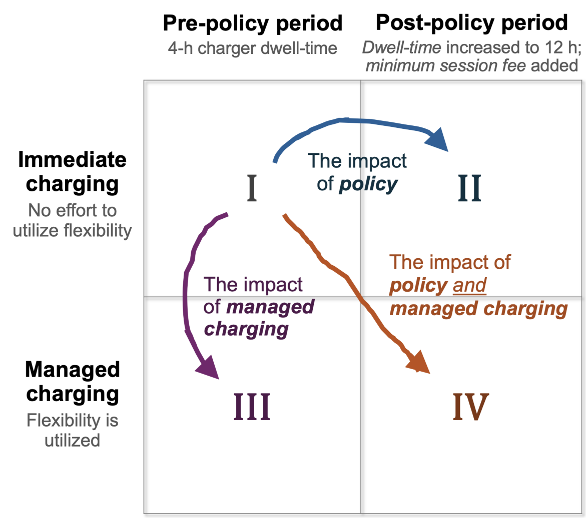

Fig. 1. The structure of our analysis. We analyze charging behavior across two distinct policy regimes (quadrants I, II) assuming immediate charging. We then apply managed charging algorithms that exploit the flexibility that drivers provide under each policy regime (quadrants III, IV). Differences in outcomes in quadrants II–IV vs. I reflect the distinct effects of policy, managed charging, and the two combined.

In the second dimension we apply managed charging algorithms to exploit the flexibility that drivers provide under each policy regime (quadrants III and IV). While many algorithms are available, we apply two from the literature that pursue goals relevant to workplaces: reducing grid congestion and increasing use of solar energy. The first, for congestion, minimizes daily EV charging load during the period of systemwide peak load (in Southern California, 16:00 to 21:00). For each session, the algorithm works by charging a vehicle first during the non-peak window, and then during the peak window only as a last resort to meet the vehicle's energy demand. It allows charging to be split into multiple discrete periods [27]. The second, for solar energy maximization, schedules charging by moving as much of it as possible into the midday 09:00–15:00 period [28]. If a vehicle's plug-in window does not overlap with the midday period, the algorithm reverts to immediate charging. With both algorithms, constraints ensure that each

[2] In 17 other parking lots, which are not a part of this study, chargers and dwell-time policy were not changed.

[3] With a y-kWh minimum fee, drivers are billed for y kWh when they draw $< y$ kWh.

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vehicle receives its full energy prior to plug-out. (We applied a third algorithm for reducing daily peak load, but found that policy changes have not significantly reshaped the potential to mitigate daily peak load.)

The structure in Fig. 1 allows us to separately quantify the effects of policy (II vs. I) and managed charging (III vs. I), as well as assess whether policy combined with managed charging produces additional gains in flexibility (IV vs. I) that neither can achieve alone.

While there are many dimensions of EV load flexibility, our focus here is intra-session temporal flexibility, i.e. the capacity to shift the energy delivered to an EV in time as facilitated by an idling period in which the EV has finished charging but remains plugged in.

III. Results

A. Timing of plug-ins, charging, and idling

Fig. 2 shows the mean timing of charging activity in the pre- and post-policy periods across the 11 parking lots that received the two policy changes. Plug-ins indicate the time-of-day in which drivers initiate charging sessions. Charging reflects the time-of-day that energy is delivered to vehicles, assuming immediate charging that begins at plug-in. Idling reflects the time-of-day over which vehicles sit idle, i.e. are plugged in but no longer charging.

Across both periods, plug-ins (Fig. 2a) follow the same general pattern: they spike from 06:00 to 09:00 as commuting drivers arrive to campus, persist at a diminishing rate through 18:00, spike again at 19:00 as overnight shift workers arrive, and diminish again thereafter. These morning patterns in particular are typical of workplace charging.

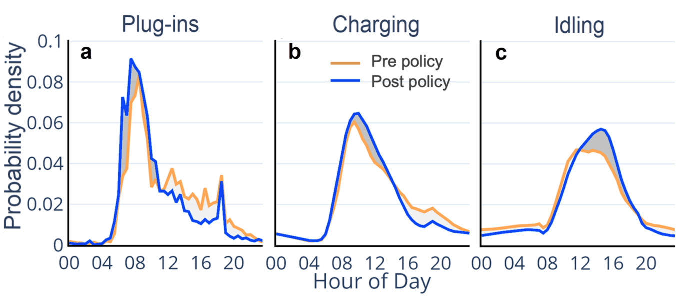

Fig. 2. Mean daily charging activity in the pre- and post-policy periods. Plug-ins indicate the time a vehicle begins charging. Idling indicates that a vehicle is plugged in but no longer actively charging. Charging and idling in *b–c* assume immediate charging at 6.6 kW Level 2 chargers. Shading shows differences between periods.

The policy changes have led to one main change in plug-ins: an intertemporal shift characterized by proportionally 23% fewer plug-ins in the afternoon (12:00–18:00) and 18% more during morning (06:00–11:00). This is intuitive: with 4-h dwell-time, drivers who arrive in the morning must in theory move their vehicle around midday, freeing up network capacity for other drivers and additional plug-ins. With 12-h dwell-time, however, drivers can plug in for the full workday, so fewer chargers are freed up around midday for a second use.

With a greater density of morning plug-ins in the post period, EV charging is more concentrated around midday (09:00 to 14:00); and with fewer afternoon plug-ins, less charging occurs in the evening from 16:00 to 21:00 (Fig. 2b). Because drivers plug in earlier and can park for up to 12 h in the post period, idling is more concentrated in the afternoon from 12:00 to 17:00 (Fig. 2c).

B. Opportunities for flexibility

Fig. 3 shows how charging and idling have changed between the pre- and post-policy periods by the hour of the day in which drivers plug in. We note three changes in behavior that, together, have led to new opportunities for flexibility.

First, independent of the hour of day, drivers are both charging and idling for longer in the post period (Fig. 3a–b). These changes are intuitive: the longer 12-h dwell-time allows for overall longer sessions, which may comprise more charging and/or idling; at the same time, the minimum session fee encourages deeper sessions. Even as drivers typically spend a greater proportion of their session charging (Fig. 3d; idling ratios are down 2% on average in the post period), total idling per session is up by 20%, on average (Fig. 3c). All else equal, greater idling means greater flexibility.

Second, the largest increases in idling are associated with sessions that begin in the morning between 05:00 and 10:00 (Fig. 3c) and end in the afternoon between 14:00 and 16:00. This means that post period gains in flexibility are greatest during midday when most EVs are plugged in—and hence can be exploited to achieve goals like maximizing use of local solar energy.

Third, the next largest increases in idling stem from sessions that begin during the 18:00–19:00 evening peak in plug-ins (Fig. 2) and end after midnight. With longer idling, these sessions could be scheduled to avoid evening systemwide peak load that occurs locally from 16:00 to 21:00.

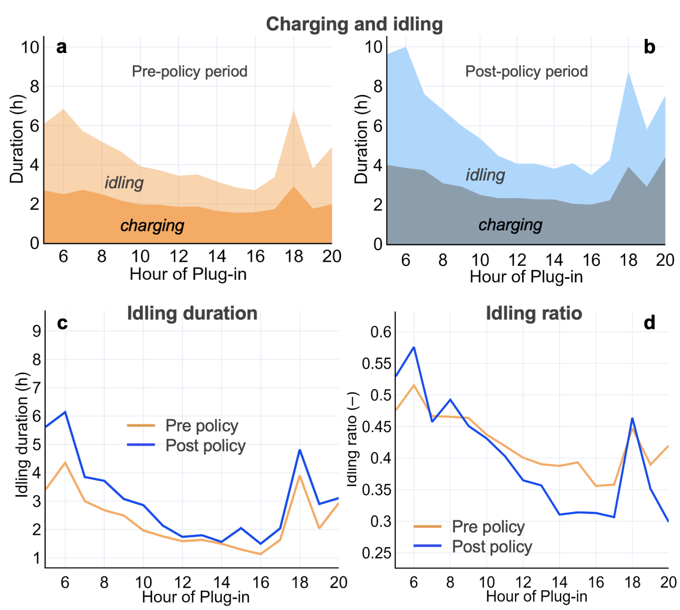

Fig. 3. Mean charging and idling duration among vehicles that plug in by hour of the day in the pre- and post-policy periods *(a–b)*; *(c)* idling duration; and *(d)* idling ratio, i.e. the ratio of idling duration to total session duration. Shown is the period 05:00–20:00, during which 95% of sessions are initiated.

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C. Effect on grid congestion

Fig. 4 shows the mean daily EV charging load under the goal to reduce grid congestion for the 4 regimes in our analysis (see Fig. 1). Regimes I–II show pre- and post-policy period EV load under immediate charging; III–IV show EV load under managed charging, which exploits drivers' flexibility to minimize charging during the 16:00–21:00 peak load window. To facilitate comparisons across the pre and post periods, we normalize daily load curves in each period by the daily maximum in the period's immediate charging curve. Differences in outcomes between regimes II and I indicate the effect of policy on the timing of charging; differences between III and I (and IV and II) indicate the effect of managed charging.

As Fig. 4 shows, most charging in the base case (regime I) occurs outside of the peak window. Nevertheless, the effect of policy (II) has been to shift charging from the peak load window to midday (cf. Fig. 2). The effect of managed charging is to delay charging until after the peak window—hence the jump in both managed charging curves (III and IV) at 21:00.

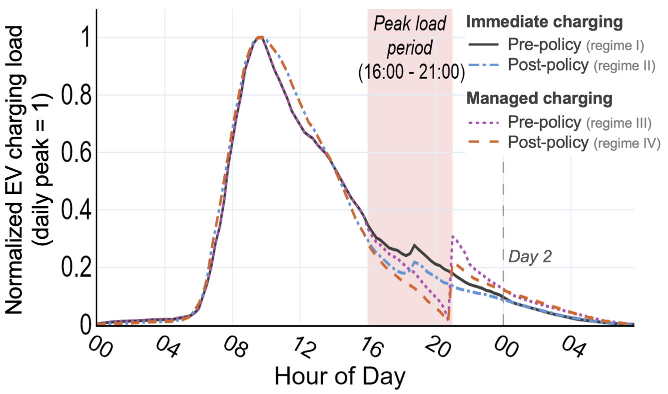

Fig. 4. Mean EV charging load curves for the 4 regimes in Fig. 1. Regimes differ in period (pre, post) and charging process (immediate, managed). Here, managed charging aims to minimize charging during the 16:00–21:00 peak load period. Load curves are the mean over all days in the period and normalized by the daily maximum of the period's immediate charging curve.

Fig. 5 reports the percentage of daily charging that occurs during the peak load window across all days that compose the 4 regimes. This reveals that both policy and managed charging (II and III, respectively) have increased the capacity for avoiding congestion, and that together (IV) their effects compound. Policy alone (regime II), by changing plug-in behaviors, reduced peak period charging from 16% to 13% (an 18% decrease). This decrease is similar to the 16-to-12% reduction achieved by managed charging alone (III). The two together (IV) reduced peak period charging from 16% to 9% (a 42% decrease).

D. Effect on use of solar energy

Fig. 6 shows the mean daily EV charging load under the goal to increase use of solar energy for the 4 regimes. Regimes I–II assume immediate charging; III–IV exploit drivers' underlying flexibility to maximize charging during the 09:00–15:00 solar window. (Fig. 6 is analogous to Fig. 4 but oriented toward

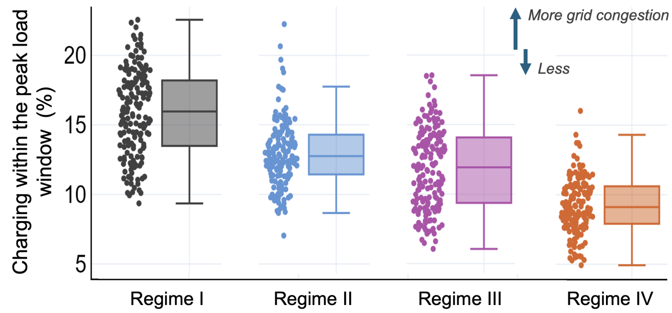

Fig. 5. Daily EV charging during the peak load window, defined as the percentage of daily charging that occurs between 16:00 and 21:00, for the 4 regimes in Fig. 1. Dots are individual days in the period.

increasing use of solar energy instead of minimizing peak period load.)

As Fig. 6 shows, most charging in the base case (regime I) occurs during the solar window. Policy changes (II) have shifted charging from late afternoon to midday, while the effect of managed charging has been to delay early morning charging until 09:00—in effect shifting it toward midday.

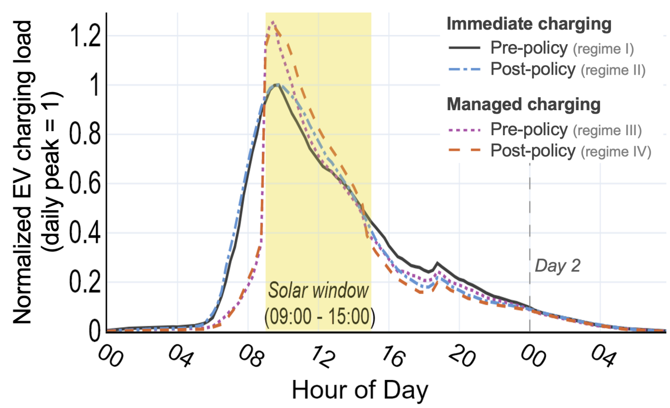

Fig. 6. Mean EV charging load curves for the 4 regimes in Fig. 1. Here, managed charging aims to maximize charging during the 09:00–15:00 solar window. Load curves are the mean over all days in the period and normalized by the daily maximum in the period's immediate charging curve.

Fig. 7 reports solar energy use across all days that compose the 4 regimes. Both policy and managed charging alone (II and III, respectively) increase solar energy use, and together (IV) they generate even larger gains. In the base case, 56% of immediate charging, on average, occurs during the solar window. Policy changes alone increased this to 59% (a 5% increase) (II vs. I). Because the new 12-h dwell-time has led more drivers to plug in during the morning (06:00–11:00) and fewer to plug in during the afternoon (12:00–18:00), more EV charging is done during the solar window. Managed charging alone increased solar energy use to 68% (a 21% increase) (III), because the drivers who plug in during the early morning provide substantial flexibility (see Fig. 3c). Together, policy changes and managed charging (IV) produce additional gains, increasing solar energy use to 72%, a 6% increase relative to managed charging alone (III vs. I) and a 29% increase from the base case (IV vs. I).

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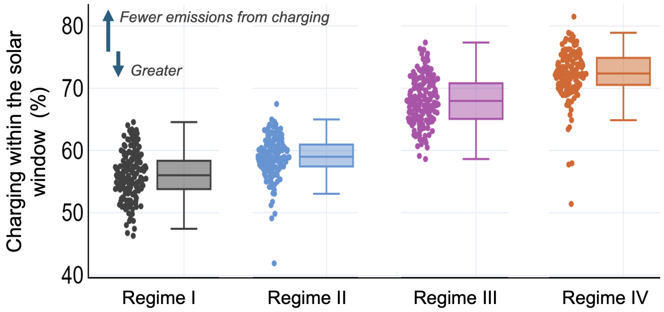

Fig. 7. Daily solar energy use, defined as the percentage of daily charging that occurs between 09:00 and 15:00, for the 4 regimes in Fig. 1. Dots are individual days in the period.

IV. Conclusion

This paper analyzed the real-world implementation of two workplace charging policies—a minimum session fee and an increase in the maximum charger dwell-time—and their combined effect on the timing of drivers' plug-ins, charging, and idling. Results show that these policies led to behavioral changes that, in turn, increased the EV load flexibility that drivers provide to the network: policy-induced behavioral changes alone reduced charging during the evening peak load period by 18%, and increased charging during the solar window by 5%. When smart charging algorithms were applied alongside policy, they further reduced peak load charging and increased solar energy use by 29% and 23%, respectively. The main takeaway is that technology and policy are harmonious: they can be implemented in ways that deliver better outcomes than either can generate in isolation.

As institutions change their charging policies, they should be mindful of the ways in which driver behavior may change in response, since these changes may present new opportunities. The policy-induced behavioral changes that we observe, e.g.—earlier plug-in times, longer idling—suggest a greater opportunity for managed charging algorithms, as well as for new policies that encourage drivers to plug in with lower battery state-of-charge so that they spend more of their session charging and not idling.

In future work, we plan to assess policy and behavioral changes from the perspective of network operators, who care principally about managing costs and revenues and finding viable business models.

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