Coupling Electric Vehicle Charging with Urban Mobility

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Transportation electrification introduces a spatiotemporal tie between the traditionally independent power and transportation infrastructures through electric vehicle (EV) charging. With the steadily increasing rates of EV adoption in urban areas, the imminent paradigm shift in electricity consumption poses a challenge for researchers to untangle the relationship between mobility and electricity demand. In this work, we provide an understanding of EV mobility by coupling origin-destination information obtained from mobile phone data with EV charging session data for the San Francisco Bay Area, USA. We first lay out a methodology to extract mobility patterns of EV drivers in the area. Next, we present the spatial and temporal characteristics of charging sessions and show that commuting patterns and EV energy consumption are

closely linked. We develop charging schemes that investigate the impact of arrival time scheduling and shifting of charging activity in shaving peak power load. Finally, we quantify and evaluate the potential benefits of such schemes to demonstrate that substantial savings are achievable. Our results advance our ability to apprehend the current and future state electrified urban mobility and the potential of solutions that aim to manage transportation based electricity demand.

Introduction

With growing population and rapid urbanization, the demand for mobility and electricity in urban areas are not only increasing in magnitude, but also are becoming more concentrated spatially and temporally. The infrastructures that serve these needs, namely the road networks and the power grids, are under high levels of stress in efforts maintain reliable service. The low costs associated with the extraction and processing of petroleum and coal have led us to historically rely on these high emission fossil fuels to meet the ever-increasing transportation and electricity demand. As a consequence, in 2013, global CO_2 levels exceeded 400 ppm, a mark previously deemed as the critical threshold above which the effects on earth's climate would be irreversible. Rising CO_2 emission levels had already triggered the widespread search for cleaner alternative fuels for the purpose of transportation decades before we reached this mark. Although the alternatives developed over the years failed to overtake conventional vehicles that use gasoline (*1*), today's electric vehicle (EV) technology is the most promising candidate up to date. Early stage issues such as range anxiety, charger availability, and high prices are slowly but surely being overcome by the maturation of battery technology, as well as tax breaks and subsidized charging programs. As EVs are continually becoming a more viable means to move, they are being adopted by drivers at steadily increasing rates. According to the US Energy Information Administration, the number of EVs in the USA doubled between 2013 and 2015 and is expected to reach 20 million by 2020 (*2*). As EVs become more ubiquitous, road networks and power grids will become tightly interlocked in their efforts to meet the mobility and electricity demand of the people. This coupling calls attention to an imminent need to understand the typical characteristics of the demand for electrified transportation to build solutions for its management.

Facilitating and expediting the movement of people and goods across cities has been a perennial goal of scientists, engineers and planners. To better plan for the mobility demand, transportation planners founded meticulous modeling practices that provide travel demand information at both aggregated and disaggregated levels. These models contain modules that capture commuting patterns, activity profiles, mode and route choices, as well as short and long term trends such as changes in rates of car ownership or population growth (*3*). In their implementation, travel demand models typically make use of synthetic populations obtained by household travel surveys to better mimic the behavior of all travelers. These surveys are costly and require a lot of labor, therefore can be carried out infrequently for small sample sizes. Recently, models that utilize mobile phone data have been introduced to the literature, providing cheaper and complementary means to generate travel demand information. Although the data used in these models lack the level of detail and precision of travel surveys, they make up for various disadvantages of surveys, as they capture the movement of millions as opposed to thousands and can be processed quickly at lower cost (*4–8*). Despite the abundance of research on this front, there currently is a scarcity of works that aim to measure and assess the mobility of EVs.

Even without the impending power load of large numbers of EVs, power grids have traditionally been vulnerable to outages that can cascade drastically. This was most recently exemplified by the severe power outage observed in India in 2012 that affected approximately 650 million people. Although smaller in comparison, large power grid failures were also observed in Europe and in the United States over the last decade (*9*). Failures of this scale signified a need to recontextualize the electricity infrastructure, and transdisciplinary approaches were promoted in tackling the complexity of the problem (*10*). In addition to this already burdened landscape, the introduction of EVs signal a substantial increase in total load as well as currently unpredictable changes in the norms of energy consumption. Therefore extending the current know-how of solutions that more efficiently manage the power grid at the urban scale has been of utmost interest to researchers. In this topic, a body of literature specifically focused on the nature of network reliability, the role of network topology on the spread of cascading failures (*11–16*). Other works analyzed urban microgrids (*17*), and the implications of the introduction of new clean sources to the energy market (*18*). In the particular subject of EVs and their impact, methods of optimization and control of EV electricity consumption (*19–22*) is a rich avenue. Problems that researchers tackle on this front include measuring impact on the grid (*23–29*), developing accurate EV models (*30*), energy management (*31–33*), smart charging strategies that probe centralized and decentralized approaches (*34, 35*), scheduling (*36, 37*), peak shaving, emissions, and pricing models (*38, 39*). Although there exist some works that incorporate mobility information into their proposed models, these attempts often stay within the relatively smaller scopes such as estimating arrival or departure hours. The literature currently lacks the incorporation of mobility patterns at the metropolitan scale into the models of electricity demand management in a systematic way.

In this work, we target these gaps in the literature to extend the current knowledge of transportation based electricity demand from a complex systems perspective. For this purpose, we bring together three independent data sources: (i) mobile phone activity of a large sample of the residents of the San Francisco Bay Area, (ii) charging sessions obtained from EV supply equipment in the same region, and (iii) census and survey information relating to zipcodes, income, and use characteristics of conventional and electric vehicles (see Methods). In the first part of the work, we estimate vehicular mobility in the Bay Area using the mobile phone activity of a large sample of residents (Fig.1A). We then present a methodology to estimate EV trips from the overall mobility patterns by utilizing information obtained from surveys regarding the income and travel distances of EV drivers (see Methods). In the second part, we analyze the various aspects of charging activity to characterize the nature of electricity demand at charging stations. We present observations regarding visitation frequencies, arrival and departure hours, typical per session energy consumption patterns, and power levels. We establish the current state of EV charging as temporally flexible, predictably regular, and greedy in terms of extraction of power. In the third part, we explore the relationship between the commuting distance distribution of EV commuters incoming to a charging station and the observed electricity demand at individual charging stations. We discuss how mobility patterns can provide insights towards a region's characteristic electricity demand profile. In the fourth and final part, we lay out a charging optimization scheme that adjusts arrival times or delays charging activity to temporally distribute power consumption and mitigate the stress on the grid. We estimate the resulting effects on the commuting travel times and estimate monetary benefits to assess the value of such optimization solutions and their viability.

Results

Estimating Electric Vehicle Mobility We begin with estimating the overall vehicular mobility of the Bay Area by following the methodology outlined in (*6–8*). In doing so, we make use of the mobile phone logs of a large subsample of the population(see Methods). This process begins with the extraction of stay locations by cleaning the noise in the trajectories of each individual (*5*). Each location is then labeled accordingly based on temporal properties of the call activity. Once home and work locations are successfully identified, sequences of trips are collected for each individual and categorized by their time and purpose as well origin and destination. When carried out for the whole sample, this process captures the observed mobility of the mobile phone users. Then, from the samples obtained for each region, the mobility patterns of the whole population in that region are estimated, in consideration of the ratio between the sample and the region population. The result is what is known as the origin-destination information (ODs): the number of car trips taken from and to different points in the area.

The next and key challenge in this section is the conversion of this OD information, representing the mobility of all vehicles, to that of EVs. In order to statistically capture EV drivers within all car drivers, we make use of the California Plug-in Electric Vehicle Driver Survey carried out in 2013 (*40*). This survey, while highlighting the increase in EV adoption, presents various sociodemographic characteristics of EV owners. One of the more noticeable results in this context is the comparison of the household income distribution of EV drivers compared to that of conventional car owners. EV drivers' income distribution is skewed towards higher income segments, unlike conventional vehicle owners where the income distribution is relatively uniform. In particular, the percentage of those with average annual income above 150K$ among conventional vehicle drivers is 15%, compared to the 47% observed among EV drivers. The survey also highlights the typical distances EV drivers travel: 64% of EV drivers travel less than 30 miles per day (Table 1). Although newer generations of electric vehicles have increasingly higher ranges, EV drivers typically have low daily travel distances. We make use of these survey findings to accurately subsample EV trips from total vehicular ODs by implementing a Bayesian sampling procedure (see Methods). In this methodology, we use income distributions at the zipcode level and typical route distance of each individual origin-destination pair to estimate the probability of that trip being made by an EV. Fig. 2 summarizes our findings by comparing the distributions of route distance, D, and the commuting travel time under free flow conditions, T, for EV trips to those of all vehicle trips. The applied methodology moderates the distribution of trip distances for EVs, more visibly for trips shorter than 5 kms and longer than 30 kms, in agreement with the findings of the survey. The observed bimodality of the distance distribution is an outcome of the commuting patterns and is not unexpected, as it arises from the unique geography of the subject region.

Electric Vehicle Charging Session Profiles In this section, we comprehensively analyze EV charging by examining various aspects such as visitation patterns and adoption rates, temporal qualities of arrivals and departures, and typical energy and power consumption levels. EV drivers display varying degrees of regularity in terms of how often they visit charging stations. Fig.3A reveals that for the majority of EV drivers, the number of sessions per day, N_{day}, beginning from the day of their first record, is less than 1. The bottom left inset of Fig.3A displays the logarithmic distribution of the number unique EV charging stations (EVSEs) visited, N_{EVSE}, by each EV driver: 95.6% of EV drivers have at least one charging activity in less than 20 distinct EVSEs. The top right inset of Fig.3A depicts the rate of EV adoption observed throughout the year. The 3000 drivers observed in January 2013 increases by an average of 1000 per month, doubling twice over the course of 2013. The implication of such a rate of adoption for the power grid is in fact more severe that at first glance, since the new EVs entering traffic will not uniformly distribute the demand across the region but rather further increase the spatial concentration. This will result in a superlinear scaling of energy demand to number of EVs in popular regions, reiterating the pressing necessity to understand electricity demand resulting from mobility needs and the development of efficient charging solutions.

Next, we look at the arrival and departure hours of charging sessions, h_a and h_d, in Fig.3B. Approximately 50% of all arrivals take place in the 6am-11am morning period, and as expected, the morning and the evening peaks are highly pronounced. This points to the parallels between the temporal component of overall travel demand to electricity demand. The morning and evening demand peaks are abundant in all travel demand models, and this observation indicates that the temporal component of charging demand is directly translated from that of travel demand. To go into further detail regarding of arrivals and departures, in the inset of Fig.3B we look at the distribution of interarrival and interdeparture times, Δh_a and Δh_d, i.e. the time between two consecutive charging sessions for the same driver ID. These distributions are peaked at multiples of 24 hours, pointing to the diurnal periodicity of EV drivers' charging behavior. In conjunction with findings regarding arrival and departure times and visitation patterns, this finding solidifies the preconception of the strong relationship between commuting and charging behavior.

Next, we shift our focus to per session measures such as energy, duration, and power. Fig.3C exhibits the average energy consumption per session, E_S. The nameplate battery sizes of Nissan Leaf (24 kWh) and Chevrolet Volt (16 kWh), two of the most commonly used plug-in EVs in the region are marked. Typically E_S are well below these capacities, indicating that EV drivers typically stay within the range of their EVs. The charging activity typically does not fill emptied batteries, like the negative hype of range anxiety suggests. In fact, at these levels of flexibility, EV drivers appear considerably free to choose whether to charge their vehicles at home or not, without having to fear not being able to complete their commute the next day. In line with this, the incentives in place that promote workplace charging (*41*) blur the one-to-one mapping between a single commuting trip and the electricity demand in the charging session that follows, as they enable EV drivers to not necessarily start their commute at full capacity. On the other hand the distribution of session durations reveals that 98.4% of all charging sessions last less than a day (Fig.3C), in line with the strong ties to commuting previously mentioned. When findings regarding commuting-like temporal behavior and flexibility in terms of battery capacity are considered in conjunction, it is reasonable to expect that the session energy E_S will likely represent not a single commuting trip, but rather a number of them.

Since the actual charging activity does not last as long as the session duration δ_S, in Fig.3D we look at how the power changes as the session continues. We divide sessions into four categories based on their session duration, and plot the average power consumption for each segment at various percentages of the total duration. At this point, it should be mentioned that there are three power rating levels observed, namely L1, L2 and L3. The first two deliver 120V and 240V, typically corresponding to 3.3kW and 6.6kW, respectively. L3 chargers are mainly for fast charging at 480V and are relatively uncommon. In fact, L1 and L2 chargers make up 99.9% of all the sessions. This composition of power ratings explains the 4 kW upper limit to average power consumption observed in Fig.3D. For sessions lasting less than 4 hours, average power stays above 3 kW up to 80% of the session duration into the session. Conversely, for sessions that last longer than 12 hours but less than a day, only in the starting 25% of the session duration there is active charging. This corresponds approximately to 3-6 hours, and the power remains zero thereafter. This is consistent with constant-current constant-voltage battery charging behavior and it suggests that currently there is no strategy to charging involved: charging begins as soon as a session begins and ends when the battery is full. In more simple terms, it can be said that EVs are served greedily despite their flexibility in terms of session durations and battery capacity.

Energy and Travel Demand Relationship As we established in the previous section, there currently is no strategy in place to better manage the load EVs impose on the power grid. In order to develop effective strategies for this purpose, understanding the unique electricity demand of each region is a necessity. In estimating a single EV's electricity demand, it is possible to make use of the fact that the charging session energy demand is an outcome of the trips that EV has previously taken. Similarly, at the spatial resolution of a zipcode, the mobility patterns of commuters to that zipcode can be used to profile the average electricity demand at that zipcode. Following this reasoning, our goal in this section is to analyze the extent to which aggregate mobility patterns can be used to estimate average energy demand of a region. For this purpose, we look at how the average electricity demand at a zipcode, measured by using charging sessions, is related to the average commuting distance to that zipcode.

We begin by analyzing d, T, T_c, and E_S, representing trip distance, trip travel time under free flow conditions, trip travel time in traffic, and session energy, respectively. The probability distributions of these metrics are depicted in Fig.4A, with the cumulative distributions in the inset. The peaks in the distribution of E_S demonstrate the heterogeneity in the electricity demand, as well as the battery capacities of various EVs. The 3-4 kWh peak is a combination of low energy demand as a consequence of short commuting trips and plug-in hybrid electric vehicles (PHEVs) that typically have a battery capacity around 4 kWh (*42*). The similarity of these distributions are in agreement with the known fact that the energy consumption of a single EV is a direct outcome of the characteristics of the preceding trip such as distance and speed. More interestingly however, it can be observed that this relationship is conserved for a population of EVs rather than at the individual level. In other words, a set of the trips represented by the OD information of EVs and the resulting distribution of energy consumption of the same population of EVs follow similar distributions. This finding signifies the potential in combining mobility and energy information to provide insights at the urban scale.

Next, we further explore the relationship between energy demand and travel demand. For this purpose, we aggregate the session energy readings of the charging sessions from each zipcode to obtain E_S^z for that zipcode. Similarly, we average the distance traveled by all morning commuters to that zipcode to find D^z. To serve as a benchmark, we implement the drivetrain model presented in (*43*) that estimates the electricity consumption of a single Nissan Leaf trip given speed and distance information. We denote this estimate as E_M, and we aggregate it for each zipcode to obtain E_M^z. To select Nissan Leafs in our charging session, we select the sessions of only the vehicles that have not had any charging sessions with total energy readings that exceed the nameplate battery capacity of a Nissan Leaf. We compare how both E_S^z and E_M^z change with respect to D^z in Fig.4B. E_S^z exhibits a relatively low slope with a positive energy intercept. In other words, EVs appear to have a fixed energy demand even for $D^z = 0$. In comparison to E_S^z readings around 9kWh, E_M^z stay within the range of 2.5 kWh to 3.5 kWh. Although the overall trends are in agreement, the scales of E_S^z and E_M^z are different. These results stem from findings from previous sections. We previously established that within the commuting distance ranges we observe, EV drivers do not always start their day at full battery capacity. This notion is strengthened by heavy subsidies supporting workplace charging. A recent report by Department of Energy suggests that 80% of partner workplaces in their Workplace Charging Challenge program provide free EV charging, compared to 20% who charge their employees a fee (*41*). In support of this finding, it is widely known that the energy added to the EV battery and the energy for the EVSE meter often differ in measurements around 10-15%. The commonality for these factors is that they are uniform across vehicles and stations, hence are constant biases throughout. This explains the constant of proportionality between E_S^z and E_M^z, energy values obtained from the sessions and the model. To account for this proportionality, we analyze the two models by their first differences. By analyzing the additional session electricity demand for the additional average commuter trip distance to a zipcode, we are able to more robustly assess the quality of mobility information as an estimator of energy demand at a zipcode. For this purpose, we sort the zipcodes by the average incoming commuter travel distance, and then estimate the change in energy demand, ΔE_S^z, for each consecutive change in sorted distances ΔD^z. We fit the following linear models $\Delta E_S^z = \alpha_S \Delta D^z + \beta_S + \epsilon_S$ for sessions and $\Delta E_M^z = \alpha_M \Delta D^z + \beta_M + \epsilon_M$ for the model using least squares, where α, β and ϵ denote the slope, the intercept and the error term, respectively. As can be observed from the inset of Fig.4B, The slope obtained from the model is in agreement with that obtained from charging sessions. This indicates that OD information and energy demand resulting from commuting patterns are closely linked, and commuting patterns into a region can be used in laying the foundation to provide the electricity demand fingerprint of a region.

Assessment of the Impact of Charging Timeshifts As mentioned, the spatial and temporal concentration makes electricity demand difficult to meet in certain regions at certain times of the day. This led to more dynamic and complex rate structures that not only bill people for the total energy demanded but also incorporate the maximum withdrawn power, time of day, and season of year. These pricing policies counteract consumption behavior that pushes the power load curve towards nonuniformity. However in a future where the number of EVs will be magnitudes more than today, achieving a temporally homogeneous load curve at the urban scale will pose a tougher challenge. In this section, we propose a methodology that aims mitigate the peak load imposed by EVs on the grid by minimizing peak power at the EVSE level. By adjusting vehicle arrival times or delaying charging activity of various sessions, we move the aggregate charging activity towards hours of the day when there is less demand. This enables the transformation of the load curve into one that is more uniformly distributed across the day. Finally, we explore the monetary benefits of the potential savings and the implications of arrival time adjustment on commuting times to discuss the viability of this class of power management approaches.

To investigate the impact of arrival time scheduling and charging activity delay on the overall peak of the EV charging demand, we cast problem as a mixed-integer linear program with discrete shifts in arrival times and charging end times as inputs. The program modifies the total power P_t measured through the day resulting from the overlapping charging activities of a population of EVs in a way that minimizes the peak power while keeping the total energy consumed constant. That is, all EVs are charged by the same amount of energy as they used to, the only difference being the temporal distribution of how that energy was transmitted. Moreover, the charging activity is never allowed to be interrupted, and the departure times are not modified so that drivers are not inconvenienced (see Methods).

In this context, we test three different approaches. The first fixes the arrival times for EVs and delays the charging by d^i, an amount specific to session i within the interval $[0, d]$. The drivers are free to arrive as they wish, however the EV charging can be delayed to minimize P_{peak}. We refer to this model as *start bound*. The second model, referred to as *end bound*, offers modifications to the arrival times by proposing drivers to arrive earlier by d^i minutes in the interval $[-d, 0]$. In this approach, EV charging begins immediately upon arrival, or in other words, greedy charging remains. The start bound and end bound models represent a tradeoff: the former generates savings at the expense of having at most one hour worth of charging less capacity when in a need to leave urgently, whereas the latter is at the expense of possibly more inconvenient arrival times. The third and the last model combines the first two models and enables the adjustment of both arrivals and charging activity, referred from here on as the *flexible* model. In this model, the charging activity is shifted in the interval $[-d, d]$. We implement these three models for a typical day at a zipcode that contains 493 sessions (see Methods).

Fig.5A illustrates an instance of the flexible model for $d = 2$ (30 minutes) and how a sample of charging sessions would have been modified. To minimize the peak power, morning sessions have their charging shifted to earlier, whereas the charging of afternoon sessions are deferred. Fig.5B demonstrates how aggregate power curves are modified under these models. The flexible model is able to push P_{peak} down 38% from 973 kW to approximately 600 kW for $d = 4$, or namely 1 hour. Start-bound and end-bound models, as expected, require higher values of d to achieve comparable savings. The wider domain achieved by the combination of arrival adjustment and delay of charging provides strong flexibility for the flexible model, in agreement with its name, enabling the attainment of more substantial savings.

One key reason why an EV driver might not want to comply with an earlier arrival schedule would be its negative influence on the travel time. To assess how realizable the benefits of these models are, we investigate the consequences of the flexible model in terms of how it affects commuting travel times. In Fig.5C, we look at how the proposed changes for varying values of d for the flexible model would affect the commuting travel times, by using the OD flows to the subject charging station. The results show that the peak power reductions can be achieved without causing major discomfort to commuters in terms of travel times. The most negatively influenced drivers end up losing a maximum of 20 minutes in the case of $d = 4$, and are orders of magnitude lower in their number than those who are unaffected by the proposed changes. In fact, the number of drivers that achieve travel time savings are comparable to those who lose time, suggesting that a win-win scenario is at least as likely.

Next, we evaluate the monetary outcomes of these models. As mentioned previously, rate structures have charges associated with peak power, referred to as demand charge. For our models, we use the E-19 rate structure (*44*) for the region to calculate the change in demand charge as a proxy of the cost in terms of dollars. This enables us to gauge the magnitude of power shaving in monetary terms. When implemented, the possible benefits of the schemes we proposed are displayed in Fig.5D: monthly potential savings in the demand charge can reach up to 1500$. Without managing charging, these savings remain unrealized, and are paid for by EV drivers or the companies that subsidize the charging activity. As a sum the savings are substantial, yet for the number sessions on a typical weekday considered here, the amount per individual is relatively small, making uniform distribution of savings a relatively unexciting reward for cooperation. However, in the light of recent studies that reveal increased user cooperation with the introduction of gamified incentive systems (*45*), it can be expected for companies to start working towards realizing these benefits.

Discussion

Rising CO_2 emission levels are increasingly threatening the moderate nature of earth's climate. In efforts to even solely sustain the quality of urban life in today's cities, decreasing fossil fuel dependency is a must. In this context, technological innovations led to EVs becoming economically and socially more viable everyday and being adopted by citizens at increasing rates. This impending paradigm shift in the interplay of electricity demand, mobility and environmental concerns creates an urgency to rethink EV mobility. In order to devise schemes that optimize or control electricity demand, we need to focus on the methods that estimate EV demand.

This work presents, to the best of our knowledge, the first exploratory analysis that couples two unique large datasets on urban mobility and electric vehicle energy consumption. We first present methods to estimate EV mobility patterns using mobile phone records and appropriate sampling methods. In tandem, we dissect EV charging sessions in the same area to look at the spatiotemporal properties of electricity demand. We observe that drivers visit few charging stations and charge their vehicles in diurnal periodic fashion, thus there is spatiotemporal regularity in EV charging. Moreover, EV charging typically begins immediately, and as expected, more often on peak hours. However, charging sessions demonstrate high temporal flexibility, in other words, the vehicles are parked for longer amounts of time than what is required to fully charge them. Therefore there is significant room for improvement in the scheduling of EV charging. Upon combining our insights from the two datasets, we also observe that mobility is a precursor to electricity demand, and the two are closely interrelated.

Building on this, we provide a method to shave the daily peak power to alleviate the load on the power grid. We find that even with simple charging delay and arrival hour adjustments that do not impose any constraints on departure times and do not violate the charging continuity, peak power values can be shed by up to 40%. This class of solutions typically perform better with higher levels of participation from drivers. To incentivize cooperation, every driver needs to be presented with a balanced composition of benefits and costs, a key determinant of the success of these types of schemes. In an effort to further strengthen our analysis regarding the applicability of the proposed and similar such solutions, we estimate the possible monetary benefits and the travel time losses resulting from the proposed schemes. Although the resulting savings are not large at the daily individual level, they are certainly substantial enough for implementation of gamification and similar reward based incentivization schemes to induce cooperation and raise awareness. On the other hand, the travel time losses are almost imperceptible to the majority of the drivers, and a substantial number of drivers in fact benefit from the adjustment of their arrival times as it aids them to escape morning traffic. These findings demonstrate that in the current setting and medium-term future, energy management in the context of electric vehicles is highly viable.

There are various avenues in which this work can be extended. A meticulous methodology to more accurately estimate electric vehicle mobility, especially with higher temporal resolution, is of prime importance. The time dependency of electricity demand is an elemental component in energy management, therefore obtaining dynamic ODs for electric vehicles is a necessary next step. For this purpose, conducting widespread surveys and complementarily utilizing the data generated by these vehicles are crucial. With improved measures of EV mobility demand, our understanding of the relationship between mobility and EV electricity demand can be improved. As drivetrain models are continually being improved, a stronger comprehension of the tie between mobility and energy demand at varying levels of spatial resolution is necessary to create bottom-up solutions. Finally, the efficient implementation of these energy management solutions in real time remains an open front.

Materials and Methods

Data The three main sources of data used in this study are described below.

1. Mobile Phone Activity: Also referred to as Call Detail Records (CDRs), this data has been widely popular in the last decade, especially in the context of mobility modeling (*4–8*). For this work, we make use of the CDRs for the Bay Area including approximately 430,000 users and about 429 million calls they made over 3 weeks. The spatial resolution is discretized to the service areas of 892 distinct cell towers. This information is used to estimate the travel demand for the Bay Area for a typical weekday.

2. EV Charging Sessions: This data contains 580,000 records of EV charging sessions in commercial EV supply equipment (EVSE) locations across the Bay Area in 2013, including any vehicle with a battery that can be charged. For each charging session, the following information is available: (i) one-time information on the EVSE location type, unique driver ID, total energy transferred, and plug-in/plug-out times; and (ii) charging power readings obtained every 15 minutes. The locations of the charging stations are anonymized to zipcode level. As a preprocessing step, we filter out records lasting shorter than 1 minute, are not in 2013, or have erroneous power measurements exceeding typical cable capacity and maximum charging rates.

3. Census and Survey Information: The census data used in this study consists of shapefiles describing zip code regions, their population, and income information. The survey information is obtained from the California Plug-in Electric Vehicle Driver Survey carried out in 2013 (*40*). This survey contains information on various sociodemographic characteristics and travel behavior of EV drivers in California. We utilize information regarding income and average daily vehicle miles travelled in the estimation of EV mobility.

Electric Vehicle OD Estimation We denote an OD-pair, a trip between a source od_s and a target od_t, as od. We denote EV as the random variable that represents the occurrence of the event that a car trip is made by an electric vehicle. I_{od} is the random variable that denotes the income of the trip maker, and $P(I_{od})$ follows a standard normal distribution centered at median income of the source zipcode, od_s. D_{od} is the random variable that denotes route distance and is equal to $D(od_s, od_t)$ between od_s and od_t, constant for the specific od. Our goal is to estimate $P(EV \mid I_{od}, D_{od})$ for each od, or in other words, the probability that a trip for a given OD pair is in fact made by an EV. We assume that for a given od, I_{od} and P_{od} are independent, and $P(I_{od}, D_{od} \mid EV) = P(I_{od} \mid EV)P(D_{od} \mid EV)$, that is, I_{od} and P_{od} are also conditionally independent given EV.

We begin with the Bayesian relation,

$$P(EV \mid I_{od}, D_{od}) = \frac{P(I_{od}, D_{od} \mid EV)P(EV)}{P(I_{od}, D_{od})} \tag{1}$$

By imposing our aforementioned assumptions on Eq.1, we obtain

$$P(EV \mid I_{od}, D_{od}) = \frac{P(I_{od} \mid EV)P(D_{od} \mid EV)P(EV)}{P(I_{od})P(D_{od})} \tag{2}$$

In estimating this value, we assume $P(EV) = 0.62\%$ as the share of EVs within all cars in the Bay Area. We make use of the EV driver survey information regarding income and distance travelled, namely $P(I_{od} \mid EV)$ and $P(D_{od} \mid EV)P(EV)$, respectively. We randomly assign an I_{od} to each od from $P(I_{od})$, and calculate the D_{od} by using a publicly available online API service for routing. Given that D_{od} is constant for all od, $P(D_{od}) = 1$. Once $P(EV \mid I_{od}, D_{od})$ is estimated, the probabilities are used to reweight the flow of each unique (z_s, z_t) pair. Fig.2 represents the D_{od} distribution of the posterior $P(D_{od} \mid EV)$.

Optimization Model We begin with discretizing a day into 15-minute intervals such that each day starts at $t = 0$ and ends at $t = 95$ (*35*). For each charging session i among N in a day at a charging station, we define t_a^i as the arrival time index, t_c^i as the time index where charging is complete, and t_d^i as the departure time index. We represent the time indices by the vector τ^i, and the power consumption by vectors $\boldsymbol{P}^i$ and $\boldsymbol{Q}^i$, all defined as follows:

$$\begin{aligned}
\boldsymbol{\tau}^i &= [t_a^i, \ldots, t_c^i]^\intercal \\
\boldsymbol{P}^i &= [P_0^i, \ldots, P_{95}^i]^\intercal \\
\boldsymbol{Q}^i &= [P_{t_a^i}^i, \ldots, P_{t_c^i}^i]^\intercal
\end{aligned} \tag{3}$$

By shifting $\boldsymbol{Q}^i$ within $\boldsymbol{P}^i$ by an amount d^i for all sessions, we can modify the overall power demand curve. We define $M^i = (t_c^i - t_a^i) + 1$ as the total number of non-zero power measurements in this charging session (i.e. total number of elements in $\boldsymbol{Q}^i$), given that charging sessions start immediately upon arrival. We enforce continuity of the charging process, the non-violation of departure times, and amounts of session energy.

To capture the constraints proposed above, we introduce the following formal constraints:

$$\left.\begin{aligned}
&\tau_j^i \geq 0 \\
&\tau_j^i \leq 95 \\
&\tau_j^i \geq t_a^i + d^i \\
&\tau_j^i \leq t_c^i + d^i \\
&t_d^i \geq t_c^i + d^i \\
&\tau_j^i < \tau_{j+1}^i
\end{aligned}\right\} \begin{aligned} &\forall i \in [1, N], \\ &\forall j \in [1, M^i] \end{aligned} \tag{4}$$

We construct the proposed constraints using a binary decision matrix to represent charging or non-charging time slots within the optimization duration. To represent the candidate time slot at which Q_j^i can be positioned, we create binary row vectors $\boldsymbol{x}_j^i$ each consisting of 95 binary decision variables: $x^i_{j,k} \in \{0,1\}, \forall j \in [1, M^i], \forall i \in [1, N], \forall k \in [0, 95]$.

$$\boldsymbol{X^i} = \begin{bmatrix} \boldsymbol{x^i_1} \\ \vdots \\ \boldsymbol{x^i_{M^i}} \end{bmatrix} = \begin{bmatrix} x^i_{1,0} & \cdots & x^i_{1,95} \\ \vdots & \ddots & \vdots \\ x^i_{M^i,0} & \cdots & x^i_{M^i,95} \end{bmatrix} \tag{5}$$

Finally, we write the variables in the constraints given in (4) using the binary decision variable as follows:

$$\boldsymbol{\tau^i} = \boldsymbol{X^i} \begin{bmatrix} 0 \\ \vdots \\ 95 \end{bmatrix} \tag{6}$$

The aggregate power vector $\boldsymbol{AP}$ is given as follows:

$$\boldsymbol{AP} = \sum_{i=0}^{N} \boldsymbol{P}^i = \begin{bmatrix} \boldsymbol{Q}^1 \\ \vdots \\ \boldsymbol{Q}^N \end{bmatrix}^\intercal \begin{bmatrix} \boldsymbol{X}^1 \\ \vdots \\ \boldsymbol{X}^N \end{bmatrix} \tag{7}$$

The resulting formulation is a mixed-integer linear program, with decision variables $\boldsymbol{X}^i$, P_{peak}, and d^i of which the latter two are integers. The problem can be proposed to minimize the daily peak load P_{peak} for a group of EVs arriving to the same zip code location:

$$\underset{\boldsymbol{X}^i, P_{peak}, d^i}{\text{minimize}} \quad P_{peak}$$

subject to (4) and the following additional constraints:

$$AP^i_t \leq P_{peak}, \;\; \forall i \in [1, N], \;\; \forall t \in [0, 95] \tag{8}$$

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Author Contributions SC and ECK conceived the research and designed the analyses. SC performed the analyses and wrote the paper. ECK helped perform the analyses. SJM and MCG provided general advice and supervised the research.

Competing Interests The authors declare that they have no competing financial interests.

Data and materials availability: All data needed to evaluate the conclusions in the paper are present in the paper. Additional data related to this paper may be requested from the authors.

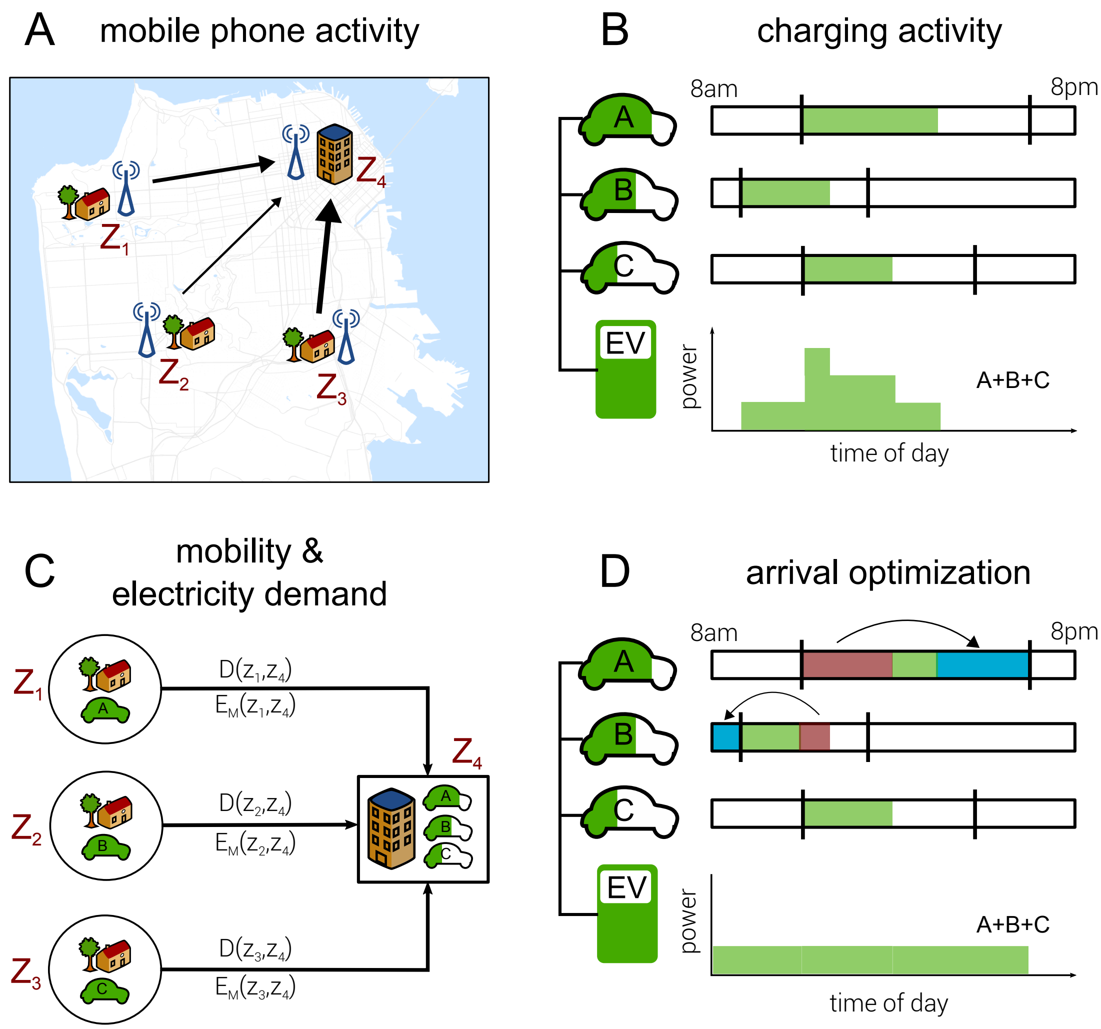

Fig.1. Coupling EV charging with urban mobility. A Mobile phone trajectories are used to estimate mobility patterns. **B** Charging sessions used to characterize session and electricity demand curves. **C** These findings are combined to analyze the relationship between commuting patterns and electricity demand. **D** Charging activity is shifted to relieve peaks in demand and generate savings.

Table 1: **Table 1. Characteristics of EV drivers.** Distribution of **A** average daily miles driven and **B** annual income by EV drivers in California, USA (*40*).

(1000$)	**Conventional**	**EV**
Unknown	20%	17%
< 50	20%	2%
50-100	30%	13%
100-150	14%	20%
> 250	15%	47%

(miles)	**%**
< 15	14%
15-30	50%
30-45	28%
> 45	8%

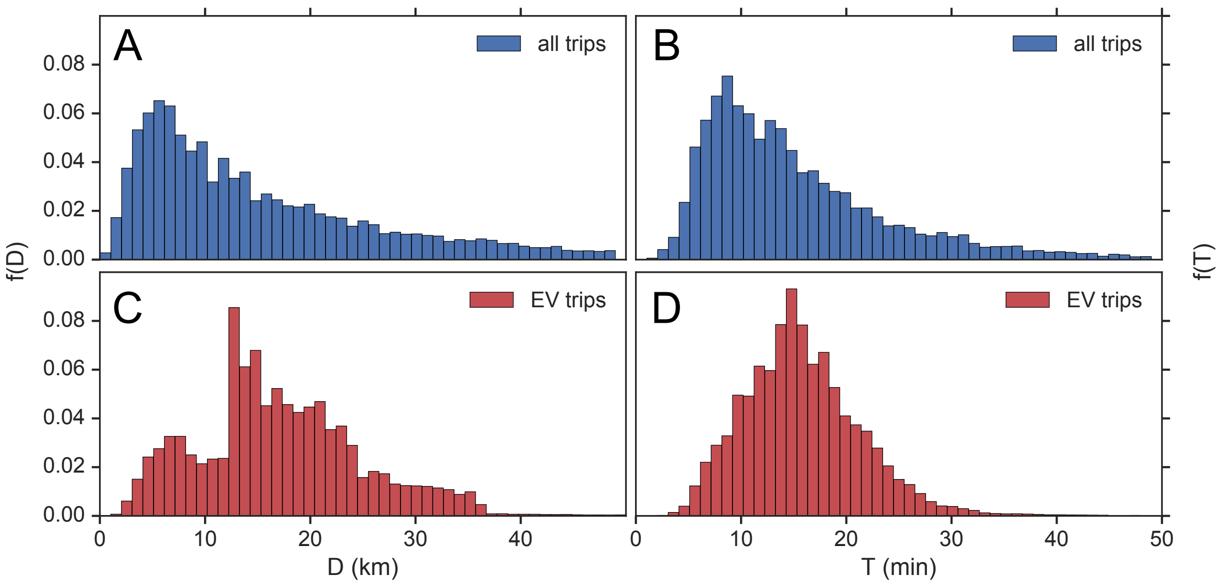

Fig.2. OD estimation for EV drivers in the Bay Area. The probability distributions of commuting distances, D, and commuting travel times, T, of all vehicle trips and EV trips estimated through income information and trip distances.

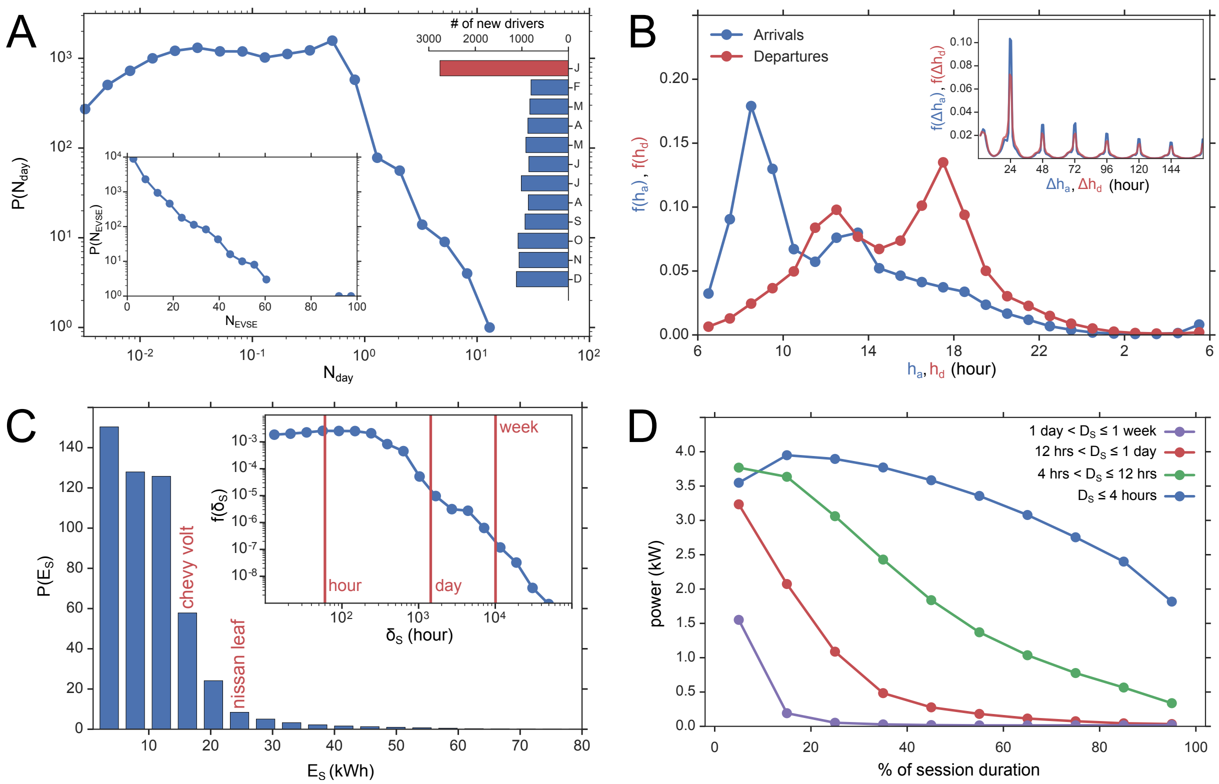

Fig.3. EV charging session profiles. **A** Distribution of N_{day} the number of sessions per day for each driver ID starting from the day of first record (right inset: number of new driver IDs added every month, left inset: distribution of N_{EVSE}, the number of unique EVSEs visited by every driver ID.) **B** The distributions of h_a and h_d, the arrival and departure hours to and from an EVSE. (inset: the distributions of Δh_a and Δh_d, the interarrival and interdeparture times for a driver ID visiting a specific EVSE.) **C** The distribution of E_S, the total energy withdrawn per session (inset: the distribution of δ_S, session durations.) **D** The power consumption as a function of the normalized session duration segmented by total duration groups.

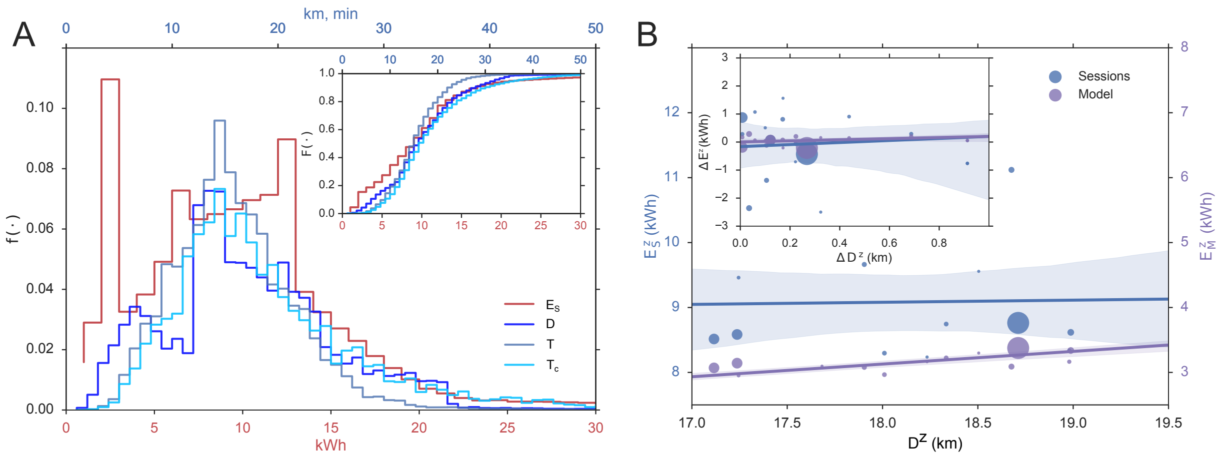

Fig.4. Relationship between OD trips and energy consumption. A The probability distributions of session energy E_S obtained from charging sessions compared to those of distance, D, free commuting travel time T and commuting travel time in traffic, T_c, estimated from ODs. (inset: the cumulative distributions) **B** Linear regressions of the average distance of Nissan Leaf commuting trips to a zipcode, D^z, versus the average morning session energy for these EVs for that zipcode, E_S^z and E_M^z. The bands represent the 95% confidence intervals, and point sizes are proportional to the number of sessions in that zipcode. (inset: a regression of the first differences of the energy and distance measurements)

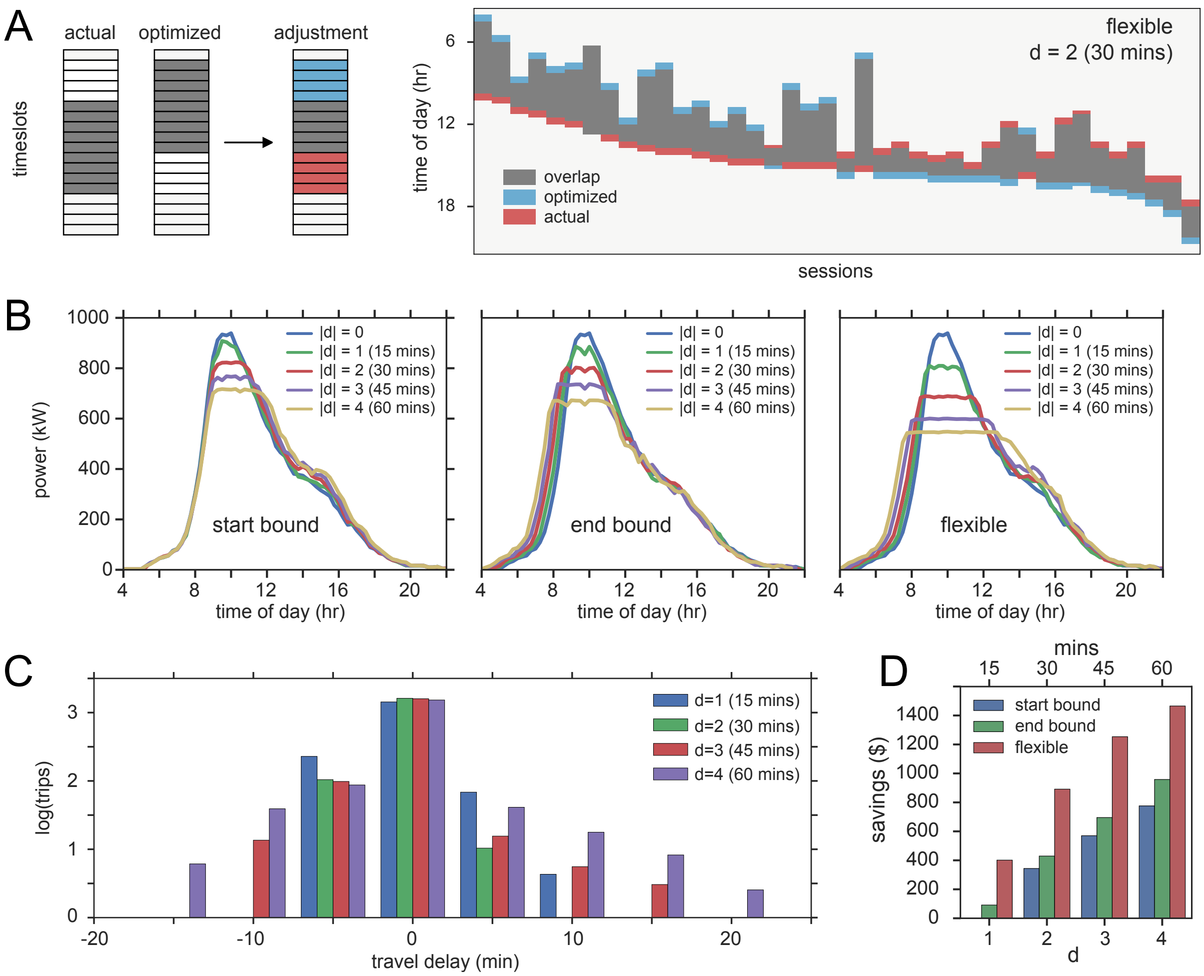

Fig.5. Assessing the benefits of minimizing peak power. A An illustration of a sample of sessions in the flexible model. The charging event within a session is shifted such that the overall peak power is minimized. **B** The decrease in peak power measurements for each model and varying d. Peak shaving of up to 38% can be achieved. **C** The influence of the proposed changes on travel times. Majority of drivers are not influenced, the worst case is a few individuals suffering from an additional 20 minute delay for $d = 4$. **D** The demand charge portion of the monthly bill and distribution of savings for varying values of d. The flexible model is able to generate savings worth approximately 1400$ for $d = 4$.