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Authors
Needell, Zachary
Wei, Wei
Trancik, Jessika E

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Strategies for beneficial electric vehicle charging to reduce peak electricity demand and store solar energy

Zachary A. Needell,[†,‡] Wei Wei,[†] and Jessika E. Trancik[*,†]

†*Institute for Data, Systems, and Society, Massachusetts Institute of Technology*

‡*Department of Civil and Environmental Engineering, Massachusetts Institute of Technology*

E-mail: trancik@mit.edu

Abstract

The adoption of battery electric vehicles (BEVs) and photovoltaic electricity generation increases in many climate change mitigation scenarios. Yet the large-scale deployment of these technologies , if left uncoordinated, can increase the costs of electricity through posing risks of increasing peak electricity demand during the evening and causing over-generation of electricity during midday. Here we examine these risks and how they interact to amplify or mitigate each other by modeling hourly electricity demand with high penetration of BEVs and photovoltaic over one year in two cities in the United States: New York, NY and Dallas, TX. We then investigate strategies for reducing these risks, measuring effectiveness with varying local travel and energy use patterns, electric vehicle adoption levels, and installed photovoltaic capacities. We focus on strategies that are easy to implement, in that they do not require travel behavior change nor new technology such as vehicle-to-grid capabilities and coordination between chargers and other networked infrastructure. In both locations considered, New York, NY and Dallas, TX, we find that easily-accessible strategies for time-shifting of charging can be very effective. Delayed home charging nearly eliminates the increases in peak demand from electric vehicles. Workplace charging can achieve a similar effect on peak demand reduction while also reducing the amount of curtailed photovoltaic electricity by half. Our analysis suggests that these two approaches could be mixed and matched to suit local conditions and decarbonization plans. Importantly, capturing these benefits would require an acceleration of electric vehicle adoption relative to current rates, through transportation policies that are timed to match those already set for electricity in many locations.

Introduction

Meeting climate change mitigation goals will require transitioning to less carbon intensive technologies for both personal vehicle travel and electricity generation, as well as in other end-use sectors.[1,2] One approach is to concurrently electrify transportation[3–5] and decarbonize electricity.[6–11] In this scenario, the transport and electricity sectors would become more closely linked, with technological transitions in one affecting the sustainability, cost effectiveness, and stability of the other.[12,13]

There are several risks associated with this transition. Depending on the charging patterns of an electrified transportation system,[14–17] the electricity grid may reach generation and distribution limits at certain times, potentially leading to transformer blowouts, electricity shortages, or reliance on expensive peaking plants to maintain supply[13,17,18]. This might occur if, for example, peak charging coincides with peak residential electricity demand in the early evening during higher-demand summer months.[19]

Decarbonizing the electricity sector by using intermittent sources such as solar or wind energy poses another set of risks. In the case of solar energy, an over-supply of electricity during midday and then decline in the evening hours can result in curtailed solar electricity, lower utilization of other power plants, and an inefficient ramp up of fossil-fuel powered plants to meet the early evening peak,[20] often called the “duck curve.”[21] If BEVs increase the evening peak demand, these effects may be amplified,[22,23] requiring additional underutilized generation capacity to meet peak loads.[24] This phenomenon can increase the costs of electricity, lower the value of additional PV installations, and increase emissions due to inefficiencies in plant operation and delayed retirement of fossil fuel powered plants.[25] At the same time, any increase in electricity prices would raise the life-cycle costs of BEVs compared to conventional vehicles,[1] potentially providing a new barrier to further electrification of the transport sector. The installation of grid connected energy storage has been proposed as a solution, but high costs for existing technologies remain an impediment to widespread installation.[21,26]

Here we investigate these risks and strategies for minimizing them that are easily-accessible and implementable without new technology or behavioral changes. We focus in particular on the excess peak demand from BEVs and the mid-day over-supply of PV, and we build on previous research identifying coordinated BEV charging as a potential tool for mitigating the duck curve and the need for other storage[27–33], [34–36]. A number of studies have examined various strategies to balance charging demand with renewable generation,[30,32–35] yet it is unclear how different strategies compare in terms of balancing electricity demand with supply considering the uncertainties in BEV adoption and performance and the variations in travel demand, electricity demand from non-charging related activities, and renewable resource availability over time and across locations. Accounting for these uncertainties and variations, two effective strategies emerge from this analysis—last-minute overnight charging, and shifting charging demand from the home to the work place—with the former greatly mitigating peak load and the latter addressing both peak load and midday solar overgeneration.

This analysis is novel in two ways. First, it focuses on easily-accessible, 'low-tech' solutions to the problem of electric-vehicle-caused excess peak electricity demand, and the potential for using electric vehicles for storing solar energy. These solutions do not require the connected charging devices and real-time communication with centralized control considered in other analyses[32,37] nor do they require upgrades to the power system to allow electric vehicle discharging,[5,38] which have yet to be tested and regulated.[22,39] The solutions also do not require changes to travel activity patterns, thereby removing a significant potential impediment to their adoption.[39] Thus these solutions are more predictably implementable than those relying on technological transitions to networked vehicles allowing for optimized charging, or significant changes to drivers' travel behaviors. Given the urgency of climate change, it is important to consider solutions that can be implemented now, alongside working on more advanced options that may become accessible in the future.

Second, we probe the relationship between three key variables—local travel and energy use patterns, the level of electric vehicle adoption, and the amount of installed photovoltaic capacity—to understand how they impact the potential for beneficial electric vehicle charging. Considering only one or two of these factors, as is the case in the current literature, leaves out consequential interactions between the transportation system and the electric power system.

Several features of our methodology supported this new approach. While other studies have probed time-shifting charging[40,41] [42], they have not considered how charging decisions fit within individual travel patterns. Our approach also adds to existing approaches by accounting for the variation in fuel economy due to detailed vehicle travel patterns and weather, and thereby adding to the model fidelity. Finally, because we do not aim to identify a single, optimal result for a transportation system simulation for a particular place and time,[40,43] under a set of assumptions about the future, and rather we probe the effects of three key variables across several different locations, the conclusions provide insight on the determinants of beneficial charging that is more generally applicable, across locations and over time.

This work is not intended to predict how things will change in the future, but instead focuses on outlining effective solutions that could be pursued. Whether or not these changes will happen will of course depend on a variety of other factors such as policy design and the preferences of drivers,[44] to be investigated in future research, alongside timelines and strategies for introducing more 'high-tech', networked solutions.

The paper's structure is aligned with each of the following steps in our analysis. We use the TripEnergy model[45] to estimate the energy requirements of a fleet of BEVs serving personal travel needs in Dallas and New York. We then use an optimization model of individual charging decisions to estimate the time-resolved electricity demand of these vehicles under different charging scenarios. Finally, we combine these charging profiles with historical electricity use and simulated PV generation to study the impacts of different technology and behavioral scenarios on the electricity grid. TripEnergy builds a detailed picture of personal vehicle energy needs in different cities, capturing the impacts of differing travel patterns, weather, and traffic conditions on vehicle energy use.[8,46–48] We combine this personal vehicle energy model with historical weather records[49] and historical electricity demand[50,51], estimating both average behavior and the rare, more extreme days that determine yearly capacity constraints.

Results

Magnitude of BEV-induced peak load and midday PV overgeneration

We begin by examining the consequences of BEV and PV transitions in isolation, using the Nissan Leaf, with a 62 kWh battery, as a representative lower-cost BEV.[1] We choose this vehicle because it costs less than the average car purchased in the US[52], and therefore could be affordable to a significant fraction of households purchasing new vehicles. We also examine BEVs with a larger battery capacity of 100 kWh in section 2 of the Supplementary Information (SI). The TripEnergy model[47,53], described in more detail in the Methods section below and section 1 of the SI, predicts that this vehicle can meet the range needs of 93% and 91% of vehicles in Dallas and New York respectively on a given weekday with once-daily charging and 95% and 93% respectively when Level 1 work place charging is also available. These days whose energy demand can be met with once-daily charging account for 84% and 82% of total personal vehicle energy consumption in Dallas and New York respectively. In our analysis, we only consider levels of BEV adoption as high as the portion of vehicle-days (days when a vehicle is used) that can be met with the given level of infrastructure availability. For example, with only home charger availability, 93% BEV adoption means that all vehicles that *can* meet their charging requirements are indeed replaced with BEVs.

By combining predicted hourly BEV charging demand and PV generation with historical electricity demand from April 2016 to April 2017, we estimate net electricity demand at each hour of the day, for each weekday of the year. For an illustrative example of excess charging demand, we assume that BEVs account for 50% of all vehicles driven and have access to 6.6 kW Level 2 charging at home, and for an example of excess PV supply we let PV generation account for 25% of total electricity demand. Under these two scenarios, we measure grid impacts in terms of peak area and valley area, compared to a base case of no substantial BEV charging or PV generation. Peak area is defined as the total amount by which electricity demand exceeds the observed yearly peak demand. If PV is installed as well, peak area is measured against the peak in net demand because, absent BEVs, adding PV capacity could allow for retirement of existing fossil fuel plants or avoidance of the need to construct new plants to meet increased demand. Therefore, peak area measures the extent to which BEVs change total generation requirements from peaking plants. Valley area is defined as the total amount by which net electricity load drops below a two week rolling minimum hourly demand, measuring the amount of either PV or baseload generation that must be attenuated. To allow comparison across cities, peak area is normalized by yearly weekday non-BEV electricity demand, and valley area is normalized by yearly weekday PV generation (both quantities are defined quantitatively in the SI).

Both of these quantities are shown in Figure 1 for a summer week and over a year. We find that loads close to the yearly peak are only reached on extreme days, clustered in the summer months. On these extreme days, BEV charging causes the highest observed hourly demand to increase by approximately 5–10% in both cities, an effect that is worsened because peak charging loads tend to coincide with peak existing loads in the early evening. We find that midday overgeneration, on the other hand, takes place throughout the year and tends to be most extreme in Spring and Fall months, when up to 30% of PV generation of some days competes with baseload generation. In both cities, but especially in Dallas, PV generation outpaces existing demand around noon but fails to entirely address high loads in the early evening as the sun begins to set. The remainder of this paper examines the degree to which BEV charging loads can be plausibly shifted to address this mismatch between supply and demand.

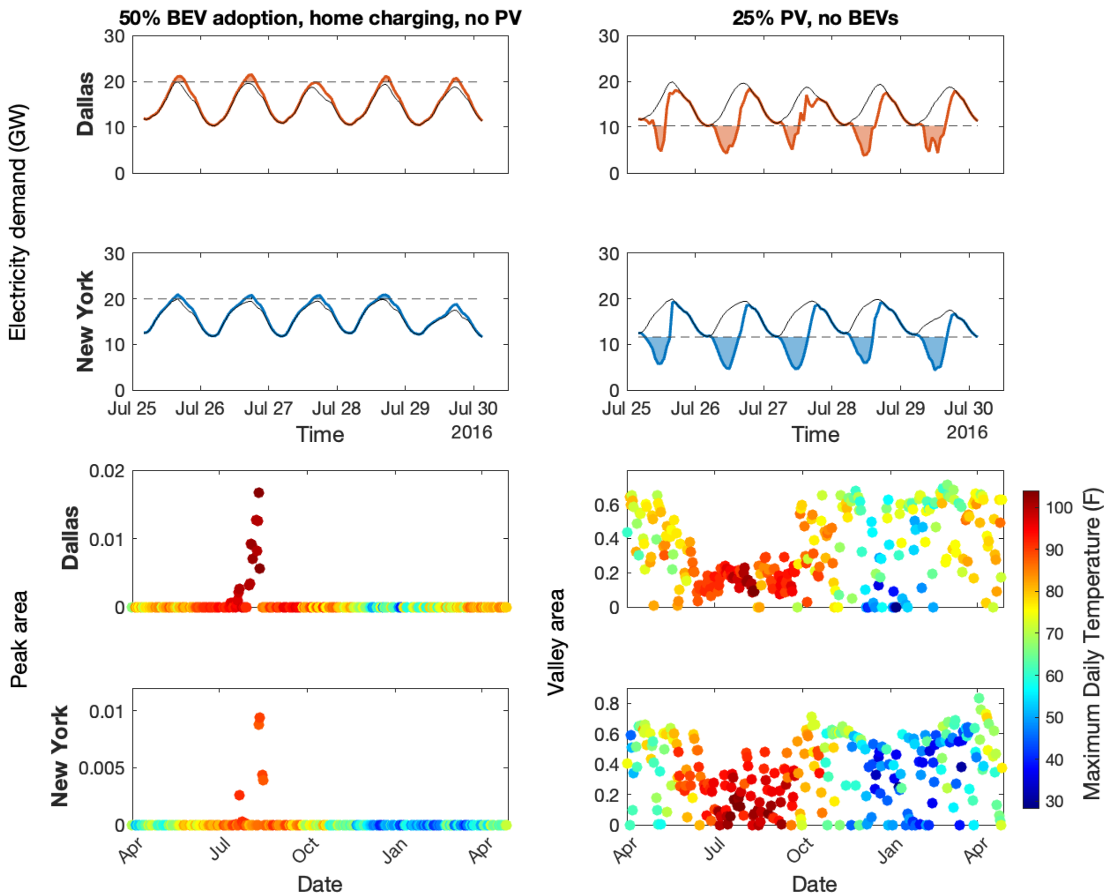

Figure 1: Hourly electricity load during a summer week in Dallas (top row) and New York (second row) in the case of 50% BEV adoption without additional PV (left column) and PV accounting for 25% of total electricity generation but no BEVs (right column). Shaded regions in the first two columns show peak area (left), measuring the extent to which BEV increases peak loads, and valley area (right), showing the extent to which PV installation displaces baseload generation. The bottom two rows show daily measurements for peak area (left) and valley area (right), unitless quantities representing the portion of electricity supply that is generated when total net demand is above or below peak and baseload demand levels, respectively, with values colored by daily high temperature. These yearly plots show that days meeting peak load constraints occur during the hottest days of the Summer but that midday overgeneration is spread throughout the year, especially temperate Spring and Fall days.

Impact of different charging patterns on BEV electricity load

Next, we examine how effectively changes in charger availability and charging preferences can shift BEV electricity loads away from high-demand times and to times when PV is generating. Along with the base case of only Level 2 charging with a charging power of 6.6 kW available at home, we examine a set of scenarios where vehicles have access to Level 1 charging at 1.8 kW when parked at work. When charging is available at both locations, we consider scenarios when charging at home either begins immediately when the vehicle is parked (the default case, which produces charging profiles similar to those observed from early BEV adopters[41,54]) or is delayed so that it finishes one hour before the first trip of the day (the "Home (Delayed)" case. The presence of this one hour buffer does not significantly affect the results). We also consider two types of charging location preference: where drivers charge as much as possible at any stop where a charger is available (the default case), and where drivers maximize the amount of their charging that takes place at the work place (the "Work (Preferred)" case, which is consistent with cases where workplace charging is free and unconstrained[55]). This leads to five total charging patterns for which hourly electricity demand is calculated over the course of a year. We examine more scenarios of charging availability and charging power in the SI. A schematic of individual vehicle charging patterns, including mean per-vehicle charging loads averaged over all vehicles across the entire year and aggregate loads on the single day with the highest observed total load, is shown in Figure 2.

Access to work place charging increases the number of daily vehicle travel patterns that could be met by a BEV. Under the home charging scenario, the always-feasible vehicle-days account for 93% and 91% of weekday vehicle-days and 84% and 82% of personal vehicle energy consumption in Dallas and New York, respectively. Under the Home and Work charging scenario, the portion of vehicle-days covered is 95% for Dallas and 93% for New York, and the portion of energy use accounted for is 85% and 84% respectively. This measure of the value added by work place charging access is sensitive to differences in weather and travel behavior between cities. Access to work place charging also causes the peak in charging demand in the early evening to become less severe in both cities, as staggered at-home arrival times and smaller charging requirements mean that fewer vehicles will be charging at once at any given time in the evening.

Given access to work place charging, changes in driver preferences of charge timing and location can shift charging loads in time across the day. Delaying home charging without a preference for charging location (the Home (Delayed)+ Work scenario) shifts the majority of all charging to lower-demand times between midnight and 6 AM, reducing charging demand in the early evening to near zero. Alternatively, introducing a preference for work place charging over home charging (the Home + Work (Preferred) scenario) creates a smoother demand profile over the course of the work day while decreasing the height of the evening peak versus the Home + Work scenario. Finally, modeling a preference for work place charging along with last-minute charging at home shifts peak charging demand to approximately 8 AM while also reducing charging demand in the early evening. In general, we find that overnight home charging is most effective at reducing peak early evening loads but that a preference for work place charging better aligns BEV charging demand with solar resource availability.

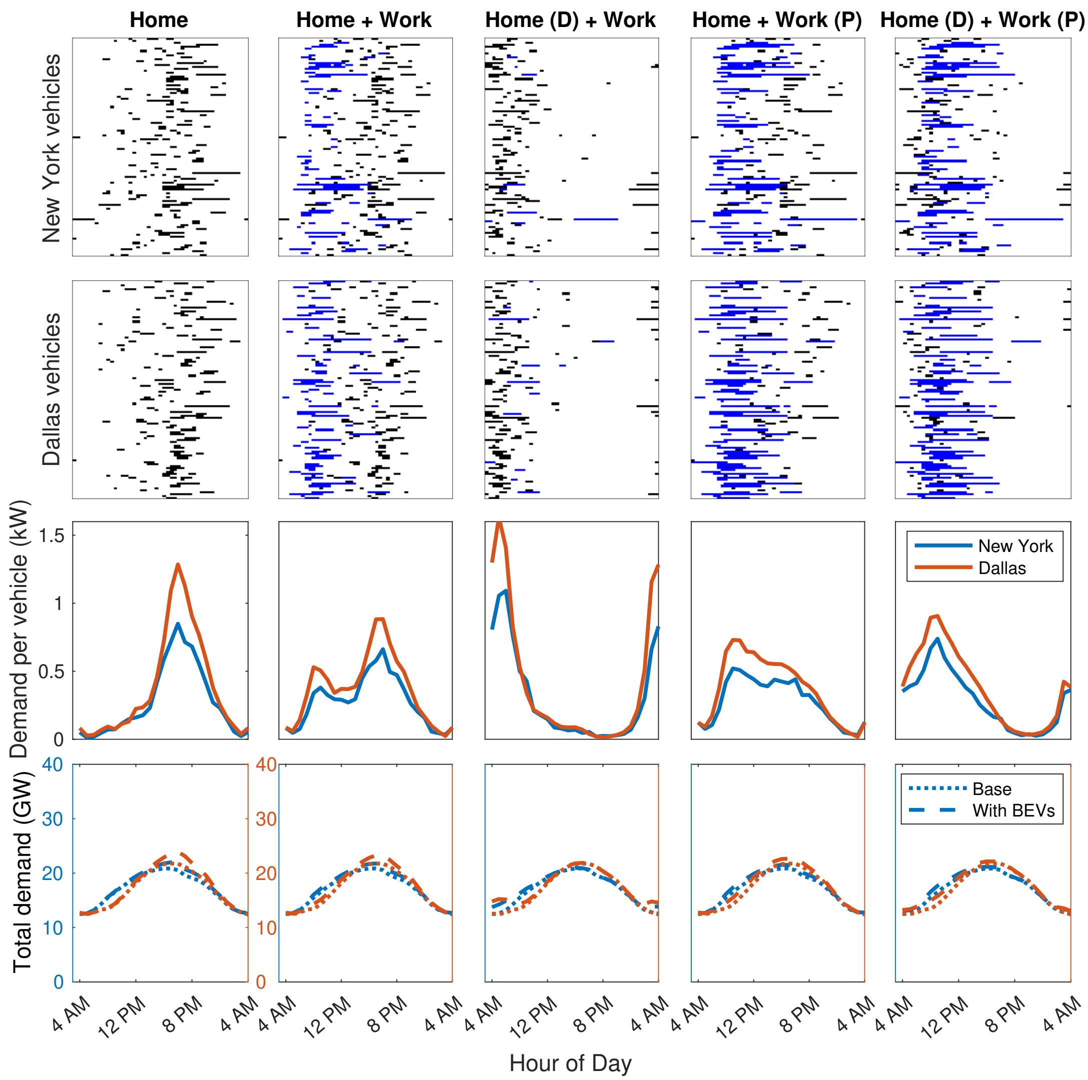

Figure 2: BEV charging patterns under different scenarios. Top two rows: Charge timing and location for 100 individual vehicles randomly selected from the surveyed travel behavior in New York (top row) and Dallas (second row), under different charging scenarios. Within a sub-figure, each row represents a different vehicle, and each column represents a consecutive time interval. Black represents Level 2 home charging, and blue represents Level 1 work place charging, and white represents no charging. Individual vehicles are assigned to consistent rows horizontally across sub-figures. Third row: Average per-vehicle hourly grid energy consumption for electric vehicles in different locations. Bottom row: Hourly charging demand profiles added to hourly electricity loads for the day with the highest observed hourly electricity load in the two regions studied, assuming 50% BEV adoption. Note the different axes for New York (L) and Dallas (R). In the column titles, (D) represents delayed home charging, and (P) represents preferred work place charging).

Potential to align BEV charging with solar resource availability

Interactions between BEV charging and PV generation depend on both average hourly demand and supply profiles and on the relative rate of adoption of the two technologies. Even if BEV charging aligns closely in time with PV generation, too high a relative BEV charging load would mean that PV could not fully meet additional electricity demand from BEVs. High relative levels of PV installation would mean that BEVs would not be able to substantially mitigate midday electricity oversupply. To quantify this overlap between BEV demand and PV supply, we measure three quantities as a function of the installed PV capacity per battery electric vehicle. As a measure of the extent to which BEV charging can successfully divert PV electricity from the electric grid, we estimate the portion of work place PV generation that could directly power charging BEVs. As a measure of the degree to which the addition of PV capacity can meet increased electricity demand from BEVs, we estimate the percentage of BEV weekday energy use that could be supplied directly by PV. We also measure the relative overlap between the two profiles, taking the total amount of energy that could be fed directly from PV to BEVs (the minimum of the two profiles at each hour) and dividing it by the sum of total BEV energy requirements and PV energy generation. This quantifies the inherent tradeoff between the oppositional goals of maximizing diversion of PV and minimizing BEV charging load on non-PV sources. These quantities are shown in Figure 3.

Currently, the transition to PV outpaces the transition to BEVs in terms of electricity supply and demand interactions. The U.S. installed approximately 11 GW of PV capacity in 2017[56] and U.S. consumers bought approximately 200,000 plug in electric vehicles.[57] This ratio of approximately 55 kW PV capacity per EV falls towards the right extreme of the horizontal axes in Figure 3, suggesting that at current rates of deployment increases in PV generation dominate increases in BEV charging demand. At this extreme, new BEVs are only able to capture a small amount of electricity generated by new PV installations, but new PV is capable of covering a substantial portion of new BEV charging demand. The extent to which BEV demand can be supplied by new PV depends on BEV charging patterns. If BEV drivers prefer to charge at work, approximately

80% of increased electricity demand from charging will be offset by decreases in net demand due to PV generation. If drivers follow convenience home charging, however, this value is reduced to under 60%.

In some climate change mitigation scenarios, BEV adoption eventually catches up with PV installation, potentially leading to situations where BEV charging demand is substantial enough to offset PV generation. In a recent paper, for example, Wei et al. present a set of scenarios for decarbonization of the western United States where installed PV capacity ranges from approximately 40 GW to 150 GW, and where the EV fleet size ranges from approximately 30 million to 50 million.[58] This range of ratios of PV capacity to EV fleet size includes the values of 1.2 kW and 1.0 kW installed PV capacity per EV that optimizes the tradeoff in Dallas and New York respectively as shown in the right panel of Figure 3. Values of per-vehicle PV capacity around 1.2 kW and 1.0 kW and preferred work place charging yield a PV utilization rate of between 70% and 80% while still allowing for about half of BEV energy to be supplied by solar panels. These results suggest that increasing the amount of BEV charging that is done at work increases overall value in this tradeoff, allowing BEV demand and PV supply to better overlap at any ratio of relative adoption but especially in situations with higher relative rates of BEV adoption seen in aggressive climate mitigation scenarios.

Sensitivity of charging load to BEV adoption level

Because any transition to BEVs will be a process with a still unknown extent and pace, we examine the generation capacity impacts of BEV charging at a range of levels of BEV adoption, with and without additional PV installation. This analysis quantifies the level of BEV adoption at which BEV charging demand will lead to significant shifts in aggregate electricity demand patterns, and it shows how the risks associated with fast BEV adoption, as well as the favorability of different mitigation strategies, change when installation of PV changes electricity generation patterns.

We first look at the case of different levels of BEV adoption given existing electricity supply, shown by the top row in Figure 4. In the base case of home Level 2 charging, we find in both cities that the generation capacity impacts of BEV charging grow super-linearly with adoption rate, requiring new or seldom-used generators to supply energy equivalent to over 1% of current yearly weekday electricity needs , where the additional generation capacity needed from charging from April 2016 to April 2017 is approximately 114 GWh in New York City and 760 GWh in Dallas at high levels of BEV adoption. The addition of Level 1 work place decreases this effect approximately by half in Dallas, and a preference for work place charging reduces it roughly in half again. A similar impact is observed for New York. We also find that when home charging is delayed and work charging is available, regardless of whether work charging is preferred, the peak areas for both Dallas and New York become nearly negligible even at a high BEV adoption level.

We then look at the impact of the same levels of BEV adoption on net electricity demand given an already-substantial level of installed PV capacity. The middle row of Figure 4 shows peak area as a function of BEV adoption with installed PV accounting for 25% of existing yearly demand (equivalent to 5.2 GW installed capacity in New York and 5.4 GW installed capacity in Dallas, which can be compared to the 8.6 GW of estimated achievable rooftop PV capacity in New York City[59] or the 1.8 GW of installed capacity in Texas at the end of 2017[60]). Given just home charging, we see that adding PV strongly reduces peak area in Dallas but has little effect in New York. This is the case because peak area is measured against the highest observed net demand and PV is more effective at reducing peak net demand in New York than it is in Dallas. Therefore addition of BEVs charging at home in New York comes with the opportunity cost of forgoing a reduction in peak net loads that could otherwise be achieved with PV. Unlike in the no-PV case, however, work place charging can reduce peak net loads in New York along with Dallas. Finally, in the third column we see that work place charging reduces valley area, especially if drivers prefer it. Overall, we find that work place charging, by shifting charging loads to the middle of the day, is able to both reduce net demand at sunset and increase the capacity of the grid to absorb electricity during high-supply midday hours.

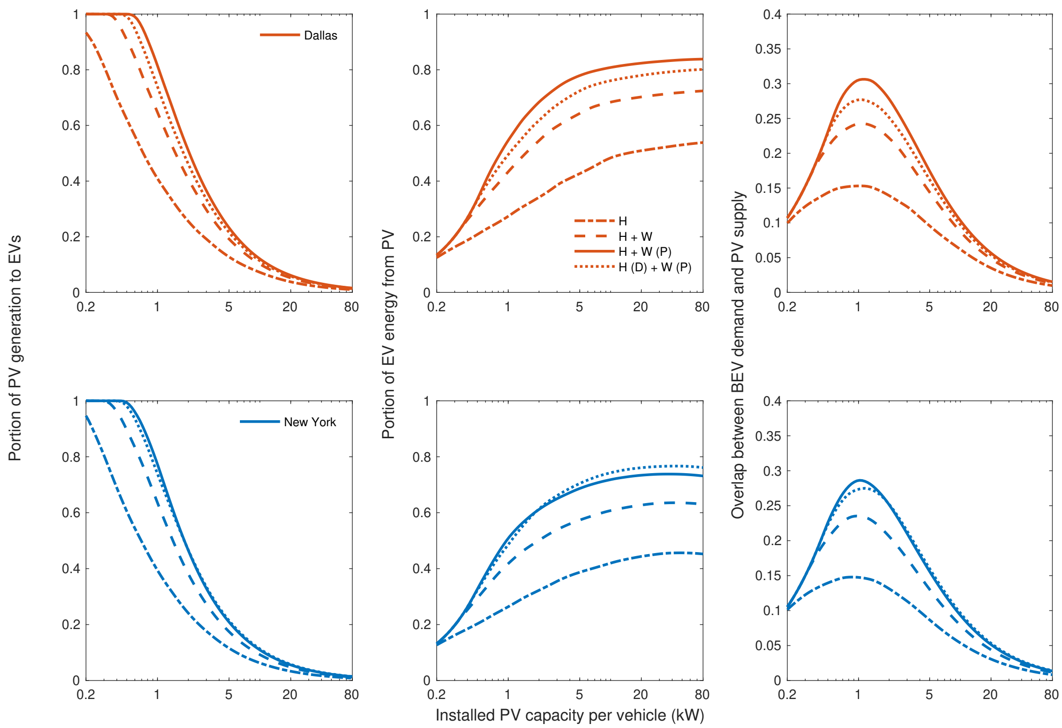

Figure 3: Utilization of weekday photovoltaic (PV) generation as a function of installed capacity per BEV, for vehicles in Dallas (top, red) and New York (bottom, blue), over a full year. The left panel shows the portion of weekday PV electricity generation that can be offset by BEV charging. The center panel shows the portion of BEV energy consumption that can be supplied by PV. The right panel shows the amount of PV generation and BEV demand that overlap and can be directly offset, divided by the total energy generated by PV and used by BEVs. Different line styles represent different charging patterns. These results illustrate the tradeoff between maximizing the portion of PV generation that can be diverted to BEVs and maximizing the portion of new BEV energy requirements that can be supplied by PV, finding that maximizing the amount of charging done at the work place increases both metrics.

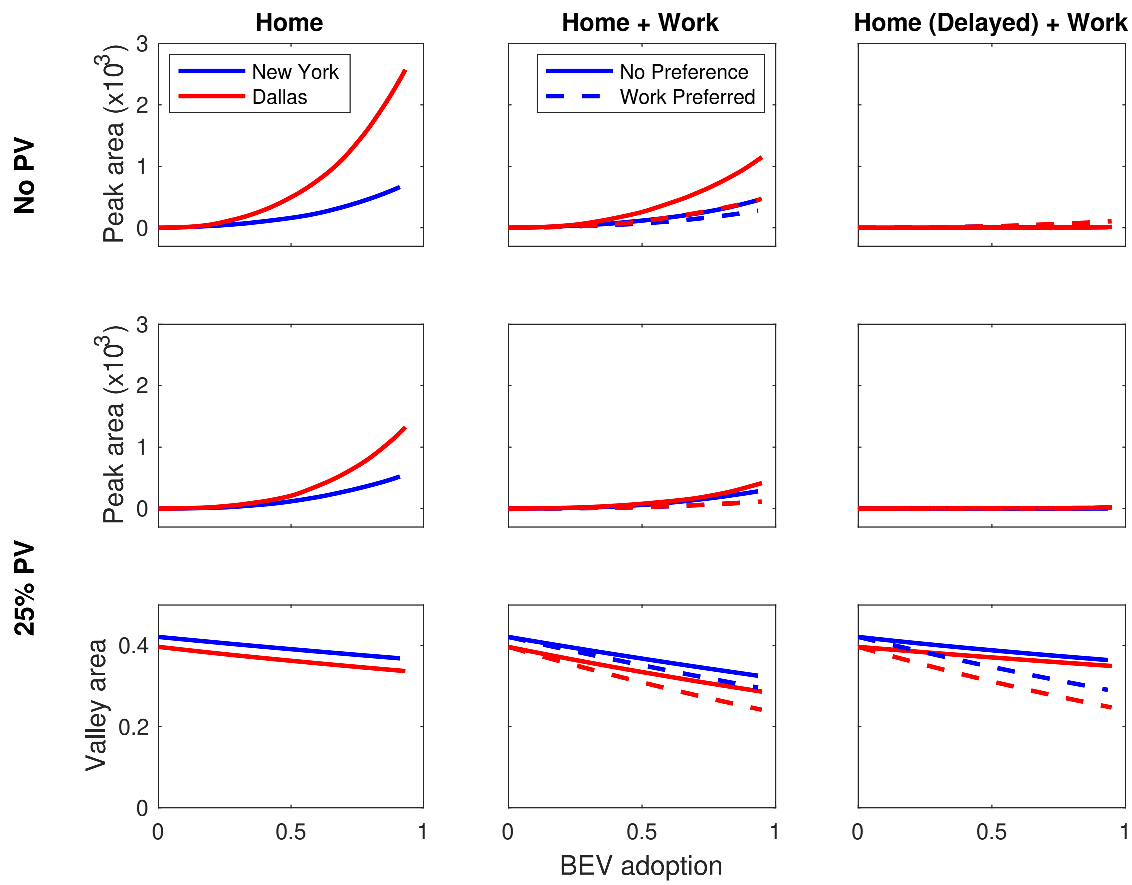

Figure 4: Levels of BEV adoption versus metrics of electricity grid impacts, for different charging patterns. The top row shows peak area in a case with no additional PV, the second and third rows show peak area and valley area, respectively, in a case with PV accounting for 25% of total electricity generation. Peak and valley area are both unitless, representing the portion of electricity supply that is generated when total net demand is above or below peak and baseload demand levels, respectively. From left to right, the columns represent different scenarios: the base case with only level 2 charging available at home; level 2 charging at home and level 1 charging at work; and access to level 2 charging at home and level 1 charging at work, =with drivers relying on last-minute charging when at home. In the right two columns, dashed lines indicate a scenario where drivers prefer work place charging when it is available. Levels of BEV adoption tested range from zero to the maximum achievable penetration rate given the modeled charging availability and fixed travel behavior.

Discussion

In this research we asked how time-shifting BEV charging can be used to mitigate two commonly-cited grid integration concerns with BEVs and PV, an increase in the evening peak demand for electricity and a surplus of solar energy during midday hours. If left unmitigated, these effects stand to significantly raise costs and potentially impede transport electrification and photovoltaics adoption.[12,21,22,24]

Our approach builds on previous work[32,37,40] but differs from it in several ways. We constrain the solutions to ones that can be pre-programmed, and therefore do not require networked devices. These solutions do not require behavioral change on the part of drivers in terms of their travel activity patterns. Schedules and locations of vehicles remain unchanged before and after implementing the time-shifting of charging, and the behaviors we simulate, such as a preference for work place charging or delaying home charging, are likely to be relatively easy to achieve through levers such as simple pricing schemes. In order to accurately estimate the energy consumption of these activity patterns, we study detailed driving behaviors and the effects of weather, both of which can significantly affect the fuel economy of vehicles and thus the need to charge.[46,53,61] Additionally, we compare locations and adoption scenarios for PV and EV, which provides insights on solutions that apply across locations and can be tailored to local preferences.

We find that delayed home charging nearly eliminates the increase in the evening peak demand for electricity. In this case, drivers would pre-program charging to finish a fixed amount of time before they intend to leave in the morning. Variability in charging requirements and departure times mean that that this solution would not lead to the sharp ramp rates associated with time-of-day-based charging schemes.[16] The delayed charging solutions proposed here can eliminate the increase in peak electricity demand coming from BEVs, even for BEV penetration levels well over 50%. We note that if vehicles within distribution networks do not follow the variation in travel activity patterns seen across the larger population, then grid reinforcements may be needed.[18] However, there is reason to expect that even within smaller geographic areas, there is enough heterogeneity in activity patterns such that demand management strategies defined here would be effective.[18] We acknowledge, however, that some distribution grid upgrades may still be needed and we point out that those areas can be identified using models such as the one presented here.

Perhaps most significantly, work-place charging emerges as a simple and effective solution for abating both the peak increase and the over-supply of PV. With substantial degrees of PV and BEV adoption, excess peak loads from charging and midday overgeneration of PV are concerns in both New York and Dallas. Commencing charging when drivers arrive at work reduces BEV contribution to the evening peak by 70% in New York and 80% in Dallas, and BEV contribution to the evening peak is practically eliminated when work place charging combined with delayed home charging. In both cities, a preference for work place charging can triple the the amount of excess PV generation that can be absorbed by BEVs, reducing PV excess generation by up to 30% in Dallas and New York. The PV would not need to be located at these work places for this solution to work. However, work places would need to provide charging infrastructure and manage any local grid impacts and surges in demand.

We find that the work place charging infrastructure installed need not be of the faster and more expensive Level 2 variety. Level 2 charging would provide little additional benefit to Level 1 charging in terms of extending the vehicles' range sufficiently to allow more vehicle-days to be electrified, and can lead to the negative effect of a sharper ramp-up in charging demand at the beginning of the work day. In addition, Level 1 charging at work has the practical benefit of being cheaper to install, potentially allowing work places to install more stations more quickly, so that drivers need not move their vehicles to allow others to charge. Further, widespread and affordable at-work charging infrastructure may make BEV ownership a more attractive option for commuters without access to dedicated charging infrastructure at home,[62] allowing for greater BEV adoption through once-daily charging at work.[47]

While the two cities are similar in terms of the effectiveness of work place charging and delayed home charging, the reasons these strategies work are different, and these differences shed light on how the strategies might be expanded to other locations. In both locations, peak-capacity requirements are defined by a small number of days with an extreme in demand for electricity. We find that New York drivers use less energy per vehicle-day than Dallas drivers and fewer New York commuters drive to work. But per-capita electricity peak use in the New York area, which tracks closely with weather extremes, is less than it is for Dallas. These effects partially cancel, leading to some of the observed similarity between New York and Dallas in terms of the peak electricity impacts of BEVs (as a percentage of the baseline peak electricity demand without BEVs). This begins to suggest that in cities with high driving mode share, long commutes, and relatively low per capita electricity use, BEVs could lead to peak-capacity problems at lower adoption rates than suggested in this paper. In other words, cities with high energy consumption in personal vehicles but lower weather extremes may, somewhat counterintuitively, experience the greatest percent increase in peak electricity demand from BEVs.

The general conclusions drawn here using the two US cities may apply more broadly to other locations and can be robust to future uncertainties in BEV battery capacity. This is because the conclusions stem from the diurnal cycle that determines human travel and electricity consumption behavior.

These results should be taken as an estimate of a technical mitigation potential of time-shifting BEV charging to mitigate peak loads and align with PV electricity generation. We do not consider the willingness of drivers to adopt these charging strategies, or of policymakers and employers to incentivize and develop the charging infrastructure that would be needed. Additional behavioral research could improve our understanding of the willingness of drivers to modify their charging routines in response to incentives or outreach programs.

We also do not consider the effect of the vehicle-days in this dataset that cannot be electrified by the BEV model considered, since their energy demand exceeds the battery capacity and charging opportunities modeled (in the Results and SI). These higher energy days can have impacts in a variety of ways, including the willingness of consumers to purchase BEVs under current models of vehicle ownership, and therefore the adoption potential that is achievable. Households with more than one car or access to other supplementary vehicles may face lower barriers initially.

There are several core implications of these results for policy-makers, technology developers, and various investors. The first relates to the striking effectiveness of work place charging for mitigating peak electricity demand and the over-supply of photovoltaics electricity. The installation of work place charging may be attractive to employers and policy makers, including local governments. Last-minute overnight charging, which delays home charging from when drivers arrive at home to as late as possible so that charging finishes one hour before the first trip of the next day, is effective at abating increases in peak electricity demand from BEVs and requires the least new infrastructure. Although it does need buy-in from drivers who might otherwise begin charging immediately. Neither of these proposed interventions requires advanced, optimized charging strategies nor networked devices with their own energetic costs and questions about robustness. These strategies also do not require V2G capabilities or fast chargers. More advanced strategies and hardware may ultimately be preferred, but these results point to the potential advantages of lower-tech, as-simple-as-possible approaches. These strategies may require only small design and regulatory changes, which may make them more likely to be adopted, which could be effective even if introduced piecemeal at a local level and without coordination.[2] Our results give a set of strategies that can be mixed and matched to different technology penetration scenarios in different locations.

The results contribute to ongoing policy discussions on interactions across transportation and electric power sectors to achieve deep decarbonization.[63–65] The results also highlight the importance of coordinating decarbonization of electricity and transportation policies to encourage compatible growth rates in electric vehicles and photovoltaics. A similar role for BEVs might be possible in the case of wind energy as well, though this requires further study. In many regions, this would require an increase in the growth rate of BEV adoption, if BEVs are to serve as storage technologies to absorb excess midday solar energy through workplace charging, while supporting a low-carbon transition in both end-use sectors. Many transportation decarbonization policies lag behind those for electricity sectors, for example among U.S. states, and this research highlights the urgency of planning across energy services to ensure that synergies are captured.

Methods

Overview: In this analysis, BEV charging profiles are constructed for individual vehicles for each day of the year. For each vehicle, trip energy requirements are estimated on a given day given the local temperature at the time of each trip and trip distance and duration. Charging patterns are then estimated for that vehicle based on trip energy requirements, charger availability, and charging preferences. The charging profiles for all vehicles whose travel patterns can be electrified are aggregated, and this aggregate charging load is scaled to estimate a day's charging profile for a given level of BEV adoption. This process was repeated for every weekday of the year to estimate yearly profiles.

Data: Travel patterns are taken from the 2017 National Household Travel Survey.[66] Personal vehicle trips are isolated from two areas, the Dallas Core Based Statistical Area (CBSA) and the New York CBSA, where in the later area trips were only considered if their household was located in New York State. Weather conditions, which influence vehicle energy consumption due to heating and cooling, were taken from hourly historical observations in the National Solar Radiation Data Base.[49] High resolution drive cycle data is taken from a set of GPS travel surveys.[67–69] Simulated hourly photovoltaic generation were estimated using historical weather data for the same set of dates as the historical electricity demand. Solar irradiation was also taken from the National Solar Radiation Data Bases and potential PV generation was estimated from solar irradiation using the method of Sengupta et al.,[70,71] with the cell's nameplate generation capacity varied as a model input. Historical electricity demand, in these two locations and for the same time periods as the weather data, is taken from ISO databases. The Dallas study area roughly aligns with the ERCOT North Central electric grid division.[50] For New York, the study area roughly aligns with the New York City, Long Island, Dunwoodie, and Millwood grid regions reported by NYISO.[51]

Energy model: For energy calculations, the test vehicle used was the 2016 Nissan Leaf, a relatively affordable and widely adopted BEV, equipped with a 62 kWh battery (consistent with the

2019 model year). Each trip's energy consumption was estimated for the Leaf using the TripEnergy model[45] by matching that trip with a set of one second resolution real-world speed profiles that were taken under similar conditions and feeding matched speed profiles into an energy model that considers ambient temperature, capturing variability in energy use due to trip profile and weather conditions.

Charging model: Charging patterns were modeled using a linear programming approach, where charging decisions are constrained by charger availability, trip energy requirements, battery capacity, and a requirement that battery state of charge is the same at the day's start and end (more details are given in the SI). For different charging behavior scenarios, a flexible objective function is tuned to model preference for charging at certain locations or times, or for immediate or delayed charging.

Data availability

Travel data used for this model comes from the 2017 National Household Travel Survey.[66] Historical weather and solar irratiation data come from the National Solar Radiation Data Base.[72] Electricity load data are taken from New York Independent System Operator[51] and the Electric Reliability Council of Texas.[50]

Code availability

Full details of the charging algorithm are given in the Supplementary Appendix. Details on the TripEnergy model are given in previous papers[47,53] and in US patent number US20180045526A1.

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