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Optimization of Electric Vehicle Charging in a Fully (Nearly) Electric Campus Energy System

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ABSTRACT

The goal of this work is to build a set of computational tools to aid decision making for the modelling and operations of integrated urban energy systems that actively interact with the power grid of the future. District heating and cooling networks incorporating heat recovery and large-scale thermal storage, such as the Stanford campus system, dramatically reduce energy waste and greenhouse gas emissions. They have historically played a small, but important role at a local level. Here we explore the potential for other co-benefits, including the provision of load following services to the electrical grid, carbon emissions reductions or demand charge management. We formulate and solve the problem of optimally scheduling daily operations for different energy assets under a demand-charge-based tariff, given available historical data. We also explore the interaction and interdependence of an electrified thermal energy network with actively managed power sources and sinks that concurrently draw from the same electrical distribution feeder. At Stanford University, large-scale electric vehicle charging, on-site photovoltaic generation and controllable building loads could each separately represent up to 5 MW, or 15% of the aggregate annual peak power consumption in the very near future. We co-optimize financial savings from peak power reductions and shifting consumption to lower price periods and assess the flexibility of both the different components and the integrated energy system as a whole. We find that thermal storage, especially complemented with electric vehicle charging, can play the role that is often proposed for electrochemical storage for demand charge management applications and quantitatively evaluate potential revenue generators for an integrated urban energy system. Although there is little value to smart charging strategies for low penetrations of electric vehicles, they are needed to avoid significant increases in costs once penetration reaches a certain threshold – in the Stanford case, 750-1,000 vehicles, or 25% of the vehicle commuter population.

KEYWORDS
District energy system, electric vehicle charging, thermal energy storage, integrated urban energy.

INTRODUCTION

More than half of the world's population currently lives in urban areas (54% in 2014), and this fraction is expected to increase to 66% by 2050 (UN DESA, 2014). Increasingly, buildings and the urban environment are becoming a nexus for different energy networks across sectors such as electricity, heat and transportation (Keirstead et al., 2012). These networks will be denser, more complex and interdependent. Heat, electricity and transportation also account for two thirds of global carbon dioxide emissions from fuel combustion, which makes the urban environment a battleground for climate change mitigation efforts. A viable pathway to addressing climate change goals is to electrify the heat and transportation sectors while decarbonizing electricity generation. Along this pathway come serious challenges however: the demand for electricity is likely to rise significantly beyond the capacity of current infrastructure,

and current options for decarbonized electricity sources largely depend on the wind and sun, so they are more variable and less controllable than the traditional thermal power generation sources that constitute the backbone of current power grids (Apt, 2015). Unmanaged, the electrification of heat and transport represent a threat to the power system. On the other hand, exploiting the inherent flexibility in these sectors could also ease the integration of larger shares of renewable generation through demand side management (Callaway & Hiskens, 2010). Enhanced sensors and actuator controls are available to manage the interactions and energy flows between the heat, electrical and transportation networks (O'Malley et al., 2016).

District energy systems have historically played a small, but important role at a local level (Rezaie & Rosen, 2012). It is expected and desirable that they will play a larger one in future sustainable energy systems (Lund et al., 2014). In particular, the optimization of district electric heating and cooling systems offers a way of incorporating large thermal storage in power systems at the transmission and distribution levels as a major flexibility asset, while increasing the value of investments by broadening the services they can provide to an ever-expanding area (de Chalendar et al., 2017). Plug-in Electric Vehicles (PEVs) are expected to represent an increasing share of electric load in power systems in the near future, which is why a significant amount of recent work has focused on studying their impact on the grid (Richardson, 2013). Given the capital cost of chargers, it is likely that workplace charging will play a large role in future transportation networks. Whereas uncontrolled charging will present a risk if not managed adequately, when connected to the grid, the batteries of PEVs represent a potential storage asset for the system operator.

The Stanford Energy Systems Innovations project is a prime case study for this work. A schematic for the campus energy system is shown in Figure 1. The main energy requirements are those of the buildings, that consume cooling, heating and power. The heating and cooling needs are met through hot and chilled water distribution networks that are supplied by the onsite Central Energy Facility (CEF). The bulk of the thermal needs are met through electric heat pumps that leverage heat recovery and are backed by thermal storage tanks. These replaced the gas-fired co-generation plant that was decommissioned in 2015. Stanford University is a perfect example of a continually evolving urban environment: large-scale electric vehicle charging, on-site photovoltaic generation and controllable building loads could each separately represent up to 5 MW, or 15% of the aggregate annual peak power consumption in the very near future.
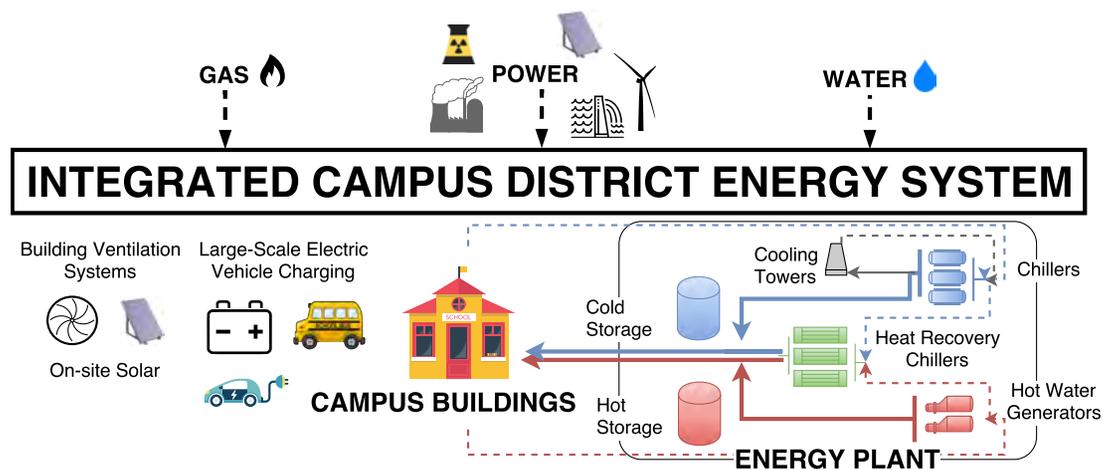

Figure 1. Schematic for an integrated campus district energy system.

The problem we are considering here is that of the optimal management of an integrated energy system in an urban environment. Since infrastructure investments in systems such as these are typically capital intensive and intended to last for many decades, ensuring that they are designed

in a way that they are not only flexible to short-term operating conditions but also longer-term evolution trends is critical to recovering invested value. In this paper we build on a previous model of the Stanford energy system to further explore the interdependence of the heat, electricity and transportation sectors at the urban energy system level. We assess the impact of different penetrations of electric vehicle charging on the campus distribution system and quantitatively determine the value of different PEV charging strategies.

METHODS
We consider an integrated urban energy system that meets its thermal needs through electric heat pumps backed by thermal storage. We call the operations scheduling problem that of determining the hourly operations at the CEF such that energy demands and technological constraints are met at minimum cost. This problem is formulated for the 8,760 hours in a year as a Linear Program (LP) with ~130,000 variables and ~170,000 linear constraints in de Chalendar et al. (2017). The objective function of this program is the campus aggregate energy bill, *i.e.* we consider financial savings in the context of a demand-charge-based system, where a time-varying, hourly price is paid for energy (measured in kWh), and a monthly price is paid for the peak power consumption (measured in kW). The decision variables of the program are the hourly power injections to the different machines at the CEF. At every time step, the campus heating and cooling loads must be met, as well as various operating constraints, *e.g.* available capacities and ramp rates. The machines available to contribute to the hot and chilled water streams are electric heat recovery chillers, electric chillers, and gas-fired boilers.

To model future interactions of the Stanford ecosystem with large-scale PEV charging, we now build a module to represent the population of PEVs on campus. This model also has an hourly resolution and tracks the energy and power flows associated with the different vehicles connected to campus chargers. The vehicles are characterized by the parameters in Table 1: they are present only for a portion of the day (arrival and departure times); their batteries have different technical characteristics (capacity and charge rate); the energy in their battery packs, or State of Charge (SoC), is different when they arrive in the morning; and finally they have different requirements for SoC levels when they leave the campus at the end of the day. We assume that when the drivers plug in to the campus chargers, they specify a minimum SoC for the end of the day and the time at which they leave, and then hand over control to the campus operator as to when the charging actually occurs. The dynamics of the SoC of the batteries in the vehicles is governed by the following equation during the hours when it is controlled by the system operator:

$$S_{t+1} = S_t + P_t^c \delta t \, \eta^c - \frac{P_t^d \delta t}{\eta^d} \tag{1}$$

where S_t is the SoC at time t, and P_t^c and P_t^d are the power charged and discharged during the time step of length δt at efficiencies of η^c and η^d, respectively. The power that is charged and discharged at every hour from the vehicle batteries are decision variables for the optimization program and represent bidirectional charging. During the hours where the vehicles are not connected to the campus chargers, we impose the constraint $S_t = 0$. The PEV module that was just described is tied to the main optimization program described in de Chalendar et al. (2017) through the total hourly electrical energy consumed by the PEV population, which is added to the aggregate campus consumption. A small penalty is also added to the objective to account for battery degradation (and prevent excessive charge/discharge cycles).

The storage dynamics represented by equation (1) hold for each of the vehicles that connects to the campus, and for small numbers of vehicles, each individual vehicle is tracked by the program. For large populations of PEVs however, the problem quickly becomes numerically intractable, and it is no longer reasonable to track every vehicle separately. Instead, we assume that the vehicles can be clustered into a set of commuter archetypes. Each archetype corresponds

to one set of parameters as defined by Table 1 (16 archetypes can be modelled here). For each archetype, a weight and the number of connected vehicles is used to scale the technical characteristics of the battery, such that all vehicles of a given archetype are grouped together as one large equivalent vehicle, and the 16 equivalent vehicles present the same technical characteristics to the distribution system as the full PEV fleet.

Table 1. Parameters for commuter archetypes in PEV model. We use $\eta^c = \eta^d = 90\%$, which corresponds to a round-trip efficiency of 81%. Arrival and departure times for each archetype are uniformly drawn from [6,7,8,9] AM and [5,6,7,8,9] PM.

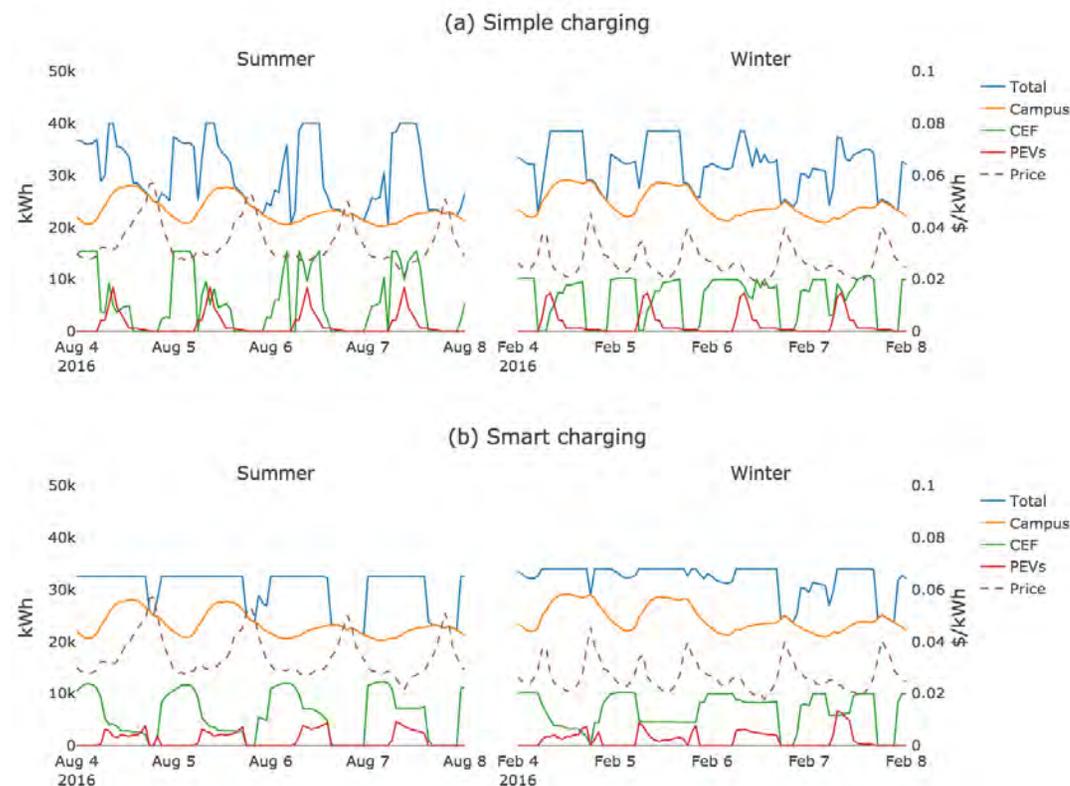| Parameter	Value 1	Value 2
Storage capacity (kWh)	20	60
Charge/Discharge rate (kW)	4	20
Arrival state of charge (%)	20	70
Departure state of charge (%)	80	100

Figure 2. Typical summer and winter operations schedules for two charging strategies for 2,000 vehicles (~60% of campus commuter vehicles): (a) simple charging, where vehicles charge as soon as possible, and (b) smart charging, where the optimization program chooses when to charge the vehicles. The schedules report the energy (kWh) consumed by each component of the energy system during each hour.

RESULTS

To assess the impact of large-scale PEV charging on the Stanford energy system, we compute optimal operating schedules for the CEF with two operating modes for PEV charging: (i) "simple" charging where the PEVs charge as fast as possible when they arrive, until they reach their departure SoC level; and (ii) "smart" charging where the charging is handled by the optimization program. Real 2016 data is used for campus thermal and electrical loads. Figure 2 shows typical summer and winter operations schedules for the two charging strategies, for 2,000

vehicles. The (controllable) CEF, respectively PEV load, is represented in green, respectively red, while the (uncontrollable) background campus load is represented in orange, and the aggregate university load is represented in blue. In the top graphs where simple charging is adopted, the system operator does not control charging, so that the uncontrollable load consists of both building and PEV loads and presents a peak in the morning. By contrast, the smart charging strategy spreads charging throughout the day to avoid raising peak power demand and to target low price periods. The program is able to distribute charging throughout the day whether it is a summer, winter, weekend or week day and chooses never to use the Vehicle-to-Grid (V2G) capability: the discharge variable P_t^d is zero for every timestep. We also compare the financial and grid benefits at different PEV penetration levels from the considered charging strategies in Figure 3. We compute the average cost of charging the vehicles as the campus electric bill increase divided by the number of vehicles for Figure 3a, and the peak monthly power demand for Figure 3b. Data for Figures 3a and 3b are normalized to one for 100 vehicles. The results in Figure 3 show that although there is little benefit in smart charging strategies for low penetrations of PEVs, not applying them becomes extremely detrimental when penetrations rise above a critical threshold (here 750-1,000 PEVs for all months except March).
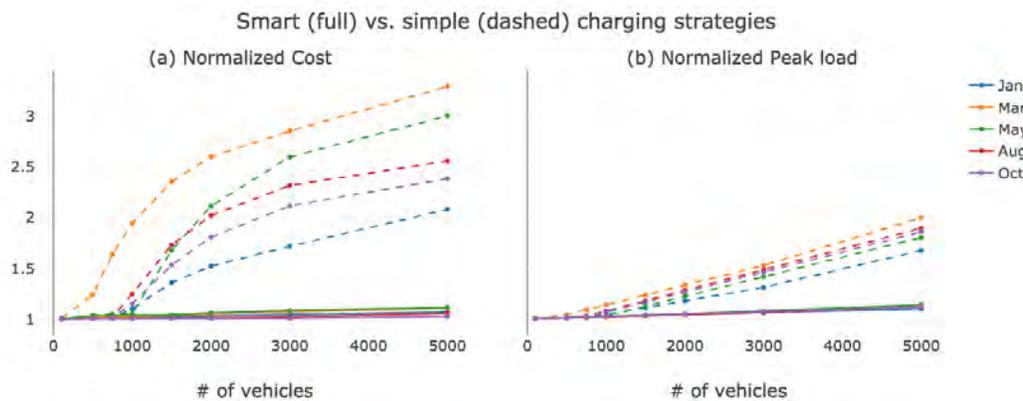

Figure 3. Comparing the benefits of charging strategies at different PEV penetration levels (from 0 to 160% of the current commuter population): (a) normalized average charging costs and (b) normalized monthly peak load. Average charging costs are computed as the increase in total campus costs from introducing PEVs, divided by the number of PEVs. In figure (a) charging costs are normalized to one for 100 vehicles, and similarly in figure (b), peak load is normalized to one for 100 vehicles. Solid lines represent smart charging, dashed lines represent simple charging.

DISCUSSION AND CONCLUSIONS

In the application presented here, multiple controllable electric loads interact, which means that different energy assets may be competing to generate the same value stream for the campus. Peak-shaving in particular is usually found to present substantial economic benefits for facilities such as the Stanford energy system. In a different setting where PEVs are the only controllable load, it could be expected that energy costs would decrease as PEV penetration increases, if the car batteries were used to provide electricity to the campus during peak demand (*e.g.* V2G). Since the CEF already possesses a very cheap way of shifting loads (by exploiting thermal energy storage) however, there is little added value left from peak shaving when PEV penetration increases. Here, the real value from smart charging lies in avoiding increased peak power charges when PEV penetration rises. As highlighted by Figure 3a, if smart charging is not adopted, the cost of charging will increase dramatically with penetration levels and peak demand will increase almost linearly, whereas charging costs can be kept almost constant through smart charging. We emphasize that only one value stream from PEV smart charging is considered here. Other more complex revenue streams may hold additional value, for instance to mitigate short-term power variations in local solar generation or to participate in frequency

response. The penetration threshold at which smart charging strategies start showing real value corresponds to a fleet of PEVs that can draw 15-20% of peak power demand, and 25% of the commuters are driving EVs[1], which demonstrates that significant interactions between the transportation and electricity sectors is not very far away. Injecting real data on PEV commuter patterns would bring even more value to this analysis to confirm these conclusions by more precisely segmenting vehicles in realistic customer archetypes. Additionally, coarser reduced-order-modeling of the PEV population may become necessary in order to increase the number of energy assets that can be managed by our optimization program. With 16 commuter archetypes, the size of the monthly optimization program jumps from 12,000 to 48,000 decision variables when adding the PEV module, which makes runtimes slower.

The results presented here have strong implications for policymakers and decision makers. They highlight how urban energy systems will become increasingly integrated across the transportation, heat and power sectors. This integration can bring real value but also presents corresponding risks if not properly managed. Given the high infrastructure costs associated with investments in urban environments, especial care should be taken in planning, in particular to consider the new energy networks that they will interact with.

ACKNOWLEDGEMENTS

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[1] ~3,500 drivers commute daily, according to: https://gup.stanford.edu/transportation-no-net-new-commute-

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