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Decarbonization of Campus Energy Systems and Optimization of Grid-Friendly Electrified District Heating and Cooling with Thermal Storage

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SUMMARY

The large-scale penetration of renewable energy is a challenge for grid operators both at the transmission and distribution levels. Demand-side management has been gaining traction for offering new ways of controlling the balance between supply and demand of electricity that is so critical to reliable grid operations. Key questions remain as to the flexibility that different dispatchable loads can provide in real-time operations, especially since they act at very different time scales (ramp rates, cycle frequency and duration). The goal of this work is to model and understand how to design and control complex energy systems or ecosystems that interact with not one but several energy carriers such as electricity, heat and fuels; and to explore the potential of flexible energy system components that can increase the security and affordability of our energy system. Specifically, we study the optimal behavior of the Stanford campus energy system under three different California energy mixes, and under different pricing structures for both energy and carbon. This study highlights the synergies that can be gained from a district energy system that couples the supply of heating, cooling and electric power and provides key insights into the relative impacts of the carbon intensity of the electric grid and different pricing structures for carbon and energy on effective decarbonization pathways for a campus energy system.

KEYWORDS

Integration of Demand Response and Distributed Resources, Role of Microgrids, Analytics for Asset Management, District Energy Systems, Demand Side Management, Virtual Power Plant, Load Management, Virtual Storage, Energy Systems Integration.

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INTRODUCTION

The Integration of Renewables is a Challenge for Power Systems

The large-scale penetration of renewable energy is a challenge for grid operators both at the transmission and distribution levels. Without buffers, output from renewable generation fluctuates much faster and with larger amplitude than generation from conventional thermal sources, and the variability of wind and solar power in particular is very different at short and long time scales. Two important results can be derived from studies comparing the variability of solar PV, solar thermal and wind by analyzing their Power Spectral Density [1-2]: (i) variability is much stronger at low frequencies (hours to days) than at high frequencies (minutes to seconds); and (ii) while the variability of wind, solar PV and solar thermal differs at small time scales, the variability is quite similar for frequencies that correspond to time periods greater than six hours. The CAISO duck curve [3] has become the canonical example of the challenge posed by utility scale solar, and also highlights that in many systems, renewable generation may induce the requirement for unprecedented ramping capabilities as an energy generation mix quickly shifts from one power source to the next. The added intermittency to the system results in physical stress as conventional generation sources struggle to follow load [4-5]. The stress is also felt at the level of the distribution network, as substations were most often designed to operate passively, with little outside intervention and were not built to accommodate the two-way power flows that are a consequence of behind-the-meter, distributed generation.

Demand-Side Resources as Virtual Storage

Supply and demand have traditionally been balanced in power systems by adapting supply to follow demand. In recent years, however, demand has increasingly attracted attention as having the potential to follow supply [6-10]. A key difference between managing loads and generation is that controlled loads typically balance the dual objectives of meeting expected customer service while minimizing costs, whereas typical generation units only minimize cost. A second is that the main source of long-term flexibility in demand-side management comes from the ability to shift loads in time rather than to consume more or less energy. Load management strategies to provide ancillary services in future low-carbon power systems must take these differences into account.

There is a wealth of previous work on managing demand-side resources, and especially on controlling residential and commercial heating and cooling loads [11-14], but also pool pumps [15] or refrigerators [16]; and there have been several field scale demonstrations [17-19]. Applications include providing operational flexibility [20], load scheduling [21], demand response [22-24], load-balancing in microgrids [25-27], or even frequency regulation [28]. These studies highlight that new types of energy management assets such as storage and deferrable loads have large potential for power system balancing operations, but may be ill-suited to participate in pre-existing power markets and would often require controlling a very large number of small assets.

Although there has been some work on integrating heat and power through Combined Heat and Power, like [29] or [30] that explored options to add heat storage in district heating networks in the North of China (where 15-25% of wind generation was curtailed in 2012 because of insufficient flexibility in the operation of heating networks), the control of fully integrated energy systems, like large district energy systems [31] that provide both heating and cooling, are much less studied, despite reports such as [32-33] that advocate larger integration of electricity and heating and cooling networks to achieve decarbonisation goals.

Electrified District Heating and Cooling

Electrifying municipal, commercial, and residential heating and cooling loads can provide a new source of flexibility and reduce heating-and-cooling-related carbon dioxide emissions by taking advantage of the fact that many systems have simultaneous heating and cooling loads. Water and energy inputs can be significantly reduced by efficient use of heat recovery chillers (HRCs); in the Stanford case, potable water consumption was reduced by 18% and up to 88% of heating loads can be met with waste heat after switching from a CHP-based system to the current electrified district heating and cooling system [34]. 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. Our goal in this work is therefore to assess and increase the services that electrified heating and cooling systems with thermal storage can provide to the power system. We frame this work in the context of a larger discussion around energy systems integration and the place of energy systems in urban environments [35].

MODELING THE STANFORD ENERGY SYSTEMS INNOVATIONS PROJECT

As the supplier of power and water to the entire campus, the Stanford Energy System Innovations (SESI) project provides an ideal testbed for energy management software and to analyze real-world data. Hot and chilled water is produced almost exclusively with electricity and stored in large tanks at the Central Energy Plant (CEP) before it is sent to the campus (figure 1), which represents an intrinsic flexibility in system operation. The SESI project offers a unique opportunity to explore the interaction between flexible loads and the transmission system, as it has already achieved Direct Access to the state's electricity markets. The flexibility in the CEP is effectively used to manage the non-dispatchable campus load. Given the current demand charge-dominated tariff system, the energy management system keeps aggregate electrical load as flat as possible. In the future, this may no longer be optimal as some low-carbon generation assets such as solar energy have more availability in the middle of the day. Aggregations of energy management assets like the SESI project can respond to control signals like real-time prices and ease the grid operator's balancing task.

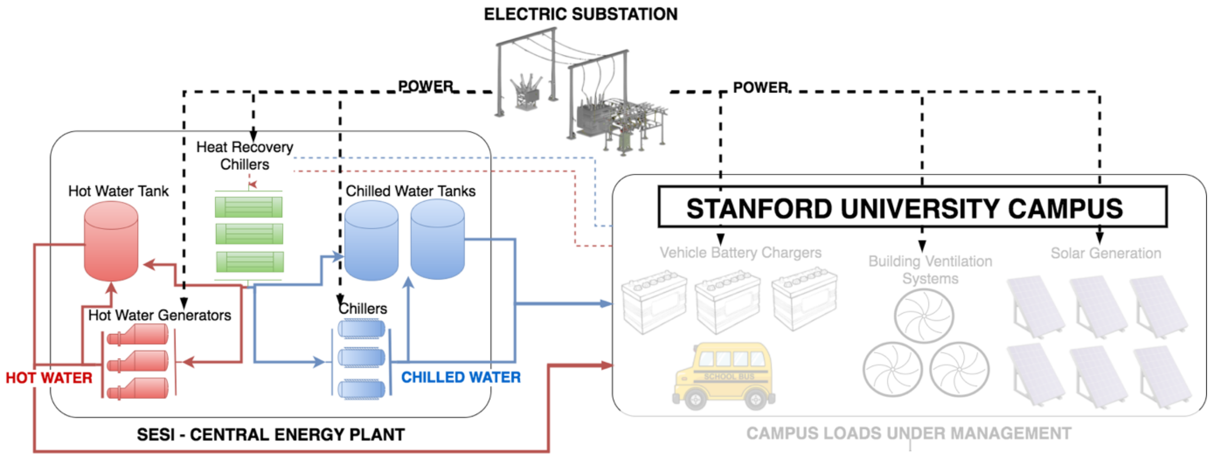

Figure 1: Schematic for Stanford Campus Energy System

In this paper, we consider a perfect information framework where the future is known and all uncertainty is removed from the analysis. The CEP imports electricity and gas to produce hot and chilled water and meet the campus electrical loads. Three types of machines are used for this purpose: chillers and heat recovery chillers (HRCs) that consume electricity and produce chilled and both hot and chilled water streams respectively (these machines are both heat pumps), and heaters that consume gas to produce hot water. Storage tanks can be used as a buffer for both the hot and chilled water streams. The problem of minimizing the cost of operating SESI subject to technological constraints can be formulated as a linear program, i.e. one that can be represented as:

$$\begin{gathered}\min \langle c, x\rangle \\ \text{subject to } Ax \leq b, \\ x \geq 0.\end{gathered}$$

c is the cost vector, x represents the vector of decision variables (the main decision variables are the amounts of electricity and gas that are bought at every hour of the year, and these are augmented with auxiliary decision variables when the problem is formulated as a linear program) and the constraints represent both the water storage dynamics; that campus demands must be met at every time step; and technological constraints for the equipment (such as ramping rates and efficiencies).[1]

The point of view adopted here is that of the manager for the campus, which makes especial sense in the Stanford setting since the entire campus is master-metered and there is one point of entry for all energy imports. The objective of the program will accordingly be to minimize the aggregate cost of operating the system, subject to different cost structures. The cost structure that is currently imposed on the system will be used as a reference cost structure to compare the optimal behavior under different scenarios in figure 4. The campus pays a flat volumetric price for gas and both a time-varying volumetric price and a demand charge for electricity. The cost structure for electricity is illustrated in figure 2, where we show in blue the aggregate electric loads from the buildings on Stanford's campus for July of 2016 (this represents the currently uncontrollable portion of the campus load). The campus pays both for the green area under the curve (weighted by a time varying energy price) as well as a charge per kilowatt for the maximum power that month (represented by the orange line in figure 2). In other words, the campus pays both for energy and for the capacity that the utility must procure to meet the highest demand over the payment period. Today, there is roughly a 9:1 ratio between the energy and demand charge portions of the electric bill.

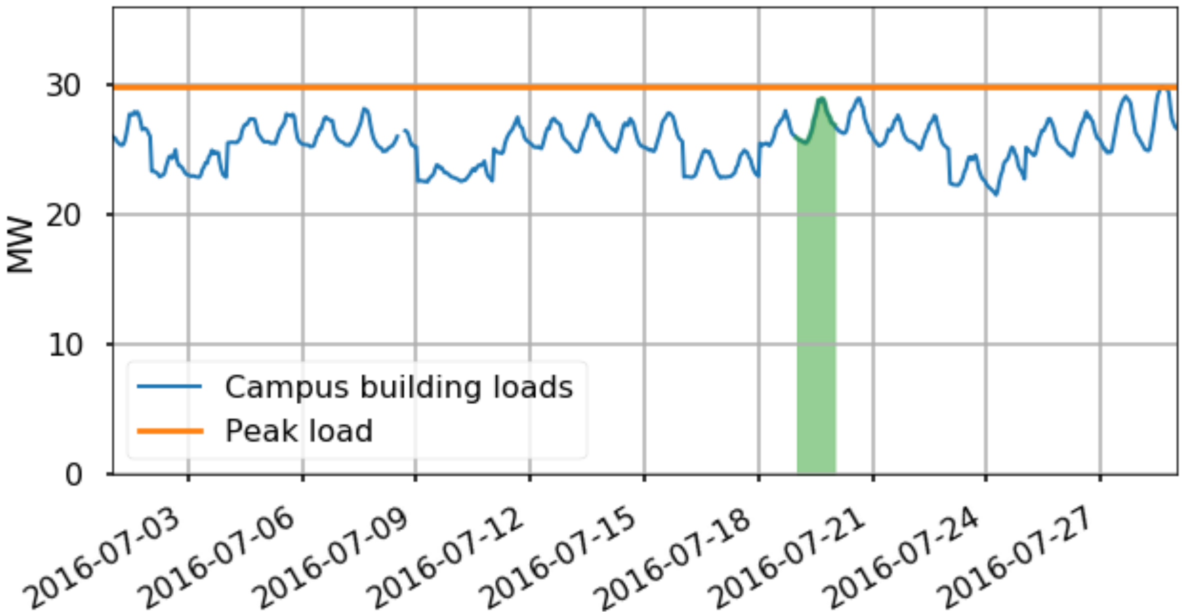

Figure 2: Background campus building load for July of 2016.

SCENARIOS FOR CARBON INTENSITY OF THE CALIFORNIA POWER GRID

Since we are considering a hypothetical future where the campus is subject to some form of carbon pricing, a decision needs to be made on how to account for carbon. In order for carbon considerations to guide scheduling decisions, we choose to attribute a carbon intensity to electricity flowing through the power system in units of CO_2/kW (metric tonne/kW), which will vary over the course of the day depending on the mix of generating sources. A common way to estimate these average carbon intensities – also called Average Emissions Factors (AEFs) – is to use Life Cycle Assessment (LCA) carbon intensities for the power generation sources in a given generation mix [36]. Recent work introduced another metric, Marginal Emissions Factors (MEFs), that it is argued is preferable over using AEFs to account for carbon [37-38]. MEFs are usually calculated by linearly regressing stepwise changes in CO_2 emissions as a function of changes in power generation (as recorded by the Environmental Protection Agency in the United States, for instance). MEFs are a potent tool for policymakers to compare the

[1] The linear program we solve has around 130,000 variables and 173,000 linear constraints.

carbon return on investment of investing taxpayer money in different clean energy projects, but they are intended to serve as a metric for investment planning. In this setting, we are paying a price for the actual carbon emissions that should be attributed to SESI, in an operational context, which is why we choose to use AEFs. We emphasize that changing from one metric to another does not affect the methodology presented in this work, although it could change the results and their interpretation.

We generate three scenarios for the hourly carbon intensity of the California power grid over an entire year, using carbon data from [36] and the hourly generation mix for California from [39]. Heatmaps for carbon intensities of three potential future scenarios for the California energy mix in the mid-2020s are shown in figure 3, and correspond to (i) the true AEFs for California in 2016, (ii) the AEFs for a scenario we generate where solar penetration is high (23% of total energy produced, up from 8% in 2016), and (iii) the AEFs for a scenario we generate where both solar and wind penetration are high (23% of total energy produced is from solar generation and 22% is from wind generation, up from 5% wind in 2016).

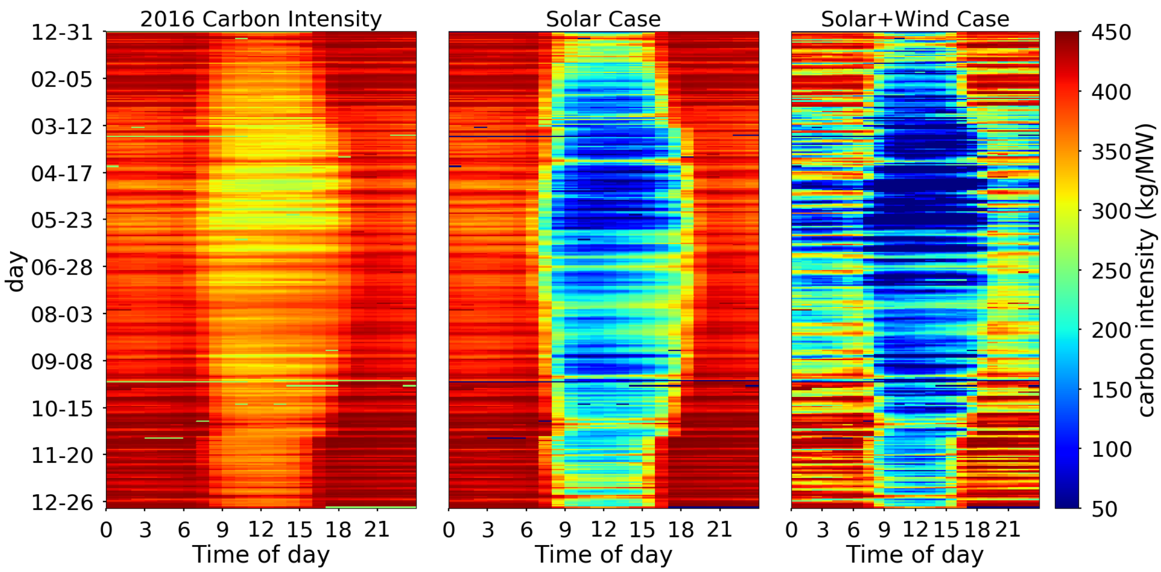

Figure 3: Heatmaps for carbon intensity under different scenarios for the California future energy mix, using data from [36] and [39]. In the images, each row corresponds to one day's worth of data, and each column corresponds to one hour of the day. All images use the same color bar.

RESPONSE OF SESI TO DIFFERENT OPERATING ENVIRONMENTS

To demonstrate the flexibility of the SESI project, we compute optimal operating schedules under the three grid carbon intensity scenarios that were defined in the previous section and with four different choices for operating conditions. All other input data apart from carbon intensity remain the same across computations and correspond to real operating data from the year of 2016 (hot and chilled water loads, background campus electricity usage, electricity prices)[2].

For each computed schedule, the aggregate bill for the campus is calculated using the demand charge-based billing system that was previously described and an internal levelized energy cost is then determined and applied to the CEP to determine the cost of operations over the year. Summary results for each of the schedules are provided in figure 4, where we display the financial cost increase relative to the base case and the carbon emissions associated with CEP operations for an entire year. We emphasize that the costs reported on the left plot of figure 4 only include the energy bill as computed

[2] Although the large-scale injection of renewables is likely to significantly change electricity prices, that is not considered here, and 2016 data is used, since the main goal of this work is to compare the relative change in cost and carbon emissions of different operating schedules, and we must therefore compare them against the same price signals.

using the current rate structure, excluding any carbon payments, for the schedules to be comparable (note that this operating cost corresponds to the actual objective being minimized only in the base case).

The base case corresponds to the current campus operating conditions, under which carbon emissions are not considered, so that the base case schedule (and therefore cost) is the same under each of the three scenarios. The objective function we use in this case is very close to the energy cost of the system, which is why this schedule yields the cheapest operating cost for the CEP. The carbon footprint of the system decreases significantly as renewable energy is injected into the power grid. Compared to the 2016 base case, the base case operations under the **Solar Scenario** and **Solar & Wind** Scenario reduce emissions by 16% and 37%, respectively.

In the "no storage" case, we remove the thermal storage tanks from the system, so that the CEP must produce hot and chilled water exactly when it is needed. This effectively removes all flexibility from the system, and highlights the value of thermal storage. Operating costs increase by 6% in this case, and carbon emissions associated with this schedule are the highest in all three carbon scenarios. Adding thermal storage to the system reduces carbon emissions by 10-18%, depending on the carbon scenario (the higher the renewable penetration, the larger the impact). To meet demand at all time steps, the number of chillers in the system must also double, and the HRCs are used less often, since the overlap between the campus hot and chilled water needs is much stronger over timescales of days then hours, so that this case would also represent a significant increase in capital costs not considered here.

We now study two options to investigate how the system could be operated to optimize carbon emission reductions. In the first option, we impose a carbon tax of a hundred dollars per metric tonne of CO_2 on the Stanford campus energy system. Figure 4 shows that the energy bill (excluding the carbon settlement) would increase only slightly compared to its optimal value in the base case, in all three scenarios because there is still some flexibility left in the system after optimizing for energy costs. The resulting decrease in carbon emissions depends on the scenario. Under the 2016 carbon intensity data, a carbon tax has practically no impact on the energy operations of the campus, because there is very little daily variation in carbon intensity, as can be seen in figure 3. In contrast, this carbon tax would lead to a ~10% reduction in CEP emissions in the solar scenario, which shows the highest daily variation. We note that we only consider the impact of a carbon tax on the operations schedule of the current system, not on investment decisions.

For the second option, the "carbon optimal" case, the operating schedule is computed using only carbon intensity to make decisions (as if the cost for energy were constant and there were no demand charge). This case corresponds to the scenario in which the highest possible emissions reductions are achieved. Once again, the magnitude of reductions depends on the daily variability of carbon intensity, and are ~19% in the highly variable solar scenario.

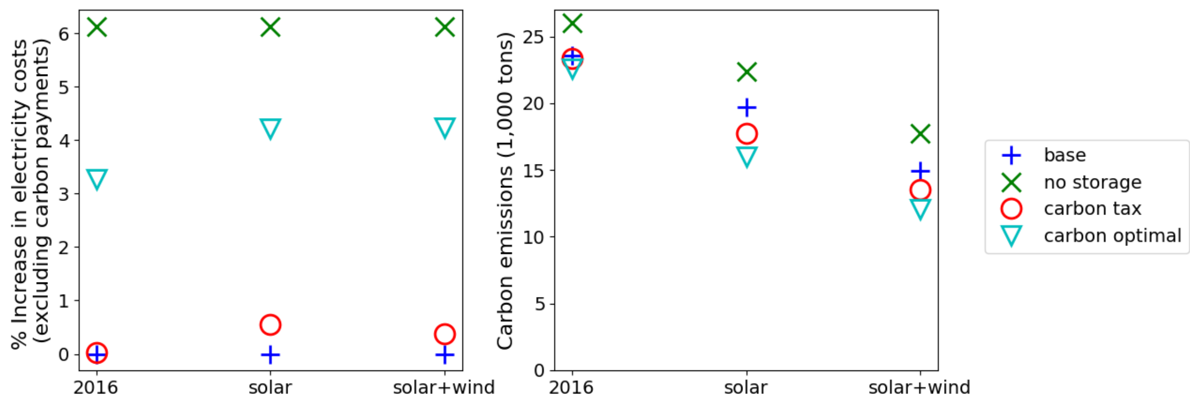

Figure 4: Operating cost increase (relative to the base case, and excluding any carbon payment) and carbon footprint of CEP operations for a year under different carbon intensity scenarios and operating conditions.

DISCUSSION AND CONCLUSIONS

The schedules presented here highlight the value of adding thermal storage to a campus district energy system. Including thermal storage lowers capital costs by enabling the use of Heat Recovery Chillers that simultaneously produce hot and chilled water and can recover waste heat from the hot and chilled water networks. In addition to coupling the hot and chilled networks in this way, thermal storage provides flexibility so that operation of the heating and cooling network can be coupled to the electric power grid by taking advantage of hourly prices (and flattening load when a demand charge system is in place), ultimately resulting in lower energy costs. Finally, the schedules in this paper, computed for significantly different environments and operating regimes, show that district energy networks with thermal storage can adapt not only to daily variations in energy supply but also to changes in the daily variation patterns. Under all three scenarios, the base case emissions are lower than in the case without thermal storage, which implies that there is already a positive correlation between electricity prices and carbon intensity in California. This correlation will probably grow as increasing amounts of zero-marginal cost, carbon-free wind and solar power are injected into the power system, which will tend to reduce the impact of, and therefore need for, a carbon tax on the operation of a system like SESI, since electricity prices are already guiding the system towards low-carbon hours[3].

In all three scenarios and for all operating conditions, a predominant fraction of the cost increase relative to the optimal base case are attributable to the demand charge, which suggests that this portion of the energy bill constrains the flexibility of the system. Figure 4 can also be used to estimate the effective cost to the system of reducing emissions, by comparing the cost of switching from the base case schedule to one that was computed by taking carbon into account to the corresponding emissions reduction. For the high solar penetration scenario for instance, the actual cost of emissions reductions estimated in this way is 12 \$/tonne CO_2 in the carbon tax case, and 50 \$/tonne in the carbon optimal case, which suggests that there are strong diminishing returns (note that the emissions reductions double from the first case to the second).

The cases that are optimized to reduce carbon emissions show how SESI can react to a carbon price and lower its associated emissions by up to 20% without significantly raising operating costs, and that the reductions increase with the variability of the carbon intensity of the grid, which shows that thermal storage is especially valuable in a power system with large shares of renewable generation sources whose daily variability is strong.

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[3] In our 2016 price dataset, prices are already low in the middle of the day and high in the mid-to-late afternoon and in the early morning, so most of the emissions reductions that are related to the introduction of a carbon tax are associated with shifting more load towards the low-carbon mid-to-late afternoon hours.

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