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ABSTRACT

With increasing penetration of intermittent renewable generation at grid and distributed scales, flexible building loads can provide significant system value and support the evolving needs of the grid. The growing value of load flexibility may complicate the traditional separation between energy efficiency (EE) and demand response (DR). EE measures may compete in some cases with a building's DR capabilities but complement one another in other cases. EE can also increase or decrease the need for DR at the system level and change the availability of DR to meet system needs. In this study we present a bottom-up approach to modeling interactive effects between EE and DR in buildings within two regions of the US electricity grid. From a library of building simulation models for different buildings and climates, we synthesize system-level demand profiles and the impacts of potential future EE portfolios. Coupling the underlying building models with a database of DR-enabling technologies, we then compute the quantity of DR that can be delivered in each scenario. The results show that EE and DR interactions are largely driven by the timing of EE savings that are measure-specific and the coincidence with system peak demand that is region-specific. We also find that perspective of the impacts matters – for instance that some EE measures reduce the system need for DR but also reduce the DR potential. Our results imply that utility EE and DR programs developed without considering interactive effects may lead to increased grid-management challenges over the long term.

Introduction

Energy efficiency (EE) and demand response (DR) resources provide important utility system and ratepayer benefits. At the same time, the rapid change in the amount of variable renewable energy (VRE), like solar and wind, is reshaping the role and economic value of EE and DR. For example, the proliferation of distributed generation has reduced electricity sales and changed the timing of net peak demand in certain regions (e.g., California). Additionally, the diurnal patterns and volatility of wholesale prices are changing due, in part, to large increases in utility-scale VRE resources with zero marginal costs (Seel et al., 2018). These changes will likely affect time-dependent valuation of EE and DR measures (Boomhower and Davis, 2017). Utilities are increasingly interested in integrating EE and DR measures and technologies (as well as other distributed energy resources) as a strategic approach to improve their collective cost-effectiveness and performance (Potter et al., 2018; York et al., 2019). However, little is understood about the specific EE and DR performance characteristics that may be best integrated, the interplay between changing EE and DR resource potential, and the resulting utility system impacts.

In this study we present a bottom-up approach to modeling interactive effects between residential EE and DR in two regions of the US electricity grid, California and Texas. Within each region we combine building simulation data with data on building stock and hourly electricity system demand and generation. We focus the analysis on interactive effects in residential buildings due mostly to limited publicly available commercial end-use savings shapes, though a planned future study will model EE and DR interaction in commercial buildings as well. We focus on one commonly implemented type of DR product, namely "shed" DR[1] used to manage utility system peak loads (typically occurring on hot summer days in these regions) and reduce the need for peaking generation resources. The study describes EE and DR interactions in terms of changes in hourly load (at the building and system level) arising from EE interventions; it does not explore EE-induced changes in customer DR participation rates (e.g., arising from improved capabilities), customer economics (e.g., bill savings) or utility costs (e.g., avoided capacity costs). Future work will consider these topics to paint a more complete picture of EE-DR interaction.

This paper is organized as follows. To frame and contextualize our modeling and analysis efforts, we begin with a summary of a broad conceptual framework[2] for thinking about interactions between EE and DR from a variety of perspectives. We then lay out our approach to modeling hourly electricity demand from buildings, scaling these up to the utility system level, and modifying the resulting building and system load shapes to simulate different EE adoption scenarios. We develop three different portfolios of EE measures, intended to illustrate different modes of EE-DR interactions, and we define two metrics for assessing changes in the potential DR resource and in the need for DR at the system level. Finally, we use these metrics to explore the interactive effects between EE and DR for our defined EE portfolios, and we discuss implications.

A Conceptual Framework for EE/DR Interactions

This study relies on a conceptual framework (Satchwell et al., 2020) to organize and identify EE and DR attributes, technological factors, and system conditions that are likely to drive interactions between EE and DR in commercial and residential buildings. EE and DR differ from each other in ways that are important for understanding how EE and DR interact, so clear definitions will be prerequisite to developing a conceptual framework. We define EE as a *persistent* and *maintained* reduction in energy consumption required to provide a fixed level of service.[3] By contrast, we define DR as an *active* modification[4] in energy demand or consumption on a limited-time basis, in response to an incentive or command signal, which may result in a reduced level of service.[5] The framework incorporates another concept, demand flexibility (DF), which we define as the *capability* associated with a building to modify energy consumption in response to utility grid needs.[6] Like DR, DF is characterized by active load management on

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[1] This is as distinct from other, more novel types of DR considered in the literature (e.g., Alstone et al., 2017), such as "shift" DR for load shifting, or "shimmy" for ancillary services (e.g., frequency reserves). These may also have important interactions with EE, which we plan to explore in future work

[2] See Satchwell et al. (2020) for a more detailed description of the conceptual framework, its qualitative application to several residential and commercial EE measures, and identification of key attributes driving EE and DR interactions.

[3] Consistent with other definitions of EE in the literature (e.g., York and Kushler, 2005; Goldman et al., 2010).

[4] E.g., reduction, increase, shift, or modulation.

[5] It is worth noting that this definition, which encompasses response to time-varying tariffs, is broader than what is sometimes used in other contexts and studies, which focus specifically on short-term load reductions.

[6] See recent literature on grid-interactive efficient buildings (GEB) (Eckman et al., 2019; Neukomm et al., 2019).

timescales consistent with utility system and grid needs. Unlike EE and DR, DF is not a resource in the traditional sense, but a potential that the utility or system operator can utilize to provide reliable electricity service. From the system operator's perspective, EE and DR are what you have in your portfolio and DF is what you can do with the resources you have.

The framework describes the interactive effects of a "change" at the building level, defined by the point at which an EE or DR investment is made.[7] EE and DR investments will change the end-use consumption on a temporal basis in different ways. When updating an end use with a more efficient technology, the load shape following the EE investment may represent an overall percent reduction, maintaining a similar shape. In other cases, the load shape may look quite different on an hourly or sub-hourly basis when an EE or DR investment includes controls technology, thermal improvements, or different operational strategies.

The framework is comprised of two levels, each of which is subdivided further into two sublevels exploring distinct interactions. The first level assesses changes that occur at the building and the second level aggregates buildings to represent utility-scale changes and describes interactions in terms of the utility system need for DR and availability of DR. Each sublevel is defined by an analytical question and metric by which the interaction between EE and DR is measured. Table 1 describes the conceptual framework, including the perspective, change metric, and definition of competitive, complementary, and neutral EE and DR interactions for each level and sublevel.

The present study focuses on EE and DR interactions at levels 1a, 2a, and 2b.[8] Level 1a is focused on the change in the building-level DF due to an EE or DR investment and asks, *in the presence of a more efficient measure, what is the change in technical potential and capability to shed, shift, or modulate the affected load?* Whether EE and DR compete with or complement each other at level 1a is a function of two distinct changes to DF: (1) the change in technical potential, as defined by the change in passive load shape, reflects whether and how the underlying load shape changes following an EE or DR investment to change the total load (e.g., if the load is lower in all hours, there is less load technically available to participate in demand response), as well as its coincidence with system need for DR; and (2) the change in capability reflects whether and how the building is more or less able to reliably[9] provide a responsive or flexible load when needed by the utility.

Level 2a is focused on the change in need for DR resources in the utility system and asks, *what is the change in likelihood that the system needs incremental demand response resources?* Level 2a specifically considers whether the EE investments made by many customers or building owners have, in aggregate, increased or decreased the likelihood of needing DR resources to address utility system conditions. At this level of the framework, an increase in system need reflects competition, and a decrease in system need reflects complementarity between EE and DR. Interactions between EE and DR at level 2a are almost entirely driven by the coincidence of the energy/demand savings at the building level and the net load driving system conditions.[10]

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[7] By a residential customer or commercial building owner (or an aggregator operating across multiple buildings).

[8] Level 1b interactions encompass changes in participation drivers (e.g., customer comfort, financial incentives) that are highly uncertain, and specific to program implementation, and beyond the scope of this study.

[9] The concept of reliability is represented here by automation or remote controllability that increases DF without changing anything about how much load can be controlled. EE may also affect reliability through other means, including changes in thermal inertia or the effectiveness of pre-cooling, but these are not explored in this study.

[10] The need for DR may also be driven by system conditions other than net load (e.g., generator unit outage). However, the probability of such contingency events would not change with a change in EE or DR resources.

The presence of controls capabilities is also an important driver, as they may increase or decrease the coincidence of energy/demand savings with system load. This depends on the specifics of how building controls are implemented.

Table 1. Conceptual framework levels, change metrics, and definitions.

Level	**Perspective**	**Change Metric**	**Competition**	**Complement**	**Neutral**
1a	Building	Demand flexibility (DF)	Less load able to shed, shift, or modulate	More load able to shed, shift, or modulate	No change in load able to shed, shift, or modulate
1b	Building	DF participation fraction	Lower fraction of DF participating as a demand response resource	Higher fraction of DF participating as a demand response resource	No change in the fraction of DF participating as a demand response resource
2a	Utility system	Demand response (DR) need	Increased likelihood of needing DR resources to meet utility system conditions	Decreased likelihood of needing DR resources to meet utility system conditions	No change in the likelihood of needing DR resources to meet utility system conditions
2b	Utility system	DR availability	Reduced availability of DR resources to meet specific system need or condition	Increased availability of DR resources to meet specific system need or condition	No change in the availability of DR resources to the system operator

Finally, level 2b is focused on the change in the availability of DR in the utility system and asks, *what is the change in the quantity of DR that is available to meet specific system needs?* Dispatchable resources, like DR, are used by utility system operators to meet system conditions and needs to maintain electricity reliability and service levels. EE may interact with DR by increasing or decreasing the amount of DR that is available to utility system operators. Whether EE and DR compete with or complement each other at level 2b depends largely on the net effect of levels 1a (change in building DF) and 1b (change in building DF participation fraction). Specifically, this depends on the interplay between the change in passive load shape, addition of capabilities (e.g., via controls or operational strategies), and change in participation.[11]

[11] The quantity assessed at this sublevel could be considered similar to the market potential in DR potential studies that measure the technical capabilities of end uses to provide DR and the propensity of customers to participate in DR programs.

Analytical Approach

Our study of load interactions between EE and DR focuses on two regions of the US electricity grid, corresponding approximately to California and Texas.[12] These regions were selected to represent different regimes of particular interest for studying EE-DR interactions in the context of VRE growth: a region with high penetration of solar electricity generation, shifting system peak loads into evening hours (California); and a region with a strong cooling load-driven peaks and high penetration of intermittent wind generation (Texas). In this study we model the contributions of residential to the system-level load, using weather and system-level demand data from calendar year 2016.[13]

Simulating the building contribution to system load

The building-level changes in EE and DR are based on simulations, weighted to reflect the present-day building stock. The simulations used 2016 weather data for 10–15 representative locations within or nearby our two modeled grid regions, selected to span the full range of climate zones[14] found within each region. Because these are the results of detailed building simulations, the representative load shapes are disaggregated into a large number of individual electrical end uses, allowing us to consider the impacts of specific EE and DR measures on the building-level demand and demand flexibility.

To represent residential buildings, we use the ResStock simulation tool (Wilson et al., 2016, 2017) from the National Renewable Energy Laboratory (NREL). ResStock computes a large number of individual building simulations, covering a wide diversity of building types, vintages, envelope characteristics, equipment configurations, and occupant behavior, to represent the housing stock in each location with high fidelity. We combine these simulations to yield load shapes that represent the average energy consumption, by end use, for several residential building types (i.e., single-family, multi-family, and mobile homes) in each representative location. We simulate these average building load shapes for a baseline scenario, representing the present-day building stock, and for several EE scenarios in which portfolios of EE measures are applied to the building stock

Future iterations of this work will represent commercial load using NREL's ComStock model, which provides similar functionality to ResStock for commercial buildings. At the time of this study, ComStock was still under development, so, as a placeholder, we used a public set of commercial building simulations for various locations in the US (EERE, 2013). These single-building simulations cannot accurately represent the full commercial building stock in detail, so we focus this analysis on the residential sector, where the ResStock simulations can yield better accuracy.

The representative building-level load shapes are then aggregated up to the utility system level. To support this, we match a commercially available dataset on US real estate parcels, to

[12] More specifically, we model system-level loads within the CAMX and ERCT grid regions defined in the electricity markets module (EMM) of the National Energy Modeling System (NEMS) from the US Energy Information Administration (EIA), as of 2016 (EIA, 2017). The EMM region definitions have been updated for 2020, but the changes do not impact our region boundaries in this study.

[13] Assuming a different year would result in higher or lower impacts than in the present study, but we would expect qualitatively similar interactive effects.

[14] We use the climate zone definitions from ASHRAE standard 169-2013 in this study.

the building-simulation locations.[15] The result is a set of geographic subregions, each of which maps to one of the representative weather locations, and an accounting of the total building floorspace, by building type, in each subregion. We represent the load for those buildings by the appropriate average load shapes for each location. Weighting the representative load shapes by the total building floor space and summing the results yields the hourly contribution to total system demand from commercial and residential buildings within each region. Figure 1 shows a schematic diagram of the procedure for aggregating representative building load shapes to a system-level contribution, for the example of small commercial office buildings.

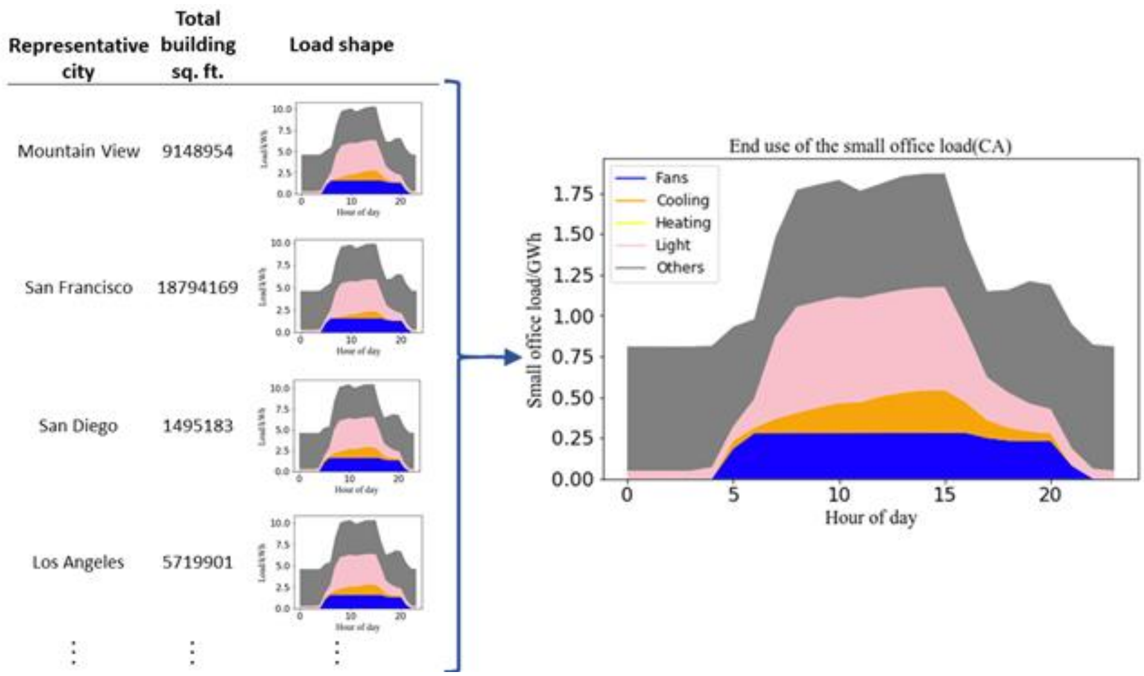

Figure 1. Schematic diagram showing the approach to aggregating building load shapes for representative cities to a system-level contribution. The example shown is for small office buildings in California; this procedure is repeated for all modeled building types and in both regions.

Last, we account for the contribution of non-building loads (e.g., industrial or agricultural loads) to ensure that the aggregated building simulations give an accurate representation of the overall demand from each sector. We augment our bottom-up model with top-down constraints based on actual system demand data, namely the hourly system-level demand in 2016 for each region, as reported by the EIA Hourly Electric Grid Monitor (EIA, n.d.-a), and the 2016 electricity sales (in kWh) by sector in each region, as reported in EIA Form 861 (EIA, n.d.-b). The Form 861 data allows us to compute the fraction of electricity consumption attributable to each sector in 2016 (e.g., in California, the residential fraction is 31%). By comparing our simulated baseline system-level building consumption to the actual system consumption, we can compute an overall calibration factor for each sector. We apply identical calibration factors to the

[15] In a small number of cases representing sparsely populated areas, there was no suitably representative weather data available for a particular climate zone within a particular region. In those cases, the model simply uses the geographically nearest representative location, regardless of climate zone.

baseline and EE scenarios as to the baseline, to ensure that all scenarios receive the same adjustment and that we do not inadvertently alter the EE savings.

With these calibrations in place, we have estimates of the contribution from residential and commercial buildings to total system load. In the baseline scenario, we can then infer that the difference between the actual 2016 system load and our simulated building load represents the non-building loads that we have not simulated. In each EE scenario, we hold this load fixed and add it to the simulated building loads to yield the system-level load after EE measures have been applied. In the baseline scenario, this approach ensures that our simulated system load is exactly equal to the actual 2016 system load. Figure 2 shows the resulting hourly average load over the course of a day from residential, commercial, and other loads in California and Texas. The total load is identical to the actual system-level load that occurred in 2016, while the building contributions are simulated.

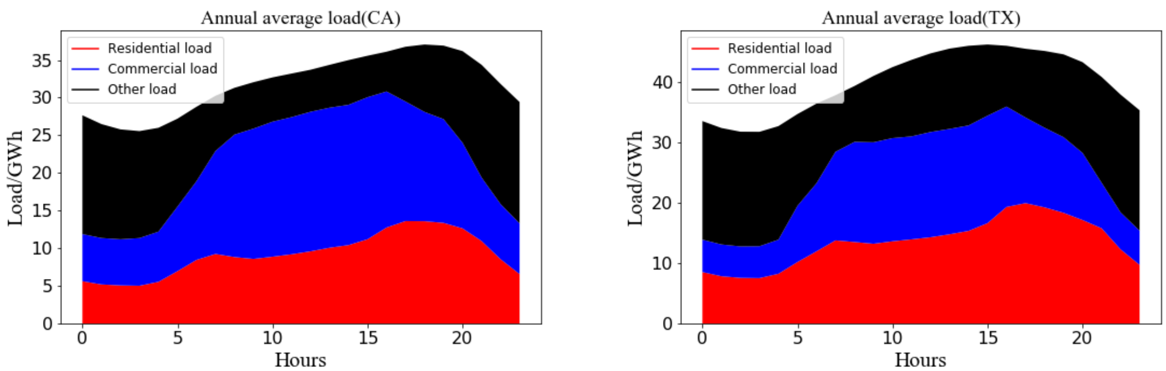

Figure 2. Simulated system-level 2016 load curves, by sector, for an average day in our modeled regions.

Simulated EE scenarios

We selected several EE measures and combined them into different portfolios for modeling in ResStock. To develop a focused set of portfolios we considered the ways in which different kinds of EE measures may interact with DR, drawing on key interactive attributes from Satchwell et al. (2020). We modeled three portfolios, each of which has different implications for EE and DR interactions in the framework:

1. An **equipment-only** portfolio, made up of efficiency upgrades to equipment across nearly all end-uses, including heating and cooling, appliances, electronics, and lighting. Equipment upgrades tend to reduce the amount of flexible load at the building level, (because of reduced overall load), but they may also relieve system-level need for DR.
2. A **controls-only** portfolio, consisting of a programmable or connected thermostat with set points manipulated to reduce consumption during overnight and unoccupied daytime hours. Controls-based EE measures will tend to increase DF at the building level; depending on the control strategies employed, they may also modify the need for DR at the system level.
3. An **envelope-only** portfolio, made up of envelope improvements including insulation, air sealing, and improved windows. Similar to equipment upgrades, envelope measures reduce the amount of flexible load at the building level; however, because they also increase thermal inertia, they tend to increase the flexibility of the remaining demand. They may also reduce the need for DR at the system level by decreasing peak loads.

Table 2 lists the specific EE measures in each portfolio, including EE metrics where appropriate. To apply these portfolios in ResStock, we treat each measure as a minimum efficiency level: for each measure, a building is upgraded if its relevant end use in the baseline scenario was less efficient than the measure. To ensure significant impacts on the total system load, the EE measures chosen were quite aggressive, upgrading all buildings to the best available technologies on today's market and yielding large (tens of percentage points) reductions in energy consumption for the affected end uses. While these EE scenarios are not particularly realistic near-term achieved savings levels, they represent stylized impacts on grid-level demand chosen to be large enough to drive readily apparent EE-DR interactions.

Table 2. Summary of detailed measures used to model the EE measure portfolios in this study. EE metric acronyms are defined in a note at bottom.

Portfolio	Affected building element	Upgrade
Equipment only	Central air conditioner	Replace with efficient two-speed air conditioner (SEER 18)
	Electric furnace or air source heat pump	Replace with efficient air source heat pump (SEER 22, HSPF 10)
	Electric baseboard heating	Replace with efficient mini-split heat pump (SEER 29.3, HSPF 14)
	Electric water heater	Replace with electric heat pump water heater (EF 2.3)
	Pool pump	25% reduction in energy consumption
	Dishwasher	Replace with efficient unit (199 kWh/yr)
	Clothes washer	Replace with efficient unit (IMEF 2.92)
	Electric clothes dryer	Replace with ventless heat pump unit (CEF 4.5)
	Lighting	Upgrade to 100% LED lighting
	Refrigerator	Replace with efficient unit (EF 22.2)
	Electronics	50% reduction in energy consumption
Controls only	Thermostat settings (for homes with no existing thermostat offsets)	*All homes with no existing offsets:* Cooling nighttime setup: 4 °F, 10 PM to 6 AM, Heating nighttime setback: 8 °F, 10 PM to 6 AM *Homes with no existing offsets AND unoccupied on weekdays:* Cooling daytime setup: 7 °F, 8 AM to 6 PM (weekdays only) Heating daytime setback: 8 °F, 8 AM to 6 PM (weekdays only) (offsets based on ENERGY STAR recommendations)
Envelope only	Wall insulation	Upgrade all walls to R-33 (R-13 cavity plus R-20 external XPS)
	Attic insulation	Upgrade unfinished attic/ceiling insulation to R-49
	Air sealing	25% reduction in ACH_{50}
	Windows	Upgrade windows to U-0.17 (R-5.9), SHGC 0.25 to 0.49 (climate dependent)
	Basement/crawlspace insulation	Upgrade insulation (R-13 to R-30 depending on climate and construction)

Acronyms—SEER: seasonal EE ratio; HSPF: heating seasonal performance factor; EF: energy factor; IMEF: integrated modified energy factor; CEF: combined energy factor; ACH_{50}: air changes per hour at 50 Pascals; SHGC: solar heat gain coefficient.

Estimating DR technical potential with DR-Path

To estimate the potential DR resource in each EE scenario, we use the resulting building and system-level loads from the above procedure as inputs into LBNL's DR-Path model. DR-Path was developed and refined to support analysis of DR potential for the California Public Utilities Commission (Alstone et al. 2016, 2017; Gerke et al. 2020). Based on the hourly system load shape, the model estimates the likelihood that DR will be needed in each hour;[16] applying this to each representative load shape, it computes the weighted-average quantity of DR that is technically available from each building type and end use. The model then couples the building-level DR technical potential with a database of DR measures having different performance levels and costs, and a model for customer participation, to analyze future pathways to enabling DR.

In this study, we focus on the DR technical potential (i.e., excluding effects from measure cost and performance or from customer participation) and examine how it changes under various EE scenarios. Limitations from the enabling technology and customer willingness to participate in DR with a particular end use will constrain the quantity of DR that can be delivered in practice, but by examining changes in the technical potential we can explore how changes in the load shape alone impact the available DR resource. In particular, we examine how EE changes the technical potential to provide DR at the building level, representing impacts at level 1a of the framework, and then we aggregate this up to the system level to explore changes in the DR technical potential at the utility scale, representing impacts at level 2b.[17]

Assessing changes in the system need for DR

We assess how the EE upgrades change the need for DR in the electricity system (level 2a of the framework) by examining changes to the annual peak demand after first subtracting the actual VRE generation that occurred in each region in 2016.[18] Specifically, in each of our scenarios and regions, we examine changes in the shape of the net load duration curve within the top 3% of hours of the year. We focus on the top 3% of hours because these have been identified elsewhere (Alstone et al., 2016) as the most probable for DR utilization.[19] Extreme peak hours such as these will need to have their demand met either by DR or by peak generation resources, such as natural gas combustion turbines, which tend to have both high cost (due to low utilization), as well as low efficiency and high emissions intensity relative to other resources. A large portion of DR's value to the grid stems from its ability to eliminate the need for peaking generation capacity, thus bringing down overall system costs and emissions (Faruqui et al., 2007).

Figure 3 illustrates the metrics we use to assess changes in the system need for DR. The figure shows net load duration curves for an illustrative baseline scenario (blue) and EE scenario (red), with the 97th percentile in demand indicated for each scenario. The EE scenario, in this example, yields a reduction in load in all hours of the year. Relative to the baseline scenario, the maximum demand in the EE scenario is reduced by an amount Δ_{peak} (see the inset panel of Figure 3). If the stack of generation resources on the grid is held fixed, as would be the case in the short-term immediately following a region-wide EE upgrade, a reduction in system peak demand indicates a reduction in the system need for DR, since there is less demand that need to be met by peaking generation resources and DR resources. Thus, the change in peak load, Δ_{peak}, can be used as a metric for the short-term impacts of EE on the system need for DR.

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[16] In general for load-shedding DR, this will be significant only in the top few percent of hours in terms of system load each year.

[17] In addition to these effects, EE and DR interactions may affect how the cost and capability of DR-enabling technology (level 1a) are affected, how the cost of securing customer participation (level 1b) changes, and how these changes impact the DR supply curve (level 2b). We leave exploration of these interactions to future work.

[18] As published by the relevant ISOs and balancing authorities.

[19] Indeed, this represents a fairly generous accounting of the potential DR hours. Other studies have considered the top 1% of hours (Faruqui et al, 2007) or even fewer (Satchwell et al., 2013).

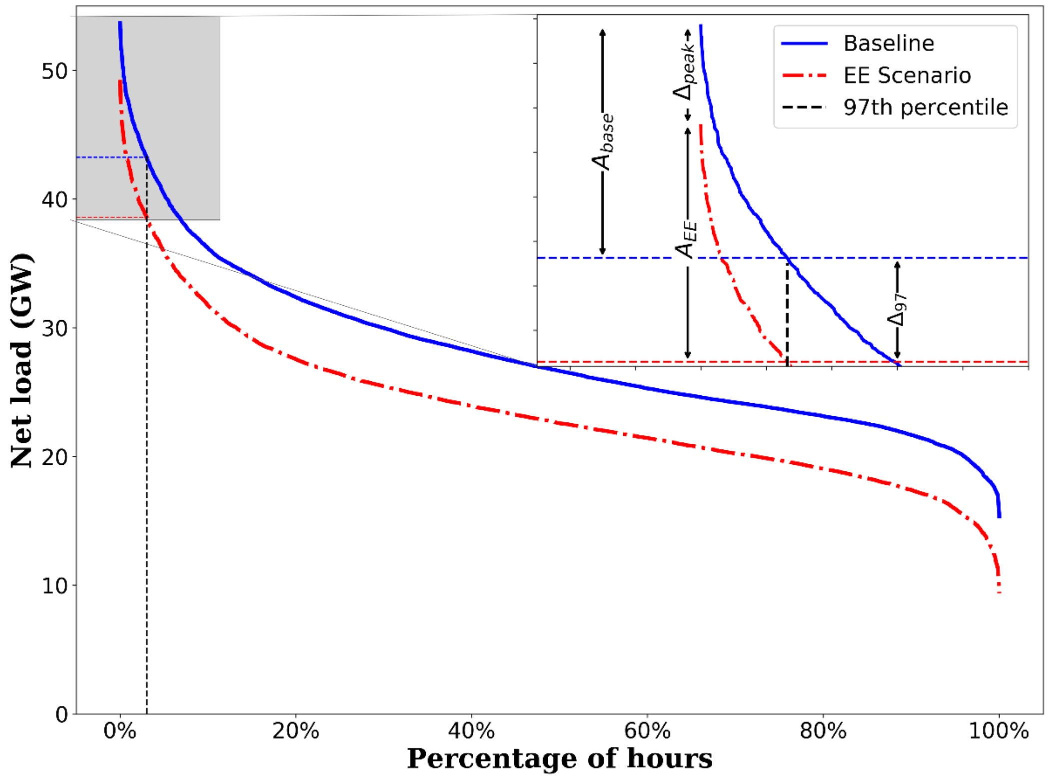

Figure 3. Schematic diagram of our approach to estimating changes in the system-level need for DR in response to EE upgrades, via examining the top 3% of hours in an illustrative load duration curve.

Over the long term, however, the generation stack will evolve through retirement and construction of new generation resources that will be selected based on their specific economics of operation in the context of expected future load. In the illustrative EE scenario, compared to the baseline, the 97th percentile of load has fallen by an amount Δ_{97} (see the inset panel of Figure 3). In that case, certain generation resources that would have been economical to operate in the baseline scenario, by serving load in more than 3% of hours, may become uneconomical in the EE scenario due to reduced utilization. Then the top 3% of hours will still need to be served by expensive peaking capacity or by DR resources. Thus, a useful long-term indicator of system need for DR is the difference in demand between the maximum and the 97th percentile. We refer to this as the "peakiness" of the system, denoted by A and illustrated in the inset panel of Figure 3 for both the baseline and the EE scenario. If the EE savings occur preferentially during peak hours, then the peak will fall farther than the 97th percentile ($\Delta_{peak} > \Delta_{97}$), and A_{EE} will be smaller than A_{base}, indicating EE and DR complementarity in the form of reduced long-term need for DR. If the savings occur preferentially outside the top 3% of hours, A_{EE} may exceed A_{base}, indicating EE and DR competition. Therefore, we use the change in peakiness, $\Delta_A = \mathrm{A}_{base} - A_{EE}$, as a metric for long-term EE and DR interaction at level 2a.

Results and Discussion

The EE measures applied in each scenario modify the load shapes of individual homes, which changes the quantity of load that is available to provide DR and drives EE and DR interactions at level 1a of the framework. Figure 4 shows the change in technical DR potential estimated by DR-Path, in each EE scenario relative to the baseline, for average single-family detached homes in selected representative locations.[20] The equipment-only and envelope-only scenarios both lead to reductions in building-level DR potential, reflecting a reduction in available load during system peak hours and indicating competition at level 1a. The controls-only scenario, by contrast, slightly increases building-level DR potential, which indicates complementarity at level 1a. This is primarily because the programmable thermostat settings used in this scenario (see Table 2) suppress cooling energy consumption during daytime and overnight hours, but must increase it to achieve the desired set point in the evening, which coincides with the typical daily system peak in both regions.[21] There is notable geographical variation in the interactions for all scenarios, which reflects a strong climate dependence in the baseline loads and in the EE load impacts, as well as variation in the building stock.

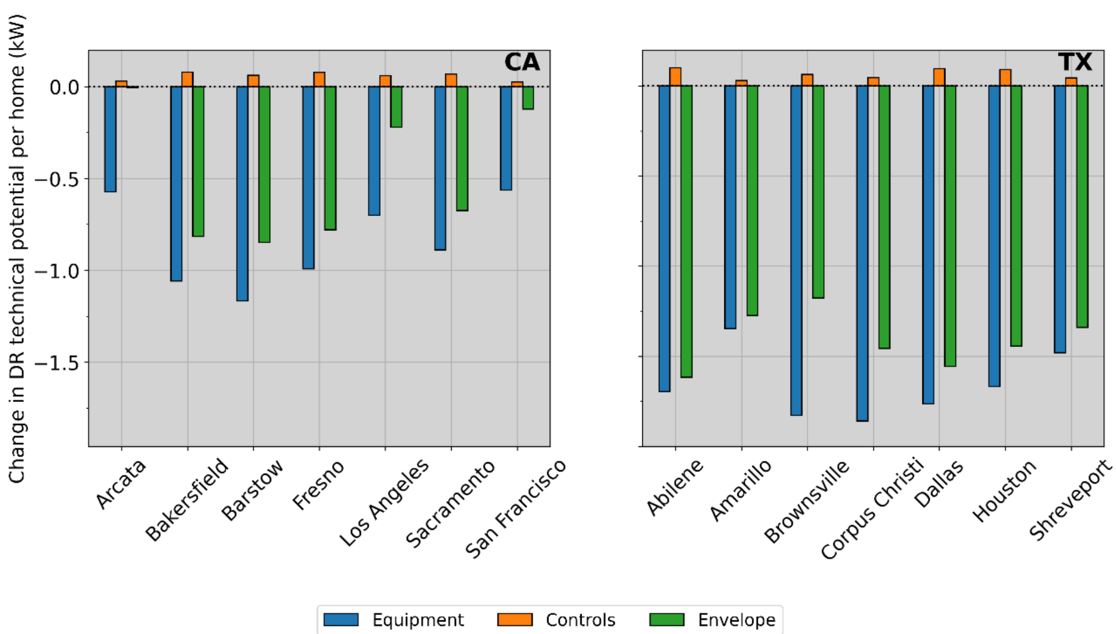

Figure 4. Bars show the change in an average home's technical potential to provide load-shedding DR, for each of our EE scenarios relative to the baseline, for single-family detached homes in selected representative locations within each of our modeled grid regions.

Figure 5 shows EE and DR interactions at level 2b of the framework as the technical DR potential from residential buildings, in the base scenario and the EE scenarios, aggregated to the system level in each region and broken down by end use (stacked bars). Figure 5 also shows the fractional change in annual residential electricity consumption for each of the scenarios (red dots) to demonstrate the EE savings achieved. Overall, Texas has a higher technical DR potential from residential loads in the base case (~26 GW) than does California (~16 GW), owing primarily to Texas's much larger residential cooling load during peak hours. In each EE scenario, there is a reduction in total electricity consumption, which varies by scenario.

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[20] Shreveport, LA, is used as a representative weather location for certain areas of Texas near the Louisiana border.

[21] The increase in DR potential may be even larger when one considers the increased DF capability that these controls enable, an effect that will be considered in future work.

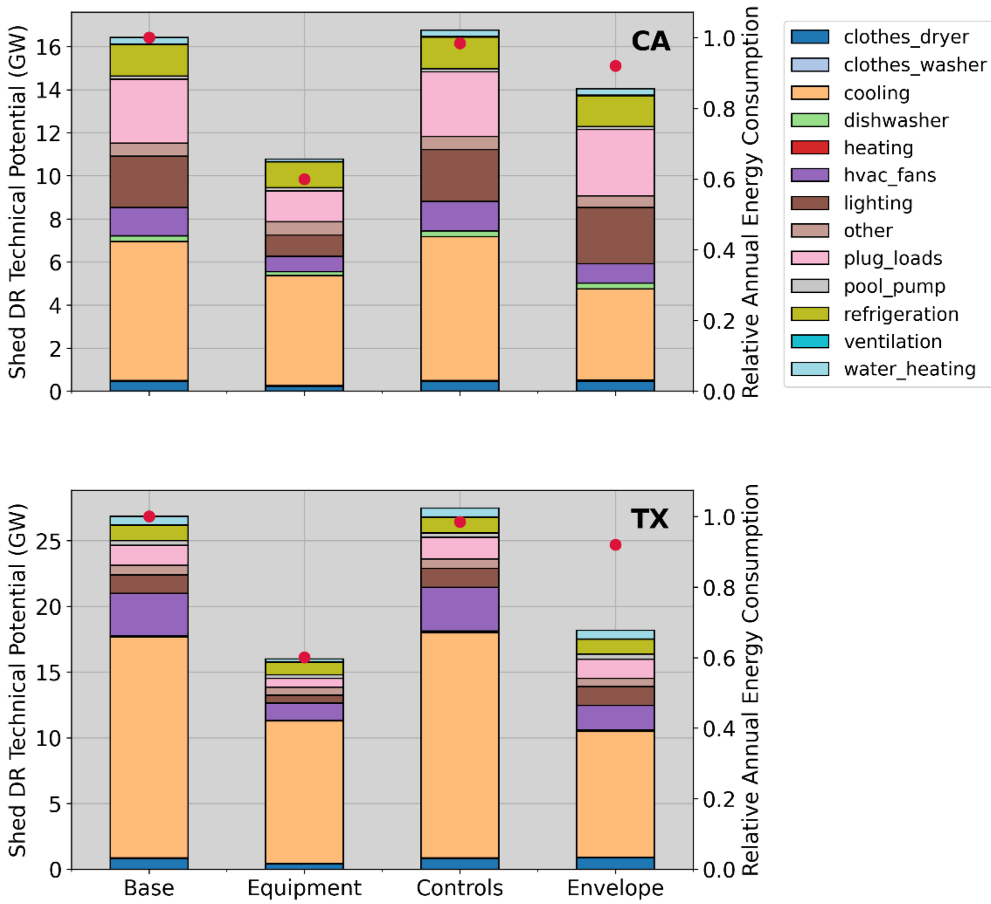

Figure 5. Bars show the absolute system-level technical potential for shed-type DR (i.e., total load in sheddable end-uses, on average during peak hours), by end use, in each of our analyzed regions, for the base scenario and each EE scenario. Red dots show the total electrical energy consumption from residential buildings, relative to the baseline scenario.

In the equipment-only scenario, DR potential is smaller for all end uses, and the reduction is roughly proportional to the reduction in residential energy consumption, since all end uses have reduced load arising from improved device efficiency. This represents the most straightforward type of EE and DR interaction at level 2b: because there is less load within each end use, the quantity of DR that can be delivered in principle is smaller and EE and DR are in competition. The envelope-only scenario also shows a smaller DR potential, but in this case the decline is notably larger than the reduction in energy consumption. This occurs because the decline in both quantities is driven by reductions in cooling load, which occur disproportionately during peak periods (in these summer-peaking systems), yielding competition between EE and DR at level 2b.[22] The situation is more complicated in the controls-only scenario. Although there is less residential energy consumption overall, the DR potential is *larger* than in the baseline scenario. As we saw at the building level in Figure 4, this arises from the increased on-peak load needed to offset daytime thermostat setups, though the setups save energy on balance. This interplay yields a modest complementarity between EE and DR at level 2b.

[22] An offsetting consideration is that envelope improvements increase thermal inertia, which may improve the capability of a building to shed cooling load, either more deeply or for a longer period of time, while maintaining occupant comfort. Thus, the overall competition at level 2b for envelope measures may be smaller than shown here.

Figure 6 presents EE and DR interactions at level 2a of the framework, relating to the system need for DR. Specifically, we show changes in the peak and peakiness metrics, Δ_{peak} and Δ_{A}, expressed as percentages of the base-case quantity. All metrics are computed with respect to the system load net VRE generation. California shows a fairly straightforward EE-DR interaction in the equipment-only scenario, with the EE upgrades reducing the system peak and peakiness, indicating both a short-term and long-term level-2a complementarity. In Texas, however, while equipment upgrades reduce system peak load, there is little impact on the peakiness (i.e., top 3% of load). This likely reflects the centrality of residential cooling to daily peak load in Texas, such that equipment EE improvements yield proportional reductions in load across the top 3% of hours. In both states, the envelope-only scenario shows a clear EE and DR complementarity at level 2a, with reductions in both system peak and peakiness arising from reductions in on-peak cooling load. In contrast, at levels 1a and 2b, the equipment-only and envelope-only portfolios led to competition, demonstrating how EE and DR interactions can have different effects at different levels.

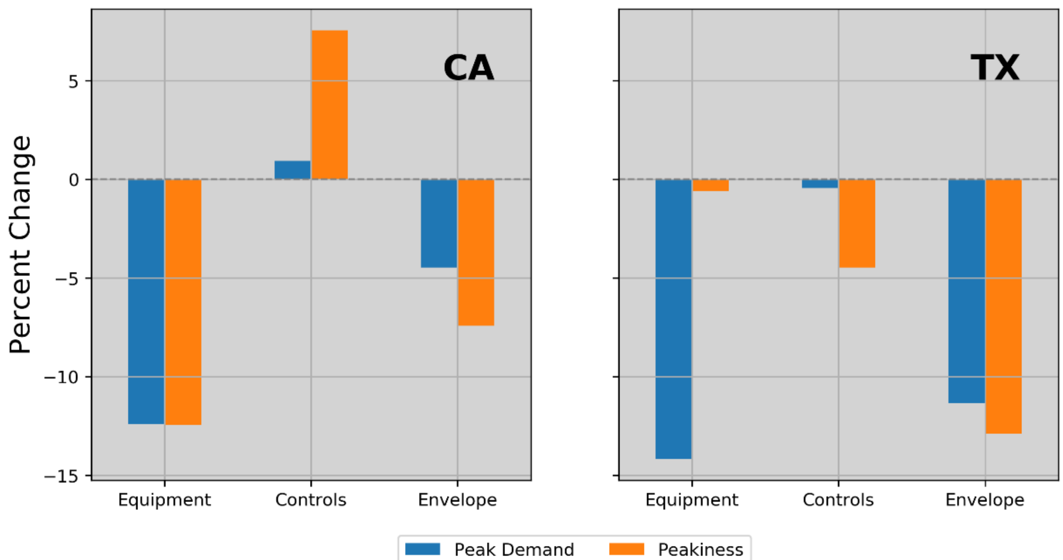

Figure 6. Metrics for the change in DR need at the system level, in each region and for each EE scenario. All metrics are expressed as a percentage of the relevant baseline quantity and computed with respect to the net system load. Negative numbers represent a decrease in the quantity being assessed, with respect to the baseline scenario, and positive numbers represent an increase

The controls-only scenario yields mixed EE and DR interactions at level 2a. In California, the system peakiness increases significantly, with a small increase in system peak. This reflects the fact that California's solar-driven net load peaks consistently in the evening hours, coincident with the increased cooling load that is needed to offset energy-saving daytime thermostat setups. By contrast, Texas sees a large decrease in peakiness and a moderate reduction in peak load, likely because the large and variable wind generation resource shifts net load peaks away from the evening hours on some days. These results highlight the importance of developing controls strategies that are appropriate for the specific system and need being addressed. In California, for instance, the energy savings achieved through daytime thermostat setups have exacerbated peak-management challenges on the system level. A thermostat strategy that instead employed pre-cooling to reduce evening peaks could mitigate the same grid-management challenges, but this might come at the expense of increased energy consumption,[23] which is another form of EE and DR competition. It is also worth noting that the available system-level DR resource has increased in this scenario (see Figure 5), and that complementarity at level 2b could offset the competition at level 2a.

Conclusion

We constructed a bottom-up simulation of the system-level demand from buildings in two regions of the electricity grid (California and Texas) that exhibit a high need for shed DR. In the context of a conceptual framework for understanding EE and DR interactive effects, we applied various illustrative portfolios of EE measures to the underlying building simulations to explore interaction between EE measure portfolios and the need for and technical availability of DR in each region. We find that interactions between EE and DR can be either competitive or complementary, depending on the framework level being considered, and the outcome is driven by the coincidence of EE savings (that are measure-specific) with system peak demand (that is region specific). For example, the equipment-only portfolio curtails energy consumption across several multiple end-uses that coincide strongly with system peak demand; this reduces building-level DR technical potential (level 1a competition), reduces the system need for DR (level 2a complementarity), and reduces the system-level DR resource (level 2b competition). EE and DR interactions also depend strongly on the specifics of the power system, particularly at level 2a. For instance, the controls-only portfolio increases system need for DR (level 2a competition) in California, where the solar-driven net load peaks at the same time as the thermostat settings increase load. But the same strategy reduces system need for DR (level 2a complementarity) in Texas where high wind penetration often shifts the net load peak out of these hours.

Our findings suggest three key considerations for EE and DR program design and utility planners: 1) it is important to consider how EE changes both the *quantity* of DR that is available and the *need for* DR in the system when considering integrated approaches to EE and DR; 2) any EE measure has interactions with DR that are nuanced and measure specific, and these can be revealed by hourly load shape analysis; and 3) the same EE measure in one system may have different DR interactions than in a different system, and controls-based measures in particular should be developed in a way that reflects system-specific needs. In future work we will consider a broader range of measure portfolios and interactive effects, including investigating combinations of equipment, controls, and envelope measures and exploring how EE and DR interact via changes in customer capability (level 1a) and willingness (level 1b) to provide DR. By considering interactive effects from a range of perspectives across our framework we will explore how to ensure that utility planners can evaluate interactive effects of EE and DR programs to help minimize overall system costs and emissions.

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[23] Resulting impacts on system costs and emissions would be limited if the increased consumption occurs during high renewable generation periods, however.

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