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Load-driven interactions between energy efficiency and demand response on regional grid scales

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ABSTRACT

Energy efficiency (EE) has long been recognized as a source of value to the electricity grid. Especially with increasing penetration of variable renewable generation, demand response (DR) can also provide system value and support the evolving needs of the grid. Yet there has been little study to date of interactions between EE and DR that may complicate their grid impacts. In this study we perform bottom-up modelling of the interactive effects between EE and DR in buildings for three representative regions of the United States electricity grid. Leveraging new simulation tools that enable detailed modelling of the building stock, we synthesize system-level demand profiles for several scenarios representing different portfolios of EE measures. In each scenario, we couple the underlying building models with a database of DR-enabling technologies to estimate building-level DR capabilities and compute a system-level supply curve for DR. We assess the resulting EE and DR interactive effects based on an existing conceptual framework. The results show a complex relationship between EE and DR, with interactive effects whose size and direction can vary widely depending on the grid system, type of DR, and the framework level being considered. Most often, the overall effect is competition between EE and DR, but significant complementarity can also occur, especially when the EE portfolio includes controls measures. Our results suggest that EE and DR programs developed without considering interactive effects may erode the benefits of both resources, whereas a more integrated approach may yield increased benefits.

1. Introduction

Energy efficiency (EE) and demand response (DR) are widely recognized as important tools to reduce power-system costs [1–4], improve reliability of electrical service [5–7], and support decarbonization goals [8,9]. Utilities regularly undertake detailed studies to assess the technical, economic, and market potential for DR that informs ratepayer-funded DR program design [10]. Additionally, regulators consider the cost-effectiveness of ratepayer-funded EE and DR programs based on deferral or avoidance of utility investments and other utility costs [11]. However, increasing penetration of variable renewable energy (VRE) resources, such as wind and solar, is driving changes in system net load profiles (i.e., system load less VRE generation) that complicate the traditional valuation of EE and DR by increasing the hour-to-hour variability of grid costs and changing the timing and frequency of high-cost periods [12]. There has been a growing recognition that the value of EE depends crucially on the timing of the energy savings [13,14] and that the most valuable strategy for DR is evolving from infrequent load reductions during peak hours to more frequent shifting of the timing of energy consumption to effectively utilize VRE resources [15,16]. As a result, electric utilities and regulators are increasingly interested in integrated EE and DR programs [17,18] and in the co-deployment of building technologies and strategies that can provide both EE and demand flexibility[1] (DF) [20,21]. In some cases, EE regulations have been modified to accommodate DR-enabling features: in the United States, for instance, a 2015 statute modified minimum EE standards for certain electric water heaters intended for use in DR programs [22], and the ENERGY STAR® program specifies “connected criteria” that grant an energy-consumption allowance in exchange for DR-enabling communication features [23].

[1] Defined as a building’s capability to modify load in response to grid needs, i.e., to provide DR [19].

Abbreviations: AMY, Actual meteorological year; EE, Energy efficiency; DF, Demand flexibility; DR, Demand response; LBNL, Lawrence Berkeley National Laboratory; NREL, National Renewable Energy Laboratory; VRE, Variable renewable energy.

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Because EE and DR both address the same underlying load, interactive effects are likely when the two resources are considered in an integrated manner. Satchwell et al. [19] developed a conceptual framework (referred to hereafter as *the EE-DR framework*), describing the various ways in which EE and DR may compete with or complement each other. They identified a complex and layered set of potential interactions that could represent either competition or complementarity between EE and DR, depending on the specific set of resources being analysed and on the perspective and the scale from which the issue is considered. To date, however, analyses of EE and DR interactions have been limited in scope and confined to a single facet of the diverse set of possible interactions identified in the EE-DR framework. A study of DR potential in California [15] found a smaller DR resource in a scenario with increased EE, and recent national-scale studies have noted that EE can reduce the amount [20] or the value [24] of DF in buildings, all of which are forms of EE and DR competition. Another recent study considered the ways in which DR-enabling capabilities can improve the cost-effectiveness of certain measures in the context of utility EE programs [25], or how certain portfolios of EE measures and storage can increase DF in residential buildings [26], which are forms of complementarity. None of these studies considered the full range of potential interactive effects identified in the EE-DR framework, however.

In this paper we present a thorough and detailed assessment of the EE and DR interactive effects that may occur as a result of EE-induced changes in load and in the characteristics of the building stock, considering competitive and complementary effects occurring at the building level and at the level of the regional grid system. Leveraging existing modelling tools that focus on EE and DR individually, we construct a novel framework to model EE-induced changes in load across a range of scales and to assess resulting impacts on building-level DR capability, system-level DR resource size and system-level need for DR, across a variety of dimensions. To our knowledge, this is the first study to analyse EE and DR interactions at such a high level of detail and across the broad range of scales and perspectives identified in the EE-DR framework.

In particular, we use the building simulation tools ResStock [27,28] and ComStock [29] to model electrical loads for a diverse population of buildings in the residential and commercial sectors. Combining these simulated building load shapes with real-world data on grid-system load, we develop a bottom-up model of the hourly load contributions from residential and commercial buildings, focusing on three U.S. grid regions with varied power-system characteristics. We repeat the building simulations and system load modelling for several scenarios representing portfolios of EE measures that could be applied in the building stock, selecting portfolios that would be expected to exhibit different interactions with DR based on considerations from the EE-DR framework. We then assess how the available DR resource changes in response to EE upgrades using the modelling framework DR-Path [15,16], which pairs individual building end-use loads with DR-enabling measures. This approach allows us to analyse changes in the size and the cost of the DR resource, both at the individual building level and in aggregate at the grid-system level. To assess how the system-level need for DR changes, we make use of a recently developed set of metrics [30] for quantifying the change in system-level need for different types of DR in response to changes in the system load shape. The analysis in this paper builds on and extends the approach from an earlier study that presented a simpler consideration of EE and DR interactive effects in residential-sector buildings [31].

When considering EE and DR interactions, it is important to distinguish clearly between the two resources, since they can sometimes provide overlapping benefits (e.g. peak reduction). In this study, we adopt definitions of EE and DR from the EE-DR framework [19]: EE is defined as a persistent and maintained reduction in the energy consumption required to provide a fixed level of service, whereas DR is an active modification in building energy demand or consumption on a limited-time basis, in response to an incentive or control signal, which may result in a reduced level of service.[2] Within the boundaries of those definitions, we adopt a broad and inclusive representation of both EE and DR. Our EE measure portfolios include equipment upgrades, building envelope upgrades, and controls strategies that can save energy. Our consideration of DR encompasses everything from episodic programs with infrequent events dispatched directly by the grid operator to time-of-use pricing programs that present a consistent price signal to customers on a daily basis, to encourage changes in energy consumption patterns. We analyse interactive effects for traditional DR programs that focus on load reductions during extreme system peaks, as well as emerging types of programs that focus on shifting the timing of energy consumption to mitigate steep ramps in demand and avoid curtailment of VRE generation. Following Alstone et al. [15], we refer to these two broad classes of DR as *shed* and *shift*, respectively.

As the first analysis to focus directly on EE and DR interactions, this study is subject to several boundaries and limitations. First, our modelled building loads and EE measure impacts are based on building simulations rather than real-world buildings, and our DR measure impacts are based on a set of data-informed assumptions about measure performance capabilities. Thus, our results, while illustrative, may not perfectly represent real-world interactions. Our load modelling is also limited to residential and commercial buildings and does not include EE and DR interactions in industrial-sector loads, which may also be important in real-world applications. Also, the EE scenarios that we simulate represent extremely aggressive measure adoption, upgrading the entire building stock at once with a wide array of EE upgrades. These portfolios are not intended to be realistic, but rather they are used to ensure that our model produces EE and DR interactions that are readily apparent in our analysis. In practice, the EE and DR interactions that occur in real-world programs would be subtler than what we observe here. Also, our analysis of DR is limited to shed and shift resources involving load modifications over a period of one or more hours; we do not consider more exotic types of “fast” DR involving shorter-term load modulation (e.g., for frequency regulation). In our consideration of EE and DR interactions, we only consider those interactions that are manifested in changes in the building-level and system-level load shapes, or in technology-cost reductions that could occur under an integrated approach to EE and DR. We do not consider changes in customer willingness to participate in EE or DR programs or in grid-operator despatch strategies or procurement patterns. We also analyse EE and DR interactions in the context of large, utility-scale power systems; we do not consider potential impacts in smaller-scale systems, such as microgrids, where interactions may be more complex. Finally, we do not analyse the impacts of EE or DR on system costs, or on the cost-effectiveness of individual EE or DR measures, and we identify this as an important opportunity for future research, which can be informed by the present study of load-based interactions.

Before proceeding, it is important to clarify the implications of competition and complementarity between EE and DR as we use the terms in this paper. If EE competes with DR in a particular grid system, this does *not* imply that EE has a negative overall impact on the grid. Indeed, load reductions from EE are likely to have a substantial benefit to the grid, in the form of reduced costs for capacity, infrastructure, and generation, even when EE is in competition with DR. However, since the flexibility that DR provides is also of value to the grid, an interaction that reduces demand-side flexibility will erode the benefits of EE to some degree, compared to what would be estimated by analysing the load reductions in isolation. This is what we mean by competition. By contrast, if EE and DR are complementary, their joint benefits may be greater than the sum of benefits from the two resources considered in isolation.

[2] We also adopt the definition of DF used in the EE-DR framework, as a potential, residing in buildings, that the utility can utilize to provide reliable service, rather than a resource in the traditional sense.

This paper is organized as follows. In Section 2 we describe our methods for simulating building and grid-system loads in several EE scenarios, estimating DR resources, and analysing EE and DR interactions. In Section 3 we present our findings on interactive effects across the various levels of interaction identified in the EE-DR framework. We discuss implications of EE and DR interactions for utility system planners, grid operators, and EE and DR program implementers in Section 4. Section 5 summarizes our findings and offers considerations for driving EE and DR complementarity and avoiding unintended competition. Two appendices present the detailed assumptions and inputs we used for our modelling of EE and DR measures in buildings, as well as detailed results for certain EE and DR interactive effects.

2. Methods

This study models three regions of the US electricity grid corresponding roughly to New England, Texas, and California,[3] using actual weather and operational grid-system data from calendar year 2016. We selected these regions to represent a variety of different climates, proportions of VRE generation, and building stock characteristics. New England has a cold climate, limited VRE penetration, and space heating primarily provided by oil and natural gas; its grid system has a moderate summer-daytime peak driven by cooling load, with a secondary winter peak. Texas has a hot climate, high penetration of wind generation, and a relatively high penetration of electric space heating; its grid system has a strong cooling-driven summer peak, with the potential for demand spikes during winter cold snaps, and day-to-day variability in net load peak and ramp timing due to the high wind penetration. California has a moderate-to-hot climate, high penetration of solar generation, and primarily natural-gas space heating; its grid system has a cooling-driven summer peak, and diurnal solar variation shifts the net load peak into the evening hours and creates steep daily net-load ramps that must be met by flexible generation resources.

For each region, we created a bottom-up model of the grid-system contribution of building loads, and we analysed how the available DR resources changed between the baseline scenario and each of the EE scenarios. Our modelling and analysis proceeded in four steps:

1. We used advanced building simulation tools to model building-level loads for a large number of building types, configurations, and locations, representing the diverse building stock in each region, and we repeated;
2. For each EE scenario, we aggregated the simulated building loads to the grid-system level using a new aggregation methodology based on real-world data on the building stock and system-level load in each region;
3. We used an existing model for estimating DR potential from building load shapes to estimate the DR resource in each EE scenario and grid region; and
4. We analysed EE-induced changes in DR resources and needs, using the EE-DR framework to structure our assessment and leveraging a recently developed set of metrics for quantifying changes in the system-level DR need.

We describe these steps—and the underlying modelling tools, data, and metrics—in more detail in the rest of this section.

2.1. Modelling EE scenarios for building load shapes

We simulated representative building loads in each region and each EE scenario using the ResStock [27,28] and ComStock [29] simulation platforms from the National Renewable Energy Laboratory (NREL). These tools model a large number of residential and commercial building prototypes (tens of thousands in each modelled region) representing the diversity of building types, sizes, configurations, and geographical locations[4] in the actual building stock. For this study we simulated building loads using actual-meteorological-year (AMY) 2016 weather data.[5] We combined the individual building-simulation results to yield an average building load shape for each unique combination of building type and location, disaggregated into individual electrical end uses. The specific building types and end uses we modelled in this study are presented in Appendix A.

These simulations resulted in a baseline set of load shapes representing average buildings in the present-day building stock. We then repeated the simulations for several EE scenarios, which upgraded the model buildings with particular portfolios of EE measures. In developing the portfolios, we considered the ways that different categories of EE measures might interact with DR, drawing inspiration from the EE-DR framework. In each case we selected an extensive and aggressive set of measures that was applied to all eligible buildings. These scenarios are not intended to reflect realistic real-world scenarios but rather to create noticeable load impacts that will have readily distinguishable interactions with DR. We modelled four EE scenarios, each of which we expect to have different implications for EE and DR interactions:

1. An *equipment-only* scenario, which upgraded equipment across a broad spectrum of end-uses, including heating and cooling, appliances, electronics, and lighting. Equipment upgrades have the potential to reduce system-level need for DR, but they also tend to reduce the amount of flexible load at the building level.
2. A *controls-only* scenario, which added controls technologies and implemented energy-saving operational strategies for various end-uses. Controls-based EE measures can increase load flexibility at the building level, and they may also modify the need for DR at the system level.
3. An *envelope-only* scenario, which improved insulation, air sealing, windows, and other building-shell properties across all building types. Similar to equipment measures, envelope upgrades may reduce system-level DR need and reduce the overall amount of flexible load; however, because they increase buildings' thermal stability, they may increase the flexibility of the remaining demand.
4. A *controls-plus-envelope* scenario, consisting of the union of the measure portfolios from the controls-only and envelope-only scenario. We consider this combination of portfolios because it increases both controllability and thermal inertia and therefore may have a particularly high potential for complementary EE and DR interactions.

The specific measures making up each of these scenarios are presented in Appendix A.

Fig. 1 shows example average daily building-level load shapes in the residential and commercial sectors, for the baseline and each of the EE scenarios. The equipment-only and envelope-only scenarios tend to reduce loads across all hours of the day. The controls-only scenario tends

[3] Specifically, we modeled system-level loads within the following grid regions defined in the electricity market module (EMM) of the National Energy Modeling System (NEMS) from the US Energy Information Administration [32]: ISNE (corresponding to the footprint of the independent system operator for New England, ISO–NE); TRE (corresponding to the footprint of the Electricity Reliability Council of Texas, ERCOT); and the union of CANO and CASO (corresponding to the combined footprint in California of the California independent system operator, CAISO, the Balancing Authority of Northern California, the Los Angeles Department of Water and Power, and miscellaneous local grid operators).

[4] The geographical locations are defined by the locations of weather stations within each region, the data from which is used as input to the simulations. For each model, we chose a set of weather stations to represent the full set of ASHRAE climate zones (defined as of 2013) in each region [33]. In a few cases, there were sparsely populated climate zones or counties that lacked a suitable weather station. In these cases, we used the geographically nearest weather station.

[5] We chose 2016 as our simulation year since it was the most recent year with comprehensive weather data that was available for use in both ResStock and ComStock at the time of analysis

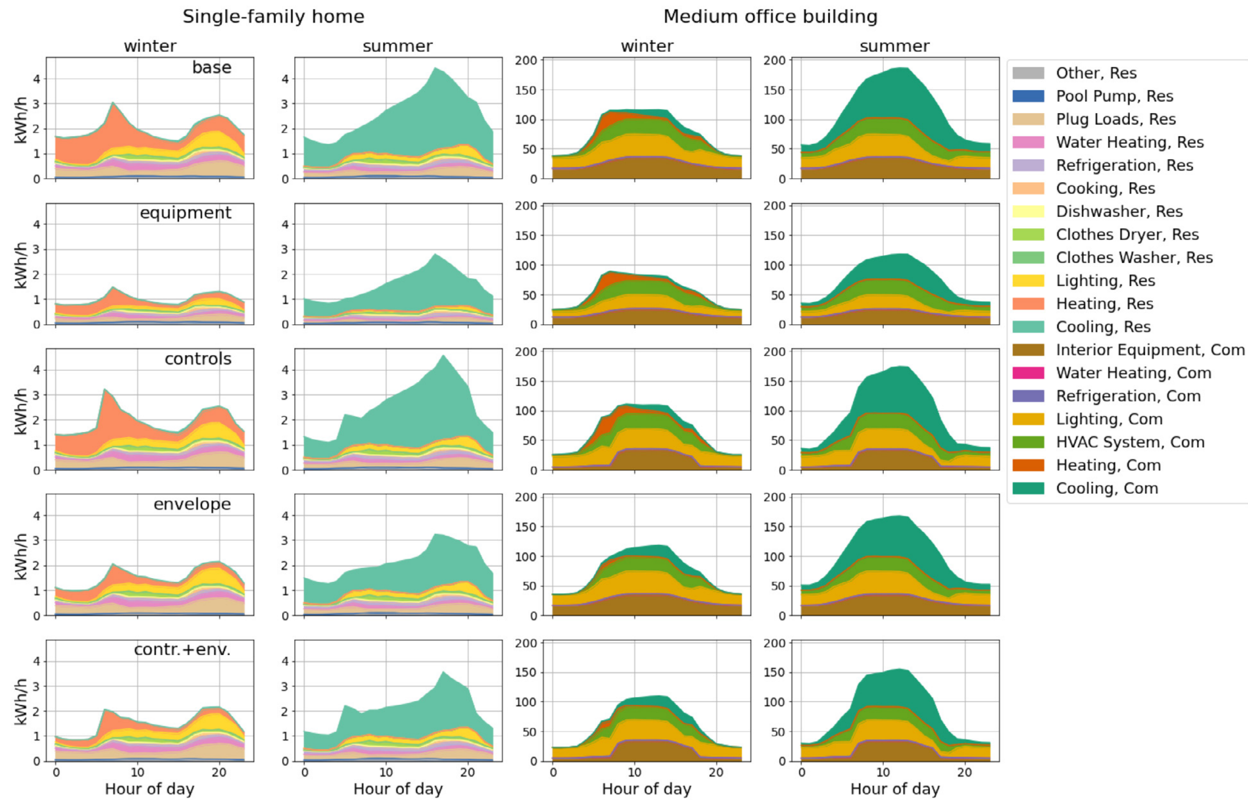

Fig. 1. Example building load shapes from ResStock and ComStock for an average simulated single-family home (left) and medium-sized commercial office building (right) in Dallas, TX. The panels show average daily load shapes in the summer and winter months (defined for these purposes as June-August and December-February, respectively), for each of the EE scenarios we modelled in this study. The different colors indicate the different end-use loads in each building, as indicated in the legend.

to reduce loads when buildings are idle: midday and overnight in the residential sector and overnight in the commercial sector. The controls-plus-envelope scenario combines the effects of its constituent portfolios. In every EE scenario, the impacts on the building load shape are readily apparent to the eye, illustrating the aggressive nature of these measure portfolios.

2.2. Aggregating system-level loads by EE scenario

To model the impacts of EE on load at the grid system level, we aggregated the representative ResStock and ComStock building load shapes using a procedure presented schematically in Fig. 2. First, we mapped each ZIP code in the region to the closest ResStock and ComStock geographic location within the same climate zone climate zone (Fig. 2a). We then scaled up the simulated representative load shapes associated with each location by multiplying each load shape by a factor made up of the product of two components:

1. A scaling factor, specific to each location and building type, representing the total floor space of buildings of that type within the ZIP codes mapped to that location (Fig. 2b), as derived from a commercially available property parcel dataset[6] [34], and
2. An adjustment factor, specific to each sector, calculated to match the total load in each sector to the actual sector-specific 2016 electricity sales (in kWh) in each region [35].

This procedure yields the simulated system-level load contribution from each building type.

To get an accurate model of overall system demand, the contribution of non-building loads (e.g., agricultural and industrial loads) needs to be represented as well. Starting from the actual 2016 system-level demand for each region [36], we added the actual 2016 rooftop solar generation profile in each region [37] to the system load to obtain the total hourly energy consumption in the system. This total was larger than the simulated building contributions that we computed using the scaling procedure above; and we assumed that the difference represented the non-building loads (labelled as “other” in Fig. 2c).

Holding the non-building load component fixed, we then repeated the building-load scaling procedure for the other EE scenarios, to construct the system-level load that would have occurred in each EE scenario. The scaled building-level and system-level hourly load shapes resulting from this procedure for each EE scenario are available for public download [45]. Given appropriate hourly system-level load data and sector-specific electricity consumption data (both of which are often public), as well as parcel-level building data (which is available from commercial sources), this procedure represents a general approach to simulating the contribution to system load from buildings, which may be applicable in future modelling efforts.

2.3. Estimating building-level and system-level DR resources

To characterize the DR resources in each region and scenario, we used the DR-Path model, which was originally developed for studies of the potential DR resource in California[7] [15,16]. We summarize the

[6] Since the set of building types in the parcel data is not identical to the set of simulated building types, we map each building type found in the parcel data to the most similar building prototype modeled in ResStock and ComStock, so that all buildings in the commercial data are mapped to a representative load shape and thus represented in the aggregate load.

[7] Previous studies with DR-path were based on actual customer load shape data in California. This study demonstrates the flexibility of DR-Path by using simulated building load shape data and modeling additional grid regions.

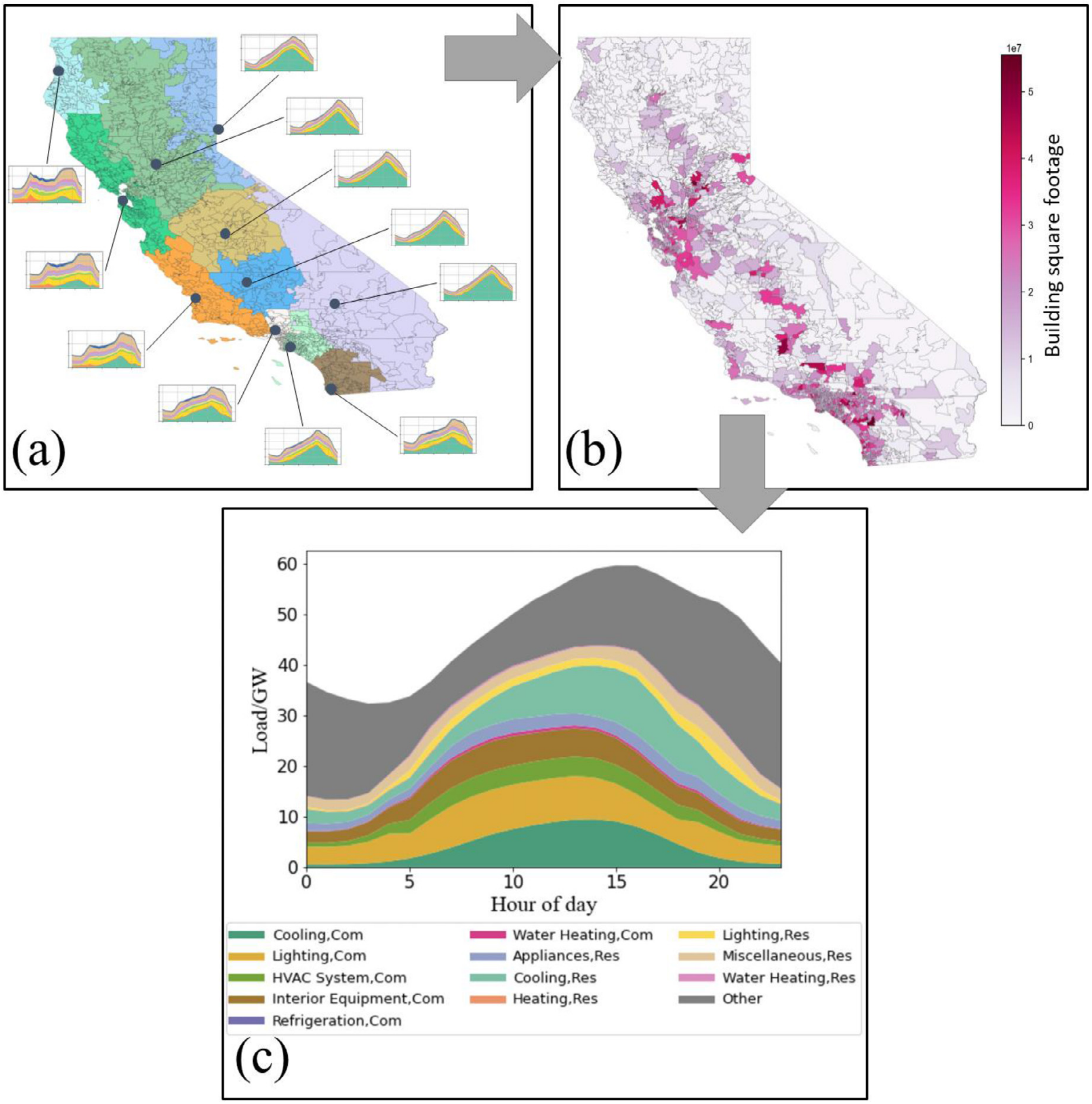

Fig. 2. Schematic diagram of our procedure for aggregating representative building loads to the grid-system level, using California as an example. (a) All ZIP codes in the state are assigned to the nearest modelled location that shares their climate, and the associated average building load shapes from ResStock and ComStock are used to represent buildings in the region. (b) The representative building load shapes are scaled up according to the total floor space of buildings, by ZIP code and summed to yield the hourly system-level contribution from buildings. (c) The resulting aggregate load from the various building end uses (coloured bands) is compared to the actual total system-level load that occurred in each hour in 2016, and the difference is attributed to other non-building loads (grey band).

model in this section and refer the reader to those earlier studies for full details. DR-Path constructs a detailed, bottom-up picture of the DR resource within a grid region. It takes three main datasets[8] as input:

- Customer cluster load shapes. A set of hourly load shapes, disaggregated into individual end uses, each representing the load from a cluster of similar utility customers over one year.
- System-level VRE generation. The hourly generation from VRE resources in the grid system being analysed, over the analysis year.
- DR-enabling measure data. A database of DR-enabling technologies or strategies for specific building types and end uses, including installation and operating cost data, as well as data characterizing measure performance in terms of the fraction of load that can be shed or shifted over different DR event durations.

In this study, the cluster load shape inputs were the average building load shapes from ResStock and ComStock, weighted by the total building square footage represented by each weather location. The VRE generation was the actual 2016 wind and solar generation in each region [36],[9] combined with the actual rooftop solar generation profile [37].

Detailed cost and performance data, sources, and assumptions for the DR-enabling measures are presented in Appendix A. Importantly, we included several assumptions about how EE upgrades can impact

[8] In some applications, DR-Path also incorporates a model for customers' propensity to enroll in DR programs. We did not consider such a model for this study since we are focusing on load-based interactions, rather than behavioral effects.

[9] Public data was extracted using ABB Ventyx (last accessed September 20, 2021)

DR measure costs and performance. A subset of our DR measures are also EE measures, or can be installed as simple add-ons to an EE measure. For such measures we assumed a reduced DR measure cost in EE scenarios that included the corresponding EE measure. For example, in the controls-only scenario, programmable thermostats (PTs) are already installed in residential buildings as an EE measure, so we assumed that installing a programmable *communicating* thermostat (PCT) as a DR measure would only incur the incremental cost of upgrading to a communicating thermostat at the time of installation. We also assumed that envelope upgrades could improve the performance of certain DR measures because a better-insulated building would allow greater load response while maintaining occupant comfort.

Based on the hourly system-level net load, DR-Path estimates the probability of DR despatch in any given hour, using statistical models developed in earlier work for shed [15] and shift [16] DR. DR Path multiplies each cluster end-use load shape by the hourly despatch probability for each type of DR and sums the result to yield the weighted average quantity of DR (kW of sheddable load or kWh of shiftable energy) that the cluster end use could provide in total, at times when DR is most likely to be dispatched. This quantity represents the DR *technical potential* for that cluster end use. The model then pairs the technical potentials with relevant technologies from the database of DR-enabling measures and computes the fraction of the technical potential that each technology pairing could deliver, along with the associated cost of installing the technology and operating it in the context of a DR program. The result is a large number of DR technological pathways, each of which has an associated DR resource size (kW of shed or kWh of shift DR) and total levelized cost ($/yr/kW of shed or $/yr/kWh of shift DR). At an array of different resource cost levels, DR-Path then selects the pathways that maximize the DR resource for each cluster end use. Summing the resource from these pathways at each cost level yields a system-level DR supply curve, representing the total quantity of DR that can be procured as a system resource at a given levelized marginal procurement cost.

2.4. Measuring EE and DR interactive effects

Interactions between EE and DR may be complex and occur on a variety of scales. To organize our consideration of these interactions, we rely on the EE-DR framework [19], which considers the impacts of a change on the demand side of the grid that is incurred by a particular EE or DR investment. The framework consists of two levels, representing different interaction scales: level 1 considers EE and DR interactions at the building level, and level 2 considers interactions at the grid-system level. Each level is further divided into two sublevels that explore distinct kinds of interactions, as described below. Importantly, a single change in the system may have different interactive effects (complementarity or competition) at different framework levels.

- Level 1a considers changes in DF at the individual building level. EE and DR competition occurs at this level if there is less flexible load available, whereas complementarity occurs when the amount of DF is increased.
- Level 1b considers changes in the proportion of building-level DF that is actually participating in DR. EE and DR competition occurs at this level if a smaller fraction of the DF is participating, and complementarity occurs when participation is increased.
- Level 2a considers changes in the *need* for DR at the grid-system level. EE and DR complementarity occurs at this level if EE reduces the need for DR at the system level, whereas competition occurs when the need increases.
- Level 2b considers changes in the *availability* of DR resources within the grid system. EE and DR competition occurs at this level if EE reduces the DR resource, while complementarity occurs if the DR resource is increased.

Because this work is focused on load-based interactions between EE and DR, we focus on levels 1a, 2a, and 2b of the framework. We do not consider level 1b, since it primarily focuses on behaviour-driven interactions.

At each level of the EE-DR framework we consider, it is important to define a clear set of metrics to assess EE and DR interactions. At level 1a, we consider changes in the building's technical DR potential, as estimated by DR-Path. At level 2b we examine changes in the DR-Path system-level supply curve, considering both the quantity and the cost dimensions of the curve, to assess changes in both the size of the DR resource and its potential cost-effectiveness. To assess EE and DR interactions at level 2a of the framework, we rely on a set of metrics that were recently developed by Murthy et al. [30], that provide various lenses to assess changes in the system-level need for shift and shed[10] DR. In particular, the level 2a metrics consider changes in the absolute size of extreme[11] net load peaks and ramps, which affects the short-term need for DR, as well as changes in the amount of excess peak load and ramping that shed and shift DR despatch would be expected to manage during those extreme events in lieu of supply-side resources, which affects the need for DR in the longer term; they also consider changes in the timing and seasonality of DR need, since these may impact decisions about DR program design. The level 2a metrics are summarized in Table 1, we refer readers to Murthy et al. [30] for more details on the development of these metrics and their rationale.

3. Results

To understand EE and DR interactions, it is helpful to first understand the impacts of EE in isolation. As we saw previously (Fig. 1), the EE measures generally reduce building loads, except that controls measures may yield increases in certain end uses (especially heating and cooling) at certain times of day. Fig. 3 shows the impacts of each modelled EE scenario on the system-level load shape, broken out by end use, for the example of ERCOT on the day of the 2016 system peak. The equipment-only scenario yields savings for all affected end uses in all hours, across a variety of end uses. The envelope-only savings are restricted to cooling and other HVAC loads and are concentrated in the middle of the day when the indoor-outdoor temperature differential is greatest. In the controls-only and controls-plus-envelope scenarios, the impacts vary by time of day and end use and even include overall *increases* in residential space cooling loads at certain times of day. These increases are driven by the thermostat strategy assumed for the residential sector, which uses temperature setbacks in the midday and overnight hours and temporarily increases cooling loads in the morning and evening to recover from temperature setbacks. Although there are package-specific differences in CAISO and ISO–NE compared to ERCOT, the EE packages result in qualitatively similar load shape impacts in all three regions. Informed by this understanding of the EE load shape impacts, in this section we examine the EE and DR interactive effects that occur in each scenario, at the various levels and sublevels of the EE-DR framework.

3.1. Level 1a: changes in responsive load at the building level

Level 1a of the EE-DR framework considers changes in the amount of DF that is available at the individual building level. As described in

[10] The level-2a metrics associate shed DR specifically with peak reduction and shift DR with mitigation of steep ramps. While it is true that shift DR can also provide peak reduction and that shed DR can mitigate ramps, the association used in the metrics identifies the most directly relevant use case for each type of DR. For instance, if a grid system has a need for peak reduction with no strong preference about the timing of offsetting load increases, this is a use case for shed DR, whereas demand ramps are most effectively mitigated by shifting energy consumption from one time to another, i.e., by an appropriately timed combination of load reduction and offsetting load increase.

[11] For the purposes of these metrics, extreme peak and ramp events are defined as the 100 highest load hours and 25 highest daily ramping events in the year, based on an assessment of the frequency of rare, extreme events in load duration and ramping duration curves, as discussed in more detail in Murthy et al. [30].

Table 1
Metrics to assess EE and DR interactions at level 2a of the EE-DR framework, which addresses changes in the need for DR at the grid-system level. For details on these metrics and their rationale, see Murthy et al. [30].

Application	Metric	Definition	Implications of changes in metric
Shed DR need	Peak demand	Peak system-level net load (gross demand less VRE generation), in MW	Changes in the short-term need for shed DR
	Peakiness	Amount of system net load, in MW, that only occurs in the top 100 net-load hours of the year	Changes in the long-term need for shed DR
Shift DR need	Routine ramping need	Maximum 3-hour net-load ramp, in MW, on the day with the 25th highest such ramp	Changes in the need for load-modifying shift DR
	Extreme ramping need	Amount of 3-hour ramping, in MW, that only occurs in the top 25 net-load ramping days of the year, in excess of the extreme ramping need	Changes in the need for dispatchable shift DR
Shed DR program design	Shed event days	Number of unique days represented in the top 100 net-load hours of the year	Changes in the duration and annual number of events expected in a shed DR program
	Shed season duration	Duration (in days) of the shortest period containing 80 of the top 100 net-load hours of the year	Changes in the seasonality of events expected in a shed DR program
Shift DR program design	Shift season duration	Duration (in days) of the shortest period containing 20 of the 25 highest net-load ramping days of the year	Changes in the seasonality of events expected in a shift DR program

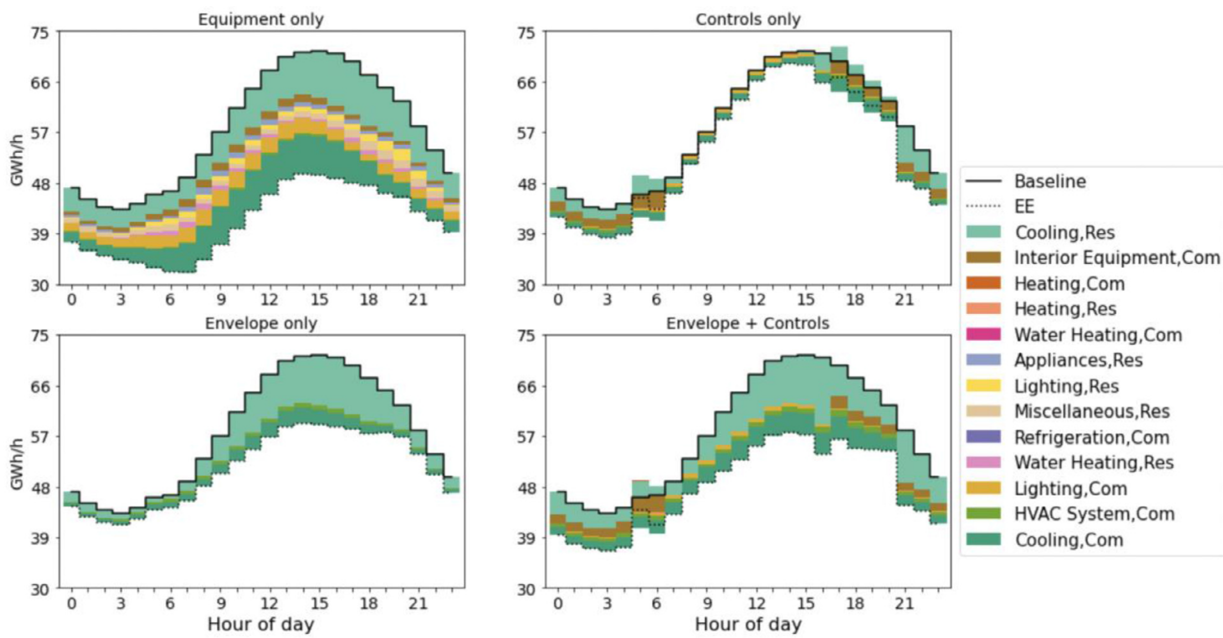

Fig. 3. Changes in the hourly system load shape induced by each EE measure portfolio, disaggregated by end use, for the example of ERCOT on the 2016 system peak day. Solid curves show the baseline system load shape, while dotted lines show the modified load shape that occurs in each EE scenario. Filled bars show the impact of EE savings from individual end uses. Bars that lie below the solid line in each panel are energy savings, while bars that lie above the solid line represent increases in consumption for that end use. The load shapes are presented in a stair step pattern to allow changes in individual end uses to be shown clearly as filled bars.

Section 2.2, DR-Path computes a large number of technological pathways to obtaining shed and shift DR from specific building end uses using particular technologies. For each representative building, we can select the pathways that maximize the building's DR resource; this represents the available building DF in each scenario. Changes to these DF values in the different EE scenarios represent EE and DR interactions at level 1a of the framework. Most often, we find that EE reduces DF at the building level, since EE reduces the overall demand that is present to provide flexibility. There are some important exceptions to this trend, however, and we observe wide variability in the scale of the interactive effects, driven largely by the coincidence of individual buildings' load shapes with times of system need for DR.

Fig. 4 shows how differences in load shape coincidence can yield variation in interactive effects at level 1a, for both shed and shift DR. The figure shows interactions for residential single-family detached homes at several locations in California. The EE measures reduce the building-level shift potential in all scenarios and the shed potential in most scenarios. The exception is the controls-only scenario, which slightly increases the shed DR potential for all buildings shown. This increase occurs because the temperature-setback EE strategy we modelled for residential programmable thermostats tends to increase cooling loads during the evening hours (see Fig. 1 and Fig. 3 [12]), coincident with California's net load peak. Fig. 4 also reveals significant geographic variability in the level-1a interactions, both in the overall size of the interactions, and in the relative impact of different EE scenarios. This variability is caused by climate-driven differences in the coincidence between building loads and system DR need, with hot inland locations (Bakersfield, Sacramento) generally having larger interactions than more moderate coastal climates (San Francisco, Los Angeles).

Fig. 5 shows how differences in coincidence can also yield significant variation in interactions by building type at level 1a. The figure shows interactions for an example set of commercial buildings, this time holding the geographic location fixed. Again, the most common interaction is competition, owing to the overall reduction in load, though there are

[12] Although these figures are for the example of Texas, qualitatively similar load shape impacts occur in the other regions as well, with increases in residential-sector load during summer evening hours.

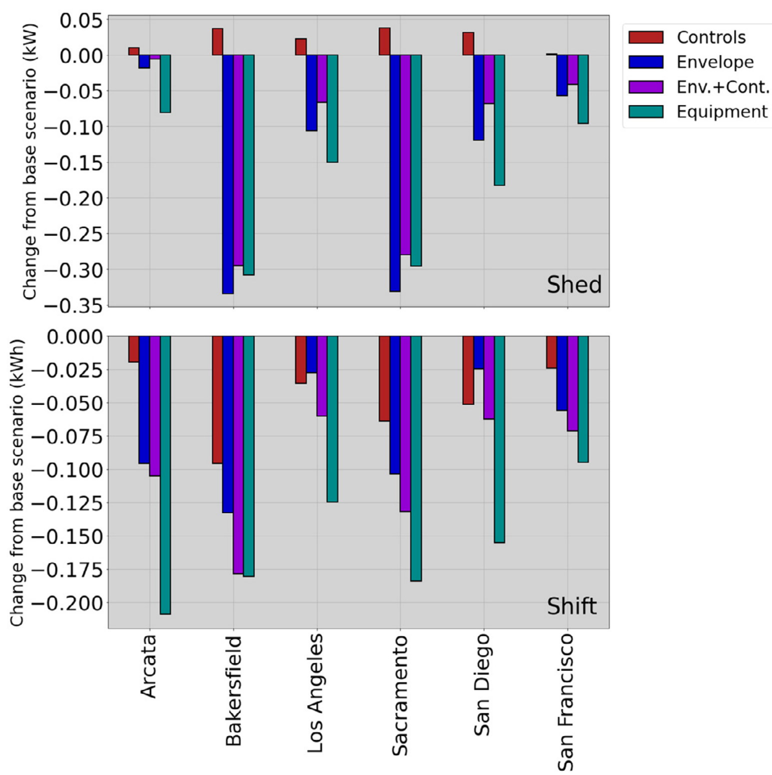

Fig. 4. Changes in the size of the building-level DR technical potential, for each EE scenario compared to the baseline, for individual single-family detached homes in several California weather locations. The top panel shows the change in the kW of load reduction a building could provide in a shed DR event, and the bottom panel shows the change in the average kWh of shifted energy consumption that the building could provide in a shift DR event.

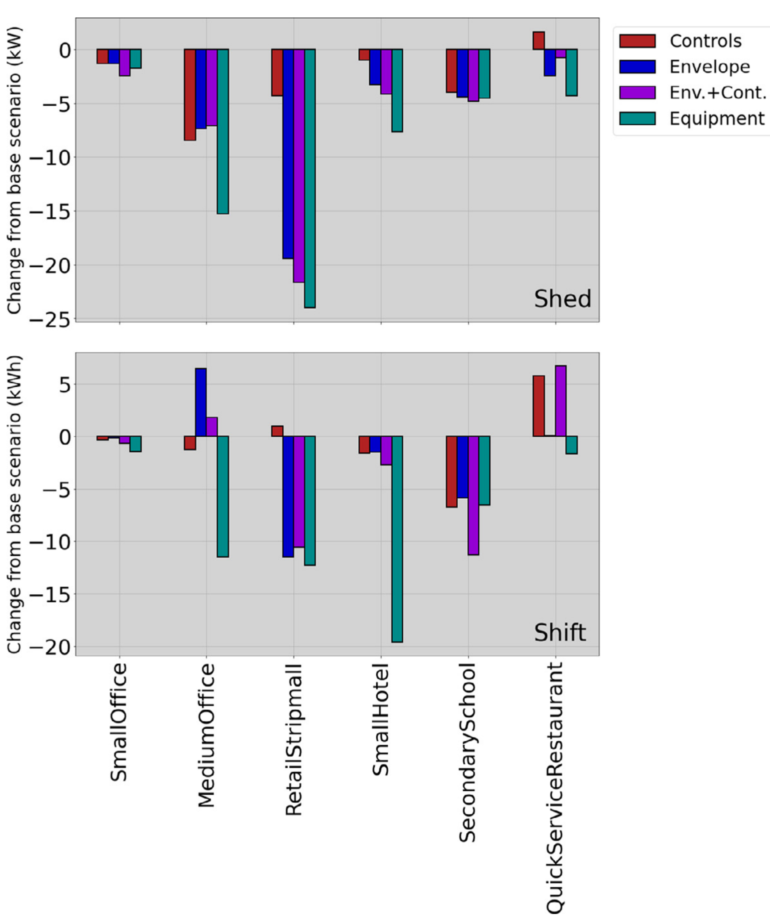

Fig. 5. Changes in the size of the building-level DR technical potential, for each EE scenario compared to the baseline, for different types of commercial buildings in an example ComStock geographic location (Los Angeles, CA). As in Fig. 4, the top panel shows changes in shed DR potential and the bottom panel shows changes in shift DR potential.

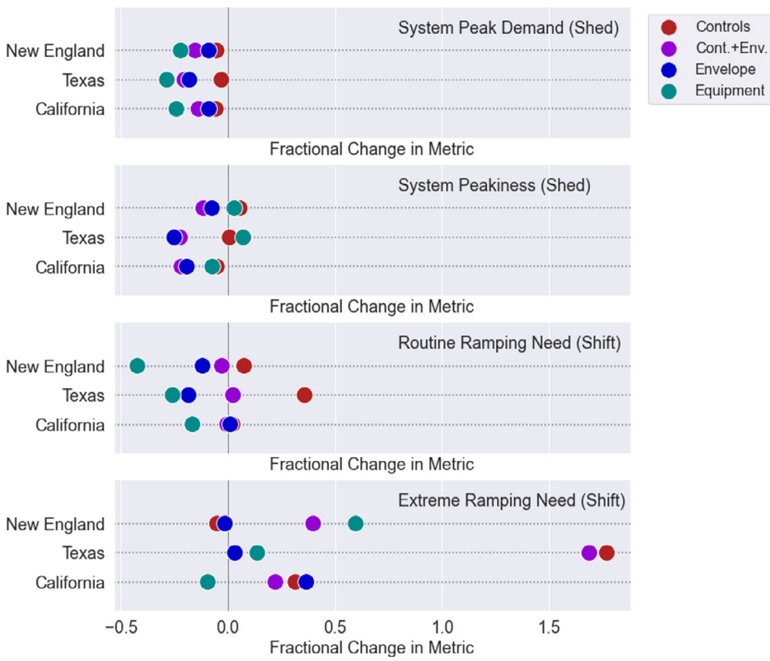

Fig. 6. Fractional changes in the metrics for system-level need for shed and shift DR resources (relative to the baseline scenario), for each region and EE scenario modelled in this study. Each dot represents the change in the relevant metric in a given EE scenario, relative to the baseline-scenario metric for the same region. In each case, a decrease in the metric indicates complementarity at level 2a of the EE-DR framework (EE reduces DR need), while an increase reflects competition.

interesting exceptions. Building types that have operations coincident with the evening system peak (e.g., quick-service restaurants) can have complementary EE and DR interactions in the case of controls-based EE measures that slightly increase loads during occupancy hours. Envelope EE measures can also complement shift DR in some cases (e.g., medium offices) because they limit passive cooling and yield a slight increase in evening cooling load during spring and fall, when steep net-load ramping is most acute in California. Notably, in all building types and sectors considered, the equipment-only EE scenario always yields competition with DR at level 1a of the framework, since it reduces loads across all hours and does not significantly alter coincidence with system load.

3.2. Level 2a: changes in the system-level DR need

Level 2a of the EE-DR framework considers changes in the need for DR at the grid-system level, which we assess using the metrics proposed by Murthy et al. [30], summarized in Section 2.3. The metrics can be categorized into those that consider changes in the system-level need for shed and shift DR and those that consider changes that might affect the design of DR programs. We consider each of these categories in turn in this section.

Fig. 6 presents the fractional changes in the metrics for shed and shift resource needs, relative to the baseline scenario, for each of our modelled regions and scenarios. Both the size and the direction of the interactions can vary widely amongst the metrics, regions, and scenarios. Considering the shed DR metrics, the EE scenarios always yield a reduction in the system peak demand, indicating a reduced short-run need for shed DR. In most cases, the peakiness metric is also reduced, indicating that the reduction in need for shed DR will persist in the long run, since there is a smaller total amount of load that needs to be carried in only the top 100 hours of the year. In particular, the scenarios that include envelope measures consistently reduce the peakiness because they tend to preferentially reduce on-peak summertime cooling load.

In a few other cases, however, the peakiness metric shows a small increase when EE measures are introduced, indicating competition between EE and shed DR in the long run. This occurs when the load is reduced across all hours, but the reduction is larger in the 100th-highest hour than in the peak hour, yielding an increase in the peakiness (for a more detailed discussion of this effect, see Appendix B). Such an increase in the amount of load that is only present infrequently would likely result in a more acute need for shed DR over the long run, since existing dispatchable supply-side resources would experience reduced capacity factors and correspondingly less revenue from generation, rendering them less economical to maintain and operate and more likely to be retired.

For shift DR, the level 2a interactions in Fig. 6 are more variable than they were for shed. In most cases, EE reduces routine ramping need, or leaves it largely unchanged, indicating a complementary or neutral interaction; this occurs because the EE savings are generally coincident with the daily system peaks and thus reduce the associated ramps, which also means that the interactive effects scale with the size of the energy savings produced in each scenario (i.e., the equipment-only scenario yields the largest interaction in each region). There are notable exceptions to this result for the controls-only scenario in Texas and, to a lesser extent, New England: the assumed residential controls strategy creates steep increase in residential heating load on winter mornings (see Fig. 1), which creates an entirely new type of steep ramping event, thereby increasing the amount of ramping that occurs on a frequent basis. It is important to note that different energy-saving controls strategies are possible, and an approach more carefully attuned to overall grid impacts might yield reduced competition.

The effects of EE on extreme ramping need are more complex and less orderly. In most cases, the extreme ramping need increases, indicating EE and DR competition, and in some cases the competition is quite severe, especially for the scenarios involving controls in Texas. (As noted above, different controls strategies may be able to mitigate this competition.) However, there is little consistency in the relative size or direction of the interaction for individual EE scenarios; for instance, the equipment-only scenario has the strongest competition in New England but the largest complementary effect in California. The significant regional differences and lack of consistent ordering by EE package from most to least complementary suggests that the details of system gross demand and VRE penetration are an important determinant of EE and DR interactions when considering extreme ramping need. The large and erratic effects observed for this metric suggest that a careful consideration of load shape impacts (including thoughtful development of controls strategies) is important when assessing EE and DR in a grid system that experiences significant challenges related to extreme ramping.

Fig. 7 shows interactive effects for the level 2a metrics related to DR program design. In all cases, EE increases (or leaves unchanged) the

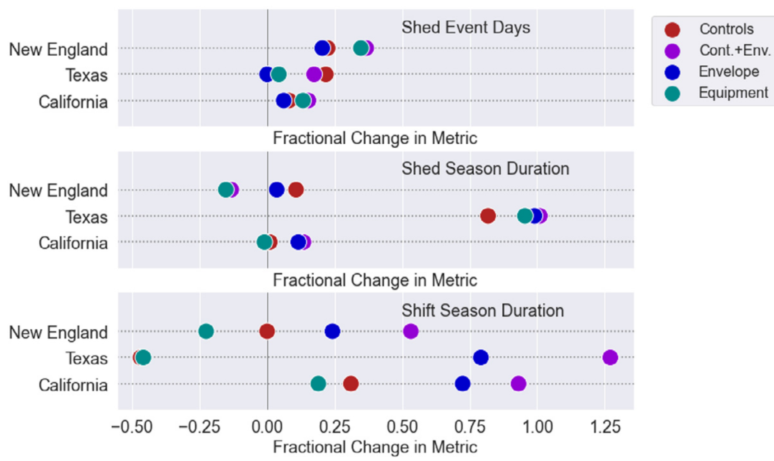

Fig. 7. Fractional changes in the metrics for impacts on DR program-design considerations (relative to the baseline scenario), for each region and EE scenario modelled in this study.

number of shed event days, suggesting that DR programs may need to call more frequent, though shorter-duration,[13] events in a more efficient system. The EE upgrades also increase the duration of the shed season in most cases (see Appendix B for a more detailed explanation of these effects). To the extent that these changes make DR participation less attractive to customers, they would represent competition between EE and DR, whereas they may be complementarity if customers are willing to endure shorter-duration events over a longer fraction of the year. For shift DR, the effects are, once again, more varied. More often than not, the shift season duration increases–sometimes dramatically–when EE measures are applied, implying competition between EE and DR on this metric. Notably, the envelope-only and controls-plus-envelope portfolios always increase the shift season duration, since they reduce cooling-driven summertime ramps, thus shifting some of the more extreme ramps into the spring and fall.

3.3. *Level 2b: changes in DR availability at the system level*

Level 2b of the EE-DR framework considers changes in the availability of DR at the system level. To assess changes at this level we consider the DR supply curves generated by DR-Path, which are strictly increasing two-dimensional curves that display the quantity of DR[14] that is available at times of system need, for a given marginal cost. It is important to consider changes along both dimensions of the supply curve because both cost and quantity determine the amount of economic DR to procure in a given system. The supply curve depends on four factors that can be influenced by EE: the *size* of the load, its *coincidence* with times of system need, the *cost* of DR-enabling technologies, and the *capability* of those technologies to shed or shift load. Appendix B presents examples of how EE impacts can play out along the supply curve for individual end uses. At any point on the supply curve, EE can increase or decrease both the cost and the quantity of DR, and the size and direction of the changes may differ for different end uses. This dynamic means that EE and DR interactions at level 2b can vary in complex ways at different points along the supply curve.

To focus on the interactions that are most likely to be important in practice, we developed real-world cost benchmarks for shift and shed DR. In general, a useful cost referent for DR is the marginal procurement cost of a traditional generation or storage resource that can provide the same grid service; a DR resource would typically need to be less costly than this to be cost-effective. A natural supply-side analogue for shed DR is a natural gas combustion turbine peaker plant, and for shift DR the closest equivalent is a behind-the-metre battery. Using cost estimates from the literature for generation and storage technologies [38,39], we estimated approximate levelized costs[15] of \$100/yr/kW for the peaker plant, and \$100/yr/kWh for the battery, with an uncertainty of around a factor of two in each case. To focus on DR resources that are likely to be cost effective compared to comparable physical infrastructure, for the remainder of this paper we will examine EE and DR interactions for “low-cost” DR resources, at a cost of \$50/yr/kW for shed and \$50/yr/kWh for shift DR.

Fig. 8 shows the change in low-cost shed and shift DR potential, in each grid region and EE scenario relative to the baseline. The equipment-only and envelope-only scenarios yield a reduction in DR resource in all cases, indicating competition at level 2b, because these EE portfolios reduce loads without increasing their controllability. By contrast, the controls scenarios always increase the low-cost DR resource–more than tripling it in the case of shift DR in California–indicating EE and DR complementarity. This occurs in part because controls-based EE measures increase building-level DF by increasing controllability. This effect manifests in the DR supply curve as a reduction in DR cost: as discussed in Section 2.2, the controllability costs are included in the EE upgrades, and the cost of enabling DR is limited to the incremental cost of adding communication technology. The envelope-plus-controls portfolio is intermediate between the two extremes, with a more muted competitive effect in most cases but a strong complementary effect for shift DR in California. This is driven both by reduced DR enablement cost stemming from the controls measures, as well as by an augmented DR capability at the building level owing to the envelope upgrades.[16] Every interaction shown in Fig. 8 is driven by underlying changes at the end-use level that offset or augment each other in complex ways; Appendix B presents these interactions in more detail.

3.4. *Overall level 2 interactions*

EE and DR are either competitive or complementary at levels 2a and 2b of the EE-DR framework, depending on the details of the grid system and EE measure portfolio. From a planning and procurement perspec-

[13] To the extent that both the peak and peakiness metrics are reduced, these events may also be smaller in magnitude.

[14] I.e., the GW of available demand that can be reduced on average in a shed event, or the GWh of energy consumption that can be moved temporally on average in a shift event.

[15] Costs in the DR-Path supply curves are the annualized marginal cost of procuring an additional kW of shed DR or kWh of shift DR, discounted assuming a 7% cost of capital. We present the costs in units of \$/yr/kW for shed and \$/yr/kWh for shift to emphasize the annualized, per-unit nature of the costs. These units can also be written equivalently as \$/kW-yr and \$/kWh-yr respectively. See Appendix B for further discussion of the cost units.

[16] As discussed in Appendix A, our assumptions about this increase in DR capability are fairly conservative, so the complementary effects may be even larger than shown here in certain contexts.

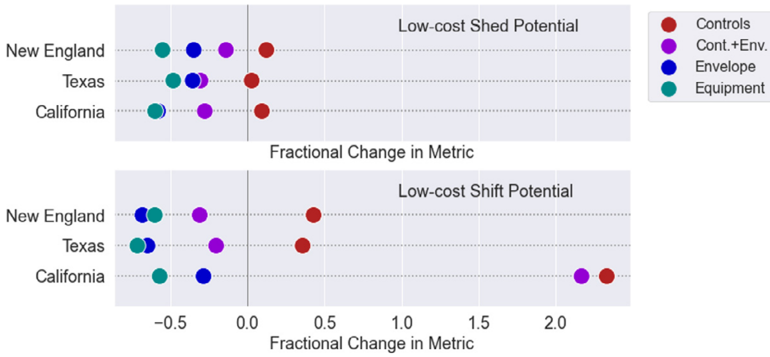

Fig. 8. Fractional changes in the low-cost resource size for shed (top) and shift (bottom) DR (relative to the baseline scenario), for each region and EE scenario. In each case, an increase in the metric indicates complementarity at level 2b of the EE-DR framework (EE increases the DR resource), while a reduction in the metric indicates competition.

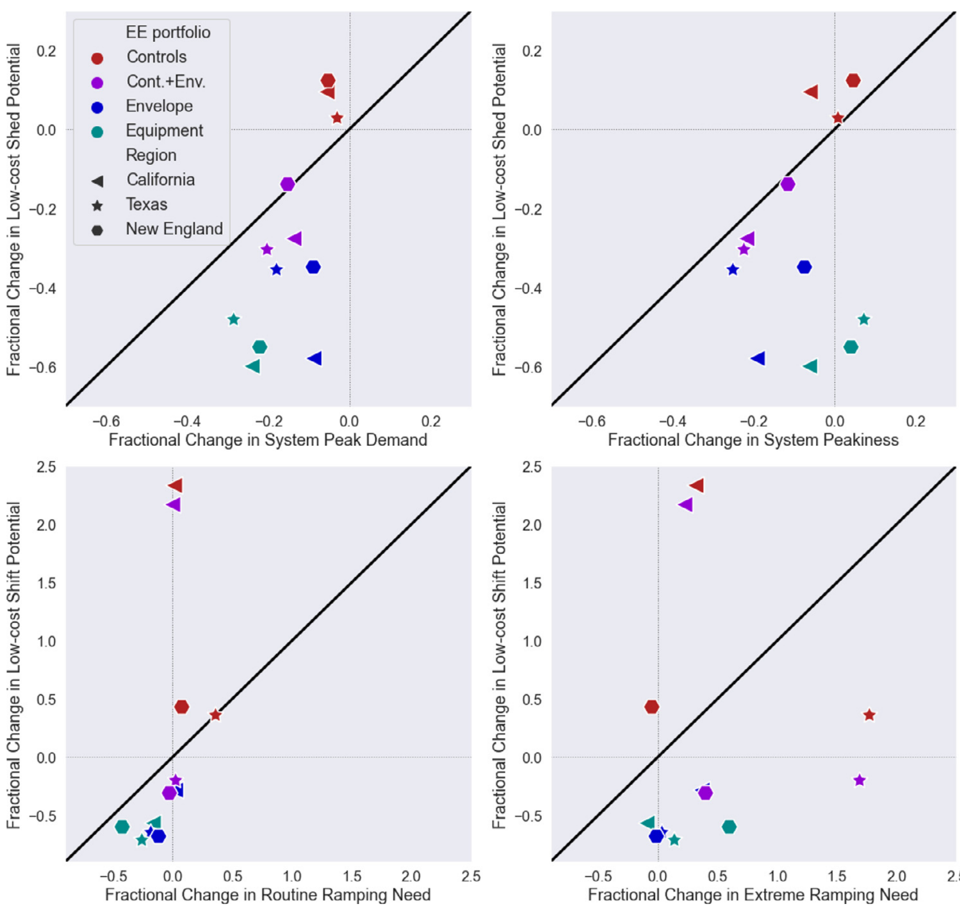

Fig. 9. Plots showing the overall EE and DR interactive effects at level 2 of the EE-DR conceptual framework, for all combinations of shed and shift metrics at level 2a (horizontal axes) and level 2b (vertical axes). Points show the fractional change in the metric (relative to the baseline scenario) along each axis. Solid diagonal lines show the locus of neutral interactions. Points above this line exhibit overall complementarity at level 2, and points below it display overall competition.

tive, it is important to consider the net effect of these interactions, since identifying and securing the economic DR resource in a grid system requires understanding both how much DR is needed and how much is available. To explore this interplay, Fig. 9 plots the level 2a effects (Fig. 7) against the level 2b effects (Fig. 8) on a two-dimensional plane, for each combination of shift and shed metrics. In each panel, a solid diagonal line indicates the locus of EE and DR neutrality, where there is no overall impact at level 2 because any competitive effects at one level are exactly offset by complementarity at the other (e.g., the need for DR is reduced by the same factor as the available resource). The region above the solid line represents overall EE and DR complementarity at the grid-system level, while the region below the line represents overall competition.

Competition is the most common outcome at level 2 for the regions and scenarios modelled in this study, and it always occurs for the equipment-only and envelope-only scenarios, regardless of region or DR type. Complementary or near-neutral[17] effects are apparent in almost every case, however, for the controls-only portfolio and in several cases for the controls-plus-envelope portfolio. In addition, adding controls to the envelope-only portfolio can mitigate EE and DR competition: in most cases the controls-plus-envelope scenario sits closer to (or on the opposite side of) the line of neutrality than the corresponding envelope-only scenario.

To understand the drivers of net interactions at level 2, it is helpful to consider the four quadrants demarcated by the dotted lines in each panel of Fig. 9. The upper left quadrant indicates portfolios that increase the DR resource and reduce the need. Such robust complementarity is rare and limited to the controls-only scenarios. Conversely, the lower right

[17] In competitive cases that lie near the line of neutrality, slight changes to the specific EE portfolio we modeled could potentially mitigate the competition.

quadrant indicates competition at both sublevels. Such robust competition is also relatively rare, except in the case of shift DR to mitigate extreme ramping, suggesting that a careful and integrated approach EE and DR program development is particularly important when there is an acute need to address extreme ramps. Most scenarios fall in the upper right and lower left quadrants, where competition at one sublevel outweighs complementarity at the other, or vice-versa. In these cases, there may be an opportunity to mitigate or eliminate competition with a careful approach to planning EE portfolios and DR programs.

Finally, although portfolios incorporating controls generally yield complementarity at level 2, a significant exception is evident for shift DR to meet extreme ramping need (bottom right panel of Fig. 9). There, the scenarios including controls in Texas show the largest overall competition of all the scenarios considered, in dramatic contrast to the case of California, where controls drive extreme complementarity. This outcome illustrates that the specifics of a particular grid system and building population can have a strong influence on EE and DR interactive effects.

4. Discussion

Our findings indicate a complex interactive relationship between EE and DR, which depends on the details of the grid system, building stock, and portfolio of EE and DR measures employed. We find no fixed overall relationship between EE and DR: EE and DR competition and complementarity are both possible at every level of the EE-DR framework. We also find that the details matter considerably. Interactive effects vary significantly amongst different EE portfolios, and for a given portfolio the interactions can vary substantially, in size and sometimes in direction, depending on climate, building type, and the grid system being considered. Because of this variability, a thorough assessment of EE and DR interactions in a real-world grid system would require granular modelling of the building stock, similar to what we have undertaken here, which is a substantial task. Moreover, the results we present in this study are dependant on specific assumptions we made when characterizing EE and DR measures, and measure portfolios with different characteristics may yield qualitatively different interactions.

Nevertheless, it is possible to distil from our analysis some general principles to guide grid-system planners, utility program designers, and regulators in considering EE and DR interactions when planning future EE and DR resource portfolios. Although our modelling in this study focuses on three specific regions of the US grid, we expect the broader principles we discuss here will be applicable in other regions both within and outside the US. As elsewhere, it is helpful to use the EE-DR framework as an organizing structure, so we will discuss each analysed level of the framework in turn before summarizing the broader implications for utility resource planning and program design.

At level 1a of the framework, we saw that the interaction between EE and DR at the building level can vary dramatically with climate and building type, with the same EE portfolio sometimes yielding opposite results in different contexts (see Fig. 4 and Fig. 5). Broadly speaking, however, EE and DR competition is the most commonly observed interaction at the building level, and exceptions to this trend are limited. Specifically, the equipment-only EE portfolio we modelled always competes with DR at level 1a, whereas portfolios that include controls or envelope measures can sometimes complement DR in certain contexts. The central driver of these interactions is the coincidence of the EE load impacts with times of system need for DR. As seen in Fig. 1, equipment-based measures tend to reduce building load in all hours of the day, which necessarily reduces the load available to provide DR. By contrast, measures involving envelope improvements and controls can shift the timing of certain end-uses, which may increase building load in certain hours (this is especially evident for the residential controls strategies we modelled here). Depending on the particulars of a building's operation schedule, these load increases may coincide with times when DR is likely to be dispatched, thus increasing the building's overall DR resource. These observations underscore that a detailed understanding of the building stock is essential to a thorough understanding of EE and DR interactions. Absent such detailed knowledge, EE and DR competition can be presumed to occur at the building level, since this is the most common outcome.

At level 2a of the EE-DR framework, we found that EE can also interact with the system-level need for DR in complex and varied ways. In a few cases, the interactions are straightforward and consistent. For instance, all modelled EE scenarios reduce the system-level need for shed DR to reduce system peak load (see Fig. 6).[18] This is a manifestation of the system benefit that EE provides by reducing system peak load in addition to overall energy consumption, which is a long-recognized form of EE and DR complementarity [40]. The EE scenarios also all increase the number of shed event days (Fig. 7), indicating a need for programs to target customers who can tolerate more frequent (though shorter duration) events. For all other metrics at level 2a, however, we find that EE can either compete with or complement DR, depending on the specific metric, EE portfolio, and grid system in question; and the interactions can vary significantly in both size and direction. The importance of these interactive effects for a given grid system depends on the existing DR needs and program designs within the system. Thus, it is important to have a firm understanding of present and expected future DR needs and programs when embarking on an integrated approach to EE and DR program design.

The cases of extreme ramping need in California and Texas illustrate the importance of considering grid-system specifics when assessing EE and DR interactions at level 2a. With its large and growing solar generation resource, California has a growing need for shift DR [16], but existing DR programs are focused primarily on shed. Our results at level 2a show that EE always complements shed DR in California, by reducing both peak and peakiness; however, most EE scenarios yield an increased need for shift DR to manage extreme ramps, and all scenarios extend the duration of the shift season. Focusing on interactions of EE with the present (shed) DR resource instead of the future (shift) DR need could yield unintended negative consequences in this case. In Texas, the residential thermostat setback strategies we modelled in the EE portfolios involving controls create new extreme ramping events on cold winter mornings; this may be a significant unintended drawback for grid management. A controls strategy that accounted more carefully for the aggregate load shape impacts might reduce these outcomes while still saving energy. By contrast to California and Texas, New England, with its low VRE penetration, has a limited need for shift DR in our model, so significant EE competition with shift DR at level 2a may be tolerable in exchange for the benefits that EE provides.

At level 2b of the framework, we consider the system level availability of DR as represented by the DR supply curve. EE can drive changes in both the quantity and the cost of DR, and the size and direction of these effects may be different for different end uses. At cost levels that are likely to be relevant in real-world scenarios, the aggregate effect is most often EE and DR competition at level 2b (Fig. 8), with the notable exception of EE scenarios involving controls, where complementarity is possible. In the specific case of shift DR in California, portfolios incorporating controls drastically increase the system-level resource, owing primarily to a reduction in DR enablement cost, which offsets any reductions in available load. As this example illustrates, in any assessment of EE and DR interactions at level 2b of the EE-DR framework it is important to consider impacts along both the quantity and the cost dimensions

[18] One may also notice that the relative size of the impact from EE measure portfolios also always comes in the same order, with equipment-only measures always having the largest impact and controls-only measures the smallest. However, this is primarily because of variation in the scope of the different portfolios: the equipment-only portfolio is the most extensive portfolio we model, with the largest overall energy savings, while the controls-only portfolio has the most limited scope and savings. A different set of portfolios might yield interactions with different relative sizes.

of the supply curve, rather than focusing only on reductions in the total responsive load.

Because many measure portfolios exhibit complementarity at level 2a of the framework but competition at level 2b (or vice-versa), we also examined the net interactive effects at level 2 of the framework. We found that the most common outcome was EE and DR competition at level 2, but EE measure portfolios involving controls could yield complementarity in many cases (Fig. 9). We also found that adding controls to a static EE portfolio could substantially mitigate EE and DR competition, although the effect varied considerably by grid region and DR type. These results suggest that the judicious use of controls measures will be an important part of developing EE portfolios that minimize competition or are complementary with DR.

Taken as a whole, our results suggest some important principles that can aid grid planners, utility program designers, and regulators in designing future EE and DR portfolios in the context of a given grid system. First, to properly assess the significance of EE and DR interactions, it is important to have a clear understanding of the present and expected future need for DR within the system, as well as of the evolution of loads that may be able to provide DR. For example, if shift DR is unlikely to be heavily used in the future, then strong competition of EE with shift DR may be tolerable in exchange for the EE benefits; whereas such interactions may be unacceptable in a system with a high need for flexibility, pointing to a need for a more appropriately tailored EE portfolio. Next, to develop EE and DR portfolios in a way that avoids significant competition–or even drives complementarity–it is helpful to have a fine-grained model of the underlying building end-use loads and the potential load shape impacts of different EE measures. Such modelling is increasingly available to planners and program designers using either advanced building simulation tools, as utilized in this study, or advanced utility metre data, as pioneered in studies of the DR resource in California [15,16,41]. Even absent such a detailed building-stock model, however, our results illustrate that an emphasis on dynamic EE measures, such as controls technologies, is an important aspect of EE portfolios can avoid competition with DR and promote complementarity, whereas portfolios that focus solely on static EE measures, such as equipment upgrades, may compete with DR and yield reduced value or sharpen grid management challenges in systems with a high need for flexibility.

Understanding future changes in the building stock and the system need for DR is especially important in the context of efforts to decarbonize buildings and the grid. Historically, EE has been a central policy tool for reducing emissions from buildings, and it also has an important role to play in decarbonizing power-grid emissions when deployed in concert with renewable generation [8]. Meanwhile, the growing penetration of VRE in generation portfolios is driving changing the nature of the DR resources that are needed to support grid operations [12]. Our results indicate that there may be significant interactive effects between EE and DR, and they suggest that the size, direction, and importance of such effects may evolve dramatically as VRE penetration grows. In addition, thorough decarbonization of the building sector will require widespread electrification of present-day fossil-fuel end uses. This will have substantial impacts on system-level load shapes and may lead to profound changes the nature and the timing of DR need, as well as the customers and loads that can provide DR. Although the impacts of future VRE growth and electrification are beyond the scope of the present study, the interactive effects between these decarbonization efforts and DR can be analysed using the same conceptual and analytical approaches we developed here, and this will be an important topic for future research.

Finally, it is important to recognize that the presence of EE and DR competition does not necessarily imply that a grid system is worse off on a cost, emissions, or reliability basis. Both load reductions and increased demand-side flexibility are likely to provide value to the grid; however, the consideration is whether the benefits of EE and DR in combination are smaller (i.e., competition) or greater (i.e., complement) than the sum of each in isolation. At the same time, we saw that it is important to consider interactions between EE and DR along the dimension of cost as well as resource size, since EE may increase the DR resource at low costs, even if it reduces the overall technical potential. This interplay of benefits and costs has important implications for approaches to calculating the cost-effectiveness of EE and DR programs. EE has historically been found to be a highly cost-effective grid resource [42], but if EE benefits are eroded through competition with DR, the cost-effectiveness of EE may be tempered somewhat. By contrast, if EE and DR are complementary, then an integrated analysis may indicate larger cost-effective EE and DR resources than would be recognized in a framework that values each resource individually. Regulators and utility program administrators should thus aim to employ cost-effectiveness frameworks that account for both the EE and the DR benefits accruing from measures that can enable both resources.

5. Conclusion

We investigated interactions between EE and DR that are driven by changes in load at the building level or the power-system level. Using an extensive set of building simulations coupled with real-world building-stock and power-system data, we constructed a detailed, bottom-up model of residential and commercial building loads in three regional grid systems. In addition to a baseline scenario representing the present-day building stock, we modelled four illustrative scenarios representing different portfolios of EE measures applied to the building stock. In each scenario, we examined the ways in which the EE upgrades compete with or complement various aspects of shed and shift DR in each system. Using a previously developed EE-DR conceptual framework to organize our assessment, we considered EE and DR interactions at the individual-building scale and the power-system scale.

Overall, we found no fixed relationship between EE and DR: depending on the details of the EE portfolio, the grid system, and the type of DR being considered, EE and DR can compete with or complement each other at every level of interaction we considered. Across all levels of the framework, EE and DR competition was the most commonly observed interaction, with especially strong competition observed for EE portfolios that focus only on upgrading equipment. However, significant overall complementarity is also possible in certain scenarios, particularly for EE portfolios that include controls technologies. Similarly, EE measures that reduce DR enablement costs (e.g., programmable communicating thermostats) can increase complementarity in many instances. Finally, in the case of controls measures, it may be possible to develop energy-saving operational strategies that avoid the kind of unintended competition with DR we observed in some cases (e.g., for the residential thermostat strategies we modelled in Texas), and potentially drive further complementarity, by taking into account the coincidence with DR potential at the building and system levels.

Our findings suggest certain key considerations for regulators, grid planners, and utility program designers when developing demand-side resource portfolios. It is important for utilities and regulators to have a thorough understanding of the grid-system need for DR, as well as detailed knowledge of the particular end uses and technologies in the building stock that can provide DR, as well as how both of these are likely to evolve in the future, in order to develop complementary EE and DR resources. As a general rule, however, EE portfolios that incorporate EE controls-based measures may avoid excessive EE and DR competition and encourage complementarity. We emphasize that the presence of EE and DR competition does *not* imply that a grid system would be harmed by implementing EE or DR. In fact, EE and DR may have significant benefits, even when in competition, although the competition may reduce those benefits compared to what each resource would provide on its own. Developing an integrated approach to assessing the costs and benefits of EE and DR can help ensure that interactive effects are properly accounted for.

We presented a detailed consideration of EE and DR interactions that may be driven by EE induced changes in the load shape of residential and commercial buildings, considering the problem across various scales from the building level to the grid system level. Although this represents the most detailed analysis of EE and DR interactions to date, there are several additional facets of the problem that warrant further study. First, our study is limited to residential and commercial buildings with present-day load profiles and generation resources. Study of EE and DR interactions in the context of industrial-sector loads, electrified building loads, and increased renewable generation would provide important additional understanding. Second, we have not considered how EE and DR interact in terms of customers' willingness to participate in utility programs or to adopt EE and DR technologies; behavioural research into joint customer decision making regarding EE and DR may reveal important new interactions. Finally, the question of whether and to what degree EE and DR interactions matter for system costs and emissions is best addressed by detailed modelling of grid despatch and capacity expansion, which are a critical input in regulatory cost-effectiveness frameworks. While modelling such effects is beyond the scope of this study, they will be important components of future work in this area.

Data availability

The modelled building-level and system-level load shapes developed in Section 2.1 for the different EE scenarios are available for public download on Mendeley Data [45].

Declaration of Competing Interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Details of the building modelling

This appendix presents the details of the building types, electrical end uses, and EE and DR measures that we used in our modelling in this study Table 2. lists the set of building types that we simulated in ResStock and ComStock,[19] and Table 3 lists the specific electrical end-uses that were included in the simulations.

[19] Owing to some limitations in the ComStock model at the time this work was completed, we were unable to model a supermarket building type in the commercial sector. Load from such buildings was included in our model among the undifferentiated "other" load described in the scaling methodology below.

Table 4 and Table 5 detail the EE measure portfolios used to model our various EE scenarios in ResStock and ComStock, respectively. The equipment and envelope portfolios are made up of static energy-conserving measures that reduce either equipment energy consumption or heating and cooling losses. The controls portfolio, by contrast, is made up of operational strategies that use controls to reduce electricity consumption during certain pre-set hours (e.g., when the building is not occupied). The controls measures significantly modify the underlying load shapes, which gives them a strong conceptual similarity to DR measures. As discussed in the Introduction, however, we define EE as a persistent and sustained reduction in energy consumption, while DR is a short-term change in energy consumption in response to a signal or incentive. The controls-based EE measures are thus distinguished from DR measures by the fact that they employ energy-conserving strategies that are the same from day to day, focusing on energy conservation, not strategies that respond dynamically to despatch or price signals to support short-term grid needs (indeed, they may conflict with certain grid needs, as seen in Fig. 6). However, as noted in Section 2.2, the presence of controls-based EE measures can reduce the cost of DR enablement, since deploying a DR measure then requires only a change in strategy on the existing controls technology.

Table 6 and Table 7 present cost and performance assumptions for the DR measures used as inputs to the DR-Path model for the residential and commercial sectors, respectively. The measures are characterized according to their cost to the DR program administrator (e.g., utility or aggregator) and their capability to shed and shift load over various time periods. We developed these assumptions based on a recent study of demand-flexibility technologies [43], and certain product-specific specifications contained in the EPA ENERGY STAR connected criteria [23], augmented where necessary by data from the most recent CPUC DR Potential Study [16]. The specific cost and performance inputs are as follows:

- *Fixed costs* are constant up-front costs for purchase and installation that apply at the level of an individual building regardless of the overall size of the load. For instance, the cost of purchasing a new appliance to install in a home would be a fixed cost per home.
- *Variable costs* are up-front costs that vary with the size of the load (measured in terms of the peak kW of demand). For instance, the

Table 2
The list of building types simulated in ResStock and ComStock for this study.

Sector	Building Type
Residential	Single-family detached
	Single-family attached
	Multi-family with 2–4 units
	Multi-family with 5 or more units
	Mobile home
Commercial	Small office
	Medium office
	Large office
	Retail stand-alone
	Retail strip-mall
	Quick-service restaurant
	Full-service restaurant
	Small hotel
	Large hotel
	Hospital
	Outpatient health-care
	Primary school
	Secondary school
	Warehouse

Table 3
The list of electrical end uses simulated in ResStock and ComStock for this study. In some cases, the models provide a finer level of detail that has been aggregated here. Some of these end uses are further aggregated into groups in certain contexts; where applicable these groupings are specified in the table notes.

Sector	End use	Description
Residential	Cooling	Central air conditioners (ACs), mini-split ACs, room ACs, and associated air handler fan electricity
	Heating	Electric-resistance heaters and heat pumps, and associated air handler fan and boiler pump electricity
	Lighting	Interior and exterior lighting
	Water Heating	Residential electric-resistance and heat-pump water heaters
	Clothes Dryer*	Residential electric clothes dryers (and electricity used by gas clothes dryers)
	Clothes Washer*	Residential clothes washers
	Dishwasher*	Residential dishwashers
	Cooking*	Electric ranges and range hoods
	Refrigeration*	Residential refrigerators and freezers
	Pool Pump†	Residential pool pumps and spa pumps
	Plug Loads†	Electronics and miscellaneous electrical plug loads
	Other†	Miscellaneous loads not otherwise specified (e.g., ceiling fans, bathroom fans, pool heaters)
Commercial	Cooling	Space cooling equipment (e.g., rooftop ACs, package terminal ACs, chillers)
	Heating	Space heating equipment (e.g., electric resistance, heat pumps)
	HVAC system	Ventilation fans, heat rejection and recovery systems, HVAC pumps, humidification, etc.
	Lighting	Interior and exterior lighting
	Refrigeration	Commercial refrigerators and freezers
	Interior Equipment	Electronics and miscellaneous loads not otherwise specified
	Water Heating	Commercial electric water heaters

* Sometimes grouped together as “appliances” for display purposes.
† Sometimes grouped together as “miscellaneous” for display purposes.

Table 4
Summary of detailed measures used to model the EE measure portfolios in the residential sector. In each case, measures are applied to all buildings that have less efficient building elements in place in the baseline scenario. 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 dependant)
	Basement/crawlspace insulation	Upgrade insulation (R-13 to R-30 depending on climate and construction)

Acronyms—SEER: seasonal energy efficiency 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.

cost of a thermal energy storage system scales with the size of the cooling load that it would be used to manage.
- *Operating costs* are the annual costs of operating a DR-enabling measure to provide DR. For most measures these costs represent costs for software licensing or subscriptions to provide automated controllability in response to a despatch signal.
- The *co-benefit fraction* represents the fraction of the costs that would be expected to be borne by the customer because the measure provides some co-benefit at the site. For example, many measures also provide energy savings or improved automation of site operations. This parameter can also be thought of as an assumption about the typical fraction of the total cost that would be provided as a rebate from the DR program.
- The *instantaneous shed fraction* is the fraction by which the measure could reduce the controlled load instantaneously in response to a despatch signal. This is used to scale the variable costs in computing the cost of installing a particular measure at a site.
- The 1, 2, and 4-hour *shed fractions* are the fractions by which the measures could reduce the controlled load in response to a DR event having a particular duration (corresponding to either the entirety of a shed event or the load-reduction portion of a shift event), while maintaining a minimum acceptable level of service.
- The *shift window* is the maximum period of time over which the measure could execute a load shift. For instance, an eight-hour shift window represents a load shift consisting of four hours of load reduction adjacent (in either direction) to four hours of load increase. The shift window is set to zero for technologies that cannot execute a controlled shift (i.e., that cannot be dispatched both to reduce and to increase load at specific times).

Table 5
Summary of detailed measures used to model the EE measure portfolios in the commercial sector. In each case, measures are applied to all buildings that have less efficient building elements in place in the baseline scenario. EE metric and technology acronyms are defined in a note at bottom.

Portfolio	Affected building element	Upgrade
Equipment only	Air conditioners (AC) and air-source heat pump (HP) units	Rooftop AC: Replace with efficient unit (IEER 17)
		Rooftop HP: Replace with efficient unit (IEER 16.5)
		Split-system AC: replace with efficient unit (SEER 18)
		Packaged terminal AC/HP: Replace with efficient unit (EER 10.45–13.1 depending on capacity)
	Chillers	Replace with efficient unit compliant with anticipated 2035 building code (min. full load efficiency 0.53–1.16 kW/ton, depending on compressor type and capacity)
	HVAC system	Add or upgrade components to conserve energy:
		Add air-side economizer for AC systems having non-DOAS outside air intake in appropriate climate zones
		Add water-side economizer for chiller systems
		Add heat recovery equipment for AC and HP systems
		Replace existing cooling towers with variable-speed units
	Motors	Replace existing motors with ECMs (except those used for service water heating or refrigeration)
	Pumps	Add VFD to existing pumps
	Lighting	Upgrade compact, linear, high-bay, speciality, and outdoor lighting to LED lighting
	Computers	Replace 50% of desktop computers in office spaces with laptops
	Electric water heater	Upgrade all small (<50 gal.) electric water heaters to heat pump water heaters (EF 3.5)
Controls only	HVAC system	Add controls and implement strategies to conserve energy:
		Enable DCV to adjust outdoor air intake based on occupancy
		Close outdoor air damper during <5% occupancy
		Interlock exhaust fan with supply fan to reduce outdoor air need
		Supply temperature reset: raise supply air temperature as outdoor air temperature drops
		Reduce VAV box minimum airflow to 0.4 cfm/sf
	Packaged terminal AC/HP	Adjust operating schedules based on occupancy
	Thermostat	Upgrade all zones with thermostats to predictive thermostat control, which adjusts set points during low-occupancy (<10%) periods
	Chilled/hot water loops	Supply temperature reset: lower supply temperature setpoint as outdoor air temperature rises, and vice-versa
	Kitchen exhaust fan	Enable DCV to reduce exhaust fan speed during low occupancy
	Lighting	Add occupancy controls to all spaces
		Add daylighting controls to selected perimeter zones
	Computers	Eliminate computer energy consumption when not in use during unoccupied periods
	Plug loads	Add advanced power strips, which reduce electric equipment energy use during unoccupied periods
Envelope only	Roof insulation	Upgrade all roofs with lower insulation levels to R-30
	Wall insulation	Upgrade all walls with lower insulation levels to R-13
	Windows	Upgrade all exterior windows with current U-factor >1.77 to windows with U-factor 0.31, SHGC 0.58, and VLT 0.70
	Roof	Upgrade all roof surfaces with current thermal emittance <0.75 to cool roof material with thermal emittance 0.75 and reflectance 0.45

Acronyms—EER: energy efficiency ratio; SEER: seasonal energy efficiency ratio; IEER: integrated energy efficiency ratio; DOAS: dedicated outdoor air system; ECM: electronically commutated motor; VFD: variable frequency drive; EF: energy factor; DCV: demand-controlled ventilation; VAV: variable air volume; SHGC: solar heat gain coefficient; VLT: visible light transmittance.

In the commercial sector, some DR measures are only applied to certain building types and sizes where the measure would be appropriate: for instance, PCTs are only applied to small commercial buildings, since energy management systems would be more appropriate in medium and large buildings. In some EE scenarios, we adjusted the fixed and variable up-front costs for certain measures to reflect that some of the cost would be accounted for when installing the EE measure, so that a DR program would only need to pay the incremental cost for DR-enablement. We also assumed that envelope EE measures could improve the performance of certain DR measures related to controlling HVAC loads because improved thermal stability can permit deeper load shedding. To estimate the size of this effect we relied on a study of pre-cooling as a DR strategy in real buildings, which found a roughly 10% increase[20] in load shedding capability for well-insulated buildings [44].

Appendix B. Detailed example interactions at framework levels 2a and 2b

In Sections 3.2 and 3.3 we saw several interactive effects at levels 2a and 2b of the EE-DR framework that may be difficult to understand intuitively. This appendix presents illustrative examples of these interactions in more detail. First, we show how changes in the load shape lead to the observed changes in certain level 2a metrics. Then we show examples of EE-induced changes in the DR supply curve at level 2b and discuss the various effects in detail. Finally, we discuss the detailed end-use-level interactions that underlie the level 2b interactions we observed for low-cost DR.

B.1. Detailed examples of level 2a interactions

In Section 3.2 we considered how EE can effect changes in certain metrics for system-level DR need that are detailed in Murthy et al. [30]. In a few scenarios, we saw the peakiness metric increase even as the peak load decreased (see Fig. 6). To illustrate how this can occur, Fig. 10 shows a portion of the modelled system-level net load for Texas in the baseline and equipment-only EE scenarios. There is a large reduction in the peak hourly demand[21] (red cross), but the top 100 hours of the year (blue points) span a wider vertical range in the equipment-only scenario than in the baseline Fig. 10. also shows how EE upgrades can increase both the number of event days and the duration of the season for shed DR: with the overall reduction in summer peak load, some of the top 100 load hours are shifted into the shoulder months, increasing the number of days with a potential shed event, and dramatically increasing the length of the season in which shed DR is likely to be called upon.

[20] We also performed building simulations that indicated that envelope improvements increased the load-reduction capability of a PCT by between 0% and 80%, depending on the details of the building and DR event day; thus, our adopted assumption of a 10% increase may be conservative.

[21] As with all of our EE scenarios, we reiterate that this scenario is intentionally very aggressive and unlikely to occur in practice.

Table 6
Measure characterization data for residential sector DR measures used as inputs to the DR-Path model.

Name	End use	Fixed cost ($/site)	EE-adjusted fixed cost ($/site)	Variable cost ($/kW)	EE-adjusted variable cost ($/kW)	Operating cost ($/yr/site)	Co-benefit fraction	Instantaneous shed fraction	1-hr shed fraction	2-hr shed fraction	4-hr shed fraction	Shift duration
Direct load control, air conditioner or heat pump	Heating, Cooling	160	–	–	–	6	–	0.85	0.7	0.7	0.65	0
Programmable communicating thermostat	Heating, Cooling	215	45[2]	–	–	15.22	0.3	0.85[3]	0.85[3]	0.75[3]	0.65[3]	4
Direct Load Control, pool pump[1]	Pool Pump	141		–	–	4	–	0.79	0.7	0.7	0.7	12
Connected dishwasher	Dishwasher	1106	187[4]	–	–	15.22	–	0.78	1	1	1	8
Connected clothes washer	Clothes Washer	1212	275.5[4]	–	–	7.61	–	0.9	1	1	1	8
Connected clothes dryer	Clothes Dryer	936	179[4]	–	–	7.61	–	0.8	1	1	0.75	4
Connected refrigerator	Refrigeration	3170	533[4]	–	–	15.22	–	0.5	0.15	0.15	0.15	8
Smart power strips	Plug Loads		–	60	–		–	1	0.5	0.25	0.25	0
Direct load control, water heater	Water Heating	160	–	–	–	6	–	1	1	0.8	0.4	0
Connected water heater + thermostatic mixing valve	Water Heating	903	273[4]	–	–	15.22	0.5	1	0.95	0.8	0.4	4
Communicating controls + thermostatic mixing valve	Water Heating	273	–	–	–	15.22	0.5	1	0.95	0.8	0.4	4
Connected light bulb	Lighting	–	–	1200	500[4]	15.22	–	1	0.2	0.2	0.2	0

[1] Connected pool pumps were not included because their incremental cost was higher than the cost of direct load control, so that the DR-Path model would never select them in practice.
[2] This price represents the incremental cost of a programmable communicating thermostat over that of a non-communicating programmable thermostat. It was applied in the controls-only and controls-plus-envelope scenarios.
[3] In the envelope-only and envelope-plus-controls scenarios, these fractions are increased by a factor of 1.1 to represent the increased thermal stability of a more well-insulated building [44].
[4] These prices represent the incremental cost of a communicating appliance over a non-communicating appliance. They were applied in the equipment-only scenario.

Table 7
Measure characterization data for commercial sector DR measures used as inputs to the DR-Path model.

Name	End use	Fixed cost ($/site)	EE-adjusted fixed cost ($/site)	Variable cost ($/kW)	EE-adjusted variable cost ($/kW)	Operating cost ($/yr/site)	Co-benefit fraction	Instantaneous shed fraction	1-hr shed fraction	2-hr shed fraction	4-hr shed fraction	Shift duration
Direct load control, air conditioner or heat pump	Heating, Cooling	100	–	60	–	6	–	0.5	0.4	0.4	0.35	0
Programmable communicating thermostat	Heating, Cooling	–	–	105	15[1]	15.22	0.3	0.8[2]	0.7[2]	0.7[2]	0.6[2]	4
Energy management system with manual control	Heating, Cooling	800	–	20	–	–	0.3	0.6[2]	0.5[2]	0.45[2]	0.35[2]	8
Energy management system with automated DR	Heating, Cooling	–	–	293	–	–	0.3	0.8[2]	0.7[2]	0.7[2]	0.6[2]	8
Space cooling thermal energy storage with automated DR	Cooling	–	–	640	–	–	0.3	1	1	1	1	8
Refrigeration thermal energy storage with automated DR	Refrigeration	–	–	756.35	–	0.3	0.3	1	1	1	1	8
Smart power strips	Interior Equipment[3]	–	–	60	43.33[1]	15.22	–	0.5	0.25	0.125	0.125	0
Direct load control, water heating	Water Heating	160	–	–	–	6	–	1	1	0.8	0.4	0
Connected water heater	Water Heating	903	273[1]	–	–	15.22	0.5	1	0.95	0.8	0.4	4
Communicating controls + thermostatic mixing valve	Water Heating	273	–	–	–	15.22	0.5	1	0.95	0.8	0.4	4
Networked lighting controls	Lighting	–	–	1760	2882[4]	–	0.75	0.8	0.65	0.5	0.5	0

[1] These prices represent the incremental cost of a communicating device over a non-communicating device. They are applied in the controls-only and the controls-plus-envelope scenarios.
[2] In the envelope-only and envelope-plus-controls scenarios, these fractions are increased by a factor of 1.1 to represent the increased thermal stability of a more well-insulated building [44].
[3] This measure applies in office buildings only. We assume that 50% of interior equipment could be controlled with smart power strips.
[4] This price represents the increased cost per kW of installing lighting controls when the load under control is smaller due to EE improvements. It is applied in the equipment-only scenario.

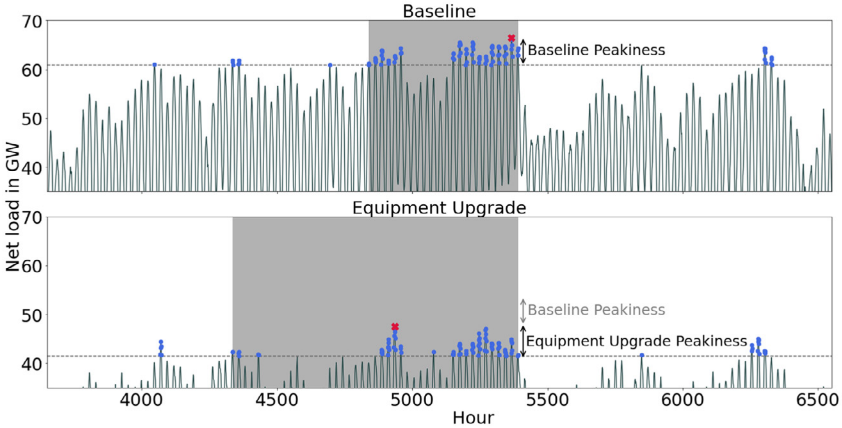

Fig. 10. System level load shapes for a portion of the year in Texas, for the baseline and the equipment-only EE scenarios. In each case, blue points indicate the top 100 hours of the year, and the absolute system peak is denoted by a red cross. The peakiness in each case is indicated by arrows, and the size of the baseline peakiness is also shown in the bottom panel for comparison. Shaded regions denote the shed season in each scenario, defined as the shortest period that contains 80 of the top 100 hours.

B.2. Example supply-curve interactions at level 2b

At level 2b of the EE-DR framework, we assess changes in system-level DR availability using the shed and shift DR supply curves produced by DR-Path, which tabulate the total quantity of DR that is available at a given marginal procurement cost. In Section 3.3, we examined the interactions that occur at a fixed cost level below some cost benchmarks that we established for shed and shift DR. Here we consider the interactions that can occur along the supply curve in more detail by considering specific examples for selected set of EE scenarios and end uses.

The quantity of DR presented in the DR-Path supply curve is either the kW of load reduction that is available on average in a shed event, or the kWh of load that can be shifted on average in a shift event. Costs in the supply curves are the annualized cost of procuring an additional unit of DR resource (kW of shed DR or kWh of shift DR). These can also be thought of as the utility's cost to procure a contract for one kW of shed capacity or one kWh of shift capacity for a period of one year. We present the costs in units of \$/yr/kW and \$/yr/kWh (for shed and shift, respectively) to emphasize that they are annualized costs. These same units are also often written as \$/kW-yr or \$/kWh-yr, which emphasizes the contracting-period perspective. For more on the units used in the DR-Path supply curves, see Gerke et al. [16].

The DR supply curves depend on four factors that may be affected by EE adoption in the building stock:

- The *quantity* of load available to provide DR,
- The *coincidence* of the load with times system need for DR
- The *cost* of installing DR-enabling technology in the building stock, and
- The *capability* of the DR-enabling technology to shed or shift load.

Fig. 11 shows example shift DR supply curves in California for the baseline, controls-plus-envelope, and equipment-only EE scenarios. EE and DR interactions at level 2b can have several effects that can occur along both dimensions of the DR supply curve:

- *Reduction in size* of the DR resource from a particular end use at a given cost,
- *Increase in cost* to enable a particular end use as a DR resource,
- *Reduction in cost* to enable a particular end use as a DR resource, or
- *Increase in size* of the DR resource from a particular end use at a given cost.

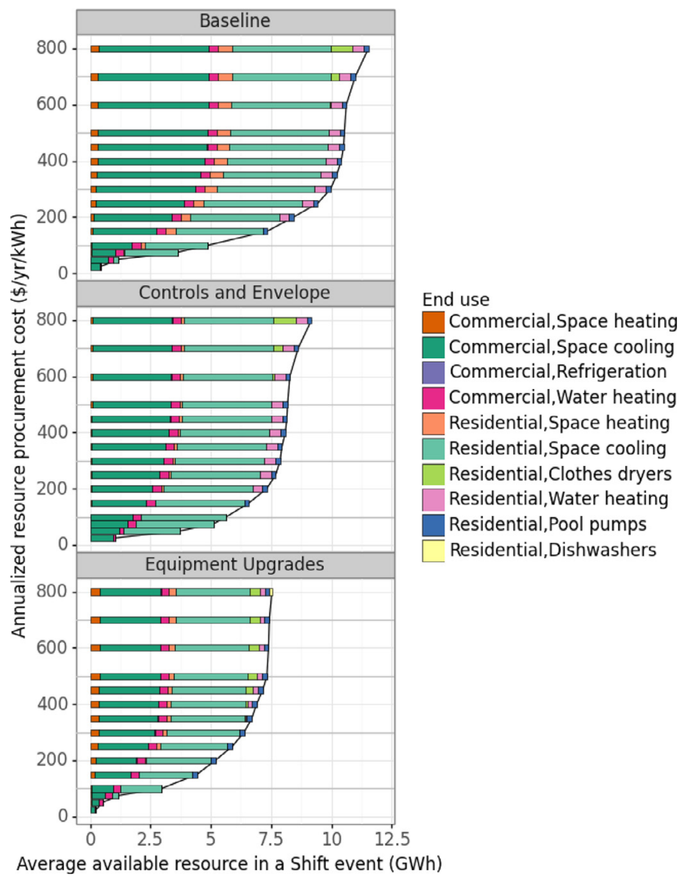

Fig. 11. Shift DR supply curves for the baseline and two example EE supply curves in California. Solid curves show the total shift DR resource, in GWh of shiftable energy consumption as a function of the annualized cost of procurement, per unit of DR procured. Horizontal bars show the size of the DR resource that is contributed by individual end uses at each procurement level.

Reduction in resource size occurs when EE reduces the total amount of load. This is clearly apparent in Fig. 11, where the DR resource is reduced at the highest cost levels in both EE scenarios. (In effect, this is an aggregation to the system level of the building-level competition we observed at level 1a.) Increase in resource cost occurs when an end use load shrinks but the DR enablement cost remains fixed, increasing the enablement cost per unit of DR. This effect is apparent for residential space and water heating in the equipment-only scenario: for both end uses, the size of the available DR resource is smaller, and becomes available at higher prices,[22] than in the baseline scenario. This occurs because the enabling technology in both cases is an add-on control technology whose price remains constant while the EE upgrade reduces load, yielding a higher

[22] For instance, residential water heating is available at a minimum cost of \$200/yr/kWh in the baseline scenario, but this rises to \$400/yr/kWh in the equipment-only scenario.

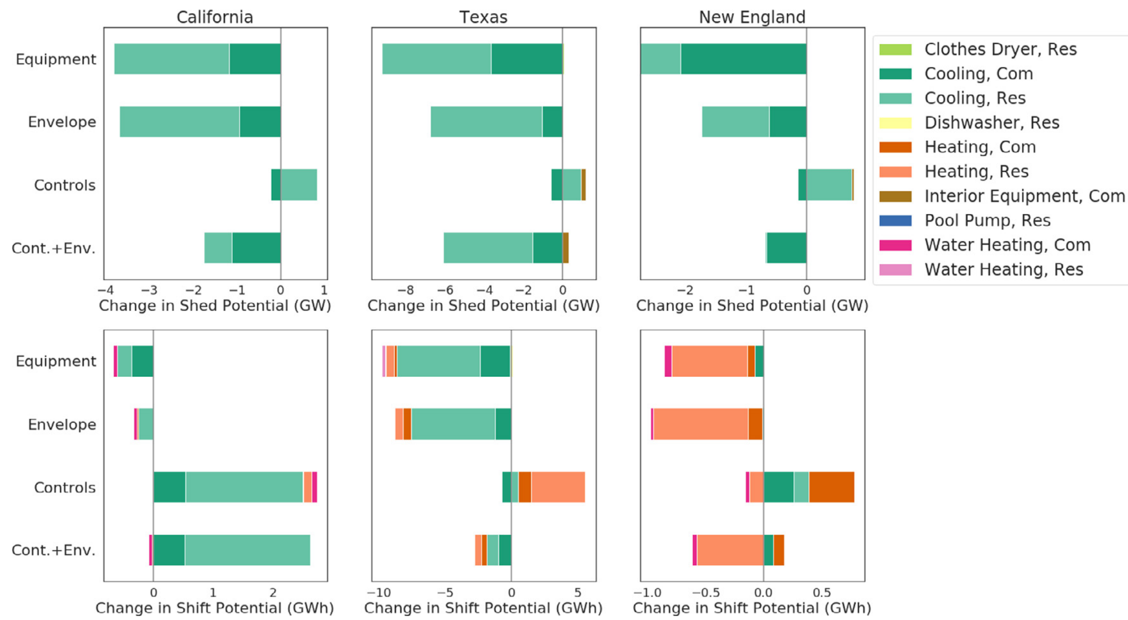

Fig. 12. Absolute changes in the low-cost shed (top) and shift (bottom) potential, for each region and EE scenario modelled in this study, disaggregated by end use.

cost per unit of consumption. Reduced resource cost occurs when the EE measure defrays the cost of installing a DR measure. This can be seen for residential clothes dryers in the equipment-only scenario: the end use becomes available at a lower cost[23] because a more efficient dryer is already being installed as an EE measure, so the DR enablement cost is limited to the incremental cost of upgrading to a connected appliance (For more on our DR measure cost assumptions, see Appendix A).

The final effect, increased resource size, occurs when EE measures increase the capability to control a particular load. This effect becomes apparent when examining the change in the residential space cooling resource at costs below \$100/yr/kWh in the controls-plus-envelope scenario. At these low costs we see a dramatic *increase* in the resource size compared to the baseline scenario–more than doubling the resource that is available at a \$50/yr/kWh procurement cost. This effect is, in fact, a combination of an increase in resource size and a reduction in resource cost. The envelope upgrades increase the amount of load that can be shifted via pre-cooling while maintaining occupant comfort, yielding an increased total resource. The resource is enabled by PCTs, whose cost is defrayed by the installation of PTs as EE measures, reducing the overall cost of the resource. This effect is noteworthy since it means that there is a substantially larger *low-cost* DR resource, even as the size of the high-cost resource shrinks, which may mean that there is a larger cost-effective resource available to the grid operator in practice; we saw it clearly in Section 3.3 (Fig. 8) as a dramatic increase in shift DR potential for California. Importantly, the size of this effect is dependant on our assumptions about the incremental cost of a PCT, relative to a PT, and about how envelope improvements improve pre-cooling performance. As discussed in Appendix A, we have made fairly conservative assumptions on the latter point, so the complementary effects may be even larger in certain real-world contexts.

B.3. Detailed end-use interactions at level 2b

As we saw in Fig. 11, there are several effects at the end-use level that can affect the DR supply curve. Thus, the level 2b interactions we saw for low-cost DR in Section 3.3 (Fig. 8) are driven by underlying end-use level interactions whose size and direction may offset or augment one another in complex ways Fig. 12. illustrates these effects in detail, presenting the changes in the shed and shift DR resources for individual end uses. Because the equipment-only and envelope-only portfolios reduce loads without increasing controllability, all affected end-uses show a reduction in DR resources. In the controls-only and controls-plus-envelope scenarios, however, there are often opposite effects for different end uses. For example, in the controls-only scenario, shed DR potential increases for residential cooling but decreases for commercial cooling, because the modelled controls strategies tend to increase residential cooling load during evening peak hours but decrease commercial cooling load at the same times. In other cases, certain end uses become newly available as sources of low-cost DR in the controls scenario, as with the commercial interior equipment end use in Texas, which becomes a new source of shed potential via the installation of controllable power strips. Finally, in some cases, the DR resource from an end use is affected by a change in coincidence with the system load, as can be seen for shift DR from water heating in the envelope-only scenario. Envelope measures do not affect water-heating load, but the shift DR potential from water heating decreases because the overall change in system load shape reduces the coincidence of water-heating DF with periods of steep ramping.

[23] With a minimum cost of \$700/yr/kWh in the baseline scenario declining to \$400/yr/kWh in the equipment-only scenario.

References

[1] Baatz B. Everyone benefits: practices and recommendations for utility system benefits of energy efficiency. Washington, DC: ACEEE; 2015.
[2] Faruqui A, Hledik R, Newell S, Pfeifenberger H. The Power of 5 Percent. Electr J 2007;20:68–77. doi:10.1016/j.tej.2007.08.003.
[3] Joung M, Kim J. Assessing demand response and smart metering impacts on long-term electricity market prices and system reliability. Appl Energy 2013;101:441–8. doi:10.1016/j.apenergy.2012.05.009.
[4] Lazar J, Colburn K. Recognizing the full value of energy efficiency. Montpelier, VT: Regulatory Assistance Project; 2013.
[5] Frick NM, Carvallo JP, Schwartz L. Quantifying grid reliability and resilience impacts of energy efficiency: examples and opportunities. Berkeley, CA: Lawrence Berkeley National Laboratory; 2020.
[6] Safdarian A, Fotuhi-Firuzabad M, Lehtonen M. Benefits of demand response on operation of distribution networks: a case study. IEEE Syst J 2016;10:189–97. doi:10.1109/JSYST.2013.2297792.
[7] Wang F, Xu H, Xu T, Li K, Shafie-khah M, JoãoPS Catalão. The values of market-based demand response on improving power system reliability under extreme circumstances. Appl Energy 2017;193:220–31. doi:10.1016/j.apenergy.2017.01.103.
[8] Langevin J, Harris CB, Reyna JL. Assessing the potential to reduce U.S. building CO2 emissions 80% by 2050. Joule 2019;3:2403–24. doi:10.1016/j.joule.2019.07.013.
[9] Lund PD, Lindgren J, Mikkola J, Salpakari J. Review of energy system flexibility measures to enable high levels of variable renewable electricity. Renew Sustain Energy Rev 2015;45:785–807. doi:10.1016/j.rser.2015.01.057.

[10] Dranka GG, Ferreira P. Review and assessment of the different categories of demand response potentials. Energy 2019;179:280–94. doi:10.1016/j.energy.2019.05.009.

[11] Arimura TH, Li S, Newell RG, Palmer K. Cost-effectiveness of electricity energy efficiency programs. Energy J 2012;33. doi:10.5547/01956574.33.2.4.

[12] Seel J., Mills A.D., Wiser R.H., Deb S., Asokkumar A., Hassanzadeh M., et al. Impacts of high variable renewable energy futures on wholesale electricity prices, and on electric-sector decision making. 2018. https://doi.org/10.2172/1437006.

[13] Boomhower J, Davis L. Do energy efficiency investments deliver at the right time? Am Econ J Appl Econ 2020;12:115–39. doi:10.1257/app.20170505.

[14] Frick NM, Schwartz LC. Time-sensitive value of efficiency: use cases in electricity sector planning and programs. Berkeley, CA: Lawrence Berkeley National Laboratory; 2019. doi:102172/1574347.

[15] Alstone P, Potter J, Piette MA, Schwartz P, Berger MA, Dunn LN, et al. Final report on phase 2 results. 2025 California demand response potential study: charting California's demand response future. California Public Utilities Commission; 2017.

[16] Gerke B, Gallo G, Smith SJ, Liu J, Alstone P, Raghavan SV, et al. The California demand response potential study, phase 3: final report on the shift resource through 2030. Lawrence: Berkeley National Laboratory; 2020.

[17] Potter J, Stuart E, Cappers P. Barriers and opportunities to broader adoption of integrated demand side management at electric utilities: a scoping study. Berkeley, CA: Lawrence Berkeley National Laboratory; 2018. doi:102172/1425437.

[18] York D, Relf G, Waters C. Integrated energy efficiency and demand response programs. Washington, DC: ACEEE; 2019.

[19] Satchwell AJ, Cappers PA, Deason J, Forrester SP, Frick NM, Gerke BF, et al. A conceptual framework to describe energy efficiency and demand response interactions. Energies 2020;13:4336. doi:10.3390/en13174336.

[20] Langevin J., Harris C.B., Satre-Meloy A., Putra H.C., Speake A., Present E., et al. U.S. building energy efficiency and flexibility as an electric grid resource. SSRN Sneak Peak 2021. http://dx.doi.org/10.2139/ssrn.3767157.

[21] Satchwell A, Piette M, Khandekar A, Granderson J, Frick N, Hledik R, et al. A national roadmap for grid-interactive efficient buildings. Washington, DC: US Department of Energy; 2021. doi:102172/1784302.

[22] Portman R. Energy efficiency improvement act of 2015. 2015.

[23] EPA US. Connected criteria for partners 2021. https://www.energystar.gov/products/smart_home_tips/about_products_connected_functionality/connected_criteria_partners (accessed September 21, 2021).

[24] Satre-Meloy A, Langevin J. Assessing the time-sensitive impacts of energy efficiency and flexibility in the US building sector. Environ Res Lett 2019;14:124012. doi:10.1088/1748-9326/ab512e.

[25] Sathe A, Maoz K, Capps T, Legett R, Ghosh D, Iyer D, et al. 2021 Energy efficiency potential and goals study, draft report. San Francisco, CA: California Public Utilities Commission; 2021.

[26] Munankarmi P, Maguire J, Balamurugan SP, Blonsky M, Roberts D, Jin X. Community-scale interaction of energy efficiency and demand flexibility in residential buildings. Appl Energy 2021;298:117149. doi:10.1016/j.apenergy.2021.117149.

[27] Wilson E, Christensen C, Horowitz S, Horsey H. A high-granularity approach to modeling energy consumption and savings potential in the US residential building stock. In: Proc. ASHRAE IBPSA-USA SimBuild 2016 Build. Perform. Model. Conf., vol. 6, Salt Lake City, UT: ASHRAE, IBPSA-USA; 2016. p. 296–406.

[28] Wilson EJ, Christensen CB, Horowitz SG, Robertson JJ, Maguire JB. Energy efficiency potential in the US single-family housing stock. Golden, CO: National Renewable Energy Laboratory; 2017.

[29] NREL. ComStock 2021. https://comstock.nrel.gov/(accessed November 12, 2021).

[30] Murthy S, Satchwell AJ, Gerke BF. Metrics to describe changes in the power system need for demand response resources. Smart Energy 2022 (submitted).

[31] Gerke B, Zhang C, Satchwell A, Murthy S, Piette M, Present E, et al. Modeling the interaction between energy efficiency and demand response on regional grid scales. Pacific Grove, CA: ACEEE; 2020.

[32] EIA US The electricity market module of the national energy modeling system: model documentation 2020. Washington, DC: United States Energy Information Administration; 2020.

[33] ANSI/ASHRAE. ANSI/ASHRAE standard 169-2013, Climatic data for building design standards. ANSI/ASHRAE; 2013.

[34] Digital Map Products, Inc. SmartParcels National Licensed Data Set 2018.

[35] EIA US Monthly electric power industry report, form EIA-861M (formerly EIA-826) detailed data for 2016. Washington, DC: United States Energy Information Administration; 2017.

[36] EIA US. Hourly electric grid monitor 2021. https://www.eia.gov/electricity/gridmonitor/dashboard/electric_overview/US48/US48 (accessed November 11, 2021).

[37] EIA US Annual electric power industry report, form EIA-861 detailed data files for 2016. Washington, DC: United States Energy Information Administration; 2017.

[38] Lazard. Lazard's Levelized Cost of Storage Analysis—Version 5.0. Lazard; 2019.

[39] Mongird K, Viswanathan VV, Balducci PJ, Alam MJE, Fotedar V, Koritarov VS, et al. Energy storage technology and cost characterization report. Richland: WA: Pacific Northwest National Laboratory; 2019. doi:102172/1573487.

[40] York D, Kushler M. Exploring the relationship between demand response and energy efficiency: a review of experience and discussion of key issues. Washington, DC: ACEEE; 2005.

[41] Alstone P, Potter J, Piette MA, Schwartz P, Berger MA, Dunn LN, et al. Interim report on phase 1 results. 2015 California demand response potential study: charting california's demand response future. California Public Utilities Commission; 2016.

[42] Frick NM, Murphy S, Miller C, Pigman M. Still the one: efficiency remains a cost-effective electricity resource. Berkeley, CA: Lawrence Berkeley National Laboratory; 2021.

[43] Nubbe V., Lee K., Valdez A., Barbour E., Langevin J. Grid-Interactive efficient building technology cost, performance, and lifetime characteristics. Lawrence Berkeley National Laboratory; 2021.

[44] Herter K., Okuneva Y. SMUD's 2012 residential precooling study – load impact evaluation. Sacramento Municipal Utility District; 2013.

[45] Gerke BF, Zhang C, Murthy S, Satchwell AJ, Present E, Horsey H, et al. Load-driven interactions between energy efficiency and demand response on regional grid scales: Data inputs. Mendeley Data 2022. doi:10.17632/nj4tdzrdt3.1.