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The California Demand Response Potential Study, Phase 4:

Report on Shed and Shift Resources Through 2050

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List of Acronyms

AAEE	Additional Achievable Energy Efficiency
AAFS	Additional Achievable Fuel Switching
ACC	Avoided Cost Calculator
ADR	Automated Demand Response
AMI	Advanced Metering Infrastructure
BANC	Balancing Authority of Northern California
BAU	Business-As-Usual
BTM	Behind-The-Meter
CAISO	California Independent System Operator
CalFUSE	California Flexible Unified Signal for Energy
CARB	California Air Resources Board
CARE	California Alternate Rates for Energy
CCA	Community Choice Aggregator
CEC	California Energy Commission
CEUS	California Commercial End-Use Survey
CPP	Critical Peak Pricing
CPUC	California Public Utilities Commission
CSI	California Solar Initiative
DER	Distributed Energy Resource
DGStats	Distributed Generation Statistics
DLAP	Default Load Aggregation Point
DOE	Department of Energy
DR	Demand Response
DRAM	Demand Response Auction Mechanism
DSGS	Demand Side Grid Support
DWR	Department of Water Resources
EE	Energy Efficiency
ELCC	Effective Load Carrying Capacity
ELRP	Emergency Load Reduction Program
EMS	Energy Management System
EV	Electric Vehicle
EVI-Pro	Electric Vehicle Infrastructure Projection
FS	Fuel Substitution
GEB	Grid-interactive Efficient Buildings
GHG	Greenhouse Gas
HEVI-LOAD	Medium and Heavy-Duty Electric Vehicle Infrastructure - Load Operations and Deployment
IEPR	Integrated Energy Policy Report
IOU	Investor-Owned Utility
IRP	Integrated Resource Plan
LADWP	Los Angeles Department of Water and Power
LBNL	Lawrence Berkeley National Laboratory
LCA	Local Capacity Area
LDEV	Light Duty Electric Vehicle
LSWG	Load Shift Working Group
MAP	Market Access Program
MECS	Manufacturing Energy Consumption Survey
MHDEV	Medium- and Heavy-Duty Electric Vehicle
MIDAS	Market Informed Demand Automation Server
MPC	Model-predictive control
NAICS	North American Industry Classification System
NEM	Net Energy Metering

NOAA	National Oceanic and Atmospheric Administration
NREL	National Renewable Energy Laboratory
OASIS	Open Access Same-time Information System
PCT	Programmable Communicating Thermostat
PDR	Proxy Demand Resource
PDR-LSR	Proxy Demand Resource-Load Shift Resource
PG&E	Pacific Gas and Electric Company
PSP	Preferred System Plan
PSPS	Public Safety Power Shutoff
PV	Photovoltaic
RA	Resource Adequacy
RASS	Residential Appliance Saturation Study
SB49	Senate Bill 49
SB100	Senate Bill 100
SCE	Southern California Edison Company
SDG&E	San Diego Gas & Electric Company
SERVM	Strategic Energy Risk Valuation Model
TES	Thermal Energy Storage
TOU	Time-Of-Use
V2B	Vehicle-to-Building
V2G	Vehicle-to-Grid
VRE	Variable Renewable Energy

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Executive Summary

Two record-setting days on the California grid in 2022 illustrate the growing importance of demand response (DR) to the state. The first was May 8, 2022, when renewable energy generation added up to a record of just over 100% of the load served through the California Independent System Operator (CAISO) for a short period. On that day, California exported up to 5 gigawatts to neighboring states, and there was still between 1-5 gigawatts of renewable power curtailed in the middle of the day. These “duck curve” dynamics introduce opportunities for demand responsive loads to **shift**, capturing and making use of the available zero-carbon energy. The second record-setting day was September 6, 2022, which saw a record high 52 GW of load on the CAISO grid. To manage this peak, all available DR resources that could **shed** load were called on, and an unprecedented emergency alert was sent to mobile phones across the state, resulting in a load reduction of more than 1 GW in a matter of minutes. These record-setting days are not anomalies but are an increasingly common occurrence in the context of a changing climate and growing deployment of variable renewable energy (VRE). DR is clearly needed in California today, and the need is likely to become more acute in the future.

The California DR Potential Study is an ongoing research effort conducted by Lawrence Berkeley National Laboratory (LBNL) on behalf of the California Public Utilities Commission (CPUC) to provide a detailed assessment and forecast of the potential DR resources that are available within the territories that the CPUC regulates in California. This report presents the findings from Phase 4 of the study, which thoroughly updates and expands upon previous phases (described in section 2.1.2), with a new, larger customer dataset, a more detailed consideration of flexible end uses, and an extension of the study forecast horizon through 2050, to capture the impacts of achieving the state’s power-sector decarbonization goals under SB100.

Our overall analytic framework groups DR services into four core categories identified during an earlier phase of this study (Alstone et al. 2017): **shape**, **shift**, **shed** and **shimmy.** For the purposes of the Phase 4 study, these are defined as:

- **Shape** captures DR that reshapes customer load profiles during significant portions of the year through price response or behavioral campaigns— “load-modifying DR”—with advance notice of months, days, or even hours.
- **Shift** represents CAISO market integrated DR that encourages the movement of energy consumption, on the timescale of hours, from times of high net demand to times of day when there is a surplus of VRE generation.
- **Shed** describes CAISO market integrated DR that curtails loads, on the timescale of hours, to provide net peak reduction and support the system in emergency or contingency events with a range in dispatch advance notice times.
- **Shimmy** involves using loads to dynamically adjust demand on the system to alleviate short-run ramps and disturbances at timescales ranging from seconds up to an hour.

The focus of this Phase 4 report is on better understanding the potential roles of **shed** DR and **shift** DR on the California grid through 2050. Phase 4 considers obtaining these resources both through traditional supply-side (dispatchable) DR programs, as well as through novel dynamic electricity pricing approaches that would capture the resources as **shape** DR. A key difference between these DR categories is that shape DR could occur in every hour of the year, in response to a continuous price signal, whereas shed and shift DR are considered "event-based", and would only be called upon in the hours of highest grid need. Therefore, it can be difficult to quantify and communicate the impacts of shape DR in units that are comparable to the event-based DR types. We therefore develop and utilize the metrics *effective* shed and *effective* shift, i.e., how much load reduction or load shifting (from shape DR) occurs at times when shed or shift events are likely to occur. We refer to these resources as "shape-as-shed" and "shape-as-shift" in this report. The final category, **shimmy**, is not included in this report.

The DR Potential Study rests on an analytical modeling framework known as **DR-Futures**, which consists of two modules:

- **LBNL-Load** is a bottom-up load-forecasting module that capitalizes on customer advanced metering infrastructure (AMI) data to project future end-use load shapes for a diverse set of customer clusters and aggregates these to the grid system level.
- **DR-Path** pairs the cluster load shapes with DR-enabling technologies to assess future pathways to acquiring DR resources, resulting in granular DR potential estimates for individual end uses and technologies that can be aggregated into a detailed DR supply curve.

The Phase 4 research effort included collecting an all-new and larger set of customer smart meter data from the investor-owned utilities (IOUs), to provide a more thorough and up-to-date picture of California customer loads. The study also included significant updates to both modules of the DR-Futures modeling framework to improve the fidelity and level of detail with which DR resources can be modeled. Key updates include:

1. Correction of customer AMI data for behind-the-meter (BTM) PV generation
2. A novel load shape-based clustering approach that groups customers based on similar demand patterns
3. A broader set of building types modeled in the load shape forecasting
4. Expanded end-use disaggregation, including numerous new end-uses such as light-duty Electric Vehicle (LDEV) charging
5. Inclusion of medium- and heavy-duty Electric Vehicle (MHDEV) charging in load forecasts consistent with CARB State SIP Strategy
6. Updated forecasting of energy efficiency (EE) and electrification using forecasts that are aligned with other statewide forecasting efforts
7. Updated models for the probability of shed and shift DR dispatch
8. An updated model for predicting customer enrollment in DR programs
9. Expanded and updated data characterizing the cost and performance of DR-enabling technologies (i.e., communication and control devices that adjust the behavior of end-use load equipment)
10. Estimation of system value and greenhouse gas (GHG) impacts of shed and shift resources using the CPUC Avoided Cost Calculator (ACC)

11. Estimation of the effective shed and shift DR potential that could be captured as shape DR via dynamically varying electricity tariffs.

Figure ES-1 presents the aggregate forecasted hourly demand from LBNL-Load for all IOU customers[1] on an average day in summer, winter, and shoulder seasons, subdivided into individual end-uses. These forecasts are based on rollout of default 2019 TOU rate structures and associated behaviors; for medium- and heavy-duty EVs (MHDEV), demand is modeled as "uncontrolled", as there are not adequate data on baseline (TOU) rate-driven behaviors to modify the load shape. The sum of the individual end-use loads, and therefore the top of the stacked colors, represents *gross demand*. Overplotted on this gross demand is the *gross load* on the grid system, which is the gross customer demand less behind-the-meter rooftop Photovoltaics (PV) generation--i.e., the aggregate demand across all customer meters. Also plotted in each panel is the *net load* on the grid system, which is the gross load less projected grid-scale VRE generation.

There are several notable features in Figure ES-1. The first is a drastic rise in newly electrified loads, particularly for EV charging, but also for water heating, space heating, and appliances. These new loads significantly alter the shape of the daily demand curve in each season by 2050, driving a strong secondary peak during overnight hours. Second, the net load ramps steepen, with the net load curve beginning to dip below zero[2] by 2025 and doing so consistently by 2040. Finally, although the peak net load continues to occur in summer in the near term, by 2040 the highest net load occurs in the *winter* months, although a smaller peak also occurs in the summer.

The changes in the forecasted load that will result if current demand patterns continue suggest a significant change in the nature of available DR resources and a corresponding need to consider changes in the type of DR sought in California. A forecasted migration of the net load peak into the winter season will eventually erode the (historically large) value of space cooling loads as shed DR resources, while the continued presence of a secondary summer peak means that flexible loads with little to no seasonal variation will have high value as shed resources. Meanwhile, the steepening net load ramps will drive a much more acute need for flexible resources, which may be met by DR or supply-side resources such as grid-scale storage; the balance of these resources should be informed by the cost effectiveness of each, which will continue to evolve as technologies develop.

[1] Loads shown are for California IOU customers only. As discussed in section 3.3.7, there are additional entities within the CAISO footprint, such as municipal utilities and government agencies, that are not captured here. Their loads make up about 20% of the total CAISO load. The VRE generation in these plots has been scaled down by an appropriate factor to be proportional to the fraction of load shown.
[2] In practice, much of the excess VRE generation would be captured by grid-scale storage and discharged in the overnight hours; however, from the perspective of estimating DR potential, dispatchable storage is no different from other dispatchable resources that are needed to meet the net load. If DR can eliminate the need for some peaking or ramping capacity—storage or otherwise—it can reduce system costs. Therefore, the net load curve plotted here is the most useful one to consider when estimating the potential for DR to support grid operations.

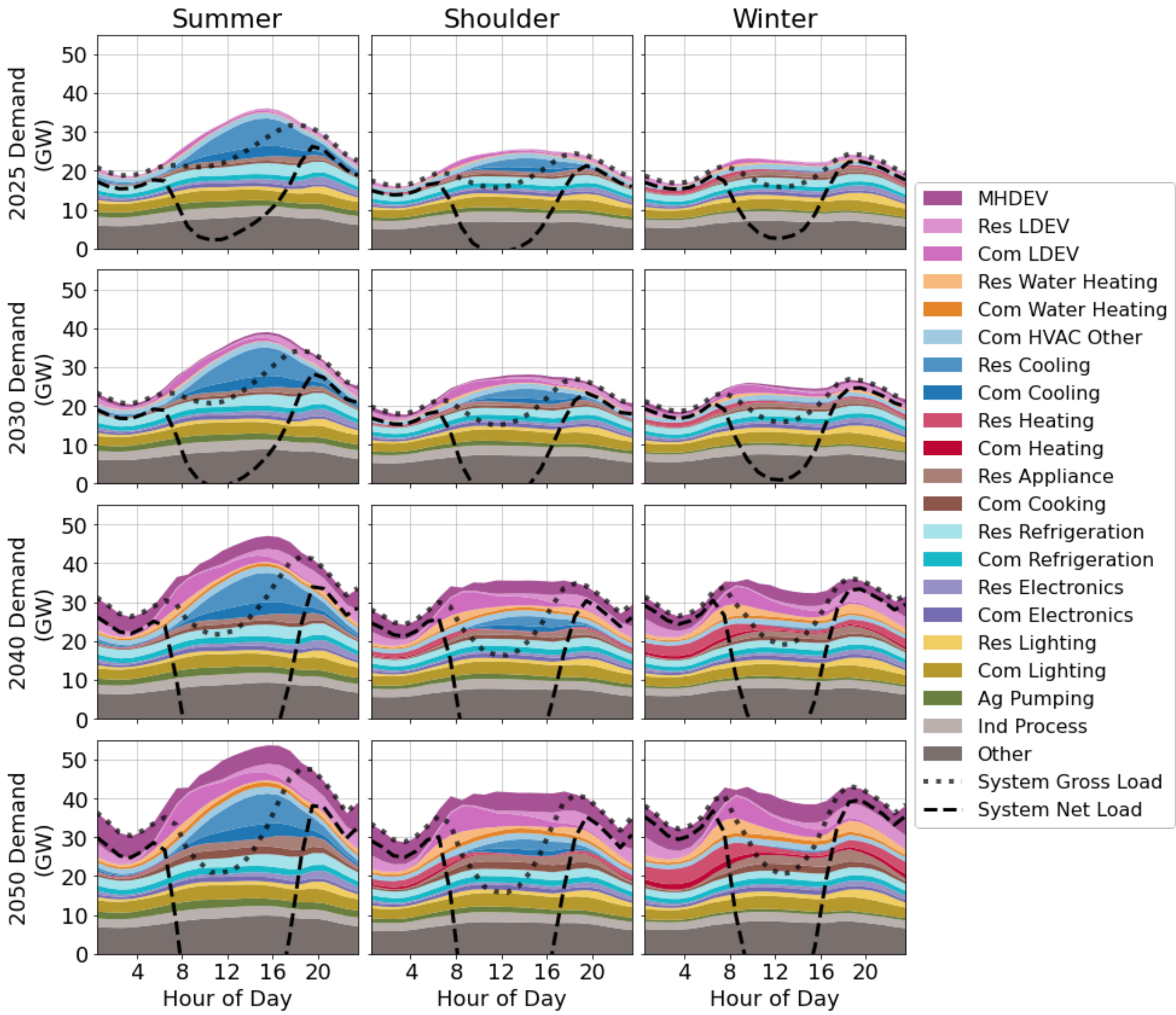

Figure ES-1. Forecasted future seasonal average system-level load shapes from the LBNL-Load modeling performed for this study. Panels show average hourly gross demand (sum of all end-use demands) over a day in summer, winter, and shoulder seasons, disaggregated into individual end uses. Overplotted are the gross system load (gross demand net of behind-the-meter rooftop PV) and the net system load (gross load net of grid-scale VRE generation). Forecasts are shown for the forecast years (from top to bottom) 2025, 2030, 2040, and 2050.

To quantify the available shed and shift resources within this evolving landscape, the Phase 4 study considers several different types of DR potential:

- **Technical potential** is the maximum DR resource that could be enabled by installing the best available technology at each customer site.
- **Economic potential** is the cost-effective subset of the technical potential, when comparing the technology cost against the avoided system costs.
- **Achievable potential** is the subset of the economic potential that can be achieved in a real-world DR program, considering customer willingness to enroll and including costs for program administration, marketing, and customer incentives.

Our model for customer enrollment is based on historical enrollment rates in DR programs, which may underestimate the enrollment that could be achieved with new approaches to customer engagement. To emphasize this, the report refers to the achievable-potential results as the **business-as-usual (BAU) achievable potential**.

Figure ES-2 summarizes the main DR potential findings of this study for shed and shift DR. Stacked bars show the economic and BAU achievable potential for shed and shift in each forecast year, broken out by the specific end uses that provide the resources. Each potential is computed at a cost-effectiveness threshold for shed or shift DR computed from the ACC. Since the ACC was principally designed to compute avoided costs for EE and shed DR programs and does not explicitly assign value to flexible generation capacity, the cost-effectiveness threshold for shift may underestimate its true value. Therefore, Figure ES-2 also presents shift potential values at an alternative cost threshold equivalent to the cost of BTM batteries, as was done in the previous phase of this study (Gerke et al. 2020). Numerical values for the end-use-level DR resources presented in Figure ES-2 are tabulated in section 4.5, Tables Table 20-Table 22. Additionally, full technical potential results are discussed in the main body of the report.

At the highest level, the results in Figure ES-2 indicate that a dramatic growth is expected in the economic potential of DR resources in California through 2050. Over the forecast period, the economic potential for shed DR nearly doubles, growing from 12 GW to 21 GW, while the economic shift DR potential undergoes a fivefold increase, growing from 5.9 GWh to 30 GWh in our primary estimate. Our estimate of the upper limit on economic shift potential, based on comparing to BTM battery costs, is 12 GWh in 2025, growing to 33 GWh by 2050.[3] The potential impacts of these DR resources are considerable. In 2025, our primary estimates of shed and shift economic potential would avoid 220 and 310 ktCO2 of GHG emissions, respectively, each corresponding to eliminating the emissions from a small natural gas generation unit operating at full capacity for a full year. Avoided system costs for the economic shed and shift resources in 2025, as estimated from the ACC, amount to $1.8B and $88M, respectively (though it is worth emphasizing that the value of shift may be underestimated).

Further, Figure ES-2 shows that, under a BAU approach to customer enrollment, the estimates of BAU achievable potential are significantly smaller potential resources, with more than a fivefold gap between the economic and the BAU achievable resources for both shed and shift DR. It is evident that significant barriers exist at present to realizing the full potential of cost-effective DR in California. Among other drivers of customers' willingness to enroll and participate in DR programs, new, more effective approaches to customer enrollment could capture a cost-effective resource that is several times larger than what present-day strategies are able to achieve.

[3] Interestingly, we estimate that if shift DR resources also provide shed DR service, the additional value they capture increases their economic potential threshold to near or above the BTM battery level, suggesting that these upper limits may be within reach.

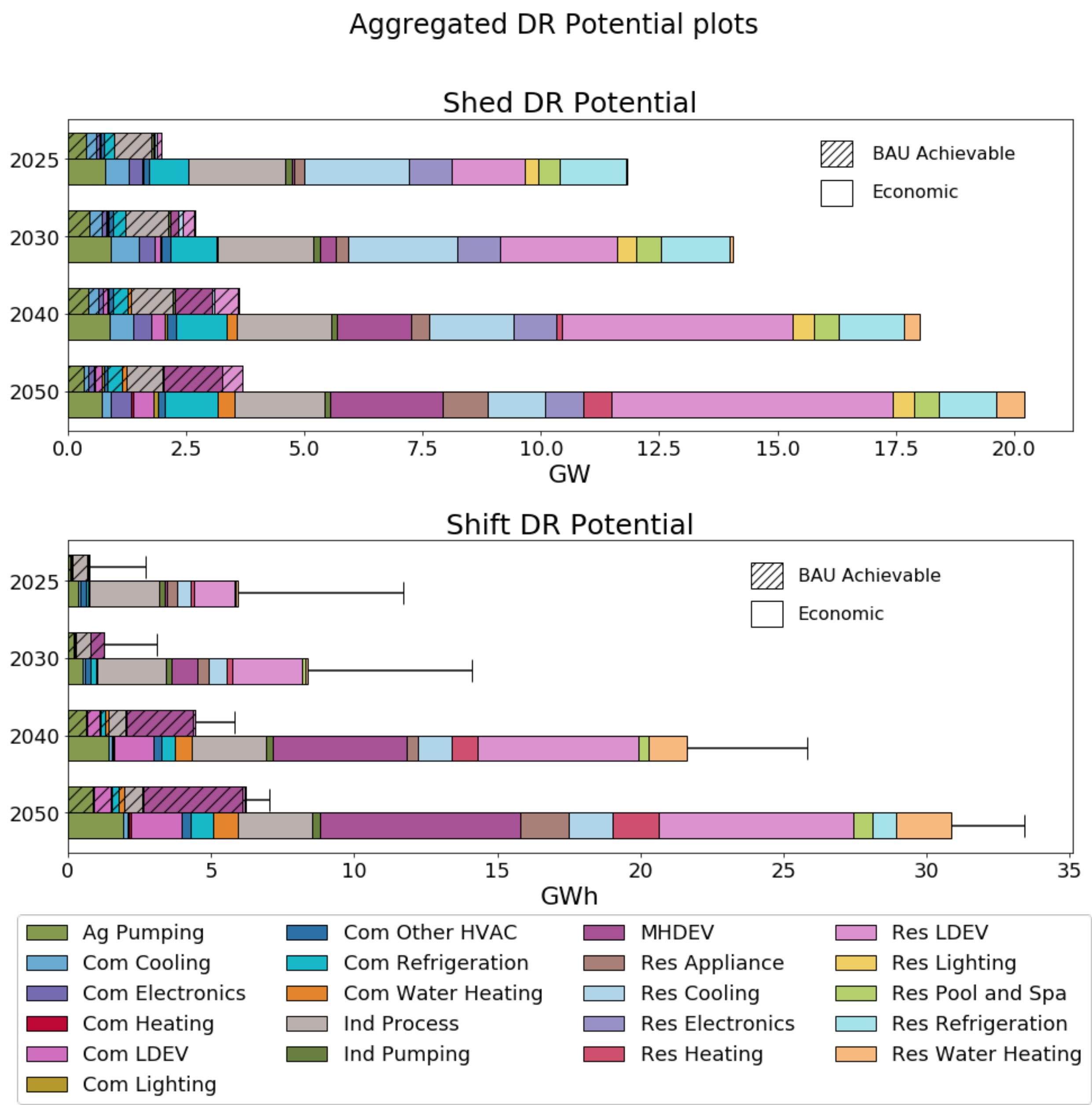

Figure ES-2. Summary of the economic and BAU achievable DR potential for shed (top) and shift (bottom) in each forecast year, disaggregated by end use, at costs estimated to be cost-effective using the ACC. For shift DR, we also show the potentially larger shift potential that is available up to the cost of BTM batteries as a horizontal whisker attached to each bar in the lower plot. Numerical values for the end-use-level potentials are tabulated in section 4.5, Tables 20-22.

Figure ES-2 also shows notable changes in the mix of end uses that make up the DR potential over the forecast period. Certain end uses represent stable sources of DR throughout the period, while others undergo dramatic growth or notable decline. We can summarize these findings by assigning the end uses to descriptive categories.

- **Steady workhorses** remain important sources of DR potential throughout the period. The most important of these are industrial process loads, agricultural pumping, and commercial and residential refrigeration.
- **Rising stars** are new electrified loads that rapidly grow to be among the largest available DR resources. These are residential LDEV charging, MHDEV charging, and residential water heating.
- **Emerging performers** are additional electrified or newly connected loads that become increasingly important, if not dominant. These include commercial LDEV charging, residential and commercial space heating, and residential appliances.
- **Declining resources** are end uses whose declining coincidence with system needs in the long term (2040 and beyond) will make them less important as DR resources. These include residential and commercial space cooling, especially as shed DR resources.
- **Development opportunities** are end use loads that provide limited DR potential relative to their share of statewide annual energy use, but could potentially provide more with further technology development. These include residential refrigeration and residential and commercial lighting and electronics.

Certain DR-enabling technologies are particularly important for capturing DR resources cost-effectively from these end uses. Most importantly, flexible EV charging infrastructure is a critical component of enabling future DR potential. Given the size of the potential resource they enable, even costly EV technologies appear in the economic potential, such as gateways for vehicle-to-building (V2B)[4] discharge or building additional workplace charging infrastructure. Communicating water heater controls--either add-on controls or connected water heaters--also emerge as an important future technology. Programmable communicating thermostats (PCTs) and energy management systems (EMSs) remain important, despite the decline in the importance of space cooling, since they can also enable DR from space heating. Connected devices such as appliances and power outlets also grow in importance as their costs fall and they become more widespread. Other relatively new technologies that appear to have an important role in the future of DR include thermal energy storage (TES) for commercial refrigeration and communicating remote controls for agricultural pumping.

Phase 4 also considers the potential to capture the available shed and shift potential via customer response to a dynamically varying electricity rate that is conceptually similar to the California Flexible Unified Signal for Energy (CalFUSE) tariff structure recently proposed by CPUC Energy Division (CPUC Energy Division 2022). Under the particular assumptions used in the analysis, with universal enrollment in a dynamic tariff, customer price response could capture some 40-50% of the technical potential for shed and shift DR in the form of shape DR, much of it being available at zero cost through manual customer response. In 2025, those zero-cost resources amount to some 7 GW of effective shed and 3.5 GWh of effective shift resource. These findings rest on a set of assumptions about customer responsiveness based on existing

[4] This study considers technologies that export energy to the grid to be outside the scope of DR resources; therefore vehicle-to-grid (V2G) technologies are not modeled. These could potentially provide even greater value.

studies and they assume universal enrollment in dynamic pricing. More research is needed on real-world customer responsiveness and willingness to adopt such tariffs.

The findings of the Phase 4 study indicate profound changes on the horizon for DR in California as the state transitions to a fully decarbonized energy system over the coming decades. Rapid growth in VRE generation and electrified loads will beget equally rapid evolution in the need and potential for DR, as well as the characteristics of the DR resource. Critical system peaks will transition from being concentrated in the summer season today to falling in both the summer and the winter by 2050. This migration will gradually erode the shed DR potential of space cooling loads, which have traditionally been a major source of shed. At the same time, substantial new sources of DR will become available from the new electrified loads, such as space and water heating, clothes drying, and especially LDEV and MHDEV charging, which are projected to rise rapidly to become the most important sources of DR in the state. Meanwhile, large and steady loads like industrial process loads, agricultural pumping and commercial refrigeration can provide consistent year-round resources.

Maximizing the potential DR resources that are captured will require a sustained and coordinated effort from policymakers, regulators, IOUs, program administrators, aggregators, researchers, evaluators, implementers, and technology firms to set appropriate policy goals and execute them through existing and new program structures and technological pathways. It will be particularly important to ensure that electrification proceeds in tandem with demand flexibility, and this will depend on statutory policy, regulatory standards, appropriate incentives, and ongoing outreach and education to customers and the workforce of installers. Through such collaborative efforts across the full ecosystem of electricity demand management it will be possible to make the potential for DR a reality and ensure a cleaner, more affordable, more reliable, and more rewarding power system for California ratepayers.

1. Introduction

Demand response (DR) is an increasingly important tool for supporting California's power system to utilize renewable electricity more effectively and to be more resilient and adaptable to climate change. Two record-setting days on the California grid in 2022 illustrate the growing importance of DR.

The first was May 8, 2022, when renewable energy generation added up to a record percentage of just more than 100% of the load served through the California Independent System Operator (CAISO) for a short period. California's aggressive deployment of renewable energy, consistent with SB100 goals, has now reached levels at which there is often a surplus in the middle of the day. The grid dynamics on May 8, 2022 are illustrated in Figure 1. At mid-day, the state's total renewable generation was equal to the in-state demand, plunging the net load to zero (there were also must-run thermal, hydroelectric, and nuclear power plants online at this time to maintain stability and reliability and to allow those plants to operate within their required limits). With this much power generation, California was able to export nearly 5 gigawatts to neighboring states, and there was still between 1-5 gigawatts of renewable power curtailed in the middle of the day. Especially in the springtime, but increasingly year-round, these "duck curve"[5] dynamics introduce important opportunities for demand responsive loads to **shift** and match renewable generator output, capturing and making use of the available zero-carbon energy.

Tuesday September 6, 2022--which saw record high load on the CAISO grid at 52 GW--was another day that illustrates how DR can help the grid manage climate change, responding to extreme heat waves. On Monday, amidst a multi-day and sustained heat wave, the day-ahead forecasts for Tuesday evening were close to the total dispatchable generation resources available. Figure 2 shows that by Tuesday morning the net loads were even higher than forecast. There were plans in place and preparations made for rolling outages. Then, from 4-9 PM, every DR resource that could **shed** load in the state was called on. The gross load was pulled back, and at about 6 PM an unprecedented and successful emergency alert was sent out to mobile phones across the state to call for additional manual load reduction. Together it all worked: the gross load on the CAISO system fell by more than 1 GW within less than a half hour. The exceptional response to the emergency alert across the state combined with DR programs and automated resources to help the grid ride through a tight but manageable evening without rolling outages.

[5] The now-famous duck curve was originally illustrated in 2012-13 by CAISO as a forecast for the coming wave of renewables. Ten years later, in 2022, the forecasts have proven correct and the grid continues to provide reliable electric service.

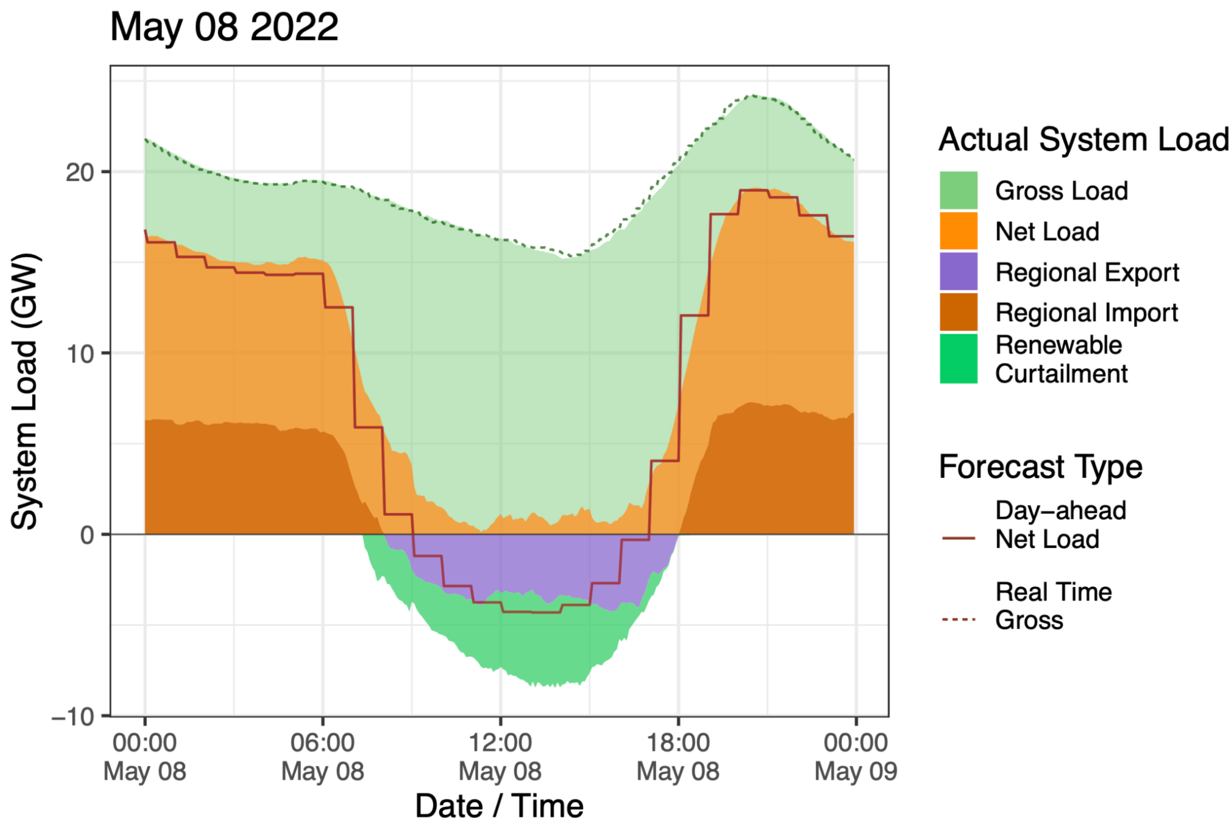

Figure 1. California grid operations summary for May 8, 2022. Data sources: Actual and forecast Gross Load and Net Load from CAISO Daily Outlook (https://www.caiso.com/TodaysOutlook); Imports, Exports, and Curtailment from Data from CAISO "Production and Curtailment" spreadsheets summarizing operational data from May 2014 through September 2022 (CAISO 2022b) .

2022 is the third year in a row with exceptional summer peak load management challenges. Rotating outages in August 2020 were followed in 2021 by measures to relax air pollution rules and let ship engines and backup generators be used to prevent blackouts[6]. It has required utilization of all available resources over the last several years to keep the grid operating at peak times. Along with DR, decades of effort to improve energy efficiency (EE) helps reduce pressure on the grid every day, along with the California resource adequacy (RA) planning process working to try to ensure enough generating capacity is available for peak days like September 6, 2022.

[6] A 2021 blog post gives an informative high-level discussion of the 2020 and 2021 summer peak conditions and responses (Specht 2021).

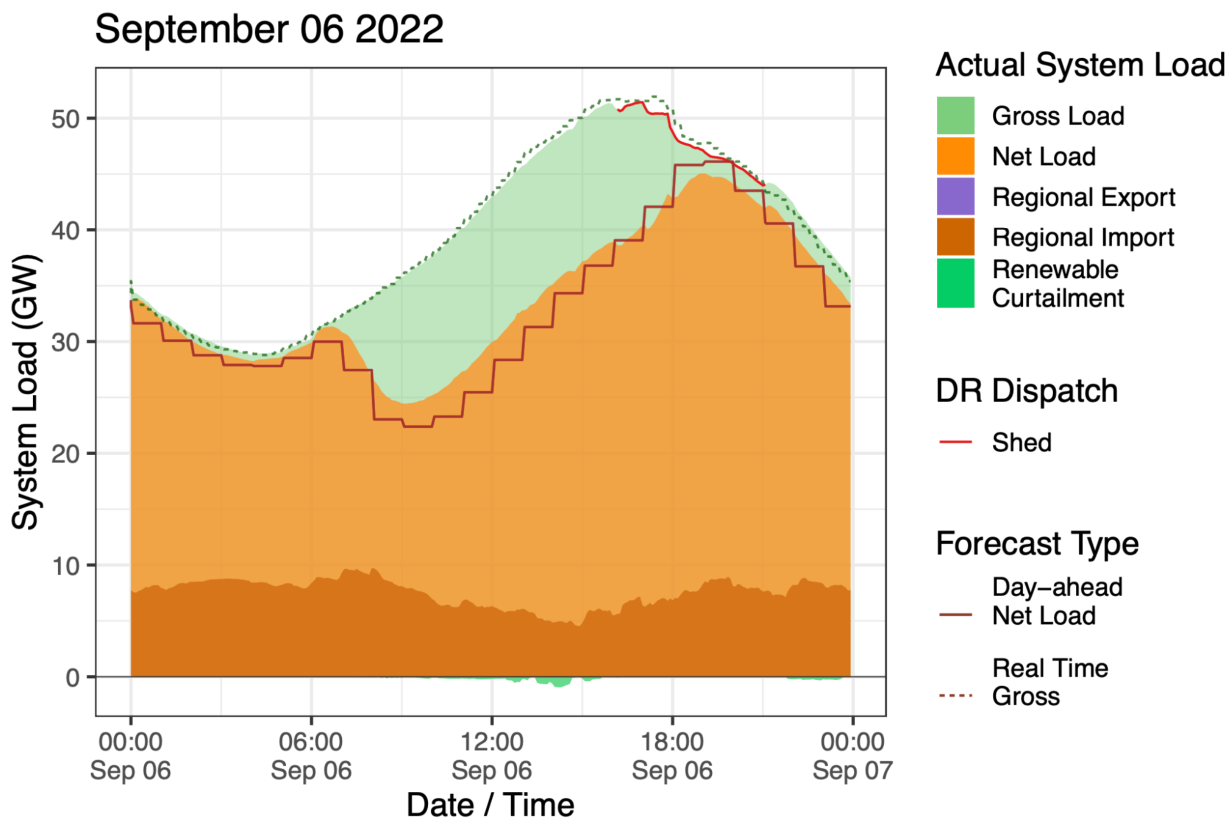

Figure 2. California grid operations summary for September 6, 2022. Data sources: Actual and forecast Gross Load and Net Load from CAISO Daily Outlook (https://www.caiso.com/TodaysOutlook); Imports, Exports, and Curtailment from Data from CAISO "Production and Curtailment" spreadsheets summarizing operational data from May 2014 through September 2022 (CAISO 2022b) .

DR is clearly needed in California today, and the need is likely to become more acute in the future. Days like May 8 and September 6 are not anomalies but are an expected and increasingly common occurrence as the climate changes, and as we deploy variable renewable energy (VRE) to mitigate still worse impacts of climate change while adapting to the changes already underway.

It is not clear whether present-day approaches to obtaining DR resources will be adequate to meet the future need. Indeed, a more notable event than either of the examples above occurred on August 14 and 15, 2020, with involuntary load curtailments ("rolling blackouts") ordered in the CAISO system in response to a generation shortfall during another heat wave, resulting in significant and sustained media and political attention. A subsequent root-cause analysis ordered by the Governor (CAISO, CPUC, and CEC 2021) found, among other causes, that DR resources, while beneficial, may not have provided all of the expected load reductions during this period.[7]

[7] Some DR providers and evaluators have argued that the apparent shortfall may stem from inadequate accuracy in baseline calculation during extreme weather events, leading to inaccurate measurement of the response. We return to this point in section 5.

In response to the August 2020 event (and a subsequent emergency proclamation from the Governor) the California Public Utilities Commission (CPUC) and the California Energy Commission (CEC) have initiated new approaches to capturing DR resources, such as the CPUC's Market Access Program (MAP), which allows EE providers and DR aggregators to be paid for peak load reductions measured at the meter, and its Emergency Load Reduction Program (ELRP), which pays customers of investor-owned utilities (IOUs) for load reductions during peak events; as well as the CEC's Demand-Side Grid Support (DSGS) program, which offers incentives for peak-load reduction to non-IOU customers.

These new programs, along with other novel approaches such as the emergency mobile-phone alert on September 6, 2022, appear to have unlocked an unprecedented customer response which have successfully averted similar load curtailments in 2022. This response makes evident that there is substantially more flexible load in California today than has historically been captured by DR programs in the state. Enabling untapped DR potential will be an essential component of decarbonizing the California energy system in a way that is cost- and resource-efficient.

The California DR Potential Study is an ongoing research effort conducted by Lawrence Berkeley National Laboratory (LBNL) on behalf of the CPUC to assess and forecast the potential DR resources that are available within the IOU service territories that the CPUC regulates in California, using a bottom-up modeling approach that leverages advanced metering infrastructure (AMI) data from a large sample of IOU customers to construct a detailed picture of customer electricity demand in the state and the diverse pathways to enabling demand response. This report presents the findings from Phase 4 of the study, which represents a thorough update and expansion on the previous phases, including a new, larger customer dataset, a more detailed consideration of flexible end uses, and an extension of the study forecast horizon through 2050, to capture the impacts of achieving the state's power-sector decarbonization goals under SB100.

2. Background, Context, and Scope

Phase 4 of the California DR Potential Study provides up-to-date modeling and analysis to support policymakers focusing on DR and load flexibility. Our work is shaped by the technology trends, DR policy issues, and statewide initiatives that are currently shaping the sector; and it is conducted within the scope of CPUC jurisdiction. These trends, context elements, and scope are described below.

2.1. History of the DR Potential Study

This California DR Potential Study report is an outcome of our ongoing effort to understand and map the resources available from load flexibility for supporting statewide energy goals. The CPUC Energy Division funds this work to support DR policymaking with research that supports ongoing efforts to incorporate cost-effective and valuable DR into energy system planning and operations.

The key questions and information need for DR policymakers have evolved over time. Grid dynamics have changed as more renewables are added to the mix. New electric loads and distributed energy systems present new opportunities for control. The policy frameworks for DR continue to change as well, both within the CPUC and at the CAISO. All of these factors inform our structure and approach for the study.

The California DR Potential Study was designed with two goals: (1) to bridge the analysis of distributed energy resources (DERs) with grid investment and operations and (2) to communicate the results of the study clearly to power system policymakers and stakeholders who need to synthesize across those domains.

In the scoping of the analysis and the interpretation of results, we attempt to be:
- **Inclusive** of the range of technology options available now or in the near future
- **Trusted** and based on multiple points of engagement with stakeholders
- **Understandable** by experts and non-experts engaged in the policymaking process
- **Relevant** for the key policy discussions going on during the current phase of the work

Our overall analytic framework groups DR services into four core categories identified during an earlier phase of this study (Alstone et al. 2017): **shape**, **shift**, **shed** and **shimmy.** For the purposes of the Phase 4 study, these are defined as:

- **Shape** captures DR that reshapes customer load profiles during significant portions of the year through price response or behavioral campaigns—“load-modifying DR”—with advance notice of months, days, or even hours.
- **Shift** represents CAISO market integrated DR that encourages the movement of energy consumption, on the timescale of hours, from times of high net demand to times of day when there is a surplus of VRE generation.
- **Shed** describes CAISO market integrated DR that curtails loads, on the timescale of hours, to provide net peak reduction and support the system in emergency or contingency events with a range in dispatch advance notice times.
- **Shimmy** involves using loads to dynamically adjust demand on the system to alleviate short-run ramps and disturbances at timescales ranging from seconds up to an hour.

Taken together, **shape, shift, shed, and shimmy** represent a complementary set of DR approaches that are available to support California’s clean energy transition and grid management.

The focus of this Phase 4 report is on better understanding two key functions that DR can play on California’s grid today and in the future: frequently-used **shift** DR to better match renewable generation and balance the daily net load, and rarely-used **shed** DR to trim peaks and avoid generation shortfalls. We consider obtaining these resources both through traditional supply-side (dispatchable) DR programs, as well as through novel demand-side approaches that would capture the resources as **shape** DR.

2.1.1. Study purpose

The DR Potential Study process has been an effort of LBNL since 2014, and since then has evolved in scope and methods to support a changing energy policy landscape. DR has supported peak load management for decades, starting in the 1980's and 90's. At the time the study was initiated in 2014, there were mature and multi-pronged programs focused on Shed DR. Large categories of DR included air conditioner load control devices, industrial facilities on call to reduce demand, and aggregations of controllable load. By the 2000's, fast load control technologies also created the potential for shimmy DR to be able to support ancillary services on the grid (MacDonald et al. 2012) though market structures have generally not been able to accommodate it to date. As more renewable energy has been added to the grid, opportunities have emerged to shift load with DR and capture excess renewable generation as well.

2.1.2. Summary of Phases 1 through 3

Phase 1: Alstone et al. (2016) (hereafter "the Phase 1 report") summarized the *shed* DR resource, with a focus on supporting the immediate needs of stakeholders, policymakers, and intervenors in rulemaking R.013-09-011. This multi-year rulemaking was initiated to "Enhance the Role or DR in Meeting the State's Resource Planning Needs and Operational Requirements."

The Phase 1 report documented that there is a large potential shed resource (ranging from 2-8 GW depending on assumptions about value and R&D pathway). It also demonstrated how our new modeling approach to DR analysis could be used to weigh the benefits of flexibility and load control against other options like battery deployment and conventional generation resources.

Phase 2: Alstone et al. (2017) (hereafter "the Phase 2 report") was the final report in support of R.013-09-011, and expanded the set of DR resources being considered to include *shift, shape,* and *shimmy* in addition to the *shed* resource.

The main contribution of the Phase 2 report was showing how the shift resource could be a significant and valuable use case for load flexibility to balance renewable energy resources. The estimated scale of the resource was 5-20 GWh, which we described could be achieved through dispatch or through price-based load modification (i.e., as shape DR).

Phase 3: Gerke et al. (2020) (hereafter "the Phase 3 report") was initiated to better understand the *shift* resource and to add fidelity and scope to the analysis. It was completed in parallel to and with the input from the Load Shift Working Group (LSWG) that was convened by the CPUC and included a cross-section of stakeholders (Gridworks 2019).

The Phase 3 report's focus on the shift resource revealed a more nuanced and detailed view of how loads can change timing to better match renewable generation. The report identified some 5 GWh of available load-shifting capacity with cost equal to or less than a behind-the-meter (BTM) batteries, with seasonal variation in the availability and need of the resource, and the possibility to double or triple the resource in the residential sector if there are efforts towards market transformation and standardization of load control.

2.2. Technology context

To know the potential role of DR, we need to know the likely status of the power system and the capabilities to flexibly operate loads. Our study includes forecasts of the power generation mix, loads, and available DR out to 2025, 2030, 2040, and 2050. These forecasts are based on the best available information, and while they are likely not correct in the details they reflect a possible trajectory given current trends in technology, policy, environmental, and social factors. Climate change is a wild card in this study, with significant uncertainty in the degree and characteristics of its impacts in the future. There is also uncertainty in how fast low carbon energy technology will be deployed and adopted. If recent history is a guide[8], many of these could get cheaper faster than we currently forecast and be deployed more rapidly.

Important next-generation energy generation, storage, and utilization technology systems that will shape the future of DR and the grid in California include:

- a range of VRE that could be added to the grid: solar PV, on- and off-shore wind power
- batteries for supporting grid management and resilience, both behind the meter (BTM) and at the utility scale
- electric vehicles (EVs), including both light-duty EV (LDEV) and medium- and heavy-duty EV (MHDEV) categories
- electrified heating for hot water, space heating, cooking, and industrial processes

As these new technologies are deployed, there will be new opportunities for DR systems to help balance the power system. The mix of DR-enabling technologies starts with many that have been in use for years: programmable communicating thermostats (PCTs), industrial load management, and aggregations of loads with advanced energy management systems (EMS). It also includes new sources of flexibility: the EV fleet represents a large new load that could be flexible, and the potential flexibility of electric heating could be enhanced with thermal energy storage (TES).

All of these DR resources are considered in the context of other sources of flexibility and reliability. Renewable curtailment, using batteries, and conventional investments in dispatchable generation and grid infrastructure are the benchmarks we measure and value future DR.

2.2.1. Decarbonization and new (flexible) electric loads

Switching from fossil fuel to electric loads powered with renewables is fundamental for averting climate change (Williams et al. 2021). Building decarbonization and a transition to EVs are two key pieces in the transition. Looking ahead, widespread electrification across the transportation, buildings, and industrial sectors is set to drastically increase electricity demand over the coming 30 years (Steinberg et al. 2017). It is natural to ask whether this transition could be supported by a strategy to integrate these new loads with the grid.

[8] For example, see this description of how key solar price and deployment forecasts have been consistently biased towards high prices and low deployment (Hunt 2020).

With battery-based EVs, hot water storage tanks, and the thermal mass of buildings being heated, much of this new load has inherent flexibility. In this study, we focus especially on unpacking the ways that new loads do not only add to the load on the grid but can also contribute to balancing and reliability through DR, sometimes out of proportion with their impact on costs and operations. Appendix E summarizes some of the key technology trends for electrification in the context of DR.

2.2.2. Continuing advances in communications and automation

Advances in information technology (IT), communications, and automation are important enabling factors for supporting expanded roles for in demand response. These technologies are fundamental for supporting load flexibility in several ways: 1) communication pathways to initiate a DR action, 2) automation and controls to modify equipment operations while maintaining appropriate service levels, and 3) telemetry and/or metering to measure and estimate the response. Many DR providers and utilities also use IT-based approaches to target customers and plan programs.

In the coming decades, growth in connected “internet of things” (IoT) devices, coupled with near-ubiquity of wireless connectivity and mobile devices will expand the potential pathways to enabling DR. Simultaneously, advanced building controls that incorporate emerging model-predictive control (MPC) strategies will open up new opportunities for DR, especially for frequently-used load-shifting applications. These broad technology trends have been recently captured in a US road map to enabling grid-interactive efficient buildings (GEB) (Satchwell et al. 2021). At the same time, existing time-tested communication technologies, such as radio broadcast and cellular communications will remain available for expanding DR to additional locations. Most importantly, much of the expanded potential for DR in California will rest on the state’s investment in AMI, or, “smart” meters, which enable granular time-of-use (TOU) pricing and many of the DR settlement strategies required to help enable mass-market DR approaches. We discuss these key technology trends for DR in more detail in Appendix E.

2.2.3. Grid modernization and clean energy

In response to the impacts of climate change and pollution, the electric power system in California is undergoing transformative changes. The plots in Figure 3 illustrate how a set of key features for grid planning and operations have changed since 2014. Renewable energy--primarily solar and wind power--is being added to the grid at a fast pace to keep up with statewide policy targets.

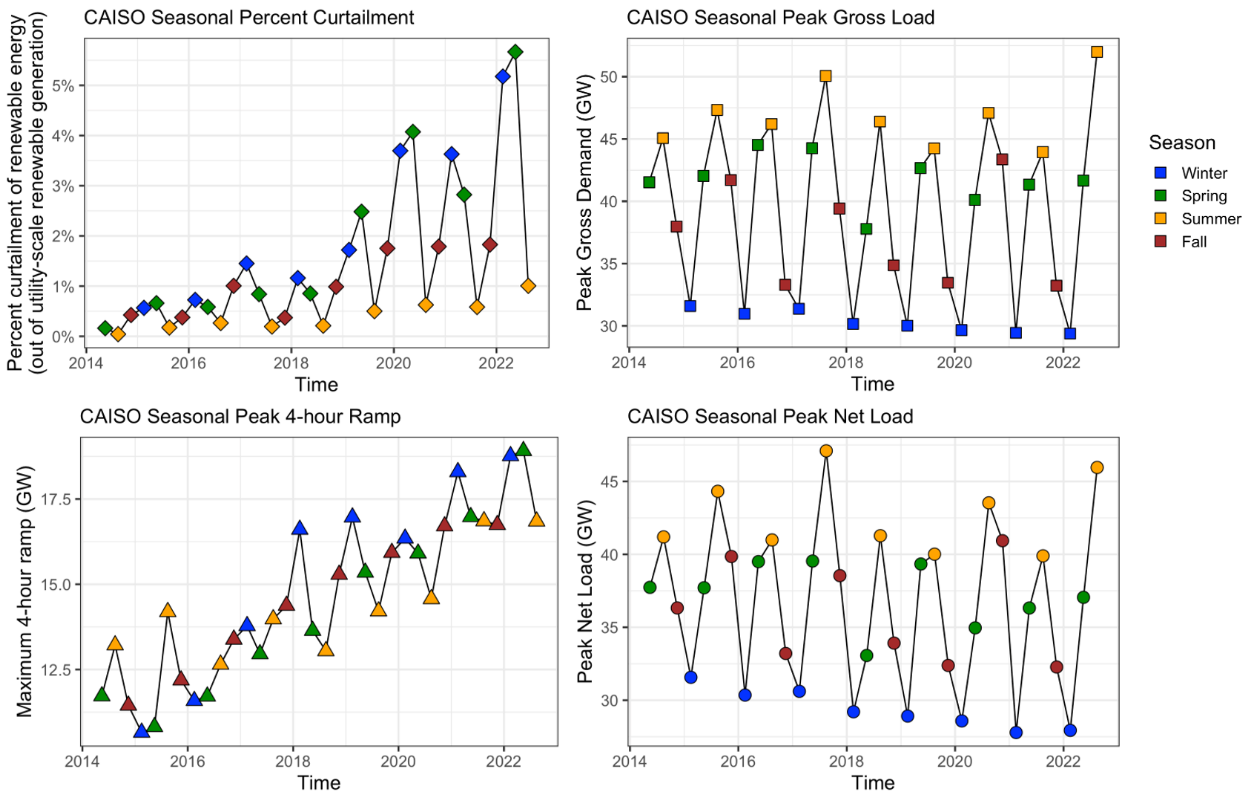

Figure 3. Seasonal trends in operational features for CAISO. Clockwise from upper left: Curtailment of potential renewable energy, the peak gross load ("Demand" with all BTM impacts included), peak net load (gross load minus front-of-meter renewable energy), and the peak evening 4-hour net load ramp. *Data Source: CAISO "Production and Curtailment" spreadsheets summarizing operational data from May 2014 through September 2022* (CAISO 2022b) *.*

One key function of DR on the grid is aiding in renewables integration with load shifting. As we have more renewables on the grid, there are increasingly times when power is in surplus, leading to curtailment. In Spring 2022, about 5% of the available energy was curtailed. Another feature introduced by renewable energy, and particularly solar, is steeper afternoon and evening ramps. The peak ramping requirements are now on the order of 17 MW over a 4-hour period. By shifting energy demand into mid-day times when renewables are in surplus, DR can reduce curtailment and the steepness of ramping requirements.

Another DR function is managing peak loads with load shed. Both the gross load and net load[9] peaks are illustrated in the Figure 3. For the purposes of resource planning, the gross load peak is the primary target. In 2022, California experienced the highest-ever statewide gross load peak at 52 GW during a historic (but increasingly common) heat wave. Renewable energy helps to meet the peak load, but only to the extent it is available. While California has about 17 GW of utility-scale solar and 7 GW of wind, these variable renewable resources do not align perfectly with loads. In practice, the summer net load peaks are about 5 GW lower than the gross load peak, after accounting for the contribution of renewable energy. In the context of shed DR to

[9] The gross load is the aggregate load from electricity customers at the meter (i.e., customer consumption net of any BTM generation), and the net load is the gross load minus supply-side VRE generation.

manage system peaks, the net load peak is most relevant. As fossil generation capacity declines in coming decades, the importance of DR to meet these peaks will continue to grow.

Moving forward, as the California grid approaches 100% clean energy by 2045 in line with SB100 goals, today's trends in grid operations will be enhanced. Curtailment will be more frequent and ramps will be steeper. In addition, as electrified heating and transportation comes online, the load shapes and seasonal patterns will change. In our projections (described in the report below), the net load peak is likely to move farther into the evening and also migrate into the wintertime. The need for DR to help balance and capture renewable energy, and to reduce stress on the grid from steep ramps and peak loads, will continue to evolve.

2.3. Policy and regulatory context

2.3.1. Recent history of California demand response policy

There has been a range of policymaking and regulatory activity related to DR over the past decade. Here is an abbreviated recent history of policy that has shaped and is changing what is possible for DR and flexible loads, and provides context to this work.

The **DR Potential Study** was initiated in 2014 to support rulemaking R.013-09-011. This multi-year rulemaking was to “Enhance the Role of DR in Meeting the State’s Resource Planning Needs and Operational Requirements.” The original focus of the effort was on peak load management using shed DR. Shed is dispatched in rare peak load events to support reliability and reduce the need for conventional generator resources, and DR policy up to 2014 focused on this important function.

Bifurcation of the DR resource into (1) supply-side resources and (2) load modifying programs was a key policy making activity underway in 2014 (CPUC 2014). The idea of bifurcation is that instead of only having utility-run programs that use DR to avoid peak load, some DR resources can and should be bid into the CAISO energy markets. These “supply” resources are dispatchable, controllable, and telemetered resources that can be dispatched in merit order along with generation and storage through the energy market. In doing so, supply resources would be eligible for resource adequacy (RA) credits directly. There have been parallel proceedings and rulemakings at CPUC and CAISO to organize bifurcation activities.

At the CAISO, the **Proxy Demand Resource (PDR)** framework was developed and integrated into organized energy and ancillary services markets to integrate controllable loads that can shed. Another resource type that was developed since 2014 is the Proxy Demand Resource Load shift resource (PDR-LSR). It accommodates loads that can shift (combining an instruction to increase and decrease load).[10] These frameworks for loads to participate in markets are the subject of ongoing use and improvement through CAISO processes.

[10] CAISO load management and DR (CAISO 2020)

Most of the value from peak load reduction comes from avoiding the need to procure alternative capacity resources (little is from energy market gains). Capacity payments to DR providers whose resources are integrated in the energy market help reflect this value. The CPUC **Demand Response Auction Mechanism (DRAM)** was initiated in 2016 to procure DR as capacity resources, and has been run in most years since by utilities. The DRAM has gone through several iterations and has resulted in procurement of between 100-200 MW of DR shed capacity in each year since 2017(CPUC 2022b).

Also at the CPUC, the **LSWG** was convened in 2017 to study the policy needs for broader use of DR in balancing renewables on the grid[11]. This group brought together stakeholders to develop pathways forward for developing the shift resource. The outcomes were a set of recommendations about policy designs for a possible "product" to better integrate load shift into operations. A range of party proposals were presented for discussion and comparison. They included reforms to CAISO PDR-LSR, approaches resembling dynamic pricing, goals of serving the distribution system needs, incorporation of real-time estimates for greenhouse gas (GHG) intensity (e.g., through the Watttime platform[12]) and market-informed demand automation services (Gridworks 2019).

"Load-modifying" DR is meant to be the other half of bifurcation beside supply-side, market-integrated resources. TOU pricing, critical peak pricing (CPP), and other tariff-based and utility-administered load shaping programs have been in use since the early 2000's. Until 2022, there have not been **dynamic or real-time pricing** options. From 2021 through 2022, the CEC convened and worked through a **Load Management Standards** Rulemaking[13] to study changes to Title 20 of the California Code of Regulations (which relates to appliance and equipment EE standards). The updates, approved in October 2022 and taking effect April 2022, will ask major utilities to do the following (CEC 2022c):

- Develop retail electricity rates that change at least hourly to reflect grid costs and GHG emissions and are approved by their governing board.
- Maintain up-to-date rates in a database called the **Market Informed Demand Automation Server (MIDAS)**, which will provide a central repository for all rate information.
- Educate customers about time-dependent rates and automation technologies to encourage their use.

A parallel set of CEC activities, in Title 20 and Title 24, will help integrate automation into new and upgraded appliances and equipment. With authorization through **Senate Bill 49 (SB49)**, the CEC is instructed to adopt and update "standards for appliances to facilitate the deployment of flexible demand technologies." These statewide pushes towards automation at the end-use level, combined with dynamic rates could make load-modifying DR a significant pathway for flexibility in the coming years. In this report, much of the shift and shed DR potential could be

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[11] LSWG materials at can be found here (Gridworks 2022)
[12] https://www.watttime.org/
[13] (CEC 2022b)

achieved via this pathway, particularly for new load categories that will ship with automation capabilities (e.g., EV charging, heat pumps, etc.).

Senate Bill 846, passed in 2022, was focused primarily on extending the life of the Diablo Canyon nuclear power plant. Another part of the bill focused on DR as one part of how to support grid operations; Section 25302.7 instructs the CEC to set load flexibility and shift targets that can reduce the net load peak, based on findings in studies like the DR Potential Study.[14]

Finally, in response to the August, 2020 rolling outages, two new **emergency DR programs** have been initiated as well. The CPUC ELRP[15] is an IOU-administered approach that pays customers to reduce load in exceptional circumstances. The other is the CEC Demand-side Grid Support Program[16]. Administered by the CEC, the program enrolls non-IOU customers who can reduce load or use backup or onsite generation to take local load off of the system. These programs, both targeted at procuring additional shed DR for exceptional circumstances, were both used in 2021 and 2022 to avoid rolling outages. These emergency programs burgeon other approaches to balance the extremes on the power system.

2.3.2. California energy and greenhouse gas policy directions

California DR is integrated into a grid being changed through rapid and sustained effort to achieve statewide decarbonization and pollution reduction targets.

Renewable and Clean Energy Targets. California has had a succession of bills, orders, and other targets for renewable and clean energy. In 2022, the state has achieved a 36% renewable portfolio of energy, most recently meeting and exceeding the target of 33% by 2020. The next targets, outlined in SB100, is a 60% renewable portfolio by 2030, and 100% renewable and low carbon energy by 2045.

Air Resources Board Pollution Reduction Efforts. The California Air Resources Board (CARB) continues to set statewide targets for local air pollution and GHG reduction to protect the public from harmful effects. As described in the statewide implementation plan (SIP) for 2022, a number of important initiatives are currently proposed that would contribute to transformation in the transportation and heating sectors. Based on their reductions in air pollution and cost-effectiveness, the SIP plan includes requiring zero-emission heating and water heating by 2030 and medium and heavy duty vehicles by 2040. A recent Advanced Clean Cars II rule will require all light duty vehicles to be zero emissions by 2035[17]. These actions will accelerate deployment for electrified heating and transportation--large and potentially flexible loads.[18]

[14] (California 2022)
[15] (CPUC 2021b)
[16] (Erne and Lyon 2022)
[17] (CARB 2022)
[18] Notably, many of these policy actions occurred after the primary modeling for this study was complete. It is thus possible that electrification will proceed even more rapidly than we forecast here.

2.4. Scope and boundaries of the Phase 4 study

2.4.1. Study scope

The Phase 4 study examines the future of DR potential through a wide lens, aiming to provide a comprehensive look at the potential for shed and shift DR in California through mid-century, including a thorough accounting of the potential sources of DR and how they change as the state decarbonizes its energy system.

Geographic footprint. Phase 4 focuses on modeling the potential shed and shift DR resources among customers of main three California IOUs in the context of the CAISO electricity grid system. The three IOUs for which DR resources are modeled are Pacific Gas and Electric (PG&E), Southern California Edison (SCE), and San Diego Gas and Electric (SDG&E). Grid-level loads and VRE generation are modeled for the full CAISO footprint.

Forecast horizon. Expanding on previous phases, which were limited to a 2025 or 2030 time frame, Phase 4 projects electricity demand and VRE generation through 2050, to estimate the impacts on DR needs and resources of meeting the state's ambitious statutory climate goals.

DR types. Phase 4 models the potential **shed** and **shift** DR resources within its footprint and time horizon. As in previous phases, shed and shift DR are estimated both as dispatchable supply-side resources (which represent the primary estimates of shift and shed potential) and as load-modifying resources on the demand side, captured in the form of **shape** DR through customer response to time varying pricing.

Potential types. The Phase 4 study considers several different types of DR potential, which variously take into account technical feasibility, cost-effectiveness, and customer willingness to enroll. These potential types, described in Section 3.5.1 are the **technical**, **economic**, and **achievable** potential, as well as the effective resource potential that may be available via customer response to **dynamic pricing** strategies similar to the California Flexible Unified Signal for Energy (CalFUSE) tariff structure recently proposed by CPUC Energy Division (CPUC Energy Division 2022). Consideration of these various potential types represents an improvement on previous phases, which generally considered only the achievable potential.

Customers, sectors, and building types. As in previous phases, the present study considers electricity demand from customers across all economic sectors, including residential, commercial, industrial, agricultural, and other customers. This phase expands modeling of DR potential to a significantly wider range of building and site utilization types than considered in previous phases, as described in Section 3.3.1.

Electrical end uses and DR-enabling technologies. Phase 4 expands the consideration of electrical end uses from previous phases, as described in Section 3.3.5, to provide a highly detailed accounting of the different end-use loads contributing to the CAISO load and to the potential DR resources. New modeled end-uses include residential appliances, residential and commercial electronics, commercial refrigeration, and a more granular set of industrial process loads. More thorough consideration is also given to forecasting loads from electrified fossil-fuel end uses, including EVs (both LDEV and MHDEV) and space and water heating loads. The additional end uses required the consideration of a broader range of DR-enabling technologies, including connected appliances, connected power outlets, and TES for refrigeration, in addition to the more traditional technologies considered in previous studies, such as PCTs and EMSs.

Connections to other California modeling efforts. A major focus of the Phase 4 study is improved coordination with other related energy-system modeling efforts in California, especially those that support CPUC regulatory decision making. As described in Section 3.2, this study makes important connections with the CPUC's EE Potential and Goals Study, the modeling process for the CPUC's Integrated Resource Planning (IRP) proceeding, and the forecasting for the CEC's Integrated Energy Policy Report (IEPR) and other efforts.

2.4.2. Study boundaries

Although the scope of Phase 4 is intentionally expansive, aiming to address a broad sweep of topics related to the future of DR in California, the study is subject to certain boundaries and limitations, as summarized below.

Excluded regions and customers. Electrical demand in California that falls outside the CAISO footprint are not included in this study. This includes the Sacramento Municipal Utility District (SMUD) and other areas served by the Balancing Authority of Northern California (BANC), as well as the Los Angeles Department of Water and Power (LADWP), certain irrigation districts, and certain boundary regions of the state. Further, customers within the CAISO footprint who are not customers of the three main IOUs are not included as potential sources of DR potential, as they fall outside of CPUC jurisdiction. (As discussed in Section 3.3.7 and Appendix A, such customers represent more than 20% of total electricity consumption in CAISO.)

DR types not modeled. As described above, this study focuses on the potential for shed and shift DR. Shimmy DR potential is not modeled, since it has not been implemented or piloted and appears unlikely to be in the near future. Further, in this study we model the shape DR potential from a hypothetical dynamic tariff similar to the CalFUSE proposal. We do not consider other approaches to capturing DR resources as shape, such as enhanced TOU rates.

Technological boundaries. Our modeling framework considers coupling customer loads with DR-enabling technologies. DR-enabling technologies include communication and control devices that adjust the behavior of a given end-use load based on pre-defined schedule settings, DR event signals, or price signals. The technologies we consider are limited to those that have a presence in the market and can be purchased by consumers at the present time. This ensures a consistent approach to estimating technology costs based on present-day prices. Emerging technologies that have not yet achieved market presence are excluded from our modeling here, though we acknowledge that new technologies under development may expand the potential for DR in the future. We also define the scope of DR to include only technologies that modify load behind the meter, not those that can export energy directly to the grid, since that represents new, distributed supply, rather than DR per se. Thus, BTM batteries that can export to the grid, or vehicle-to-grid (V2G) EV charging strategies are excluded from our analysis. Additionally, we consider potential manual response to DR events as a "technology" in our model framework.

Forecasting limitations. When forecasting future electrical loads, we were not able to include certain expected future trends due to a lack of appropriate data to support well-informed projection. Specifically, we do not attempt to forecast the electrification of present day fossil-fuel end uses in the industrial sector, such as process heating. There are numerous pathways to decarbonizing this set of end uses, and the specific route to decarbonization is poorly constrained at present. Also, although we forecast new electrified space heating loads from a transition from natural gas furnaces to electric heat pumps, we were not able to project the resulting effects on space cooling. These effects would include new space cooling loads for customers who do not currently have air conditioning, as well as reduced space cooling loads due to EE improvements for customers who do have air conditioning.

3. Methodology

3.1. Overview of the DR-Futures Framework and updates for Phase 4

The California DR Potential Study rests on an analytical modeling framework known as DR-Futures, which projects future hourly loads from individual electrical end uses for a set of several thousand granular customer classes, aggregates these up to the utility and system level, and considers pairing them with a set of potential DR-enabling technologies to determine the cost of achieving different amounts of DR, resulting in a detailed supply curve for DR that can be disaggregated across various dimensions to determine promising future pathways to capturing the potential resource. The DR-Futures framework consists of two modeling modules, called **LBNL-Load** and **DR-Path**. These two modules have gone through several rounds of development specific to each previous phase of the DR Potential Study, and full details of the modules can be found in the Phase 2 and Phase 3 reports. Here, we briefly describe the modules and summarize the key updates to each for the Phase 4 study, which are further described in the following sections and thoroughly detailed in Appendix A.

3.1.1. LBNL-Load

LBNL-Load is a bottom-up load-forecasting module that capitalizes on customer AMI data provided by the IOUs to project future end-use load shapes for a diverse set of customer clusters. Key updates to LBNL-Load in Phase 4 include:

12. A completely new set of customer demographic and AMI data from the IOUs
13. An updated strategy for sampling customer AMI data based on demographic characteristics
14. Correction of raw customer meter data for BTM Photovoltaics (PV) generation as well as Public Safety Power Shutoff (PSPS) events
15. A broader set of building types/sub-sectors modeled in the commercial, industrial, and agricultural sectors
16. A novel load shape-based clustering approach that clusters customers together based on similar demand patterns
17. New customer clustering algorithms that dynamically generate clusters according to the load shape clustering and other demographic characteristics

18. More granular disaggregation of temperature-dependent load into heating and cooling end uses, with new allowances for thermal inertia and time-varying customer behavior
19. Expanded end-use disaggregation including numerous new end-uses in the residential, commercial, and industrial sectors
20. Disaggregation of LDEV charging load in the base year and projection into forecasted years
21. Demand forecasts extending to 2050
22. Updated forecasting of EE and electrification using forecasts that are aligned with other key statewide forecasting efforts
23. Inclusion of MHDEV charging in load forecasts, including estimated load shapes based on vehicle type and geographic location

3.1.2. DR-Path

DR-Path couples the forecasted cluster load shapes from LBNL-Load with a database of DR-enabling technologies to assess future pathways to acquiring DR resources, resulting in granular load flexibility potential estimates for individual end uses and technologies that can be aggregated into the final supply curve. Key updates to DR-Path in Phase 4 include:

- New functionality to compute different types of DR Potential, including technical, economic, and achievable potential
- Updated models for the probability of shed and shift DR dispatch based on expected avoided system costs
- An updated model for predicting customer enrollment in DR programs in response to incentives
- Expanded and updated data characterizing the cost and performance of DR-enabling technologies
- Estimation of system value and GHG impacts of shed and shift resources using the CPUC Avoided Cost Calculator (ACC)
- Estimation of the effective shed and shift DR potential that could be captured as shape DR via dynamically varying electricity tariffs.

3.2. Integration with other California energy research and modeling efforts

A major methodological focus of the Phase 4 study was improving the integration of California DR potential modeling with other ongoing state-level modeling efforts related to forecasting load, demand-side energy resources, and energy capacity and storage resources. The Phase 4 study made significant strides in integrating its inputs, assumptions, and approaches more closely with the following statewide modeling efforts:

- The CPUC EE Potential and Goals Study[19]

[19] (Sathe et al. 2021)

- The California Energy Demand Forecast from the CEC's Integrated Energy Policy Report[20]
- Long-term load forecasting in support of the SB100 Joint Agency Report[21]
- The modeling efforts underpinning the CPUC Integrated Resource Plan (IRP) and Long Term Procurement Plan Proceeding[22]

The primary goal is to ensure that the demand-side EE and DR resource potentials used as inputs to the IRP capacity-expansion modeling are computed in an internally consistent manner, such that any EE-induced changes in the system load are properly reflected in the DR potential. This section summarizes the efforts undertaken to integrate the California DR Potential Study with these other modeling efforts; readers interested only in DR results need not read it.

3.2.1. The CPUC Energy Efficiency Potential and Goals study

Since EE and DR affect the same underlying loads, the two resources can interact with each other in important ways. A recent series of LBNL studies gives a comprehensive discussion of the potential implications of these and other EE and DR interactions at the building and grid levels (Satchwell et al. 2020; Gerke et al. 2022; Satchwell et al. 2022). The Phase 4 DR Potential Study team at LBNL worked in coordination with the 2021 EE Potential and Goals Study team at Guidehouse Consulting throughout the development of both studies to characterize and account for possible interactions. The EE study estimates EE savings potential by considering cost-effectiveness metrics for a detailed and granular set of EE measures that could be deployed at customer sites in the state. The two teams identified a subset of the EE measures that also had the capability to enable DR, such as PCTs and connected appliances. The two teams then worked in tandem to characterize the interactive effects between the EE and DR capabilities of these technologies.

One such interaction has to do with the cost-effectiveness of these technologies in providing EE. EE measures that can also provide DR have an additional value stream represented by the avoided system costs that can be achieved through participation in DR programs. These additional benefits have the potential to boost the amount of cost-effective EE potential arising from joint EE-DR measures. In collaboration with the Guidehouse team, the LBNL team developed a methodology to characterize these avoided costs for each identified EE-DR measure and provided these as inputs to the EE study. The detailed methodology and results can be found in the 2021 EE Potential and Goals Study (Sathe et al. 2021).

Future adoption of EE measures generally, and of joint EE-DR measures specifically, also has implications for the DR potential that is available from each affected end use. For instance, an equipment-replacement EE measure that reduces peak load from a particular end use will also reduce the amount of shed DR that end use can provide,[23] all else equal, whereas a controls-based EE measure may increase the available DR potential by adding controllability. The EE

[20] (Javanbakht et al. 2022)
[21] (Gill, Gutierrez, and Weeks 2021)
[22] https://www.cpuc.ca.gov/irp/
[23] To be sure, the benefits of the EE can outweigh the losses from the reduced DR resource in this scenario.

Potential and Goals Study results in a set of goals for EE adoption in the state. To ensure that the resulting impact on DR resource availability is properly reflected in this study, the Guidehouse team provided two key outputs of their modeling as inputs to the DR Potential Study.

The first input from the EE study was projected load reduction factors representing the additional achievable energy efficiency (AAEE) represented by the EE goals, as well as load growth factors representing the increased electricity consumption from electrifying natural gas end uses under the additional achievable fuel switching (AAFS) targets that also resulted from the study, through 2030. These factors were provided on a highly granular level representing specific end uses, EE measures, building types, and geographic regions. These factors could then be directly applied as corrections to the projected load growth for individual customer cluster load profiles, as discussed in Section 3.3.6.

The second input was projected saturations (i.e., percentage of buildings incorporating the measure) for the set of joint EE-DR measures identified by the teams at the outset of the EE study. The LBNL team incorporated these saturation forecasts into the technology characterization inputs for the DR-Path model, to properly account for the presence of DR-enabling measures that are expected to be adopted through future EE programs. The inclusion of future saturation projections in DR-Path is described in Section 3.5.5.

3.2.2. CEC and joint agency load forecasting efforts

The modeling of future DR potential in this study rests on a detailed forecast of future loads on the level of granular customer clusters and specific energy end uses, as discussed in Section 3.3.6. To ensure consistency with other statewide modeling studies, where appropriate, the DR Potential Study bases its load modeling on the results of existing forecasts from state agencies.

Most centrally, the baseline forecast of customer demand growth through 2030 is based on scaling the customer cluster load shapes according to the Mid-demand baseline scenario of the California Energy Demand Forecast from the 2021 IEPR (Javanbakht et al. 2022). As discussed above, EE and FS impacts are applied based on outputs from the EE Potential and Goals Study, which are consistent with the AAEE scenario 3 and AAFS scenario 3 in the IEPR forecast.

Because the 2021 IEPR forecast only runs through 2032, a different approach was needed to forecast loads through 2050 for the Phase 4 study. For consistency with other long-term modeling efforts, we relied on the PATHWAYS model from E3 Consulting that was used to support the 2021 SB100 Joint Agency Report (Gill, Gutierrez, and Weeks 2021) and which projects future growth in different end use loads in California. Specifically, we used the High Biofuels scenario from that model, which is planned to be used to forecast loads for upcoming IRP modeling efforts.

In addition to these comprehensive load forecasting efforts, a key element of the load modeling in the Phase 4 study is the evolution of EV charging load shapes through 2050, both for LDEVs and MHDEVs. Numerous efforts have been undertaken by the CEC to model EV load in the state. For consistency with the latest such efforts, we derived LDEV charging load shapes from the most recent version of the Electric Vehicle Infrastructure Projection (EVI-Pro) model (NREL 2022a) from the National Renewable Energy Laboratory (NREL) that was used to support CEC modeling of EV charging infrastructure needs (Bedir et al. 2018). We also derived MHDEV charging load shapes from the latest modeling performed at LBNL in support of the CEC's Medium and Heavy-Duty Electric Vehicle Infrastructure - Load Operations and Deployment (HEVI-LOAD) tool (Bin Wang, private communication). Growth in the aggregate EV charging load was derived from the forecasts in the IEPR and the PATHWAYS models, as described above.

3.2.3. The CPUC Integrated Resource Plan modeling process

Throughout the Phase 4 modeling effort, the DR Potential Study team coordinated closely with the IRP modeling team at E3 Consulting to ensure consistency in assumptions and to improve the incorporation of DR Potential Study results into the IRP modeling process. This coordination ensured that the IEPR and PATHWAYS forecast scenarios used in Phase 4 (described in the previous section) were the same that were planned for use in the upcoming IRP modeling effort. The teams also worked closely together to develop a framework for incorporating shed and shift DR potential into the RESOLVE capacity expansion model used for the IRP, so that these resources can be compared appropriately with other generation and storage resources in the model.

As a result of this effort, the Phase 4 DR Potential Study team has provided the following model outputs to the IRP team to be used as inputs to the IRP modeling:

- A supply curve of shed DR, disaggregated by end use, representing the typical amount of load reduction that could be expected during DR events under historical customer enrollment patterns.
- A detailed hourly representation of the supply curve and load shifting duration for shift DR resources, consisting of 8760-hour time series of the maximum load reductions and maximum load increases that can be achieved by individual end uses at specific procurement cost levels, as well as the maximum duration of load shifting that each end use can achieve.

3.2.4. Outcomes

The goal of integrating more closely with other state energy modeling efforts in the Phase 4 study was to improve consistency and accuracy in the demand-side resource estimates used as inputs to the CPUC IRP modeling process. Prior to the Phase 4 integration efforts, coordination was more tenuous among the various modeling efforts described in this section. Previous phases of the DR Potential Study, for instance, forecasted EE load impacts based on IEPR forecasts that were informed by earlier EE Potential and Goals Studies, rather than using projections directly from the EE study. As a result, it was possible for the EE projections in the DR Potential Study to be out of date with respect to the latest EE goals used as inputs to the IRP. Also, earlier IRP modeling efforts modeled shift DR based on the Phase 2 shift supply curve without including important operational constraints on the resource that are included in the DR Potential Study modeling. The integration efforts undertaken as part of the Phase 4 study will ensure that future modeling efforts are more properly synchronized and internally consistent, yielding a more accurate assessment of the role of EE and DR in future California grid system planning.

3.3. Modeling customer and system loads in California with LBNL-Load

The LBNL-Load module is a “bottom-up” approach for forecasting hourly electricity end-use loads and aggregating them to the CAISO system level. It capitalizes on IOU-provided demographic data for the full set of approximately 13 million utility customers and hourly load data for 411,000 customers across the three California IOUs. Using these data, we develop 5422 representative customer clusters. Each cluster’s 2019 total hourly consumption is estimated from the available load data, then disaggregated into its constituent end uses based on temperature regression and engineering estimates. These end-use baseline load shapes are then forecasted for several future years in various weather and electrification scenarios. The resulting baseline load shapes are the key input to DR-Path, our techno-economic model for demand response.

This section provides a brief step-by-step description of the key data inputs and modeling steps for LBNL-Load, as well as description of key updates since Phase 2. More details are provided in Appendix A.

3.3.1. Customer data and sampling

The Phase 4 research effort included collecting all-new data from the IOUs, which had last been collected in 2015. CPUC convened several meetings between the LBNL team and each of the IOUs so that LBNL could develop an understanding of general data availability. LBNL then developed a two-stage data request to the IOUs. The first stage requested descriptive data on all IOU customers, such as tariffs, North American Industry Classification System (NAICS) codes, climate zone, DERs, electrified end uses, and annual energy consumption (see Appendix A for a full list), as well as data on customer participation in DR programs. Information on 13.6 million accounts was included in the demographic files provided in response to this request. LBNL used these demographic files to develop a sample of 3% of meters that were included in the second stage of the data request, which asked for AMI interval data from calendar years 2018 and 2019. Additionally, the second stage data request included requests for aggregated system-level load data and information on public-safety power shutoff events.

Several utility-provided indicators were used to thoroughly classify each account to enable more granular customer grouping during the AMI sampling process as the final customer clustering process described in Section 3.3.4. Tariff codes were used to map each customer to a relevant sector (residential, agricultural, or commercial/industrial) and flag if they were on a TOU rate, an EV rate, or a California Alternate Rates for Energy (CARE) rate. The tariff was also used to classify non-residential customers as small, medium, or large if peak demand data was not provided. Each non-residential customer’s NAICS code was mapped to a more specific sector assignment (commercial, industrial, agricultural, or other) and building type (or industrial subsector) shown in Table 1. A total of 32 non-residential building types and industrial sub-sectors were considered; this represents a significant expansion from previous phases of the report where, for example, only four building types were separated out in the commercial sector.

Table 1. Table of sectors and building types (or industrial sub-sectors) used in the modeling.

Sector	Building Types
Agricultural	(5) Animal, crop, indoor, water, other
Commercial	(14) Assembly, dining, education, lodging, medical, office, datacenter, retail (4; separated by food or non-food and wholesale or non-wholesale), warehouse (2; refrigerated and not), other
Industrial	(8) Chemicals and petroleum, equipment manufacturing, food and beverage manufacturing, goods manufacturing, materials production, military, water, other
Other	(5) Construction, transportation, utilities, waste, other

Geographic information provided for each account included ZIP code, climate zone,[24] latitude and longitude, Sub-LAP, and whether or not the account was in a local capacity area (LCA). Climate zones were mapped to three climate regions (marine, cold, and hot-dry) to align with the definitions used in the EE Potential and Goals Study (see Appendix A for the detailed climate region mapping). Data from the CalEnviroScreen tool (California OEHHA 2017) was also used to denote which customers were located in Disadvantaged Communities (DAC) based on their latitude and longitude or ZIP code. Lastly, some utilities provided EV rebate data as part of the first stage data request. This enabled us to flag customers that are likely EV owners even if they were not enrolled in an EV tariff.

The process used to develop the 3% customer sample is described in detail in Appendix A. Due to the diversity of the non-residential sectors, we decided to sample 2% of residential accounts (as well as “other” sector and “other” building types) and then use the remaining allocation to sample the commercial, industrial, and agricultural (CI&A) sectors. This resulted in our being about to sample 16-18% of CI&A accounts for each utility. Customers were grouped into sampling groups (which are distinct from the final customer clusters developed later for use in DR potential modeling) in order to ensure that customers were sampled as evenly as possible across geography, energy use, and demographic characteristics (Appendix A describes the indicators used to form these groups). Each sampling group was then stratified based on total 2019 consumption; customers with more than 10 GWh of demand were all sampled, customers with a kWh entry of zero were not sampled, and the remaining customers were split into eleven groups--one for customers with negative net energy consumption (due to the presence of distributed generation resources), and ten for deciles of non-negative energy consumption--and

[24] Specifically, we considered building climate zones as defined by CEC Title 24.

sampled evenly. The resulting distribution of sampled accounts and sampled load are shown in Appendix A.
In total, meter data was requested for calendar years 2018 and 2019 for 411,000 out of 13.6 million accounts (3%). Because the sampling strategy favored large and non-residential customers, data was requested for 66.1 TWh out of 188 TWh of total load (35%). Corrections and manipulations to the time series data are described in Section 3.3.3.

3.3.2. Other key data inputs

In addition to the customer descriptive data and hourly AMI data, to model the 2019 load for the three IOUs using the customer data and forecast it to 2050, we used the following datasets.

- **Hourly outdoor temperature data** for each customer based on the nearest weather station was obtained from the National Oceanic and Atmospheric Administration (NOAA 2022)
- **Hourly end-use load shapes** developed for the CEC by ADM associates for various residential and commercial end-uses across several building types (Baroiant et al. 2019)
- **Saturation and annual average energy consumption values** for various residential end-uses derived from Residential Appliance Saturation Study (RASS) for 2019 (Palmgren et al. 2021). In case of commercial sector, we use a combination of data from California Commercial End-Use Survey (CEUS) (Itron 2006) and California Commercial Saturation Survey (CCSS) (Itron 2014)
- **Rooftop PV system parameters** from the California Solar Initiative (CSI) Distributed Generation Statistics (DGStats) website (CSI 2022)
- **EV charging load shapes** for characterizing residential and commercial EV charging patterns using EVI-Pro (Bedir et al. 2018)
- **Fraction of energy consumption by each end-use** based on Manufacturing Energy Consumption Survey (MECS) for industrial, agricultural and other sector load disaggregation (EIA 2021)
- **Short-term aggregate load forecasts** (through 2030) from the California Demand Forecast (Javanbakht et al. 2022) of the CEC’s 2021 IEPR.
- **Long-term aggregate load forecasts** (through 2050) from the PATHWAYS model of E3 Consulting (E3, private communication)
- **Detailed AAEE and AAFS and EE measure saturation data** from the 2021 EE Potential and Goals Study (Guidehouse Consulting, private communication)
- **Data on the California vehicle population** from the CARB (CARB 2019) and CEC (CEC 2022a, 2015), used to estimate the present-day EV penetration
- **Forecasts of MHDEV charging load** from LBNL’s HEVI-LOAD model, under development for the CEC (Bin Wang, private communication).

3.3.3. Time series correction and temperature disaggregation

Several processing, modeling and correction steps were necessary to perform on the customer time series data prior to constructing customer clusters. Basic data processing had three main components. First, the data provided by the three IOUs had varying formats that had to be harmonized, and some timestamps had to be adjusted to account for daylight saving time. Next, many non-residential customers have 15-minute interval data, which was aggregated to hourly intervals for consistency with the residential customer data. Finally, data were tabulated separately for energy delivered to the customer and energy received from the customer in the case of customers with distributed generation resources (like rooftop PV) who were on net energy metering (NEM) tariffs. We subtracted the hourly received energy from the delivered energy to yield a single time series representing each customer's net hourly consumption at the meter. Once these initial processing steps were completed, we performed several more involved modeling steps to account for PV generation, temperature-dependent loads, and PSPS events.

PV correction

The first step in modeling customer load is correcting the raw time series files for BTM PV generation. This analysis is new for Phase 4 of the study, as the previous phases' data (from 2014) included sufficiently small instances of PV generation that those customers could simply be excluded from the analysis. We ran the NREL System Advisor Model (Blair et al. 2018), using locational solar irradiance data from the National Solar Radiation Database (NREL 2022b), to construct 2018-2019 PV generation estimates for each customer with rooftop PV. The PV system modeling also used information on each customer's PV system capacity and orientation from the DGStats database (CSI 2022), coupled with IOU-provided identifiers that linked individual customers to the anonymized data in DGStats. To account for occasional over- or under-prediction by the model, we computed adjustment factors for each modeled profile to ensure consistency with the customer's hourly metered export data, which represents a lower limit on the amount the customer was generating in each hour. Finally, we added the modeled PV generation back to the customer AMI data to yield an estimate of the total consumption behind the meter for each customer.

Temperature normalization and space conditioning disaggregation

We then disaggregated each PV-corrected residential and commercial customer load profile into temperature-dependent and non-temperature-dependent loads using a temperature regression framework developed for the Phase 2 study. The framework is based on a change point regression model with two change points, corresponding to building set points for heating and cooling, which are estimated as parameters of the model. Above the higher change point, the model estimates a slope representing the correlation between temperature and space cooling load; below the lower change point, the model estimates a slope representing the correlation between temperature and space heating load; and between the two change points, the model estimates the non-temperature-dependent load. The model regresses customer load against hourly temperature data from the nearest NOAA weather station.

Details of the modeling approach are presented in the Phase 2 report. In Phase 4, we implemented several updates and improvements to the temperature normalization framework:

- Space cooling and space heating loads are now separately modeled (previously, all temperature dependent loads were estimated as a single space-conditioning end use)

- Model parameters were estimated independently for weekdays and weekends, seasons of the year, and times of day (morning, midday, evening, and overnight) to account for variation in customer usage patterns (e.g., thermostats programmed with different set points throughout the day)
- The model was estimated with different time lags between the temperature and the customer load data, to account for the effects of thermal inertia or existing customer load shifting (e.g., pre-cooling) strategies. The time lag that yielded the best fit to the data for each customer was used in the final estimation.

Once the model has been estimated for each customer, we can project customer load in different weather scenarios by subtracting the fitted heating and cooling load based on actual 2019 temperature data, and then using the model to project heating and cooling load using a temperature time series corresponding to the desired weather scenario. For the Phase 4 study, we constructed two weather scenarios:

- A **1-in-2** weather scenario, constructed by selecting the median year, in terms of cooling degree-days, for each weather station, from among the 20 years of NOAA temperature data preceding 2019
- A **1-in-10** weather scenario, constructed by selecting the 90th percentile year, in terms of cooling degree-days, from among the 20 years of data preceding 2019.

Correction for PSPS events

Using the temperature-disaggregated loads, customer demand profiles were modified to account for the significant PSPS events that occurred in 2019. PSPS events generally occur during times of exceptional heat, wind, and dryness, when wildfires are most likely to occur; they can last for several days in some instances (and did so in 2019). Each IOU provided an accounting of the start and end times of all 2019 events and the customers affected. For each affected time series, we estimated the load that would have occurred had power not been shut off by first averaging the same-hour non-temperature-dependent load for the surrounding days, then estimated temperature-dependent load using the temperature regression model described above, applied to local NOAA weather-station temperature data during the event.

3.3.4. Developing customer clusters

After correcting the time series data, the next step is to segment the 411,000 customers into a granular set of customer clusters. Previous phases of this study segmented customers based on geographic and demographic characteristics. In this phase, we also incorporated the aspect of heterogeneity in their load shape patterns by performing load shape clustering. We developed a multi-step clustering approach where we first identified the most commonly occurring load profiles in each sector and then clustered the customers based on how frequently they exhibited each of these patterns. We identified 9 load shape patterns for residential and 7 for commercial sectors. We then combined the results of load shape clustering with the earlier approach based on demographic characteristics to generate 5422 clusters across all sectors. This section describes the approach at a relatively high level, and additional details are presented in Appendix A.

Load shape clustering

Figure 4 provides a flow diagram to summarize the approach to load shape clustering. In the first step, referred to as "Level 1 clustering", we developed a set of prototypical daily load shapes by clustering all of the individual daily load shapes represented by the customers in a given sector. Next, the cluster centers from Level 1 clusters were regrouped further into similar groups, or "superclusters," based on descriptive analysis. Finally, customers were clustered based on how frequently each supercluster pattern is displayed. This step is referred to as "Level 2 clustering". Load shape clustering was performed separately for the residential and commercial sectors' customers. Industrial, agricultural and other sector customers were not considered due to the lack of specific information beyond their building type to identify and explain their load characteristics. We identified 9 residential and 7 commercial load shape patterns. For a detailed description of the load shape clustering algorithm, see Appendix A.

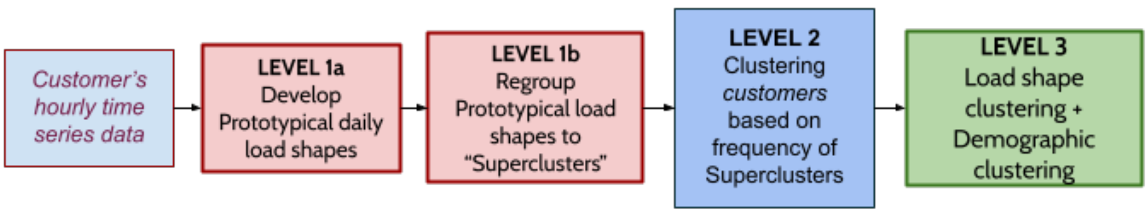

Figure 4. Overview of the multi-step clustering approach.

Final customer clustering

Finally, we combined the results of the load shape cluster assignments with other geographic and demographic characteristics for the customers, and we used these characteristics to segment the customers into a final set of customer clusters. Following on from the load shape clustering, we refer to this as "Level 3" clustering. We considered the following customer characteristics when constructing the final customer clusters, in descending order of priority:

- Sector
- Utility
- Building type
- Customer size category[25]
- Climate region[26]
- Receipt of CARE low-income subsidy
- Local capacity area[27] (LCA)
- Load shape cluster

[25] Customers were subdivided into approximate small, medium, and large subcategories according to their peak demand as reported in the IOU data, as described in Appendix A.
[26] In this study, CEC Title 24 climate zones were mapped to three aggregate climate regions (hot-dry, marine, and cold) in accordance with EE Potential and Goals Study (Sathe et al. 2021). See Appendix A for details of the mapping.
[27] Local capacity areas, also known as local reliability areas, are transmission-constrained regions of the CAISO grid used in system planning. They include areas such as the Greater Bay Area, Greater Fresno, Los Angeles Basin, and so on. See Appendix D for more discussion of LCAs.

- Quintile of total annual energy consumption within the final segment defined by the characteristics above.

The level 3 clustering algorithm proceeded through this list of characteristics using a hierarchical strategy. First, customers were subdivided by sector, then utility, then building type, and so on until the list of characteristics was exhausted, or until it was impossible to create a cluster containing at least a preset minimum number of customers, N_{min} (calculated as the sum of customer weights of the time series samples). Where no segmentation was possible on a given characteristic (e.g., load shape cluster in the industrial and ag sectors, which was not computed), that level of the hierarchy was skipped. If segmenting on a particular characteristic would yield fewer than N_{min} customers in a cluster, we recursively recombined clusters with neighboring clusters until we obtained a sufficiently large cluster. As a result, many clusters represent customers aggregated across several load shape clusters, LCAs, and/or climate regions, especially for large customers or uncommon building types. (For more details of the segmentation and recombination logic, see Appendix A.) For the clustering in this study, we set $N_{min} = 100$ for residential clusters and $N_{min} = 15$ for non-residential clusters, to support the anonymization step below.[28]

Adjustment for time-of-use rate impacts

Between 2019 and the present, residential IOU customers have been transitioned to default TOU electricity tariffs, with higher prices during peak periods and lower prices during off-peak periods. Customers would be expected to modify their energy consumption patterns in response to these tariffs, and the expected impacts have been captured in load impact studies considering the load shape impacts of transitioning to default TOU rates in the residential sector (Hansen and Armstrong 2020; Bell, Savage, and Lehman 2020; Bell, Jiang, and Savage 2020). These studies estimated the expected load shape impacts separately for each LCA, in both a 1-in-2 and a 1-in-10 weather year.

To capture the TOU load shape impacts in our cluster load forecasts, we developed hourly fractional load impacts from the load impacts computed in the above load impact studies, for each LCA and weather scenario. We applied these hourly fractional impacts to the relevant residential-sector customer load shapes before aggregating them into cluster load shapes in the following step. In general, these load impacts are quite modest, on the order of 1%.

Cluster load shape aggregation and anonymization

Finally, for each cluster, we aggregated the 2019 load data of all sampled customers that belonged to the cluster, weighted by their assigned energy use weights from the sampling process and modified for default-TOU impacts, to produce an hourly cluster-level aggregated load shape for each cluster. In the next sections, we discuss disaggregating these cluster load shapes into individual end uses and forecasting their growth through 2050. These aggregated

[28] In addition to these limits on the total number of customers in each cluster, we also required that each cluster contain at least 15 time series samples to ensure a reasonable statistical sample in each cluster.

cluster load shapes represent the primary load inputs to the DR-Path model in the Phase 4 study.

In order to release the cluster load shape data publicly, we also computed a separate set of cluster load shapes according to the “15-in-15” anonymization criteria that are often used for the public release of aggregate energy consumption data. This requires that each cluster contain at least 15 customers (100 in the residential sector), with no customer representing more than 15% of the total consumption in the cluster. Since we set N_{min} appropriately when creating the clusters, the first criterion was met. To meet the second criterion, for any cluster with more than 15% of load from a single customer, we adjusted the customer weights recursively and redistributed the surplus weight to other members in the cluster until no customer represented more than 15% of the total cluster consumption. These anonymized clusters were not used in the study but will be released as an approximate, fully anonymized representation of the study input data.

3.3.5. End-use disaggregation

In Phase 4, we significantly expanded the number of end-uses in load disaggregation across sectors. With the advent of smart technologies, retrofits and communicating devices, utility DR programs have also expanded in recent years to include a variety of end uses. We considered these end uses because they are either already targeted by existing DR programs or have the potential to be targeted by future ones. Table 2 shows the end-uses and building types considered for disaggregating the cluster level load data. Entries indicated in red are the newly added ones in Phase 4; as shown, we have significantly expanded the end-uses and building types in each sector compared to previous phases. The key updates to our disaggregation procedures are outlined here; details can be found in Appendix A.

Table 2. The building types and end-uses considered in each sector for load disaggregation in the Phase 4 study. Red indicates newly added end use or building type.

Residential Sector		**Commercial Sector**		**Industrial/Agricultural Sector**	
Building Types	End Uses	Building Types	End Uses	Building Types	End Uses
Unknown Single-family Multi-family Master meter	Cooling Heating Ventilation Indoor Lighting Outdoor lighting Cooking Dishwasher Clothes Washer Clothes Dryer Refrigerator Freezer Pool pump Spa heater Spa pump Television Office equipment	Office Retail-food Retail-other Dining Lodging Medical Education Assembly Datacenter Warehouse Refrigerated warehouse	Cooling Heating Ventilation Indoor lighting Outdoor lighting Office equipment Refrigeration Water heating Datacenter IT Misc. EV charging Rooftop PV	Ag-crop Ag-animal Ag-indoor Ag-other Chem/petrol Food/bev Mfg-equipment Mfg-goods Mfg-materials Military Water	Boiler Process heat Process cooling Machine drive Electrochem. Process Other process Non-process Pumping Rooftop PV

	PCs Water heating Misc. EV level 1 EV level 2 Rooftop PV				

As discussed in Section 3.3.3, we disaggregated heating and cooling loads from the individual customer AMI data using a change-point temperature normalization model. These disaggregated loads are carried through the cluster load shape aggregation process, so that the initial cluster load shapes consist of separate heating, cooling, and non-temperature-dependent loads at the cluster level. We then disaggregated the cluster-level non-temperature-dependent load into a variety of different end uses as follows.

As we can see in Table 2, we were able to disaggregate the cluster-level hourly non-temperature dependent load across a variety of end-uses. This disaggregation largely employed the following methodology. We used sector-specific end-use survey data to ascertain the saturation and annual energy use values for each end-use. We combined these values with representative end-use load shapes and normalized it to determine the hourly fraction of non-heating/cooling load from each end-use. Finally, the hourly consumption of each end-use is calculated as the product of the estimated load fraction and non-temperature dependent load. In the case of industrial and agricultural sectors, we used a more simplified approach by applying a single fractional value of each end-use across all hours owing to the lack of temporal variation in the available datasets.

LDEV disaggregation

In the residential and commercial sectors, disaggregation of LDEV charging load was one of the significant updates to the study. We considered residential private EVs and commercial fleet EVs for load disaggregation. Previous phases of the study did not disaggregate LDEV load from the customer AMI data, instead forecasting EV charging as new future load. However, owing to significant EV penetration[29] in California as of 2019, we developed a methodology to disaggregate existing LDEV charging load and then use that to forecast its growth out to 2050.

In the residential sector, we developed load shape for level 1 (120 V slow charging) and level 2 (240 V faster charging) charging using EVI-Pro (Bedir et al. 2018), including load shapes for both uncontrolled (i.e., on-demand) and controlled (i.e., scheduled) charging. To determine the total EV saturation in each cluster, we relied primarily on IOU-provided data indicating customers who were on an EV-charging tariff or who had applied for an EV rebate. Comparing the resulting EV penetration estimates to independent estimates of the 2019 vehicle population from CARB (CARB 2019) and the CEC (CEC 2015, 2021) indicated that EV ownership rates were higher than the fraction of customers who opted for an EV tariff or applied for a rebate, so we used the other agencies' data to scale up the EV saturation in each cluster to account for

[29] Battery electric vehicles and Plug-in hybrid EVs' sales increased to 1.9% of total sales of Light Duty vehicles by the end of 2019 (CEC 2021).

these additional LDEV owners. Using data from the 2019 RASS study (Palmgren et al. 2021), we subdivided LDEV owners into those who charged their EVs completely at home and customers who charged partially at work or a public charging station in addition to home charging. We also subdivided at-home charging into level 1 and level 2, and we computed average annual energy consumption values for each category using the RASS data. To develop a final load shape for each cluster, we assumed that customers on EV tariffs used controlled charging, and other EV owners used uncontrolled charging, and we combined the EVI-Pro load shapes accordingly and used the resulting load shape along with the saturation and annual energy consumption estimates to disaggregate the EV charging load for each cluster.

In the commercial sector, we adopted a multi-step approach to disaggregate cluster-level EV load. First, we used RASS to compute the difference between the annual energy consumption values of at-home versus away-from-home EV charging load to determine the total load for charging privately owned LDEV in the commercial sector. We augmented this with an estimate of commercial fleet vehicle charging load based on CEC estimates of the ratio of commercial private EVs to commercial fleet EVs (CEC 2015). We selected the residential clusters with EV charging load in each climate region and LCA and identified the corresponding commercial clusters in the same climate region and LCA. We computed load shapes for workplace and public[30] charging from EVI-Pro. For convenience, we applied workplace charging load only to the office clusters and public charging only to retail clusters[31]. We then apportioned the total commercial charging load proportional to those clusters' total energy consumption (in practice the 2019 commercial EV charging loads are quite small compared to the total load in these clusters, so the impact on other disaggregation steps below is negligible). The resulting disaggregated load shapes reflect the amount of EV charging load in the commercial sector.

Other end uses

To disaggregate the remaining (non-EV, non-temperature-dependent) end uses in the residential sector, we primarily used data from RASS for saturation and annual energy consumption values, and load shape data developed by ADM associates (Baroiant et al. 2019) for the CEC. In the commercial sector, we used saturation data from the CEUS (Itron 2006) and the CCSS (Itron 2014), combined with commercial-sector load shapes from the ADM study. For those end-uses where hourly load shape data was not available, we selected a proxy load shape from the set of available load shapes. For data center building type, we used the bottom-up energy use modeling of the U.S. data center industry that showed Information Technology (IT) equipment is responsible for 65% of electricity use, cooling for 28%, and other end uses for 7% (Shehabi et al. 2016). We applied these fractions to all hours of the year due to lack of temporally-resolved data on end use behavior.

[30] Workplace charging refers to workers charging at their place of work during the workday, which is potentially flexible load. Public charging refers to opportunity charging at retail establishments or other public places and is assumed to be inflexible in this study.

[31] Although there is more diversity than this in the location of commercial-sector EV charging infrastructure, the location of the charging load will have no impact on the resulting DR potential that we compute, so there was no value in improving the accuracy of this assignment for the purposes of this study.

We used the data from the MECS to disaggregate load in the industrial sector (EIA 2021). First, we mapped the NAICS code of each customer in the cluster to the nearest NAICS code in the MECS database, and calculated the fraction of load across NAICS codes in the cluster. Next, we took the breakdown of electricity consumption across end-uses for each relevant NAICS code and weighted by the cluster-specific fraction. Due to lack of data on temporal usage of these end uses, we applied the final end-use fraction to all hours of the year. For the agricultural sector, we disaggregated demand into pumping and non-pumping loads based on assumed pumping fractions of 100% for crop and water agriculture types (according to NAICS code mapping), 50% for agriculture activities related to livestock or indoor crops, and 80% for other designations.

The resulting set of disaggregated load shapes are key inputs to forecasting future years' load profiles and estimating DR potential. The accuracy of the disaggregation depends on the accuracy of the input end-use load shapes and saturation values; since these largely derive from recent and California-specific data sources, our disaggregation should be as accurate as can be computed with present data. Example outputs of the end-use load disaggregation are discussed in Section 3.3.8.

3.3.6. Forecasting

The forecasting process takes the 2019 disaggregated cluster load shapes and forecasts them to 2025, 2030, 2040, and 2050. Forecasts consider baseline changes in demand due to population growth, industry forecasts, and demand trends, as well as impacts from EE programs and fuel substitution (FS) (i.e., electrification) efforts. Passenger EV forecasts as well as expected growth in MHDEV are considered. Appendix A describes the data sources, processing steps, and assumptions used in this process in detail.

Baseline load forecasts are first calculated using two key datasets. We used the California Demand Forecast data from CEC's 2021 IEPR (Javanbakht et al. 2022) to forecast baseline changes in energy use (including LDEV charging growth), customer count, and rooftop PV generation to 2025 and 2030. Specifically, we used the Baseline Forecast - Mid Demand Case. We further forecasted loads to 2050 using the PATHWAYS model used in California's 2021 SB100 Joint Agency Report (Gill, Gutierrez, and Weeks 2021). The scenario used for this study is called the "High Biofuels Scenario", which is consistent with recent analyses conducted for the IRP process. In general, the forecast data is used to calculate load multipliers for each given utility and sector, and those multipliers are applied to the relevant clusters across all hours of the year.

We then added EE and FS impacts to the baseline forecasts. Through 2030, we used modeling outputs from the 2021 EE Potential and Goals Study (Guidehouse Consulting, private communication). In particular, we use model scenario outputs that correspond to the IEPR's core AAEE and AAFS scenarios (Scenario 3 or Mid-Mid). From this data, we are able to compute electric energy (MWh/year) impacts for specific EE or FS measures occurring in a given utility, sector, building type, and climate region, and map those results to our study's clusters and end-uses. From this data, we calculate load multipliers for each end-use in each cluster, and then apply those to all hours of the year. For FS measures, we also adjust the end-use saturation data for each cluster accordingly. EE savings are held constant to 2050 to keep 2030-2050 load growth consistent with the PATHWAYS model while still considering the EE savings that are expected to occur through 2030. To extend the FS forecasts through 2050, we use end use-specific electrification forecasts from the PATHWAYS model for residential clothes drying and residential and commercial space heating, water heating, and cooking (E3 Consulting, private communication).

As described above, the majority of the forecasting effort involves scaling up the existing loads based on expected changes in total electricity consumption. However, for the forecasting of MHDEVs an entirely new load must be added to the model. We worked closely with the developers of the CEC's HEVI-LOAD model at LBNL to develop these load profiles, obtaining an assortment of data based on what was available from recent model runs (Bin Wang, private communication). All data provided was for modeling conducted consistent with the CARB's State Strategy for the State Implementation Plan. Aggregate 24-hour load profiles from 2020-2037 for nine vehicle types were provided, then extended to 2050 using estimates for vehicle adoption from 2020-2050. These were then converted to an annual demand profile using the raw data for weekdays and scaling the profile down for weekends depending on the vehicle type. We distributed these data across counties based on annual county-level adoption estimates for each vehicle type, provided by the HEVI-LOAD team. Finally, we created new synthetic clusters consisting only of MHDEV load in each Sub-LAP, with each county's distribution across Sub-LAPs being estimated based on the distribution of electricity demand for the most relevant sectors and building types to the vehicle type.

3.3.7. System-level load aggregation

After disaggregating the cluster load data across all relevant end-uses, we aggregate the total load to compare the results of our modeling approach with the actual CAISO-level load data for 2019 to verify a reasonable representation of the actual load. We compute the sum of hourly load across all end-uses net of rooftop PV generation for each cluster. We then sum the load across each utility and hour of year for 2019 to arrive at the system level aggregated load.

We compared this data with CAISO's system-level aggregate data for the Default Load Aggregation Point (DLAP) corresponding to each IOU's service territory from the CAISO OASIS tool (CAISO 2019). We found that the modeled load represented somewhat less than 80% of the total CAISO load. This apparent discrepancy can be explained by considering what loads fall within the IOUs' customer base. Our aggregated cluster load shapes represent a model of the total load from California IOU customers on the CAISO grid, including customers of community choice aggregators (CCAs), whose power delivery and metering are handled by the IOUs. However, there are also certain other loads within the CAISO system that do not fall within the IOU customer base and which appear to be "missing" when comparing the aggregate IOU loads to the actual CAISO system load. These entities are detailed in Appendix A and account for some 21% of the total energy consumption in CAISO. They are not IOU customers and fall outside CPUC jurisdiction; therefore, they are outside the scope of this study and are not considered as potential sources of DR potential. Notably, these loads include large pumping loads for water conveyance by the California Department of Water Resources (DWR), the federal Bureau of Reclamation, and the Metropolitan Water District of Southern California. To account for these customers when computing the total aggregate CAISO load, we scale up our modeled aggregate system load shape by an additional factor of $1/0.79$ throughout this study.

3.3.8. Cluster load modeling results

In this section, we describe the results of the level 1 and level 2 load shape clustering that clustered customers according to their energy consumption patterns. We also present results from the final cluster load shape generation and disaggregation into end uses. We highlight interesting details of several example load shape clusters in both residential and commercial sectors by looking at the average daily profiles by season.

Load shape clustering results

As mentioned in Section 3.3.4, Level 2 clustering yielded 9 residential and 7 commercial load shape clusters representing typical consumption patterns in each sector. These patterns are useful to understand the specific end-uses that drive the load shape, occupant behavior, characteristics and operational patterns of specific building types.

The average daily profiles of the 9 residential load shape clusters are shown in Figure 5. A meaningful name is assigned to each based on their shape. The NiteFlat shape has regular load increases at night only, which is a somewhat unexpected pattern. Inspection of individual customer load shapes in this cluster shows that this pattern is very regular for these customers, and we interpret it as deriving from vacant buildings or parking lots that have automated outdoor or security lighting loads but no significant occupant-driven loads. The Flat load shape, as the name suggests, represents a pattern with little to no diurnal variation. The FlatCool shape, on the other hand, has a combination of flat and some evening peaking load shapes, driven by cooling demand in the summer. The AllDay shape represents homes that are occupied during the daytime (e.g., families with stay-at-home parents, remote workers, or people outside the labor force) and a higher proportion of homes with rooftop PV suggesting that either PV adoption may be correlated with high daytime load, or that our modeling approach over-estimated daytime generation for some customers with PV. The DayEve and MrnEve shapes are typical double-peaking residential patterns. The EarlyEve and LateEve profiles consist of evening peaking load shapes (single and double peak) and could indicate a variety of occupant behavior such as working until late night, cooling demand, uncontrolled EV charging, usage of cooking appliances and other plug loads. The NitePeak shape preferentially includes customers with Level 2 EV charging capabilities responding to EV TOU rates.

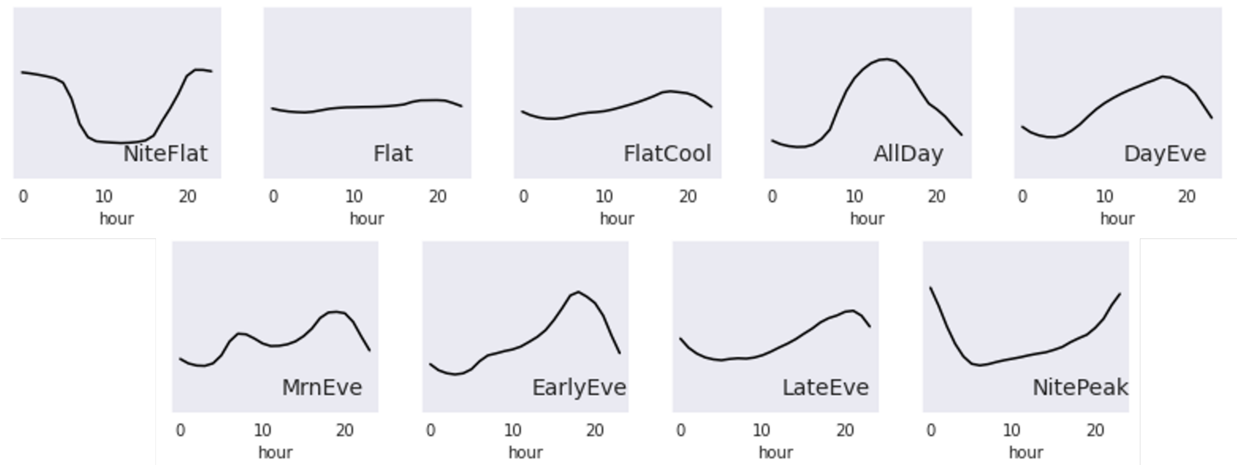

Figure 5. Average daily load profiles of Level 2 residential load shape clusters.

The average daily profiles of the commercial load shape clusters are shown in Figure 6. The NiteFlat pattern occurs again, and we interpret it similarly to how it was interpreted in the residential sector. The Flat load shape again represents buildings with limited diurnal variation in energy consumption, suggesting continuous operations. The DayEve shape represents a significantly higher fraction of restaurants and other dining facilities than other clusters, reflecting the distinctive operation hours for such establishments, with peaks at midday and in the evening. The LongDay and LateDay shapes preferentially include retail buildings and grocery stores that open later in the day. Finally, the MrnEve shape is a double peaking profile with a larger peak in the evening. This represents the load shape of buildings such as fitness centers and performance theaters with a moderate morning/daytime load and a higher evening load.

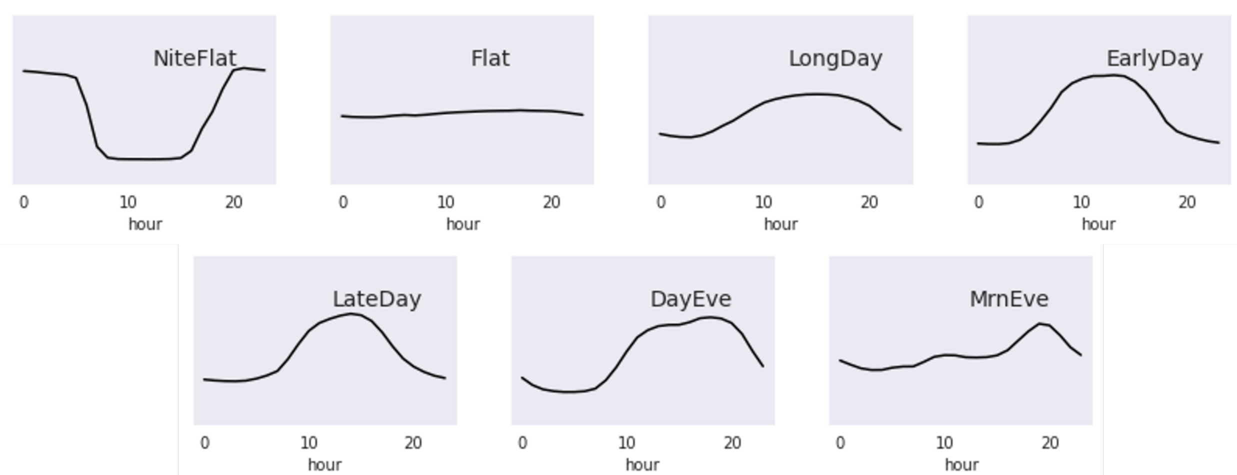

Figure 6. Average daily load profiles of Level 2 commercial load shape clusters.

Final customer clusters and disaggregated load shapes

In Level 3 clustering, we combine the results of load shape clustering along with the customers' demographic and geographic attributes as detailed in Section 3.3.4. This step yielded a total of 5422 clusters across all sectors. The breakdown of the number of clusters in each sector and utility is provided in Table 3.

Table 3. Summary of the number of Level 3 clusters by sector and IOU.

	PG&E	SCE	SDG&E	Combined[32]	Total
Residential	521	633	230	-	1,384
Commercial	1,416	1,042	327	-	2,785
Industrial	474	252	74	1	801
Agricultural	202	134	27	1	364
Other	56	25	6	1	88
Total	2,669	2,086	664	3	5,422

The aggregated cluster-level load shape for each of the 5422 clusters is disaggregated across several end-uses as described in Section 3.3.5. As described above, the Phase 4 study expanded the number of end-uses across sectors and building types (see Table 2) and also improvised the disaggregation of heating and cooling loads. We will use a few sample clusters in each sector to highlight some of the key takeaways from the end-use load disaggregation step. Appendix A provides more detailed information with results from additional sample clusters.

Figure 7 shows the winter and summer seasonal[33] average load profiles of some sample residential clusters disaggregated by end-use. In the first row, we see a cluster of single-family homes in a hot-dry climate region in the SCE service territory. Here, the cooling load is indicated in turquoise, showing how different the winter and summer cooling profiles are. In contrast, the second row shows a residential cluster in the PG&E service territory located in the marine climate region, which sees only a modest increase in the cooling demand in summer. This demonstrates how the disaggregation methodology has considered the effects of climate for each cluster. Further, we can also see significant rooftop PV generation here since this is a cluster with AllDay load shape pattern, which predominantly consists of single-family homes and homes with rooftop PV. The third row shows the seasonal average profile for a multi-family cluster in the SDG&E territory. This is a typical double-peaking residential load shape pattern with the peaks occurring before and after work hours. We also notice a significant heating load in winter indicated by the orange band and a small midday cooling load in the summer season. Finally, in the last row, we see a residential cluster in the PG&E territory with the NitePeak load shape pattern. Recall that NitePeak load shape cluster consists of a significant fraction of customers who are on an EV TOU rate. In this figure, Level 1 and Level 2 EV charging load is indicated in light and dark purple respectively. Here, we can see how EV charging load,

[32] As discussed in Appendix A, certain customer accounts were categorized as “large generators” due to large power exports that seemed to indicate that these were generation units. These were not included in the load shape clustering. In the final step of clustering, we combine the data from all these accounts by sector into a single cluster and remove their exports from the tabulated load. We do not disaggregate end uses for these clusters or consider them as potential sources of DR in the remainder of this study.

[33] Winter season is defined as the months of December, January and February, whereas summer season is defined as the months from June to August for the purposes of illustration.

particularly Level 2, drives the overall load profile that peaks at around midnight. We can also notice heating load in winter, which can also contribute to an overnight peak.

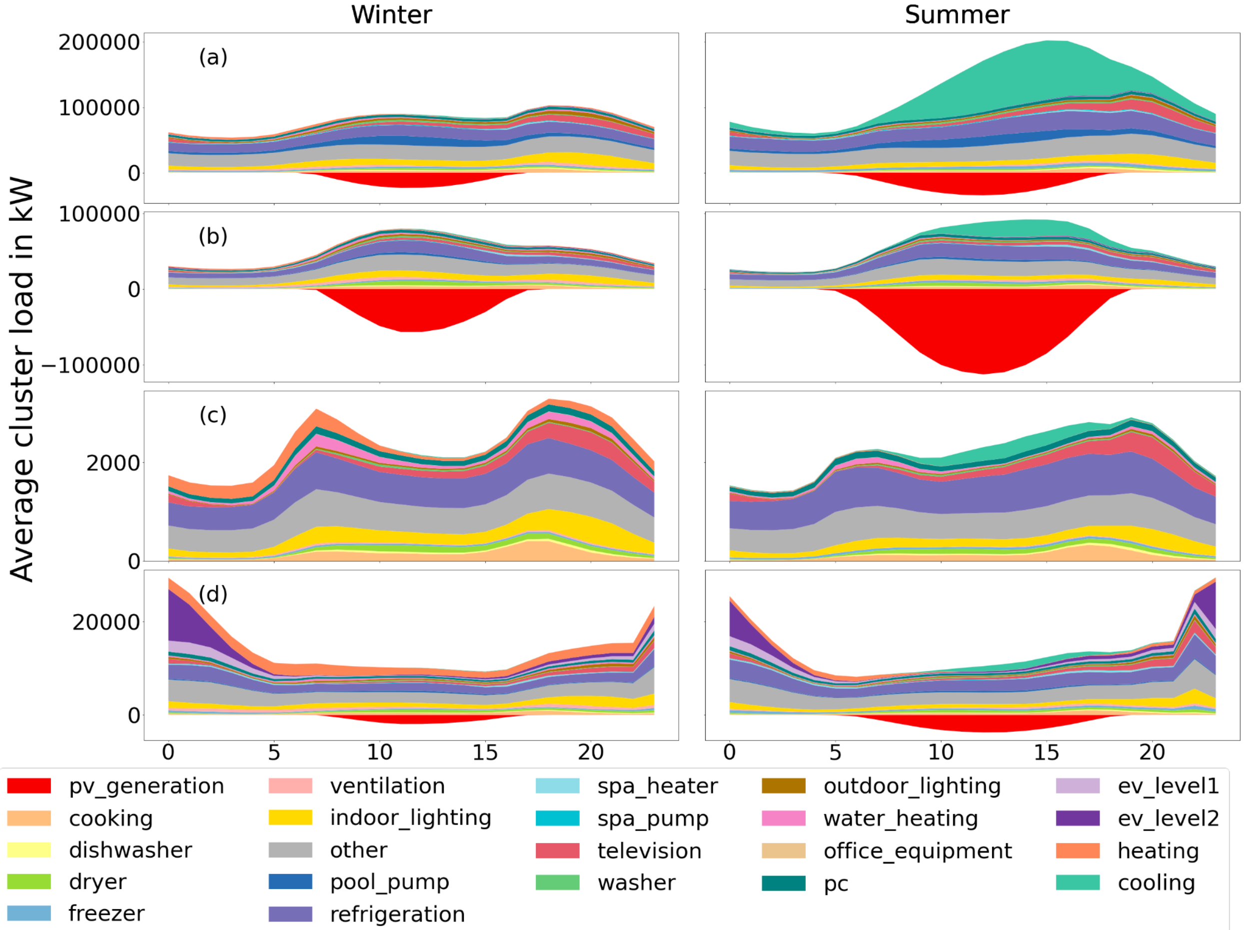

Figure 7. Seasonal average plots for sample residential clusters disaggregated by end-use. Plots on the left indicate winter seasonal average and plots on the right indicate summer seasonal average profiles. (a) This is a single family cluster in a hot-dry climate with DayEve load shape in the SCE territory, (b) This is a residential cluster in a marine climate region with AllDay load shape in the PG&E territory, (c) This is a multi-family cluster in a hot-dry climate with MrnEve load shape in the SDG&E territory, (d) This is a residential cluster in a marine climate with NitePeak load shape in the PG&E territory.

Figure 8 shows the winter and summer seasonal average load profiles for example commercial clusters. The first row indicates a cluster of large lodging buildings in the SCE service territory with a mixture of climate regions and load shapes in it. Here, we can notice how outdoor lighting, indicated in dark yellow, turns on outside of the daytime hours. In contrast, indoor lighting load, indicated in light yellow, is somewhat constant across all hours of the day. We can also see that cooling load increases the overall demand in summer. In the second row, we see a cluster of grocery stores and other retail food outlets in the PG&E service territory. Refrigeration load indicated in purple makes up a significant fraction of the overall load profile in these types of buildings. In the next row, we see a cluster of assembly buildings (e.g., theaters) with MrnEve load shape pattern in SDG&E service territory. MrnEve is a double peaking profile that represents the load shape of buildings such as fitness centers and theaters with a high morning load and evening load signifying specific peak occupancy timing of such buildings. The fourth row indicates a cluster of small dining establishments with a DayEve load shape in the PG&E service territory. Recall that the DayEve load shape cluster consists of a higher fraction of dining facilities. We can see that there is a higher cooking load indicated in peach from the middle of the day until the evening. We can also see outdoor lighting turning on after daytime hours. Refrigeration is an essential component of restaurants and makes up a considerable fraction of the load across both seasons. Finally, the last row shows a cluster of medium office buildings with a Flat load shape in the PG&E territory. The cooling demand in summer is moderate since this is in the marine climate region. However, we see tiny slivers of Level 1 and Level 2 EV charging load in the middle of the day that demonstrate the charging behavior at work. It also consists of significant fractions of ventilation (i.e., air handling, exhaust, and outside air intake) load and office equipment load that stay relatively constant across the two seasons.

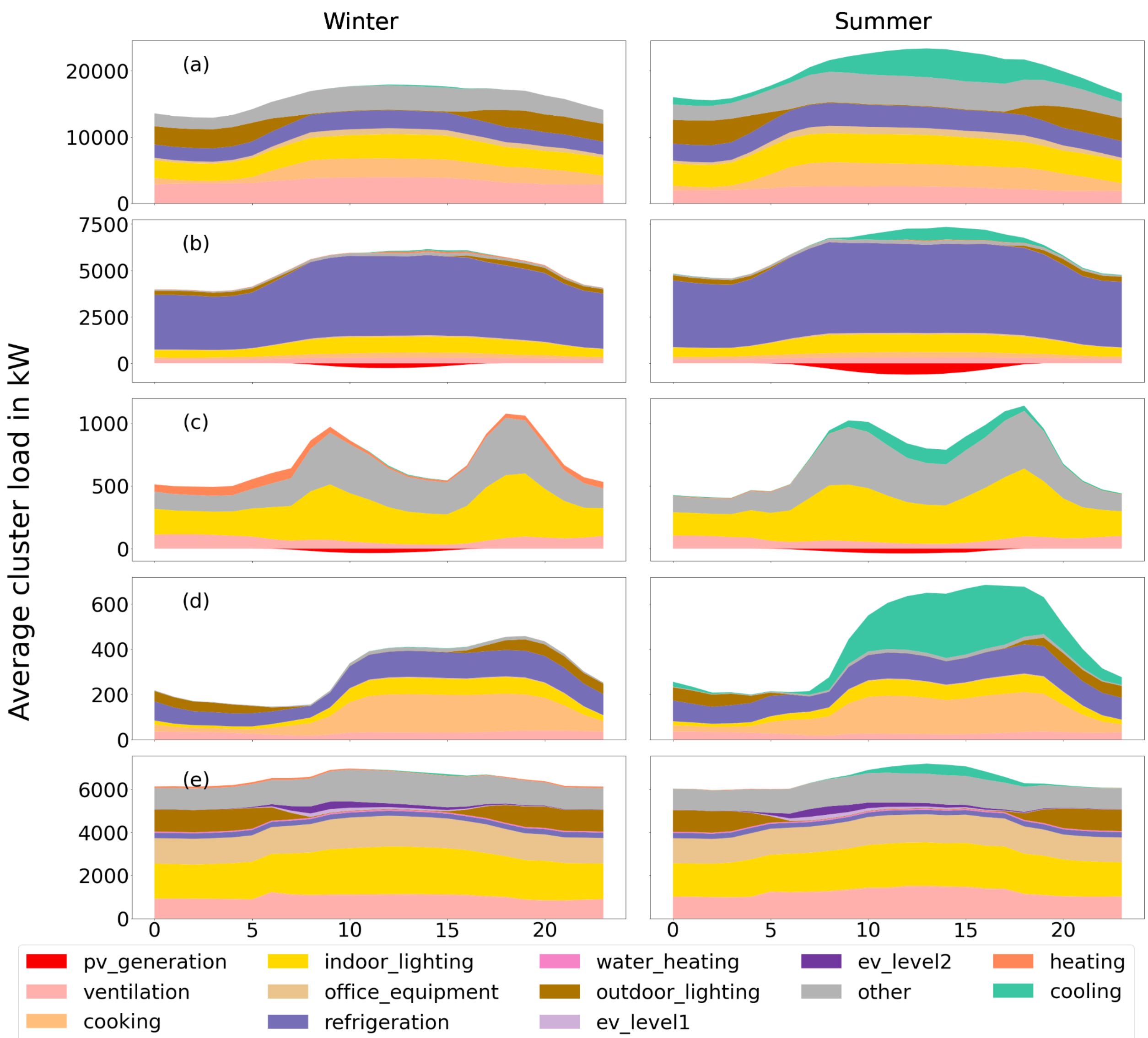

Figure 8. Seasonal average plots for sample commercial clusters disaggregated by end-use. Plots on the left indicate winter seasonal average and plots on the right indicate summer seasonal average profiles. (a) This is a large lodging cluster with a mixture of climate regions and load shapes in the SCE territory,

(b) This is a medium food retail cluster in a marine climate with LongDay load shape in the PG&E territory, (c) This is a small assembly cluster in a hot-dry climate with MrnEve load shape in the SDG&E territory, (d) This is a small dining cluster in a hot-dry climate with DayEve load shape in the PG&E territory, (e) This is a medium office cluster in a marine climate with a Flat load shape in the PG&E territory.

Figure 9 shows sample industrial and agricultural cluster load disaggregation across different end uses for summer and winter. The first row in the figure shows an industrial-sector cluster made up of water supply and wastewater facilities in the SCE service territory. Pumping is their most notable load indicated in blue. Notice that there is a dip in the energy consumption during the summer peak hours. This suggests that some of these facilities are already responding to peak energy prices during these hours by reducing their consumption (see Section 4.5.2 for further discussion of market integration of water pumping loads). The next row shows an agricultural cluster of medium sized facilities in the PG&E service area's marine climate region. Pumping is the most notable load here as well. Notice how large and different the consumption levels are in the summer versus winter indicating their operational patterns. They also exhibit significant consumption during the peak hours. Finally, the last row shows a small materials manufacturing industrial cluster in the SDG&E territory. As mentioned above, owing to the lack of temporal distribution in the available datasets, we had to apply single fractional values to each end-use throughout the year. But, we can see several process loads broken down into different categories along with boiler and other non-process loads.

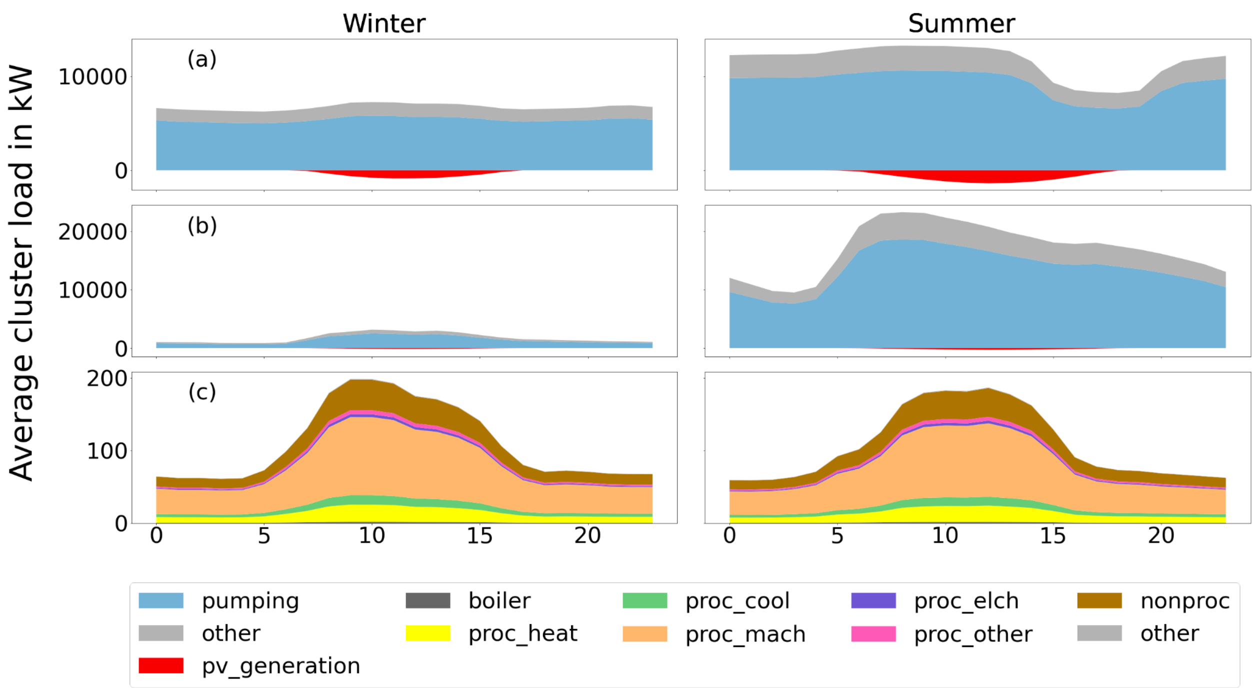

Figure 9. Seasonal average plots for sample industrial and agricultural clusters disaggregated by end-use. Plots on the left indicate winter seasonal average and plots on the right indicate summer seasonal average profiles. (a) This is a large industrial cluster in the SCE service area involved in activities such as waste water treatment or water supply and it has a mixtures of climate regions, (b) This is a medium agricultural cluster in the marine climate region of PG&E service area involved in miscellaneous agricultural activities, (c) This is a small industrial materials cluster in the hot-dry climate region of SDG&E service area.

3.3.9. Changes to the CAISO system load shape 2025-2050

The data sampling, processing, and clustering process results in a set of cluster load shapes that provide a complete representation of the hourly loads from California IOU customers across all sectors and customer types. Summing the loads across all clusters yields a forecast of the expected future demand on the California grid, including detailed information regarding the load contributions from different sectors, building types, geographical regions, and end uses. These forecasted load curves paint a rich picture of the loads that may drive the need for DR in each forecast year, as well as the loads that may be capable of providing DR.

Figure 10 shows the system-wide average daily *gross demand* for electricity in each forecast year, which is the total aggregate customer demand for electricity, including self-consumed PV generation. The gross demand has been subdivided into the individual end-uses modeled in LBNL-Load.[34] Overplotted on the gross demand is the *gross load* on the grid system[35], which is the gross customer demand less rooftop PV generation--i.e., the aggregate demand across all customer meters--where the distributed PV generation is forecasted according to the 2021 IEPR as described in Section 3.3.6. Also plotted in each panel is the *net load* on the grid system, which is the gross load less grid-scale VRE generation, which has been projected based on the most recent IRP forecast. (For more discussion of the VRE forecasting, see Section 3.5.5). Notably, by 2030, the net load falls below zero on average in the middle of the day, and this becomes more severe by 2040 and 2050. In practice, of course, much of the excess VRE generation during these hours would be captured by batteries or other storage and discharged in the overnight hours, which would modify this net load curve significantly. However, from the perspective of estimating DR potential, a dispatchable grid-scale battery is no different from other dispatchable resources that are used to meet net load. If DR can eliminate the need for some peaking or ramping capacity—battery or otherwise—it can serve to reduce system costs by obviating the need for that capacity to be built at all. Therefore, the seemingly naïve net load plotted here is the most useful one to consider when estimating the potential of DR to support grid operations.

[34] In fact, some of the end-uses plotted in Figure 10 are disaggregated more finely in the LBNL-Load modeling (e.g., home appliances include dishwashers, clothes washers, clothes dryers, and cooking appliances); some end-use groups have been reaggregated in the figure for the sake of readability.
[35] Loads shown are for California IOU customers only. As discussed in Section 3.3.7, there are additional entities within the CAISO footprint, such as municipal utilities and government agencies, that are not captured here. Their loads make up about 20% of the total CAISO load. The VRE generation in these plots has been scaled down by an appropriate factor to be proportional to the fraction of load shown.

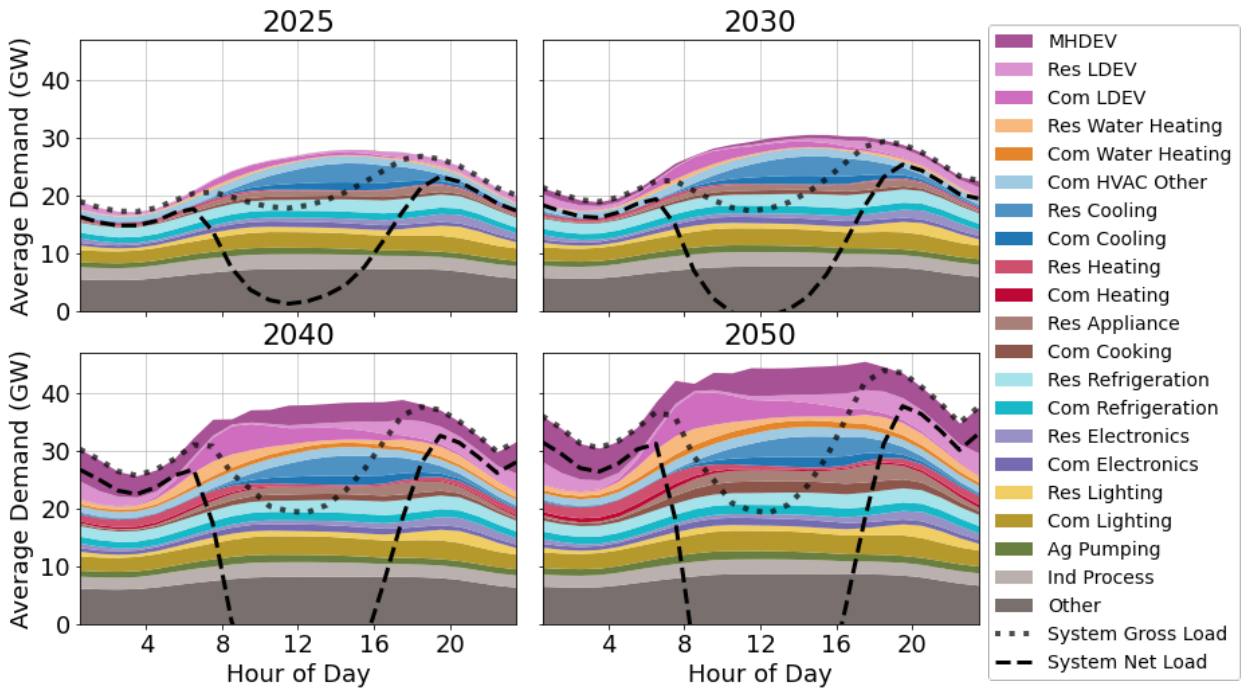

Figure 10. Forecasted future annual average system-level load shapes from the LBNL-Load modeling performed for this study. Panels show average hourly gross demand over a day in each forecast year, disaggregated into individual end uses. Overplotted are the gross system load (gross demand net of rooftop PV) and the net system load (gross load net of grid-scale VRE generation). Forecasts are shown for the 1-in-10 weather scenario.

Figure 11 shows the total annual electricity demand in each forecast year, with the growth in demand from electrified end uses highlighted. As shown, demand rises from less than 200 TWh/year to about 350 TWh/year. Figure 10 shows that total customer electricity demand averages around 25 GW in 2025; by 2050, this grows to nearly 40 GW. Growth in the 8 or so end-uses on the bottom of the plot, representing industrial, agriculture, and other sectors as well as residential and commercial lighting, electronics, and refrigeration is minimal. Growth in space cooling is also minimal, as all forecast years are modeled using the same weather year and therefore these loads only change based on population growth and EE. Induced cooling demand driven by increased adoption of air conditioning is not captured in this model. Space heating and water heating end-uses see considerable growth by 2040, while commercial cooking becomes significant in 2050, as further highlighted in Figure 11. Finally, the most dramatic growth in end-use load is in EVs. In 2025, EVs are a negligible fraction of total demand. By 2050, LDEVs are responsible for 9.7% of demand while MHDEVs make up 12% of the total. Section 4.1 will explore the peak load impacts of these changes in demand.

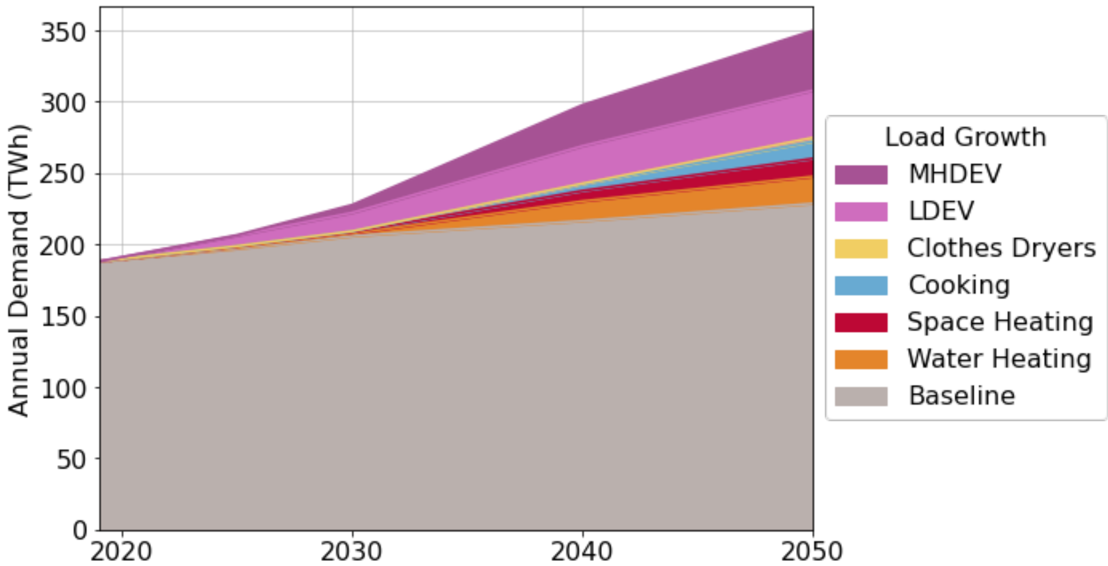

Figure 11. Total annual system-level demand for 2020-2050 forecasted in LBNL-Load for the 1-in-10 weather scenario. The growth in annual demand caused by electrified end-uses is highlighted; note that this is the total growth in the relevant end uses, which is largely but not entirely caused by electrification.

Figure 12 shows the aggregated and forecasted hourly demand from all IOU customers for an average day in summer, winter, and shoulder seasons[36] subdivided into the same end uses as in Figure 10. As with Figure 10, the gross and net loads are overplotted on the gross demand. Several features are worth noting in Figure 12. The first is a drastic rise in newly electrified loads, particularly for EV charging, but also for water heating, space heating, and appliances (driven primarily by clothes dryers and cooking). These new loads significantly alter the shape of the daily demand curve in each season by 2050, driving a strong secondary peak during overnight hours. Second, we see that the net load curve begins to dip below zero by 2025, and it does so consistently by 2040. Finally, looking at the net load curve (dashed lines), we see that, although the peak net load occurs in summer in the near term (as it has historically done in California), by 2040, the highest net load occurs in the winter months, driven by evening EV charging and space heating loads, despite the fact that the gross load and gross demand continue to have pronounced summer peaks.

[36] Specifically, summer is defined as the months of June through September, which is the period commonly used for summertime rates in California electricity tariffs; and winter is defined as the months of December through March.

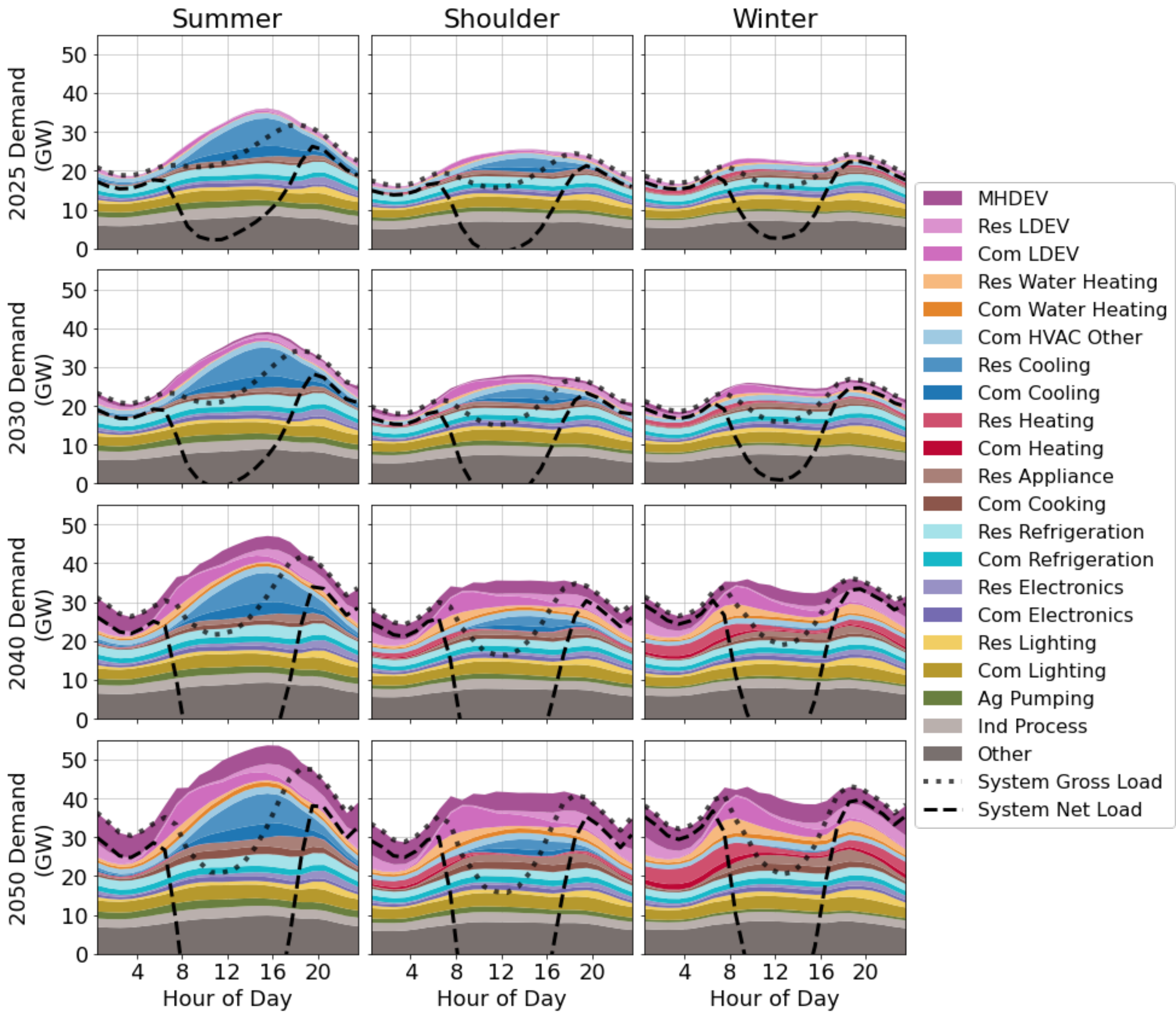

Figure 12. Forecasted future seasonal average system-level load shapes from the LBNL-Load modeling performed for this study. Panels show average hourly gross demand over a day in summer, winter, and shoulder seasons, disaggregated into individual end uses. Overplotted are the gross system load (gross demand net of rooftop PV) and the net system load (gross load net of grid-scale VRE generation). Forecasts are shown for the 1-in-10 weather scenario for each of the forecast years in order, from top to bottom.

3.4. Assessing the evolving need for DR

The changes in the forecasted load will result in significant changes in the need for DR in California. For example, we see substantial growth in the electrification of space and water heating, VRE generation and transportation electrification, all of which will have profound impact on the overall net-load at the system-level as described in Section 3.3.9. These changes in net-load will also affect the need for DR both in terms of magnitude and timing. In order to quantify these changes, we use a set of net-load based metrics from literature (Murthy, Satchwell, and Gerke 2022) that capture how the need for shed DR and shift DR changes in each forecasted year relative to 2019. Assessing these changes can help us identify the value of shed and shift DR to the system and improve the DR program design by understanding the seasonality of DR events, thereby better aligning the customers and end-uses with the need. Table 4 provides a summary of the definition of these metrics We use three sets of metrics - one each to quantify the changes in the need for load shedding, load shifting and DR program design.

Table 4. Summary of the metrics for system-level need for DR.

Category	Metric name	Metric Definition
Shed DR	Peak load	Maximum value of hourly net load in a year
	Peakiness	Height of the peak net load above the 100-th highest net load
Shift DR	Routine ramping	Maximum daily absolute 3-hour net load ramp on the day with 25-th largest such ramp
	Extreme ramping	Size of the maximum annual 3-hour absolute net load ramp compared to the 25-th largest ramp
DR program design implications	Shed event days	Number of unique days represented by the top 100 net loads
	Shed season duration	Duration of the shortest period consisting 80 out of the top 100 net load hours
	Shift season duration	Duration of the shortest period consisting of 20 out of the top 25 ramping days

Shed DR. Metrics to quantify how the need for shed DR changes considers the top 100 net load hours as the peak hours. Generally, high loads during these hours might require the utilization of expensive peaker plants. Shed DR instead can provide value to the system by eliminating the need for such expensive resources. In the first metric, we compare the *peak net load* values between the baseline and each forecasted year. An increase in this metric indicates an increased need for shed DR, in the short-term, with a fixed generation stack. The second metric, *system peakiness*, is defined as the quantity of additional load that is required only in the top 100 hours. This roughly represents the total amount of load that is served by peaker plants. Over a period of time, as the generation stack evolves with retirement of old plants, system economics also change. So, an increase in this metric would indicate a higher need for DR in the long-term.

Shift DR. The metrics to study how the need for shift DR changes are based on the maximum daily three-hour absolute net load ramps in the system. Flexible generation is used for managing upward and downward ramps in the system. Shift DR instead can reduce the need for flexible generators thereby reducing high production costs and also emissions in these hours. The first metric is the change in the need for *routine ramping*. Routine ramping is defined as the 25-th largest ramp in a system and represents moderately high ramps that can be managed by load modifying strategies (e.g., TOU rates). Increase in routine ramping indicates an increased need for such load modifying approaches or DR programs to deal with them. Ramps more severe than these would require a dispatchable shift resource. Hence, the second metric, change in the need for *extreme ramping* quantifies this as the additional ramping required only in the top 25 days in a year. An increase in the extreme ramping need indicates an increased need for dispatchable shift resources to manage it.

DR program design implications. We also consider how the timing of occurrence of the top net loads (or ramps, in case of shift DR) change in each forecasted year by looking at their frequency and seasonality. These are useful from the perspective of DR programs in targeting the specific end-uses and customer groups that can respond during DR events. There are three metrics - two for shed and one for shift DR. The first metric is the *shed event days*, defined as the number of unique days consisting of the top 100 net loads. An increase in this in the forecasted years would indicate a higher number of DR events each lasting for a shorter duration. The second metric is *shed season duration*, defined as the shortest duration in days consisting of the 80% of the top 100 net load hours. The third metric is *shift season duration*, defined as the shortest duration in days consisting of 20 of the top 25 ramps. An increase in the season duration metric would imply an increased need for a broader range of technologies and end-uses required to meet the load during the relevant hours.

The results of applying these metrics to the forecasted years are presented and discussed in Section 4.1.2.

3.5. Modeling DR resources with DR-Path

The DR-Path model leverages the disaggregated cluster load shapes from LBNL-Load, a database of DR-enabling technologies, a probabilistic model of DR dispatch, and a model of customer enrollment probabilities, to construct a detailed picture of the various pathways to achieving DR resources in California. DR-Path has been developed incrementally throughout the previous phases of the DR Potential Study. The Phase 2 report provides a specification of the full model as originally developed, and the Phase 3 report describes extensive updates to the computation of shift DR resources. In Phase 4, we have added several upgrades and new features to the model. In this section, we provide a conceptual overview of the types of DR potential that are modeled in Phase 4. We then give a brief review of the DR-path calculation framework and model inputs. Finally, we summarize several key updates for Phase 4, which are described in more detail in Appendix B.

3.5.1. Types of DR potential modeled in Phase 4

As discussed in Section 2, this study focuses on shed and shift DR resources considering both the potential that could be captured through supply-side programs as well as the effective potential available as shape DR via novel approaches to dynamic electricity pricing. The study also broadens the consideration of DR potential to cover multiple different types of DR potential by considering the layered technical and behavioral elements that constrain the size of the potential resource.

For supply-side resources obtained through dispatchable DR programs, we consider the three types of DR potential below, adopting conceptual naming conventions that have been commonly used in other studies of EE potential (DOE 2020) and DR potential (Dranka and Ferreira 2019).

Technical Potential. This is the maximum DR resource that could be enabled by installing the best available technology at every customer site, under the assumption that all customers are willing and able to participate in DR using that technology. The absolute technical potential is irrespective of cost, but in this study, we will typically express the technical potential in terms of a supply curve, representing the maximum DR resource that could be technically enabled at a given cost. We will refer to this as the *cost-conditional technical potential.*

Economic Potential. This is the cost-effective subset of the technical potential. It is equal to the cost-conditional technical potential at a price level that is cost-effective from the perspective of the utility. In this study, we estimate the cost-effective price level by considering the expected annual avoided costs from operating DR, as discussed in Section 3.5.7.

Achievable Potential. This is the subset of the economic potential that can be achieved in a real-world DR program, accounting for the costs of program administration, marketing, enabling control technology, and customer incentives, as well as the willingness of customers to enroll in the program for a given incentive level. Throughout this report, we will express the achievable potential in the form of a supply curve, and we will refer to the potential at the cost-effective price level as the *cost-effective* achievable potential, which is a subset of the economic potential. It is also important to note that we compute the achievable potential in this study using a model for customer enrollment that is based on recently observed enrollment levels in existing DR programs. It is possible that higher enrollment rates could be achieved in the future with novel customer enrollment strategies or with changes to the rules governing program eligibility. That is, the "achievable" potential is not necessarily the *maximum* achievable potential. To emphasize this point, we will often refer to the achievable potential presented in this study as the *business-as-usual (BAU)* achievable potential; that is, the potential that appears to be achievable under recent practice.

In addition to the above three types of supply-side potential, we also consider the load-modifying *shape* DR potential that may be available from shape DR through customer response to dynamic electricity pricing that varies hourly (or more frequently) in response to day-ahead or real-time grid conditions. An example of such a tariff is the recent proposal from CPUC staff for a tariff structure called CalFUSE (CPUC Energy Division 2022). Customer response to such a tariff may include customers who would not otherwise enroll in a supply-side DR program, or technologies that would not be cost-effective from the utility perspective; and it may also consist of manual or behavioral responses that would not be captured by a dispatchable program. The dynamic pricing potential thus may include subsets of the achievable, economic, and technical potential for supply-side DR, as well as other sources of potential that are not included in any of those DR types. Figure 13 provides a conceptual illustration of the overlap among the different types of potential we model in this study.

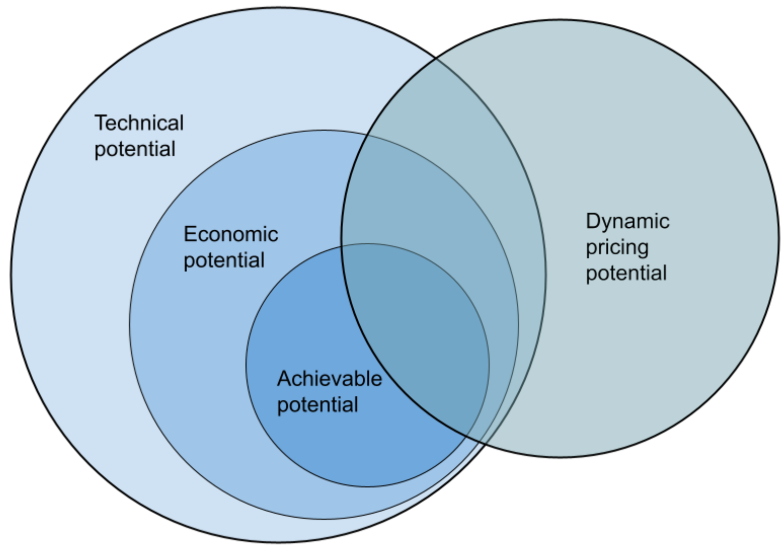

Figure 13. Diagram showing the conceptual relationship among the different types of DR modeled in this study.

3.5.2. Overview of the DR-Path model

Figure 14 presents a schematic depiction of the DR-Path model. As reflected in that diagram, DR-Path computes a bottom-up estimate of statewide shed and shift[37] DR resources via a series of calculation steps, each of which is associated with a key analytical component of the model, as follows.

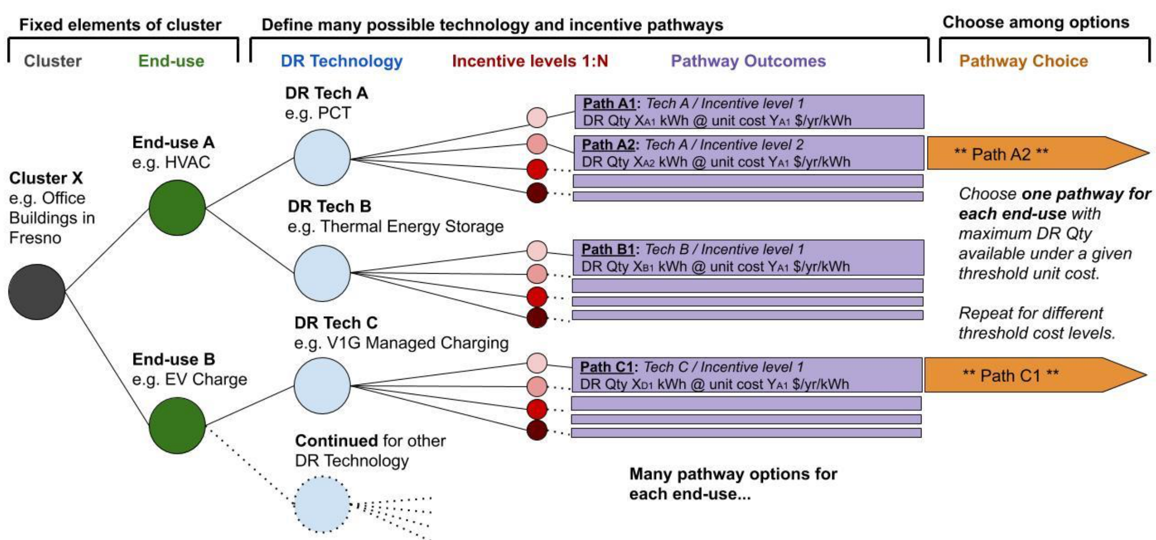

Figure 14. Schematic diagram of the calculation procedure in DR-Path, combining cluster end uses with technologies and a customer incentive/enrollment model to select optimal future DR pathways.

[37] The process for estimating shape DR resources from dynamic electricity pricing takes a different approach, based on some of the key analytical components described in this section. The approach is described in section 3.5.10.

- **Calculating DR Filters.** DR-Path incorporates probabilistic models for shed and shift DR that estimate the probability that each type of DR will be dispatched in a given hour, based on features of the system-level net load (forecasted by LBNL-Load as in Section 3.5.5). The hourly probabilities resulting from the dispatch models in each year are referred to as the *shed and shift filters.*
- **Calculating DR Features.** For each cluster (gray circle in the diagram), the DR filters are applied to the forecasted load shape for each end use (green circles) to yield weighted average quantities of shift and shed DR that would theoretically be available from each cluster end use during a typical DR event. These are referred to as the *DR features*, and they represent the maximum amount of DR that the end use could provide, if the full amount of load could be shed or shifted.
- **Calculating Site Installations.** The DR Features are coupled with a database of DR-enabling technologies (blue circles), each of which can enable different levels of load flexibility, characterized as a fraction of the DR feature, at different costs, including both up-front costs and ongoing operating costs. Each feature-technology combination is a *site installation*, with an associated quantity of DR potential and levelized cost.
- **Incentive-Adoption Calculation.**[38] An enrollment model is then applied to each site installation for an array of different customer incentive levels, yielding the percentage of customers who would be expected to enroll in a DR program at a given incentive (red circles). The resulting array of enrollment percentages are known as *incentive-adoption* combinations. Program administration costs are then added for participating customers, and marketing costs are added for all customers.
- **Selecting DR Pathways.** The result of the incentive-adoption step is a large set of future DR pathways, each of which represents a particular DR resource that could be procured by the utility at a particular cost (purple boxes). DR-Path then selects the pathway that maximizes each feature's DR resource at a given procurement cost (orange arrows) and sums the resulting set up to yield the total resource available at a given cost.
- **Building a DR Supply Curve.** Repeating this procedure for an array of prices yields a supply curve for DR, characterizing an overall system-level DR resource that increases monotonically with cost built up from a detailed set of specific underlying customer classes and end uses.

The supply curve outputs from DR-Path depict the total quantity of DR resource available (i.e., GW of available load reduction in the case of shed, or GWh of shiftable energy in the case of shift) for a given levelized cost of procuring the marginal DR resource. The levelized cost is the equivalent annual cost that would need to be paid, from the utility's perspective, to procure an additional unit of DR beyond what has already been procured. The calculation of this cost includes all costs associated with bringing a DR resource online that are borne by the utility or aggregator. These include:

[38] When computing technical DR potential, the incentive-adoption calculation is skipped, since customer enrollment probability is not relevant to the technical potential.

- Amortized up-front costs for equipment and installation, less any costs expected to be borne by the customer (which are estimated as the value of any co-benefits the site receives from installing the enabling technology, such as reduced energy costs)
- Annual costs for operation and maintenance of DR capability at the site (e.g., the cost of communications software for connected devices)
- Annual costs for program administration, marketing and customer outreach
- Annual incentives to encourage and maintain customer enrollment in DR programs.

For further discussion of the cost accounting model in DR-Path, see the Phase 3 report. The next section gives an overview of the supply curve visualizations we will use in this study, a guide to their interpretation, and a discussion of the units in which they are expressed.

3.5.3. A guide to DR-Path supply curves and units of measure

Figure 15 shows a schematic diagram of a DR-Path supply curve for the case of shift DR. The vertical axis shows the procurement price for a marginal kWh of shift. The horizontal axis shows the quantity of shiftable energy that could be enabled to be available, on average, during a shift event, for a given levelized cost. The black curve in Figure 15 represents the total supply curve. As the price increases, the supply curve steepens, representing diminishing returns to additional investment in more expensive sources of DR. The horizontal bars disaggregate the supply by the detailed sources contributing to the total resource (e.g., end use or building type) at a discrete set of prices.

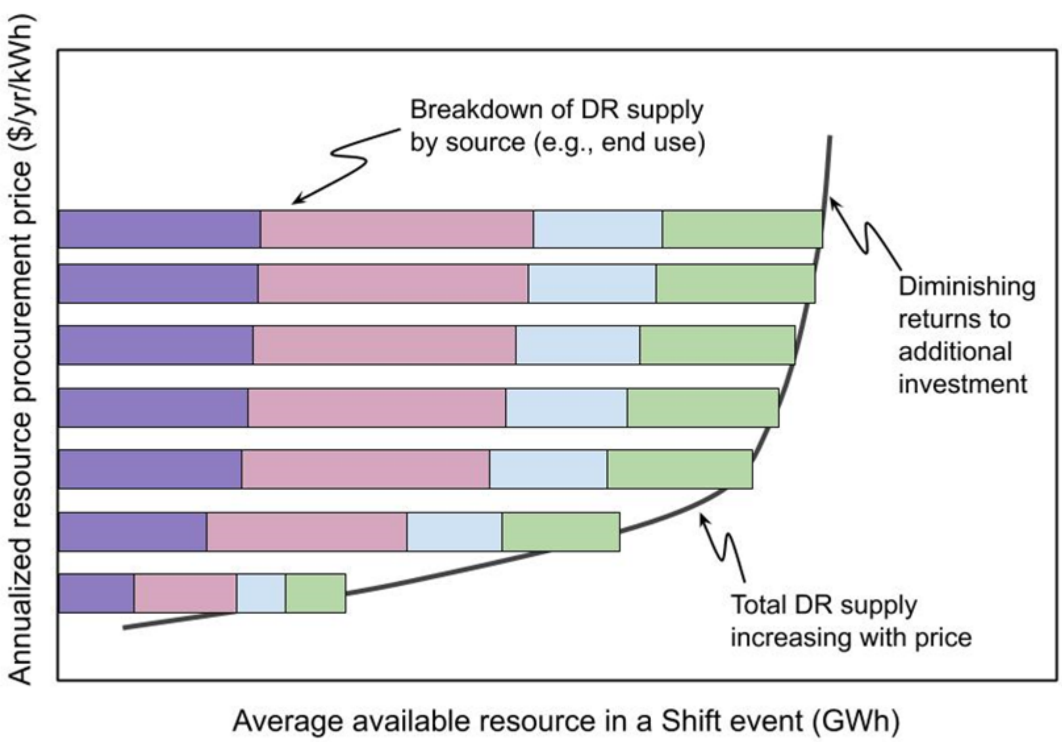

Figure 15. Schematic diagram of a DR supply curve plot for Shift, showing the total DR supply and a disaggregation by source.

It is important to understand the units of measure used to express the supply curve. The quantity of DR on the horizontal axis is expressed either as the total GW of available load reduction (on average) during shed DR events, or as the total GWh of energy consumption that can be temporally shifted (on average) during shift DR events. The levelized procurement costs are expressed as the equivalent annual expenditures (i.e., the annual amortized costs, in $/yr) necessary to enable a marginal kW of shed or a marginal kWh of shift resource. In this report we will write our cost units in the form $/yr/kW for shed and $/yr/kWh for shift. In discussions of capacity procurement, these units are commonly written in the more compact (and mathematically equivalent) forms $/kW-yr for shed and $/kWh-yr for shift. These forms can be confusing to non-specialists, however, since the denominator of the former unit, kW-yr, looks naively like a unit of energy equal to 8760 kWh, and the denominator of the latter unit, kWh-yr appears to contain two different units of time. To make the units more accessible to a broad audience, we choose a form that emphasizes the fact that this is an annualized payment for a unit of power capacity or storage capacity. Specialists who are used to the more commonly used forms may substitute them freely for the forms we use here, as they are equivalent mathematically.

When presenting supply curves in this study, we will often also plot price benchmarks on the same chart, as horizontal lines. These benchmarks represent reference prices at which it is particularly interesting or useful to consider the available DR resource. One set of benchmarks is the price of BTM batteries, computed for both residential and non-residential batteries, which have different costs. We compute this benchmark by including batteries as DR-enabling technologies within DR-Path. Rather than display the battery-enabled resource as part of the supply curve, however, we make note of the price at which batteries appear as enabling technologies in the supply curve, and we use this as a benchmark reference price. We do this because, in theory, it would be possible to procure an arbitrarily large quantity of BTM battery storage at this marginal cost, dwarfing any load flexibility resources that might be available at or above that cost, while providing shed and shift resources that do not disrupt customer energy service. The BTM battery thresholds thus represent the maximum price level at which procuring DR is likely to be worthwhile in most situations. The other cost benchmark we consider is the avoided system-level costs that are expected to be achieved by procuring a unit of DR and dispatching it over the course of the year. The avoided-cost benchmark represents our estimate of the cost-effective level of DR procurement in each year. It is calculated by applying the DR filters to the 2021 CPUC ACC (E3 Consulting 2021b), as described in Section 3.5.8.

3.5.4. Key data inputs for DR-Path

DR-Path is a complex model that draws together a variety of heterogeneous data inputs to build a bottom-up model of the DR potential in California. As a reference, we briefly summarize here the key data inputs and sources that feed into DR-Path. The data sources are described in more detail in Appendix C. The primary data inputs for DR Path are the following.

- **Forecasted cluster load shapes** from LBNL-Load, for each forecast year, which are developed based on IOU customer load shape data and a wide array of other modeling inputs summarized in Section 3.3.

- **Forecasted hourly CAISO gross load** for each forecast year, which is developed from the LBNL-Load cluster load shapes and a correction factor of $1/0.79$ developed with reference to the actual 2019 CAISO load, to account for non-IOU customer load in CAISO (see Section 3.3.7).
- **Forecasted hourly VRE generation** for each forecast year, which is projected from the actual 2019 VRE[39] generation based on the VRE generation forecasts from the CPUC IRP 2021 Preferred System Plan (PSP) modeling (E3 Consulting 2021a).
- **A database of DR technologies**, characterizing costs, performance, and expected future market penetration, using data drawn from a wide array of sources detailed in Appendix C.
- **Modeled customer enrollment probabilities** as a function of customer type and DR program incentive level, based on the DR enrollment model described in Section 3.5.7.

In the remainder of this section, we summarize various technical upgrades and new features added to the modeling capabilities of DR-Path in support of the Phase 4 study. These updates are described in detail in Appendix B.

3.5.5. Updated DR Technology characterization

In light of the expanded set of building types and end uses, we undertook a substantial update to the DR-Path technology characterization database in Phase 4. We developed an extensive list of DR-enabling measures for potentially demand-responsive end uses in the sectors and building types highlighted in Table 2. Previous phases included controls technologies such as (among others) PCTs, commercial EMSs, connected EV charging infrastructure, TES for commercial space cooling, and automated demand-responsive controls for industrial processes and agricultural pumping. Characterization data for each of these previously modeled technologies were reviewed and updated for Phase 4. We also characterized new controls technologies, such as connected appliances and water heaters, connected power strips and outlets, and TES for commercial refrigeration. For the DR-enabling technologies, we collected the following types of characterization data.

- **Cost data**, including up-front costs for equipment and installation, as well as annual operating costs.
- **DR performance data**, tabulated as the fraction by which the controlled load could be reduced in a DR event of a given duration, as well as the maximum time window over which the load could be shifted.
- **Price trend projections** for DR-enabling technologies
- **Saturation estimates** and future projections for DR-enabling technologies in California buildings.

Key data sources for the technology characterization were a recent report characterizing demand-flexibility technologies (Nubbe et al. 2021), the ENERGY STAR Connected Criteria

[39] Data publicly available on the CAISO website (CAISO 2021) but extracted for this study using the commercially available ABB Ventyx tool (last accessed 18 February 2021).

(EPA 2021), and the NREL Electricity Annual Technology Baseline (NREL 2021). Details of the technology characterization data sources and parameters are provided in Appendix C.

3.5.6. Including the effects of existing DR technology saturation

DR-Path estimates the cost of enabling DR by installing specific different DR-enabling technologies at customer sites. An important update to this calculation for Phase 4 is improved accounting for enabling technologies that are expected to be adopted outside of DR programs. For instance, many customers may be expected to adopt PCTs on their own, either by leveraging EE program incentives, or through natural preference for the improved features these devices offer. These customers could be enrolled in bring-your-own-thermostat DR programs without the need to pay a technology incentive or rebate, thus lowering the cost of enrolling these customers in DR compared to customers without PCTs. Previous iterations of DR-Path did not consider this pathway to DR enrollment, instead assuming that all customers would incur a technology cost when enrolled. The details of this methodological update are presented in Appendix B.

3.5.7. Updated dispatch models for DR filters

Phase 4 includes a major update to the methodology for calculating the shed and shift DR dispatch probabilities that constitute the DR filters in DR-Path. We summarize these updates briefly in this section, and full details are presented in Appendix B.

In the previous phases, the DR filters for shed and shift were assumed to be proportional to the inverse rank of total net load (for shed) or to the absolute four-hour ramp centered on a given hour (for shift). In Phase 4, we improved the dispatch probability calculations using inputs derived from the CPUC's 2021 ACC (E3 Consulting 2021b).[40] The ACC uses load forecasts and grid modeling consistent with the IRP PSP to calculate the avoided costs of marginal load reductions (or increases) at an hourly level. Avoided costs in the ACC are disaggregated into several different types of cost (e.g., capacity costs, production costs, and cap-and-trade costs), providing useful information that can improve the dispatch probability modeling and cost calculations for shed and shift. To support this modeling effort, E3 Consulting provided the underlying hourly net and gross load forecasts that were used to develop the ACC.

Shed DR is dispatched to reduce non-critical loads when there is a shortage in generation capacity; thus, it is considered as "virtual peaking generation capacity" from the grid operator's perspective. To calculate the shed DR filter, we ranked the hours of the year according to the ACC net load and fitted an exponential decay function with ACC's hourly generation capacity value as a function of the net load rank. We then normalize this function so that it sums to 1 to yield the final shed DR filter.

Unlike shed, shift DR is envisioned as being dispatched to flatten the net load curve by shifting loads within time windows and reducing ramps. Shift does not only enable system operators to better utilize the electricity generated from renewable energy resources but also lower system

[40] Recurve Analytics provided pre-calculated, machine-readable outputs from the ACC spreadsheet tool, which substantially streamlined our calculations.

operating costs. In this analysis, we first calculated the height of the largest four-hour ramp (either forward-looking or backward looking) that would need to be managed in each hour of the year. Assuming that a portion of the net loads are moved across the ramp from high to low (when the ramp heights are greater than zero), we calculated the system costs that can be avoided by shifting load (i.e., the differences in the avoided cost of energy and losses across the ramp). Similar to shed, we fitted an exponential decay function to these avoided costs versus the rank of ramp heights. We then normalize this function to yield the final shift DR filter.

3.5.8. Updated customer enrollment model

The incentive-adoption layer of DR-Path estimates the fraction of customers who would enroll in a DR program for a given financial incentive. The enrollment model used in Phases 1 through 3 of the study was based on a study of DR enrollment from more than a decade ago, and its parameters were not readily modifiable. To better reflect present-day DR enrollment and enable more flexibility in modeling, we developed a new DR enrollment model for DR-Path in Phase 4.

We estimated the new enrollment model using DR program enrollment data provided by SCE[41] for the Phase 4 study by following four steps.

- First, we counted the number of DR program participants by customer type and class.
- Next, we reviewed the sign-up and/or retention bonus (i.e., the credits earned by maintaining the DR program participation regardless of the actual load shifting or reduction) that each program provides.
- Then, we calculated the per-kW incentive offered by dividing the total expected incentive by the customer's peak annual kW load. In the case of customers who were not enrolled in any DR programs, we treated them as having declined the maximum incentive they would have been eligible to receive.
- Finally, using these incentive and participation data, we conducted fractional regression analyses to predict the enrollment probabilities.

The regression model predicts enrollment as a function of the sector, income level (CARE vs. non-CARE), building type, site size, climate region, and per-kW incentive. Details of the model specification and estimation, and parameter results, can be found in Appendix B.

3.5.9. Estimation of avoided costs and GHG emissions from DR

Using the updated DR dispatch probability functions described in Section 3.5.7, we estimated the avoided costs associated with shed and shift events. Similar to what we did for the dispatch probability calculations, we used the avoided cost values from the 2021 ACC (which was the most recent version of the ACC at the time this analysis was conducted) as the inputs for calculation of avoided system costs and emissions from DR. Specifically, we calculated 1) the

[41] Data on DR program participation was requested of, and provided by, all IOUs for this study; however, the format and organization of much of the data was not convenient for this analysis. Therefore, we chose to focus on SCE programs, for which the data was the most accessible, and we assumed that customer willingness to enroll is similar across IOUs.

average marginal avoided costs and emissions per unit of load shed or shift during a DR event, and 2) the annual avoided costs and emissions, per unit of shift or shed DR, arising from the expected dispatch of these resources over a full year. The full details of the calculation are presented in Appendix B; we summarize the calculation briefly here.

The marginal avoided costs of shed DR in a single event can be calculated by summing up the product of the normalized shed dispatch probability with the total avoided costs over the full year. The annual value per unit of shed, however, requires separate consideration of generation capacity-related cost savings and the other cost savings as the value of shed comes from two different sources: by providing virtual generation capacity and by actually reducing demands during shed events. The generation capacity cost was captured by the total levelized generation capacity costs adjusted by effective load carrying capacity (ELCC) in the ACC.[42] The other avoided costs that occur during shedding events were captured by multiplying the marginal avoided costs of shedding (other than generation capacity cost) by the expected number of shed events estimated from the shed dispatch filter in DR-Path.

Unlike shedding, which curtails loads during peak time periods and thus uses total avoided costs for the value calculations, shift DR smooths variation in the net load by reducing load during periods of high load and reducing it during adjacent periods of low load. Thus, the value of shift comes from the *differences* in avoided costs (i.e., the arbitrage opportunity) between the high and low load periods.[43] Similar to what we did for the shift dispatch probability calculation, we calculated the differences in the total avoided costs in a given hour and the cost either 4 hours before or after, depending on which direction has the larger difference in net load. The marginal avoided costs of shift in a single event were calculated by summing up the products of the calculated differences in total avoided cost and the normalized dispatch probability for shift. The annual value per unit of shift was calculated by multiplying the marginal avoided cost of shifting by the expected number of annual events calculated in DR-Path.[44]

In addition to the value calculations, we estimated the avoided GHG emission impacts of shed and shift DR, using the marginal GHG emission rates provided in the 2021 ACC. The marginal GHG emission of shed and shift was calculated by summing up the products of marginal GHG emission rates or (differences in emission rates) and the dispatch probabilities for shed or shift. The annual GHG emission impact of shed or shift is calculated by multiplying the marginal GHG emission impacts by the expected number of events per year in DR-Path.

[42] The ACC's capacity expansion modeling uses a battery storage resource with a 4-hour duration and a 20-year useful life. Considering that the ELCC of a 4-hour battery to provide generation capacity is expected to be diminished, the capacity value of the 4-hour battery needs to be derated (E3 Consulting 2021b). Here we would like to highlight that we used the ELCC adjusted capacity costs instead of Net CONE of battery storage as we are interested in the costs of avoided virtual generation capacity to serve peak loads.
[43] Arguably, there could also be a capacity value stream for shift, associated with the flexible capacity that it can provide toward meeting CPUC's Flexible RA requirements. However, there is currently no protocol for compensating DR as flexible RA, and the ACC does not include flexible capacity value. As we discuss in section 4.2.2, this may underestimate the true grid value of shift DR.
[44] Specifically, this is calculated by mapping the shift dispatch probability onto the unique ramping events identified by DR-Path, as described in Appendix B.

3.5.10. Calculating the potential shape DR resources from dynamic electricity pricing

Time varying electricity pricing can capture shed and shift potential in the form of shape DR. A recent white paper from CPUC staff (CPUC Energy Division 2022) presents a concept for a dynamic tariff called CalFUSE that includes a variety of categories of utility cost (e.g., energy, marginal generation capacity, and marginal distribution capacity costs) in a time varying rate that encourages utilization of electricity during periods of oversupply and strongly discourages use during peak times. During periods of high price, customers might reduce their consumption in order not to incur extremely high electricity bills, and when there is a large price difference across a steep generation ramp, customers may change the timing of their energy consumption to capture the lower prices. We refer to the effective DR resources captured by this load response as *shape-as-shed* or *shape-as-shift*. In Phase 4 we added a feature to DR-Path that estimates shape-as-shed and shape-as-shift potential for an assumed dynamic tariff. We summarize the approach here; for full details of the methodology and assumptions, see Appendix B.

The CalFUSE proposal, broadly speaking, envisions a dynamic rate that apportions various types of grid costs across the hours of the year, including wholesale energy costs and costs for generation and delivery capacity, and stacks the avoided costs in each hour to yield a tariff that reflects the real-time cost of serving a marginal kWh of consumption in each hour. This is similar to the way that the ACC stacks avoided costs in each hour of the year. Therefore, for this study, we use the hourly ACC values to represent a nominal dynamic tariff that is similar conceptually to a CalFUSE tariff. As discussed in Section 4.2.2, however, the ACC value stack does not include value for flexible generation capacity, which limits the incentive for load shifting under a dynamic rate. Therefore, when computing shape-as-shift, we also consider a "higher flex value" price scenario, based on a dynamic tariff study conducted by LBNL for the CPUC (Gerke et al. in preparation).

When computing shed and shift potential, DR-Path pairs DR features with applicable DR technologies, each of which is assumed to have a fixed shed or shift capability during a DR event. To model dynamic pricing potential in DR-Path, we consider a more nuanced response, scaling the responding fraction of each DR feature according to an assumed price elasticity of demand during the hours when DR is likely to be dispatched. To include impacts of both manual response to dynamic prices and response driven by the use of automated DR technologies, we apply a base elasticity for manual customer response and boost it by a multiplier in the case of automated technologies to represent the more reliable response that automation can enable.

To apply the elasticity, we must compute the typical price change that a customer would face during DR events under a dynamic tariff, relative to their present-day tariff. Since the dynamic tariff is identical to the ACC, the typical price[45] faced by the customer during shed and shift events is identical to the marginal avoided costs that we computed in Section 3.5.7. To compare this to present-day prices, we compiled the default TOU rates applicable for each sector and

[45] Or price arbitrage opportunity in the case of shift.

utility as of 2019. For each of these rates, we calculate the average price customers on that rate face during the hours when DR events are likely to be dispatched.[46] We then compare the typical dynamic price to the typical present-day TOU price to compute the shape-as-shed and shape-as shift potential, as follows.

Shape-as-shed potential. In the case of shed DR, we apply an assumed price elasticity to the ratio between the typical dynamic price and the typical present-day price during periods when shed is likely to be dispatched. We modeled two scenarios - a low elasticity scenario that consists of a low value for manual response with a high boosting factor for automation technologies, and a high elasticity scenario that consists of a high value for manual response with a moderate boosting factor for automation technologies. A past study of price elasticity under time-varying tariffs (Neenan and Eom 2008) provides a range of elasticity values from which we selected the base values of elasticities and boost factors for these two scenarios. The values of elasticities for each scenario are summarized in Table 5.

Table 5. Summary of elasticity values assumed for each scenario for calculating the DR potential from dynamic pricing.

Scenario	Elasticity value for manual response	Elasticity value for automated response
Low elasticity	0.05	0.15
High elasticity	0.1	0.2

Shape-as-shift potential. In the case of shift DR, we take a slightly different approach. For shiftable end-uses,[47] we estimate the change in the amount of load that a customer would shift from peak to off-peak times in response to changes in the peak-to-off-peak price difference during times when shift is likely to be dispatch, informed by the revealed customer response to time-varying rates in the IOUs' load impact reports for default TOU pricing (Hansen and Armstrong 2020; Bell, Savage, and Lehman 2020; Bell, Jiang, and Savage 2020). Full details of the calculation are in Appendix B. For automated technologies, we boosted the response by a factor of 3 based on the same elasticity study we used for the shed scenarios. As described above, we considered one scenario using the ACC-based dynamic tariff and another "high flex-value" scenario based on ongoing work at LBNL. In the latter scenario, the peak/off-peak price difference was $0.20/kWh.

Finally, for both shape-as-shed and shape-as-shift, at a given procurement cost level, we select the feature and end use combination that provides the highest potential, as in the standard DR-Path calculation. The result is a supply curve of shape-as-shed or shape-as-shift potential that can be enabled by a dynamic tariff for different levels of technology procurement cost.

[46] This calculation is similar to the calculation described in Section 3.5.7 for the avoided costs, but it is applied to the TOU rate instead of the avoided costs.
[47] Certain end uses are assumed not to be shiftable, namely lighting, television, cooking, office equipment and other.

3.6. Key scenario parameters and assumptions for Phase 4

The LBNL-Load and DR-Path modules that make up the DR-Futures framework include a variety of parameters and assumptions that can be used to generate different scenarios for forecasting, cost accounting, and DR event duration. Because we are considering many different types of DR potential across a wide range of forecast years, In the main body of this report we will primarily focus on a single reference scenario, and we will present select results from alternative scenarios in Appendix D. This section summarizes the different scenario parameters included in the modeling for the Phase 4 study as well as the reference values that are primarily presented in the main body of this report.

3.6.1. Load forecasting scenario parameters and assumptions

Forecast years. As discussed in Section 3.3, we forecast customer and system loads, starting from the base year represented by the customer meter data, 2019, to four future years: 2025, 2030, 2040, and 2050. These years are chosen to cover the near term on a relatively frequent five-year cadence, while also enabling a longer-term forecast to understand how the DR landscape will evolve as the state progresses toward its climate goals by 2050.

Weather scenarios. As discussed in Section 3.3 and Appendix A, we developed two different scenarios for the hourly location-specific temperature profiles used to model customers' heating and cooling loads, namely a 1-in-2 scenario, representing a typical year, and a 1-in-10 scenario representing an extreme year, defined by drawing sample years from historical weather data. We will use the 1-in-10 scenario to show our primary results in this report, to reflect the increasing frequency of extreme weather years due to the changing climate. The 1-in-2 scenario results are shown as alternative supply curves on the main supply-curve plots.

Load growth. We forecast future customer loads (and therefore future system loads) based on various central-estimate scenarios of the CEC's California Energy Demand forecast from the 2021 IEPR (Javanbakht et al. 2022). For the initial projection of load, we used the baseline mid-mid scenario without any additional EE or fuel-substitution assumptions. To account for the expected impacts of adoption of additional achievable EE and FS through 2030, we applied detailed end-use level projections of EE load savings and FS load impacts from the CPUC's 2021 EE Potential & Goals study (Sathe et al. 2021), which are consistent with the mid AAEE and AAFS scenarios in the 2021 IEPR forecast (Scenario 3). To project load growth from 2030 through 2050, we relied on the aggregate load projections from the E3 PATHWAYS model[48] that was used to support modeling for the 2021 SB 100 Joint Agency Report (Gill, Gutierrez, and Weeks 2021). Specifically, we used the high-biofuels scenario for our projections, to ensure consistency with the expected forecasting approach in the ongoing CPUC IRP proceeding. We held the EE impacts fixed from 2030 through 2050. Given the variety of DR types analyzed in the Phase 4 study, in the interest of analytical tractability, we did not consider alternative load forecasting scenarios besides the scenarios described here.

[48] www.ethree.com/tools/pathways-model/

3.6.2. DR potential estimation scenario parameters and assumptions

VRE growth. A critical component of estimating the need for DR on the CAISO grid system is the expected future level of VRE generation. In the Phase 4 study, we modeled growth in VRE generation based on the future generation projections from the 2021 IRP PSP (E3 Consulting 2021a). Specifically, we project grid-level VRE based on the actual hourly CAISO wind and solar generation from our base forecasting year, 2019 (CAISO 2021); and we project distributed solar generation based on the modeled rooftop PV generation in the LBNL-Load clusters. We scale both according to the expected growth in the relevant type of generation from the PSP between 2019 and the forecast year. We do not consider any alternative forecast scenarios for VRE generation.

Shed event duration. The technology characterization database that is input to DR-Path quantifies shed DR performance for each DR-enabling technology as an estimate of the fraction of load reduction that the technology could achieve while maintaining acceptable energy service, for periods of one, two, and four hours, as detailed in Appendix C. When estimating the shed DR potential in this study, we use the performance data for a four-hour shed period, since this is the event duration required for DR to be included in CPUC RA compliance filings (CPUC 2021a). This is also consistent with the duration assumed for shed in the Phase 2 study. Since most enabling technologies are able to shed more load over shorter periods of time, considering a shorter shed event duration would yield a larger apparent resource. We consider the shed potential for a one-hour event duration in Appendix D.[49]

Cost frames. The Phase 2 study introduced various cost frames for calculating the levelized procurement cost of DR, which included different costs and revenues that might be considered from the perspective of different market actors. In this study, we primarily use the *net-co-benefit* cost frame, which includes the full cost of each enabling technology, less the estimated value of any co-benefits that would accrue to the customer. This net cost is intended to represent the technology rebate or incentive that would be needed to effectively encourage adoption of the technology. The resulting costs represent the total technology costs borne from the perspective of the utility or aggregator. In Appendix D we present alternative supply curves in the *gross* cost frame, which includes all costs without subtracting any customer co-benefits.

Dynamic pricing. As discussed in Section 3.5.10, we considered a low and a high elasticity scenario for estimating shape-as-shed, and a low and high flex-value scenario for shape-as-shift. For our primary results, we present the low elasticity scenario for shed and the high flex-value scenario for shift. Alternate scenario results are presented in Appendix D.

4. Findings

This section presents the main findings from Phase 4 of the California DR Potential Study. First, we consider the ways in which growth in electrified loads and VRE generation may change the

[49] In the case of shift, no assumption about the event duration is needed, since technologies are characterized by a technology-specific shift window of two, four, eight, or twelve hours, and each technology is assumed to shift over its assigned window

need for DR in California through 2050. To help in estimating the value of DR, we then present estimates of the avoided costs and GHG emissions that would be expected from shed and shift DR. Next, we present detailed results for shed and shift DR, in turn, including the technical, economic, and BAU achievable potential, including overall results and results disaggregated by location, end-use, and enabling technology. Finally, we present the effective potential DR resource that may be available in the form of shape DR, based on dynamic electricity pricing approaches currently under discussion in California.

Throughout this section, when presenting results, we will use the 1-in-10 weather scenario as our reference scenario, rather than the 1-in-2 weather scenario. This choice is intended to reflect the reality of the changing California climate, in which historically extreme weather conditions will occur with increasing frequency, as well as the fact that shed DR for peak management is most likely to be important during extreme weather events such as would occur in a 1-in-10 year.

4.1. Changes in the need for DR in California through 2050

We saw in Section 3.3 that seasonal load shapes and the timing of system peaks in CAISO are expected to undergo a dramatic transformation by 2050. In this section, we consider how the need for DR in California will evolve in response to the changing load on the grid, in terms of both timing of the need for DR and the types of loads that may be most valuable for providing DR in the future.

4.1.1. Changes in the timing of DR need

In Section 3.3.9, we saw that the highest daily net load, in a seasonal average sense, is projected to migrate from the summer season today to the winter season by 2050 (Figure 12). To better illustrate the change in system peak timing, its key drivers, and how it may impact the need for shed DR in California, Figure 16 shows the forecasted system-level load shapes for IOU customers,[50] in each forecast year, on the days corresponding to three different three different types of system peak.

- The *peak gross demand* is the highest total customer demand for electricity (including self-consumption of distributed generation).
- The *peak gross load* is the highest aggregate customer demand at the meter. With the increasing penetration of distributed PV, which reduces metered load during daytime hours, the peak gross load may no longer correspond to peak electricity usage by customers.

[50] As in Figure 12, the loads shown are for California IOU customers only. As discussed in section 3.3.7, there are additional entities within the CAISO footprint, such as municipal utilities and government agencies, that are not captured here. Their loads make up about 20% of the total CAISO load. The VRE generation in these plots has been scaled down by an appropriate factor to be proportional to the fraction of load shown.

- The *peak net load* is the day with the highest absolute net load on the system, where the net load is equal to the gross load minus utility-scale VRE (or, equivalently, gross demand minus total VRE).

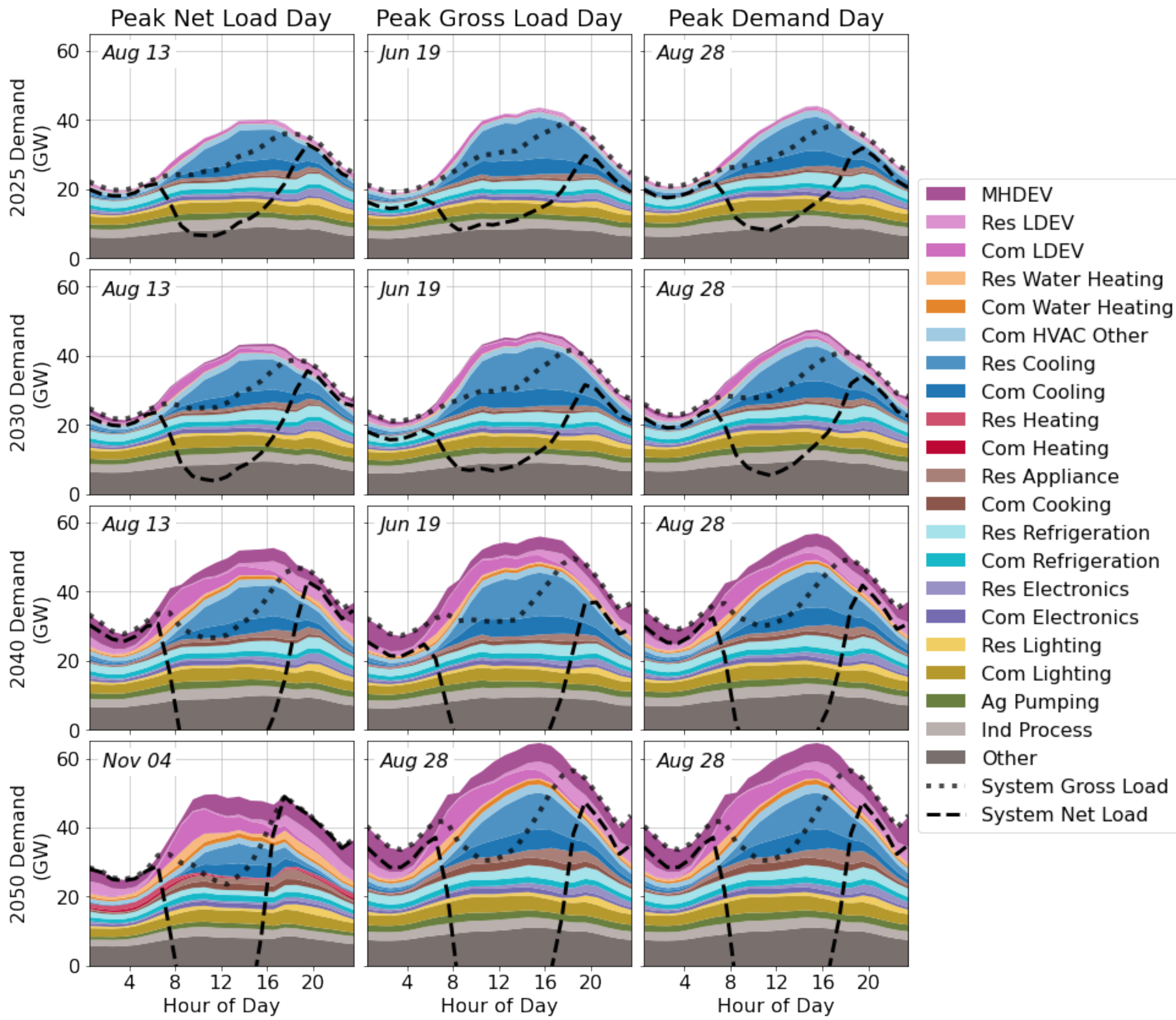

Figure 16. Forecasted future peak-day system-level load shapes from the LBNL-Load modeling performed for this study, in the 1-in-10 weather scenario. Panels show the hourly gross demand over a single day for the three days corresponding to the peak total customer demand, the peak gross load on the grid (gross demand less distributed PV), and the peak net load on the grid. Overplotted are the gross and net system load curves. Load curves are shown for each of the forecast years in order, from top to bottom.

In a system with negligible VRE generation, all three of these peaks would be simultaneous. As shown in Figure 16, though, these three peaks are diverging, already occurring on three different days in 2025. The peak gross load day on June 19th has a slightly higher evening gross demand than does the peak gross demand day on August 28th (possibly because the later sunset in June drives larger evening cooling loads), and this leads to a slightly higher gross load as the sun goes down and distributed PV wanes. The peak net load day on August 13 has a higher net load after sunset owing to a relatively small amount of wind generation in comparison to the peak gross load day. All three peaks occur in the summer season, however, which reflects the cooling-driven nature of the gross demand peak.

Recalling that the forecasted customer load in LBNL-Load is calculated using the same underlying weather data in each forecast year, and that the forecasted VRE generation is based on scaling up the actual 2019 VRE generation, it is not surprising that the three peaks occur on the same dates in the 2030 forecast. They also remain stable in 2040 despite the considerable growth in electrified end uses and VRE. By 2050, however, a notable shift has occurred, with the peak net load occurring in the autumn, on a day with negligible evening wind generation (as evidenced by the correspondence between the evening gross and net load) and with space heating load from some customers occurring simultaneously with significant space cooling load from other customers (reflecting California's wide climate variability). Strikingly, the maximum gross load and gross demand on this day are drastically lower than their annual peak values, indicating a thorough decoupling of the net load from customer demand under extremely high VRE penetration.

Nevertheless, the importance of wind generation (or the lack thereof), as well as mixed space conditioning loads, indicates that weather will continue to be an important factor in determining the system peak, but with a broader range of elements to be taken into consideration than only high temperatures. To illustrate the transformed importance of weather, we can compare the 1-in-10 weather year forecasts (Figure 16) to the 1-in-2 weather year forecasts presented in Figure 17. In this case, with a less dominant cooling-driven peak in the summer, VRE-driven changes in the peak dates appear earlier in the forecast period, and, by 2050, the peak net load occurs on a day with negligible evening wind near the winter solstice, with minimal space cooling load but substantial space heating during the peak.

Strikingly, there is also limited solar generation during the daytime hours on this day, presumably due to widespread cloud cover, and there is inadequate VRE generation to meet load at any point during the day. This poses an important challenge for a 100% decarbonized grid, as battery storage, hydropower or other dispatchable resources will need to be available to carry load for more than 24 hours straight. Events such as these illustrate the importance of long-duration storage in meeting California's climate goals. Novel forms of long-duration DR (e.g., seasonal load shifting) may also have a role to play in managing such events, though modeling such resources is beyond the scope of this study.

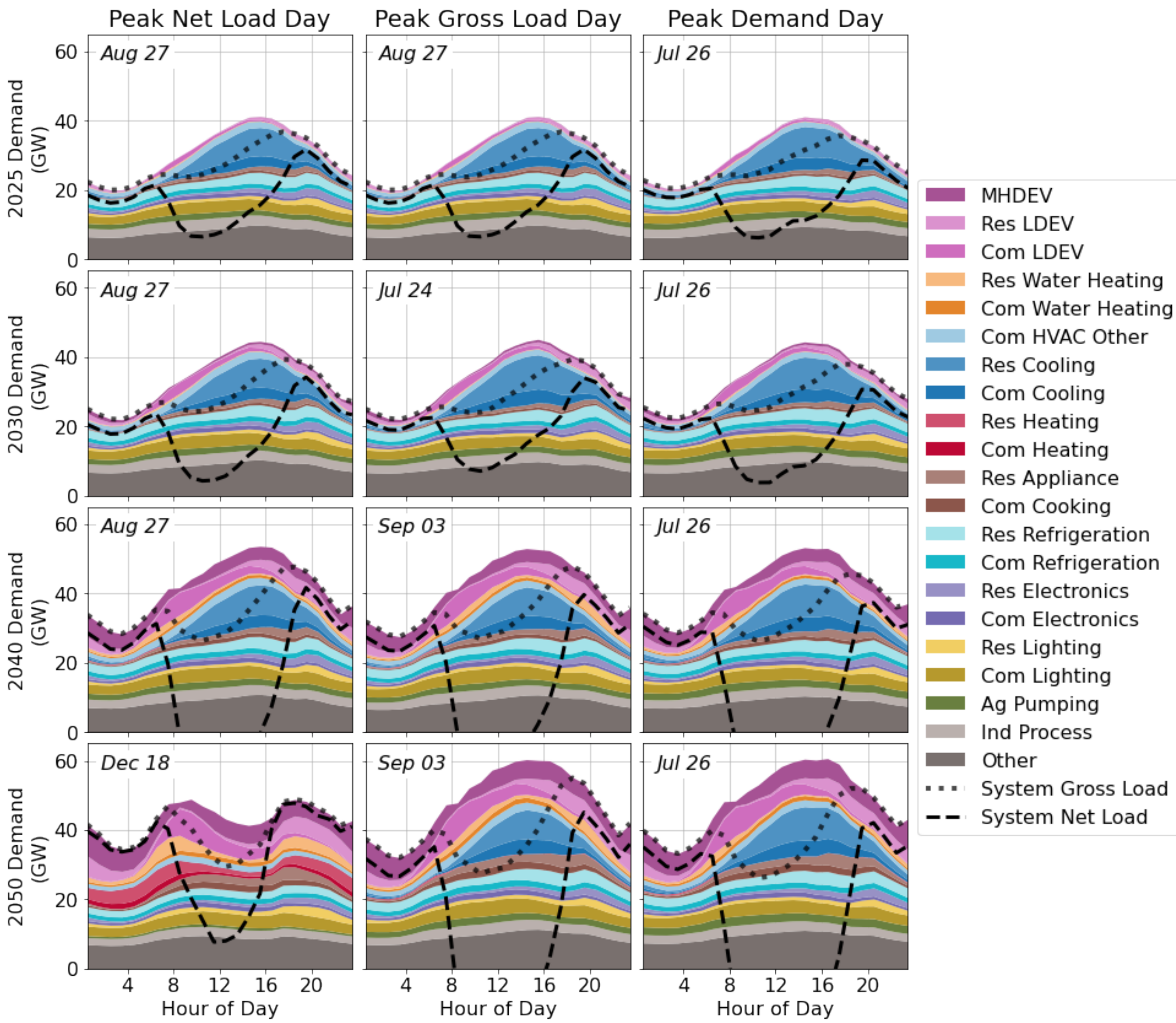

Figure 17. Forecasted future peak-day system-level load shapes from the LBNL-Load modeling performed for this study, in the 1-in-2 weather scenario. Plotted information is as in Figure 16.

To illustrate the shift in the seasonality of peak loads more clearly, Figure 18 shows the modeled CAISO system-level[51] gross (gray) and net (blue) hourly load from LBNL-Load in 2019 and in each forecast year (for the 1-in-10 weather scenario). The yellow shaded region shows the "summer" season as typically defined in California IOU tariffs (June 1 through September 30), and orange points indicate the top 250 net-load hours of the year, during which shed DR is most likely to be dispatched. In 2019, there is a pronounced summertime cooling-driven peak in both the gross and net load. In each subsequent year, a proportion of these peak hours migrate to non-summer months, and, by 2050, although some peak hours still occur in summer, a clear majority fall outside the summer months, and a large proportion fall deep in the winter. It is clear that the nature of the shed DR resource that is needed in CAISO will evolve considerably by 2050. Whereas many of today's DR programs target space cooling loads, this end use will

[51] Here, the gross and net loads have been scaled up from the loads shown in Figure 17, to account for ~20% of CAISO load that is not from non-IOU customers and not explicitly modeled in LBNL-Load, as described in section 3.3.

diminish in importance both as a driver of and as a resource for managing the system peak. Future DR programs will need to evolve to capture the end uses driving the changing peak.

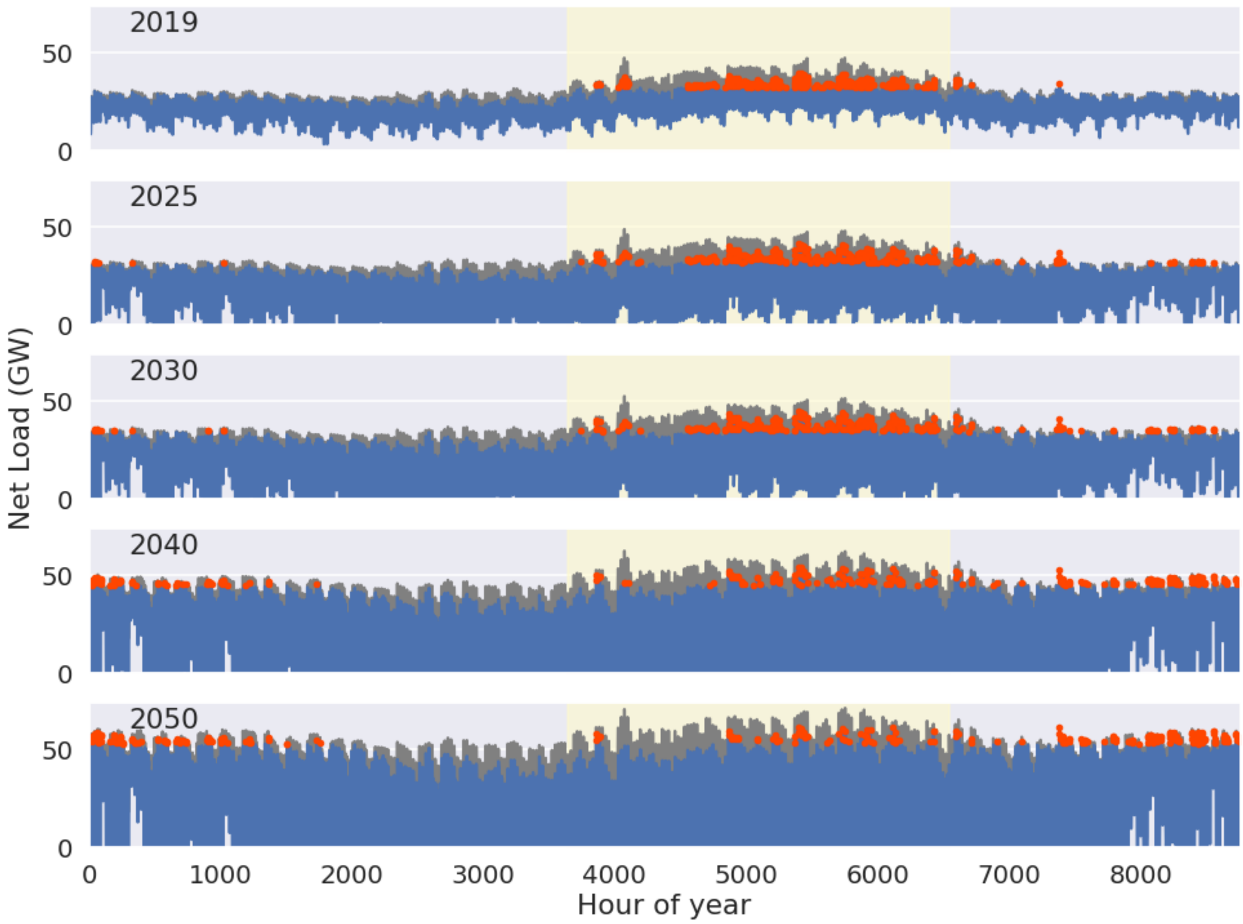

Figure 18. Modeled aggregate CAISO hourly gross load (gray) and net load (blue) in each forecast year. Orange dots indicate the 250 highest net load hours of the year, which are the hours in which shed DR is most likely to be needed. The yellow shaded region indicates the summer months of June through September.

It is also important to consider how the timing of the need for shift DR may evolve in the coming decades. Figure 19 shows the value of the maximum daily four-hour net-load ramp[52] (either upward or downward) occurring in CAISO, in 2019 and in each of the forecast years. Orange points indicate the top 50 ramping days, which are the days on which shed DR is most likely to be needed. The seasonality of steep ramps is more stable over the forecast period than we saw for the net load peaks, with few very steep ramps occurring during the summer months in any forecast year. Over the forecast period, as the shape of the net load ramps become increasingly

[52] Ramps are computed based on the naively calculated net load, given simply by subtracting the projected VRE generation from the gross load. By 2030, this net load is frequently negative during midday hours, and presumably this excess generation would need to be curtailed, exported, or used to charge storage, so that the net load never falls below zero. However, since shift DR can be viewed as a replacement for physical storage, the naively computed absolute net load ramp is the most relevant quantity for considering the system need for shift, since shift may be able to offset the need for additional storage to manage the steepest absolute ramps.

driven by the diurnal solar generation pattern, the highest ramps become increasingly concentrated in the spring and fall periods, with fewer events in the winter. Overall, however, unlike the situation with shed, the end uses that are available to provide shift DR would be expected to remain reasonably consistent over the forecast period.

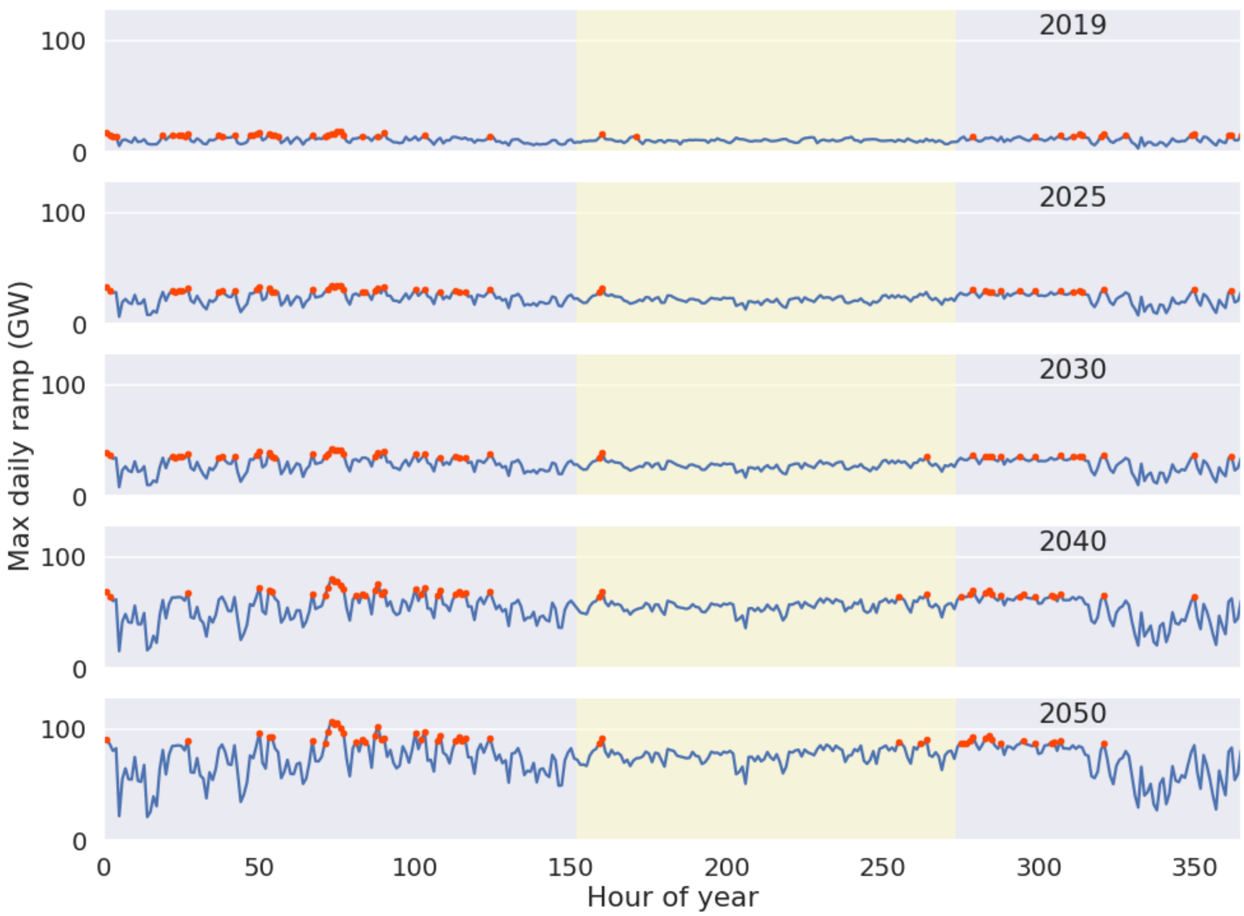

Figure 19. Maximum daily ramp values in the modeled net load in each forecast year. Orange dots indicate the 50 highest daily net load ramps of the year, which are the events in which shift DR is most likely to be needed. The yellow shaded region indicates the summer months of June through September.

4.1.2. Metrics for the evolving DR system need

In Section 3.4, we described the metrics used to analyze how the DR needs in the system changes. In this section, we will discuss the results of applying these metrics to the modeled loads in the forecasted years by comparing them to the 2019 load data. The key takeaways from our analysis indicate that with each forecasted year, the peak net loads and the three-hour net load ramps tend to get bigger implying that the need for DR increases. However, MHDEV charging load contributes to consistently high loads across all hours of the year and reduces the peakiness significantly. Further, we also notice that the top 100 net loads and the biggest ramps tend to spread across all seasons of the year implying that DR programs might have to tap into a larger variety of end-uses and technologies in order to serve the load in these hours. Appendix D discusses the details of the forecasted net-load in the form of load duration curves.

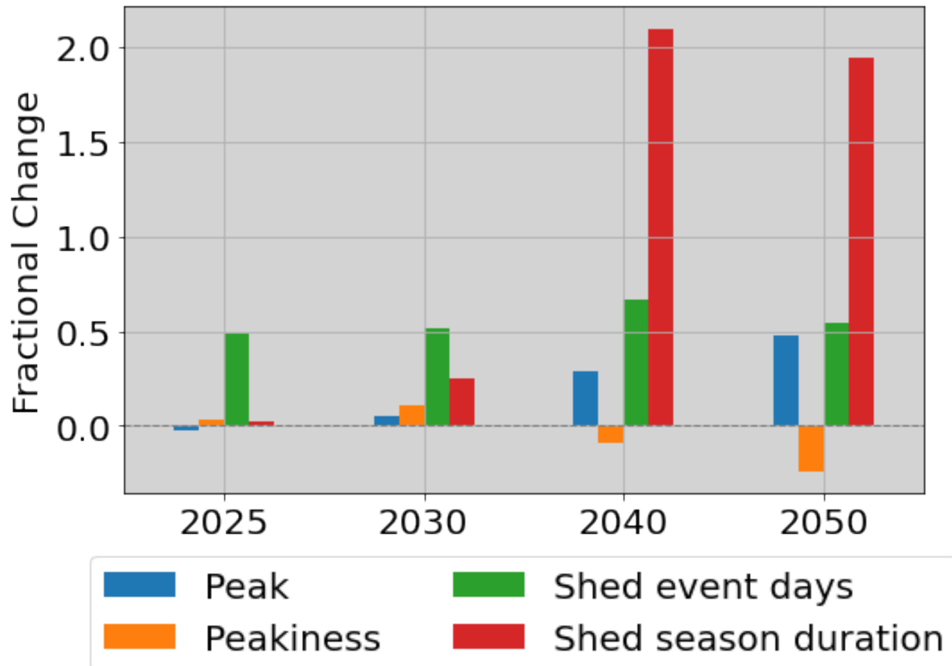

Figure 20. Results of applying DR need metrics to quantify how the need for shed DR changes in terms of magnitude and seasonality. Positive values on the y-axis indicate fractional increase and negative values indicate a fractional reduction in the need for shed DR.

Figure 20 summarizes how the need for shed DR changes in each forecasted year compared to the baseline 2019 data by quantifying the changes in peak, peakiness, event days and season duration. The definitions of these metrics are provided in Section 3.4. Positive values of fractional change indicate an increased need and negative values indicate a decreased need in shed DR. Here, we notice that the peak load value indicated in blue bars mostly increases in each forecasted year (with a minor decrease in 2025), which could be attributed to expected annual load growth and electrification of end-uses. Additional load served only in the top 100 hours tends to increase in 2025 and 2030, hence increasing the peakiness (indicated as orange bars). However, we see that this reduces considerably in 2040 and 2050. This is because higher penetration of MHDEVs 2040 onwards increases load across all hours (see Figure 16 for details). Further, the number of shed event days indicated in green increased overall indicating an increased frequency of DR events lasting for a shorter period. Finally, shed season duration shown in the figure as red bars also increased overall. This reinforces the observation made in Section 4.1.1 that in each subsequent year, the hours with peak net loads fall out of summer days and into winter days significantly changing the nature of shed DR resources.

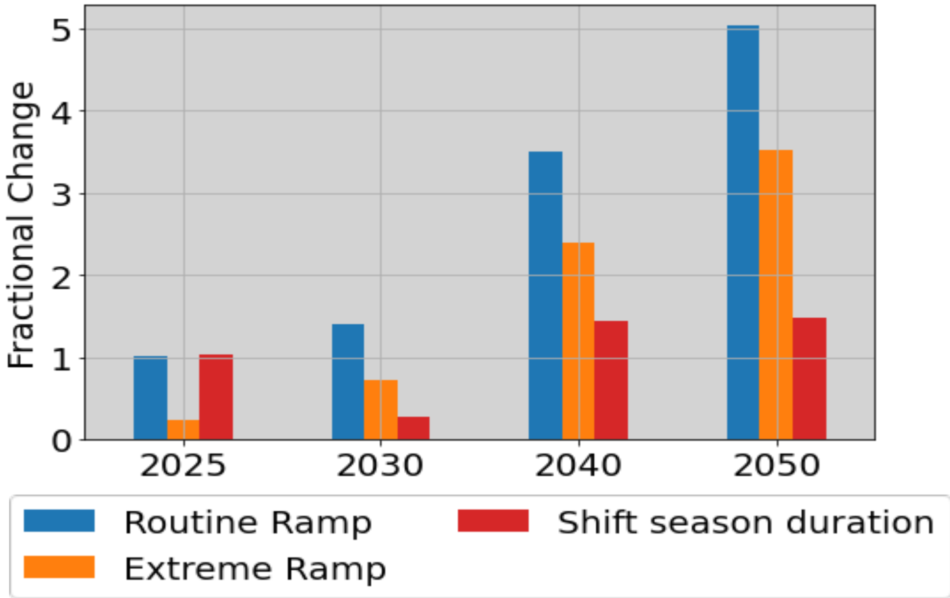

Figure 21. Results of applying DR need metrics to quantify how the need for shift DR changes in terms of magnitude and seasonality. Positive values on the y-axis indicate fractional increase in the need for shift DR.

In order to compute the metrics to determine how the need for shift DR changes, we consider three-hour net load ramps and select the absolute daily maximum from these. We quantify change in the need for routine ramping, extreme ramping and shift season duration relative to the 2019 values and the results are shown in Figure 21. The metrics definitions are described in Section 3.4. Positive values of fractional change indicate an increased need in shift DR. We see that the need for routine ramping (indicated in blue bars) and extreme ramping (indicated in orange bars) steadily increase from 2025 to 2050 possibly because of the increase in VRE generation, solar in particular, that increases ramping overall. We also see an increase in the duration of shift season. As shown in Figure 19, most of the steep ramps are found outside of the summer months and with the increasing diurnal pattern of solar generation, we see that the steep ramps are more prevalent in spring and fall days than winter with each forecasting year. This means that agricultural pumping becomes an important DR resource for managing ramps during the spring season, but the other load shifting end-uses largely remain the same across the two seasons when shift DR is most required.

4.2. DR avoided costs and emissions

4.2.1. Shed DR avoided costs and emissions

As described in Section 3.5.7, we calculated the marginal avoided costs per unit of load reduction in a shed DR event and expected annual avoided costs per unit of shed DR resource using the updated DR-Path dispatch probability for shed DR and avoided cost estimates from the ACC. See Table 6 for the summary of the avoided costs of shed. Supplementary tables and figures in Appendix B summarize the avoided costs divided by components of avoided costs in each reference year. One important caveat to these results is that all the inputs generated from ACC are based on the CPUC's Strategic Energy Risk Valuation Model (SERVM) up to 2031 under the "No New DER" scenario. Beyond 2031, ACC assumed the net load shape and generation stack to be constant and only adjusted fuel costs following assumed growth rates. Therefore, results beyond 2030 may not fully reflect the impacts of future evolution in the generation portfolio.

Table 6. Summary of the marginal avoided costs per unit of load reduction in a shed DR event (left) and expected annual avoided costs per unit of shed DR resource (right) in the reference years.

Year	Marginal avoided costs per unit of load reduction in a shed DR event (2020$/kWh)	Expected annual avoided costs per unit of shed DR resource (2020$/yr/kW)
2025	2.1	150
2030	1.2	130
2040	0.41	120
2050	0.65	150

We estimated the impacts on marginal and annual GHG emission from dispatching shed DR. See Table 7 for the summary of marginal and annual GHG savings from shed. Additional information can be found in Appendix B. The hourly marginal emission rates were calculated using the SERVM production simulation results through 2031, and then extrapolated beyond 2031 under the assumptions that the net load shape and generation stack hold constant; thus, there is limited evolution in marginal and annual GHG emissions beyond 2031.

Table 7. Summary of the marginal GHG emission savings per unit of load reduction in a shed DR event (left) and annual GHG emission savings per unit of shed DR resource (right) in the reference years.

Year	Marginal GHG emission savings per unit of load reduction in a shed DR event (kgCO2/kWh)	Expected annual GHG emission savings per unit of shed DR resource (kgCO2/kW-Yr)
2025	0.64	18
2030	0.44	7.2
2040	0.39	8.4
2050	0.42	9.0

4.2.2. Shift DR avoided costs and emissions

Similar to the approach for shed, we calculated the marginal avoided costs per unit of energy shifted in a shift DR event and the expected annual avoided costs per unit of shift DR, using the updated dispatch probability of shifting and avoided cost estimates from the ACC. See Table 8 for the summary of the avoided costs of shift. Supplemental tables and figures in Appendix B summarize the avoided costs divided by components of avoided costs in each forecast year. As was the case for shed, the results beyond 2030 are affected by the limited timeframe of the ACC production simulations.

Table 8. Summary of the marginal avoided costs per unit of load reduction in a shift DR event (left) and expected annual avoided costs per unit of shift DR resource (right) in the reference years.

Year	Marginal avoided costs per unit of load reduction in a shift DR event (2020$/kWh)	Expected annual avoided costs per unit of shift DR resource (2020$/yr/kWh)
2025	0.084	15
2030	0.092	16
2040	0.12	21
2050	0.17	30

When considering these calculated avoided cost values for shift DR, it is important to note that the 2021 ACC does not explicitly include flexible capacity cost among its tabulated cost components, instead assigning 100% of capacity costs to the hours of highest system load. California utilities are required to meet CPUC-mandated flexible RA levels to provide ramping capacity, however, so it is arguably the case that some capacity value should also be assigned to the hours around steep ramps.[53] This would increase the marginal and annual avoided costs of shift, potentially by a considerable amount, but estimating this additional value is beyond the scope and resources of the present study. We will therefore use the values in Table 8 for our main cost-effectiveness calculations. To give a sense of the additional resource that may be available at a higher shift valuation, we will also compute alternate resource estimates using BTM batteries as a cost benchmark, as was done in the Phase 3 report.

Finally, we estimated the impacts on marginal and annual GHG emissions impacts from dispatching shift DR. See Table 9 for the summary of the results and Appendix B for more details. The limited timeframe of the ACC production simulations also impacts these results after 2030.

Table 9. Summary of the marginal GHG emission savings per unit of load reduction in a shift DR event (left) and annual GHG emission savings per unit of shift DR resource (right) in the reference years.

Year	Marginal GHG emission savings per unit of load reduction in a shift DR event (kgCO2/kWh)	Expected annual emission savings per unit of shift DR resource (kgCO2/kWh-yr)
2025	0.30	53
2030	0.31	56
2040	0.32	57

[53] A counterargument is that, if most future peaking capacity is in the form of grid-scale batteries, which are inherently flexible resources, then meeting peak capacity needs will necessarily provide adequate flexible capacity, so it is not necessary to tabulate additional value for flexibility. However, if the set of possible peaking capacity resources is not so narrow, this approach leaves out a significant value stream for demand flexibility. The ACC is primarily used to compute avoided costs of EE and DR programs, and there are no shift DR programs at present, so this issue does not become relevant in that context.

2050	0.32	57

4.3. Shed DR Potential in California 2025-2050

4.3.1. Technical and Economic Shed Potential

Figure 22 presents the cost-conditional technical potential supply curve for shed DR in each of the forecast years considered in this study. Each panel shows the overall supply curve for the 1-in-10 weather scenario as a solid black curve. For an array of discrete procurement costs, the supply available from individual end uses is shown as colored bars, while the aggregate supply available from each modeled sector is shown as shaded regions in the background. The total supply in the 1-in-2 scenario is also shown as a solid gray line. Horizontal dashed lines indicate different cost benchmarks corresponding to the levelized costs of BTM batteries,[54] as well as the annual avoided costs per unit of shed DR that we presented in Section 4.2. As discussed in Section 3, the avoided-cost benchmark represents our best estimate of the procurement price that would be cost-effective from the perspective of the grid; the technical shed potential at that threshold is our estimate of the economic potential. In situations where DR can also help support a constrained region of the distribution system, DR may be cost effective up to the relevant battery threshold for customers in that region.

[54] In this figure, only non-residential BTM battery costs are shown, because residential BTM batteries remain too costly to appear on the plot through 2050. When we present shift supply curves, residential BTM battery thresholds will also appear.

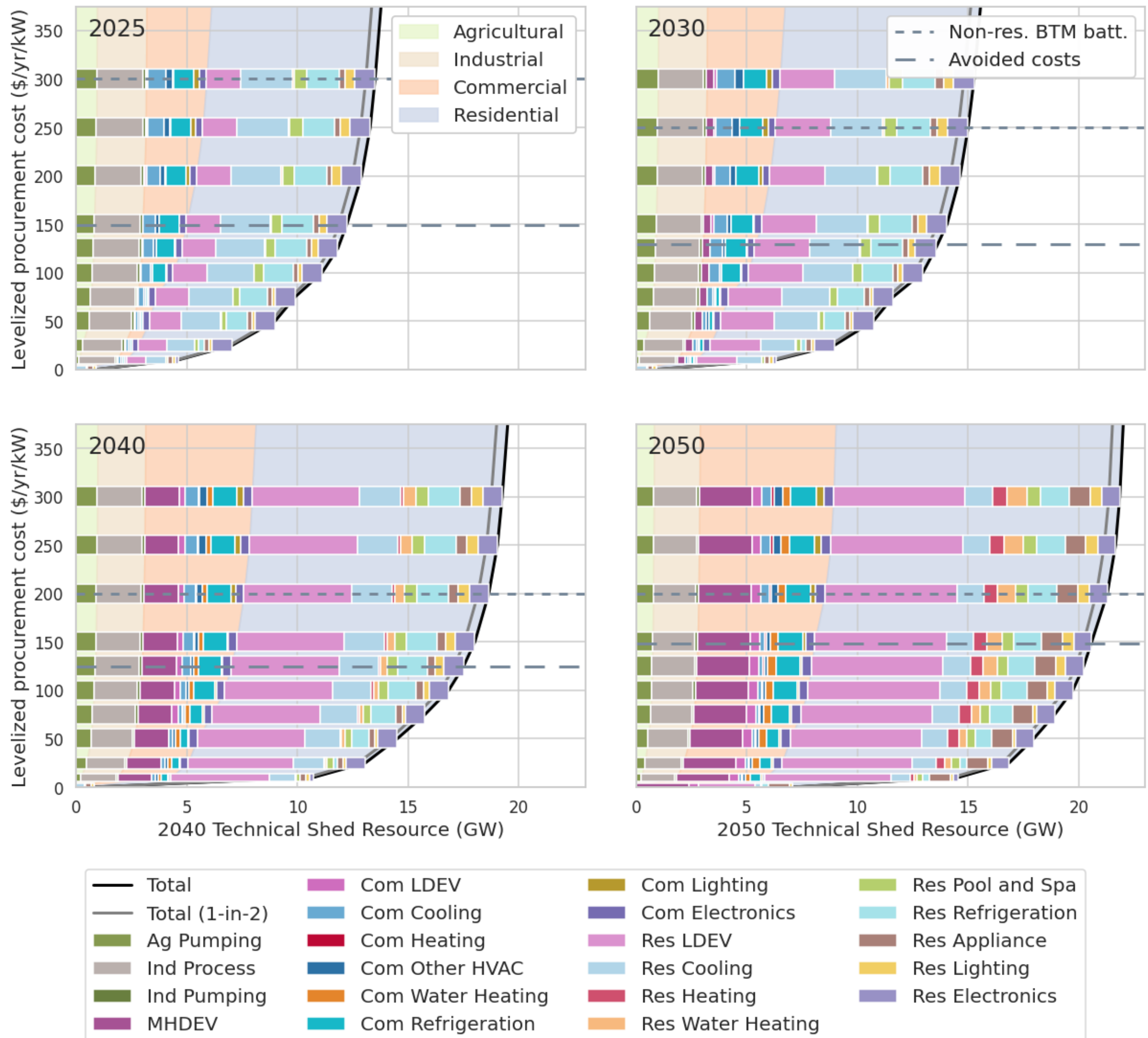

Figure 22. Supply curves for the cost-conditional technical potential of shed DR in California for each of the forecast years considered in this study. The solid black line shows the available shed resource, as a function of procurement cost, in our default 1-in-10 weather scenario. The sources of the shed DR resource are broken out by end use (colored bars) and sector (shaded regions). The solid gray line shows the supply curve for the 1-in-2 weather scenario, and dashed horizontal lines show cost benchmarks corresponding to the estimated avoided costs from shed DR in each year, and the costs of non-residential BTM batteries if they were used solely to provide shed service (the cost of residential batteries is too high to appear on these plots).

Notably, the cost thresholds for BTM batteries, regardless of sector, remain above the avoided-cost threshold in all years.[55] This indicates that there is value in procuring the full economic potential. Furthermore, BTM batteries are unlikely ever to be cost-effective sources of shed DR over this time frame, if they are installed solely for the purposes of providing shed. To be sure, such batteries can still be valuable sources of shed if they are installed for other purposes, such

[55] Indeed, Figure 22 shows only the threshold for non-residential BTM batteries, and residential BTM batteries do not appear at all, as their costs at or above $400/yr/kW throughout the forecast period.

as resiliency, as evidenced by the widespread use of distributed batteries as virtual power plants in CAISO in 2022, but their cost is unlikely to be justifiable on the basis of their shed capabilities alone. We emphasize that this analysis only considers *BTM* batteries as a benchmark for DR. Comparing DR to grid-scale batteries, which are not on the demand side, and whose effectiveness will be complicated by system losses and competition with other supply-side resources, is beyond the scope of this work.

As shown in Figure 22, the economic potential for shed DR in California is considerable, with more than 10 GW of potential resource in 2025. Because much of the potential comes from end uses other than space conditioning, the potential exhibits little weather dependence, with only a small difference in potential visible between the 1-in-2 and 1-in-10 weather scenarios. The supply curves in Figure 22 also indicate that substantial evolution is expected in the quantity and the nature of shed DR that will be available on the California grid over the coming decades. At all cost levels, there is dramatic growth in the total shed technical potential from 2025 to 2050, amounting to an increase of roughly two-thirds in the total shed resource size. This growth is driven primarily by the rapid increase in availability of flexible loads from EV charging, especially for LDEVs in the residential sector and for MHDEVs in the commercial sector. For both of these end uses, load flexibility technologies are available at low cost in all years, and they grow to be the largest sources of shed potential by 2040.

Certain other end use categories also exhibit sharp growth through 2050, primarily due to the expected widespread electrification of these end uses: commercial and residential water heating and residential space heating both increase from near-zero to become significant resources by 2050, as do residential appliances primarily via the electrification of clothes dryers. In the case of space heating, the growth as a shed resource occurs in part because of the migration of system peaks to the winter, in addition to the electrification of the end use. Meanwhile, the size of the shed resource from space cooling undergoes a notable decline, also due to the changing seasonality of the need for shed DR. Several other end uses provide significant technical shed potential that is relatively stable over time: agricultural pumping, industrial process loads, commercial and residential refrigeration and lighting, residential pool and spa (including both pumps and heaters), and residential electronics. We will discuss the shed potential from particular end use categories of interest in more detail in section 4.5, including the specific end uses and enabling technologies that contribute to each.

We estimate the economic potential for shed as the cost-conditional technical potential at the avoided cost thresholds shown in Figure 22. Table 10 presents the total economic shed potential, and Table 11 presents the emission savings of the total economic shed potential in each service territory and overall. The economic shed potential in California is 12 GW in 2025, growing to 21 GW by 2050. These numbers represent large potential reductions in peak load compared with the record peak CAISO demand of 52 GW. If all of the potentials in the table could be realized, based on the avoided GHG emissions calculated in Section 4.2.1 the annual avoided GHG emissions from dispatching the resource throughout the year are estimated at 220 ktCO_2 in 2025, corresponding roughly to the emissions of a 50 MW natural gas plant operating for a full year. Enabling the full economic shed potential in 2025 is estimated to avoid \$1.8B annually in system costs, which is notably higher than the approximately \$470B in total annual budget that the IOUs have requested (PG&E 2022; SCE 2022; SDG&E 2022) for DR programs for the 2024-2027 period. This suggests that there remains significant opportunity to capture more potential cost-effectively.

Table 10. Total economic shed DR potential, in gigawatts, by IOU in each forecast year.

Year	PG&E (GW)	SCE (GW)	SDG&E (GW)	Total (GW)
2025	5.5	5.9	0.9	12
2030	6.1	6.5	0.9	14
2040	8.0	8.1	1.3	18
2050	9.7	9.2	1.7	21

Table 11. Total annual GHG emission savings in ktCO2 (left) and annual value of shedding in 2020$ Million (right) to be achieved through total economic shed DR potential in the reference years.

Year	Total emission saving (ktCO2)	Annual economic saving (Million 2020$)
2025	220	1,800
2030	98	1,700
2040	150	2,200
2050	190	3,100

Figure 23 shows the economic potential for shed DR in each of the three IOU service territories in each forecast year. Stacked bars show the DR potential broken out by end use category in a particular forecast year. Figure 23 allows us to see the evolution in the economic shed potential for different end uses in more detail, as well as the variation in the resources across IOU service territories. There is clear variation in the relative importance of certain end uses among the different IOUs, owing to differences in climate and customer types in each territory. For example, PG&E has the largest contribution from agricultural pumping among the three utilities, reflecting its larger population of agricultural customers, whereas SDG&E has a relatively small contribution from industrial process loads, reflecting its smaller, more urbanized footprint. The growth in EV charging and other electrified end uses can be observed across all three IOUs, with a slightly larger growth in the space heating resource apparent for PG&E service territory, reflecting the cooler climate regions served by that utility. Commercial water heating also appears to have greater relative importance in SDG&E service territory, but this is largely due to the relatively smaller contribution of other end uses such as industrial process loads.

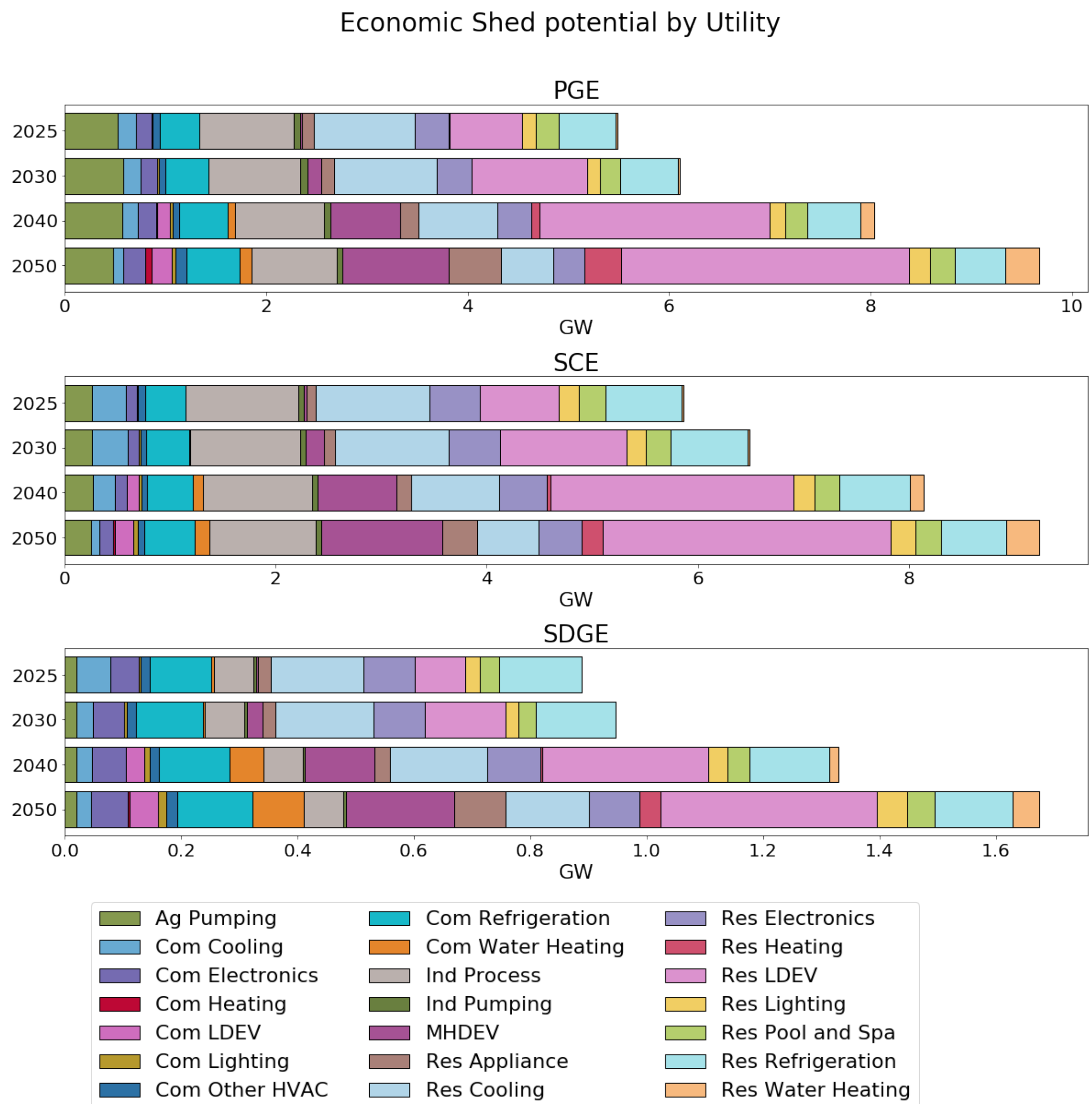

Figure 23. Estimated Economic shed DR potential resources for each IOU, broken out by end use, in each forecast year. The economic potential in each year is taken to be the cost-conditional technical potential at each year's avoided-cost benchmark, as shown in Figure 22.

4.3.2. BAU Achievable Shed Potential

Figure 24 shows the supply curve of BAU achievable shed potential in each forecast year, broken out into end-uses and sectors. This figure also shows the same cost benchmarks for BTM batteries and avoided costs as in Figure 22. As discussed in Section 3.5.1, the achievable potential includes costs for DR program administration and marketing, as well as customer incentives, which increases the cost of DR resources across the board, thereby reducing the size of the resource at a given procurement cost. In addition, and more significantly, the BAU achievable potential is modulated by a model for the probability of customer enrollment in DR at a given incentive level. This can significantly reduce the quantity of DR that is available at a given procurement cost, especially at lower incentive levels. It is worth emphasizing that the enrollment probability model is based on historical enrollment in traditional DR programs. New approaches to customer engagement or changes to program eligibility rules could allow a greater fraction of the technical potential to become achievable, beyond what is captured in the BAU achievable potential.

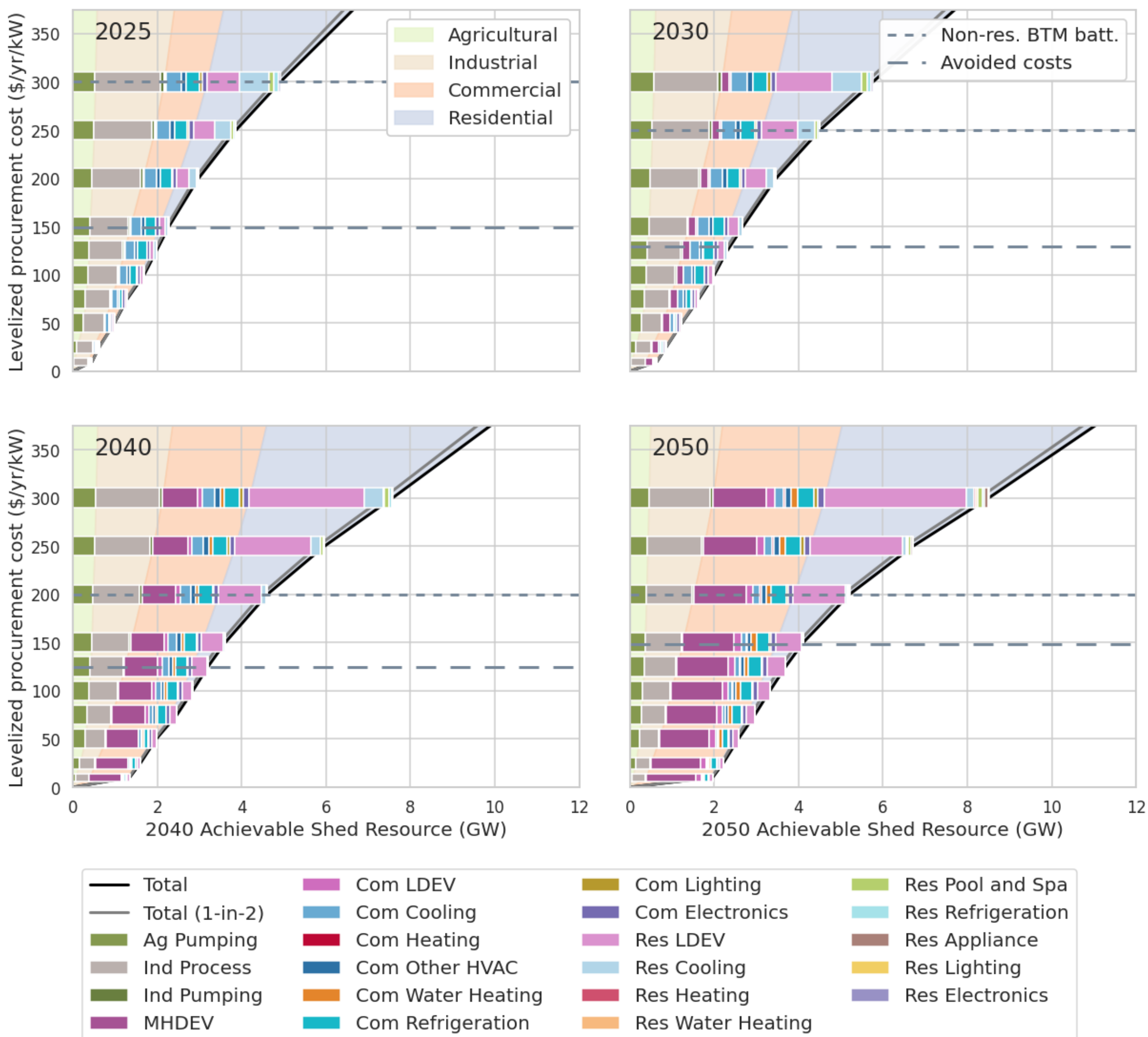

Figure 24. Supply curves for the BAU achievable potential of shed DR in California for each of the forecast years considered in this study. Meanings of the lines and shaded regions are as in Figure 21.

The BAU achievable shed potential (Figure 24) is significantly smaller than the technical potential (Figure 22) at all cost levels. At the avoided-cost threshold, the achievable resource amounts to less than one-quarter of the economic potential. This reduction in potential is unevenly distributed among sectors, with the residential sector seeing the biggest reduction, moving from being the largest source of economic potential to the smallest source of BAU achievable potential at the avoided-cost threshold. (At higher costs, the residential sector regains its dominance, but such costs are likely to be prohibitive for most applications.) The diminished contribution from residential space cooling means that the difference between the 1-in-10 and the 1-in-2 weather scenarios is quite small for the achievable shed potential supply curve.

Despite the reduced overall potential, we still observe dramatic growth in the BAU achievable shed supply curve from 2025 through 2050. This growth is driven primarily by EV charging load, especially at costs near the avoided-cost threshold. As was the case for the technical potential, the large contribution of non-space-conditioning loads to the achievable potential means that there is limited weather-dependence in the achievable potential supply curve. Other electrified end uses become valuable only at higher costs in the BAU achievable supply curve.

Table 12 presents the cost-effective BAU achievable shed potential. This potential is 2.3 GW in 2025, growing to 4.1 GW by 2050. For comparison, the total shed resource procured in the IOU service territories in the summer of 2020 amounted to some 1.6 GW (CAISO, CPUC, and CEC 2021), indicating that the near-term BAU achievable potential is slightly, but not substantially, larger than what has been achieved in the recent past. This result is consistent with the fact that our customer enrollment model in Phase 4 is based directly on recent DR enrollment data. It is also worth noting that these values represent a weighted average resource during hours when DR is likely to be dispatched. On an extreme peak day, the available load reduction may be slightly increased. Further, because of the way DR-Path computes DR features, these numbers represent the amount of load that would be expected to be present during DR events, rather than the non-coincident peak load; that is, these values have been effectively “de-rated” to account for their expected availability during events.

Despite the reduction from the technical potential, these numbers still represent extremely valuable potential peak-load reductions, with the 2025 value amounting to 3.8 percent of the record CAISO system peak of 52 GW. Table 13 presents the total annual avoided GHG emissions and system costs from the cost-effective BAU achievable shed potential in each service territory and overall.

Table 12. Total cost-effective achievable shed DR potential, in gigawatts, by IOU in each forecast year (GW).

Year	PG&E	SCE	SDG&E	Total
2025	1.0	1.1	0.15	2.3
2030	1.0	1.1	0.16	2.3
2040	1.4	1.5	0.26	3.2
2050	1.8	2.0	0.35	4.1

Table 13. Total annual GHG emission savings in ktCO2 (left) and annual value of shedding in 2020$ Million (right) to be achieved through total cost-effective achievable shed DR potential in the reference years.

Year	Total emission saving (ktCO2)	Annual economic saving (2020$ Million)
2025	41	340
2030	17	300
2040	27	400
2050	37	610

Figure 25 presents the BAU achievable shed potential at the avoided-cost threshold, which is our estimate of the cost-effective achievable resource given historical enrollment patterns, in each of the IOU service territories for each forecast year. The stacked bars show the breakdown of the resource by end-use category. The evolution of the end-use resources and their variation across IOU service territories is broadly similar to what we saw for the economic shed potential. Charging of LDEVs and MHDEVs drives much of the growth in the overall resource, with a smaller contribution from electrified water heating and space heating in the commercial sector. Notably, commercial refrigeration provides a substantial and consistent resource throughout the forecast period. Electrified end-uses are notably absent from the residential-sector resource, as is refrigeration, owing to the sharply limited customer enrollment levels that are available at the avoided-cost thresholds. Finally, as we saw for the economic potential, space cooling loads represent a shrinking resource from 2025 to 2050, owing to the changing seasonality of the need for shed.

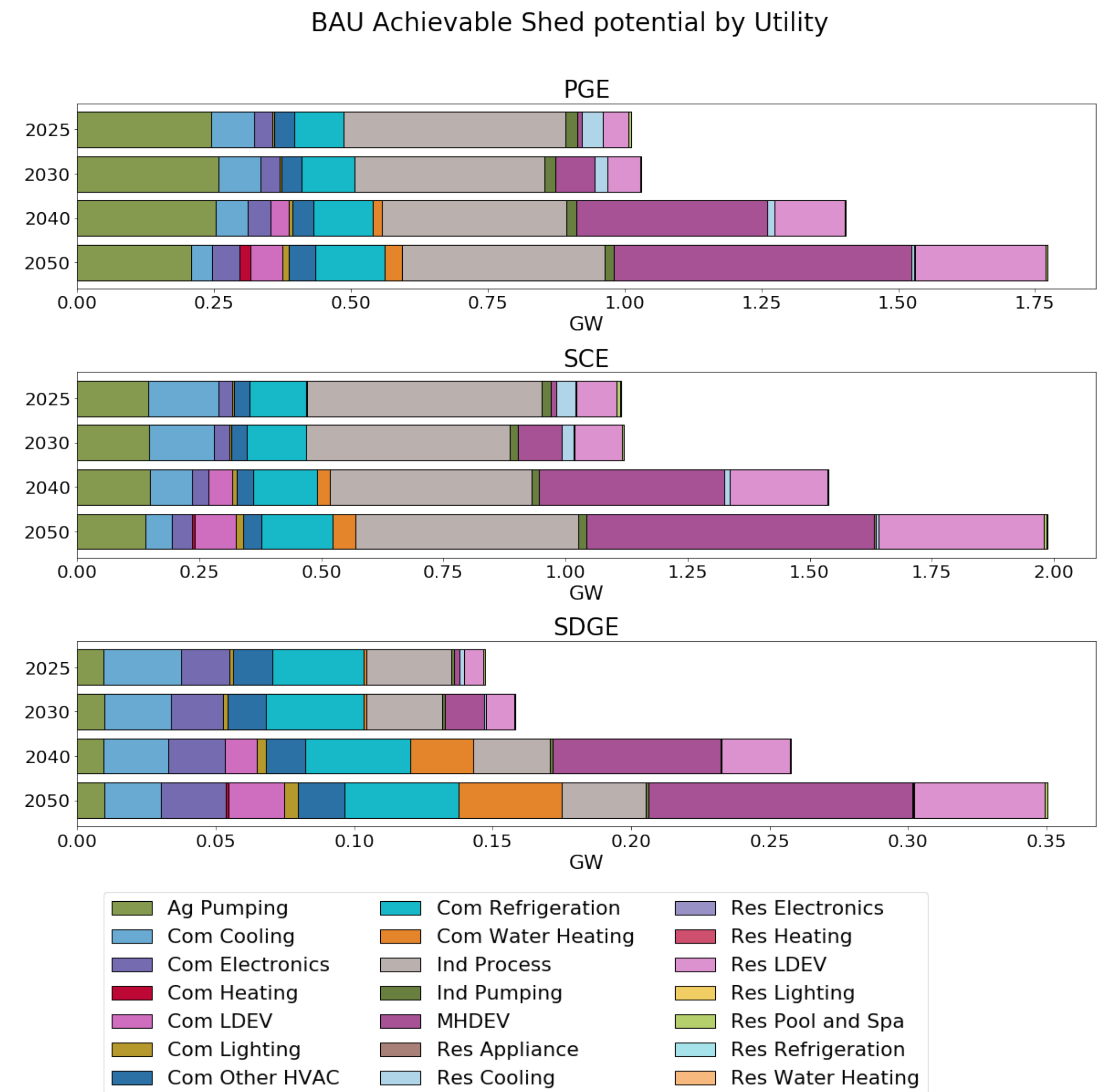

Figure 25. Estimated cost-effective BAU achievable shed DR potential resources for each IOU, broken out by end use, in each forecast year. The cost-effective potential in each year is taken to be the BAU achievable potential at each year's avoided-cost benchmark, as shown in Figure 24.

Previous phases of the DR Potential Study only considered the potential that we are calling the BAU achievable DR potential in this study. In Phase 4, we have comprehensively updated the input data on customer load, DR-enabling technologies, and electrification forecasting, as well as developing new models for the dispatch probability of shed and for customer enrollment in DR programs. To understand how the estimates of the shed potential have changed as a result, we can compare our results here for the 2025 forecast year to the 2025 results presented in the Phase 2 study. At the $150/yr/kW avoided-cost level that we consider here in 2025, the Phase 2 study reported roughly 5 GW of shed potential, considerably higher than we report here. The discrepancy can be attributed to the following differences between the Phase 2 analysis and the present one.

- First, as discussed in Section 3.3.7, our customer load modeling in Phase 4 includes only loads from IOU customers, which constitute roughly 80% of the total consumption in CAISO.[56] Previous phases of the study did not account for non-IOU loads, instead scaling up the modeled loads to match the CAISO load, which likely did not accurately represent non-IOU loads. As a result of the improved accuracy of the aggregation in Phase 4, the quantity of shed DR available will be roughly 20% smaller than in previous studies, all else equal.
- The Phase 2 study considered BTM batteries as a DR resource, identifying roughly 1 GW of shed potential from batteries at $150/yr/GW. The present study instead considers batteries as a price benchmark and does not consider the resource that might be available from BTM batteries, since it is in principle very large if batteries are cost-effective.
- The Phase 2 study also identified roughly 1 GW of shed potential from commercial lighting, whereas this potential is much smaller in the present study. The difference arises in part because of rapid improvements in lighting efficiency[57] since the base year of the Phase 2 study. The current study also disaggregates indoor and outdoor lighting into separate end uses and assumes that outdoor lighting is not flexible, whereas the Phase 2 study considered all lighting loads as a single end use. In addition, the present study includes somewhat more conservative assumptions about the shed capability of lighting controls.
- The present study disaggregates industrial process loads more finely than was possible in the Phase 2 study, allowing for a more realistic assessment of which process loads can contribute to shed DR. The result is a modest reduction in the estimated resource from industrial loads
- The present study disaggregates commercial heating, cooling, and other HVAC system loads (e.g., air handling and ventilation) into separate end uses, whereas the Phase 2 study aggregated these a single HVAC end use. The present study assumes that HVAC system loads cannot be controlled by as many technologies as heating and cooling loads, leading to a reduced overall resource from commercial HVAC loads.
- The probabilistic dispatch model for shed DR used in this study (detailed in Appendix B) is less heavily weighted toward the absolute system peak day, compared to the Phase 2 study, yielding a modestly reduced average resource from space cooling.
- Finally, this study uses a new model for customer enrollment in DR, based on recent historical data, which predicts somewhat lower enrollment at a given incentive than the model used in Phase 2.

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[56] More specifically, the modeled system-level load was scaled up to represent the full CAISO load for the purposes of computing the system net load and calculating DR features, but only the unscaled IOU-customer loads were considered as potential DR resources.
[57] This includes both the transition to LED lighting, which reduces overall lighting load, as well as increasing adoption of occupancy sensors in commercial spaces, which reduce lighting load during the evening peak.

4.4. Shift DR Potential in California 2025-2050

4.4.1. Technical and Economic Shift Potential

Figure 26 presents the cost-conditional technical potential supply curve for shift DR in each forecast year. The presentation of the curves is the same as the shed supply curves in Section 4.3, with primary results shown for the 1-in-10 weather scenario and the 1-in-2 supply curve shown as a gray curve. The breakdown of the shift potential by sector and end use is shown by shaded regions and colored bars, respectively. Horizontal dashed lines indicate different cost benchmarks corresponding to the levelized costs of BTM batteries for residential and non-residential customers, as well as the avoided costs per unit of shift DR that we calculated in Section 4.2.

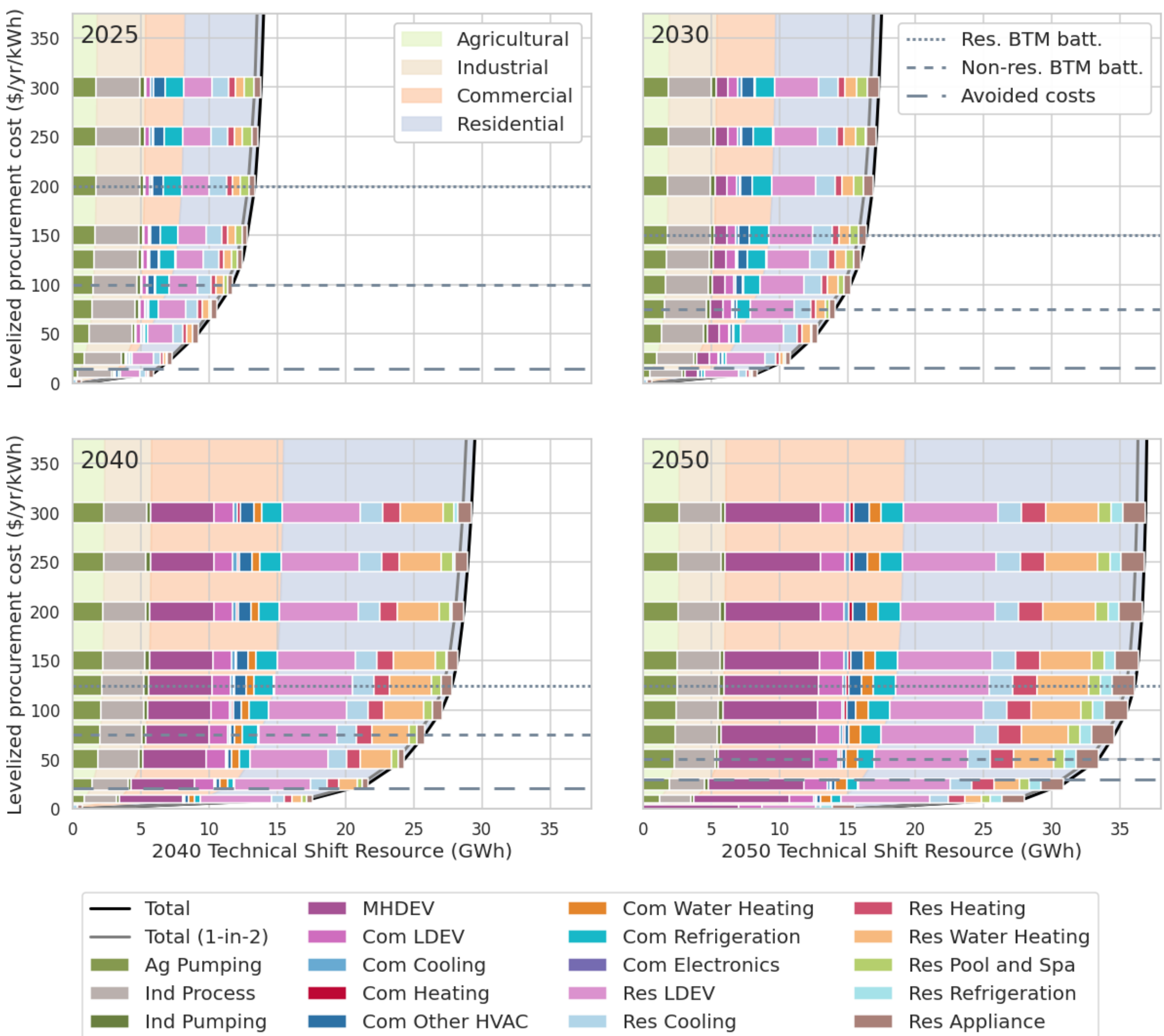

Figure 26. Supply curves for the cost-conditional technical potential of shed DR in California for each of the forecast years considered in this study. Meanings of the lines and shaded regions are as in Figure 21, except that the resource shown is shift DR, measured in GWh.

As was the case for shed, the technical potential for shift DR is expected to grow dramatically through 2050, driven primarily by growth in electrified end use loads, primarily charging of LDEVs and MHDEVs, but with a significant contribution also from space heating, appliances (primarily clothes drying), and especially water heating, which has the third-highest potential after MHDEV and residential LDEV charging by 2050. Other end uses remain consistent or increase modestly throughout the forecast period, including agricultural pumping, industrial processes, space cooling (both residential and commercial), commercial refrigeration, and residential pool and spa loads. Interestingly, residential refrigeration appears as a potential shift resource in 2050 (this is because our technology inputs assume that connected refrigerators will become widespread by this time). We will discuss the shift potential from particular end use categories of interest in more detail in Section 4.4.3, including the specific end uses and enabling technologies that contribute to each.

Our primary estimate of the economic shift DR potential is equal to the cost-conditional technical potential at the avoided cost thresholds shown in Figure 26. Table 14 presents the total economic shift potential in each IOU service territory and overall.
Table 15 presents the avoided system costs and emissions associated with this potential. The GHG values are substantial and undergo dramatic growth. Avoided GHG emissions from economic shift DR amount to 310 ktCO2 in 2025, roughly equivalent to eliminating 70 MW of natural gas generation in all 8760 hours of the year, increasing to 1.8 MtCO2 in 2050, or roughly 410 MW of avoided gas generation over a full year. Meanwhile, avoided system costs from shift DR increase from $88M in 2025 to $920M in 2050.

Table 14. Total economic shift DR potential, in gigawatt-hours, by IOU in each forecast year.

Year	PG&E (GWh)	SCE (GWh)	SDG&E (GWh)	Total (GWh)
2025	2.9	2.7	0.35	5.9
2030	4.1	3.8	0.53	8.4
2040	10	9.6	1.7	22
2050	15	14	2.5	31

Table 15. Total annual GHG emission savings in ktCO2 (left) and annual value of shedding in 2020$ Million (right) to be achieved through total economic shift DR potential in the reference years.

Year	Total emission saving (ktCO2)	Annual economic saving (Million 2020$)
2025	310	88
2030	470	140
2040	1,200	460
2050	1,800	920

As discussed in Section 4.2.2, the avoided costs calculated from the ACC do not place a value on flexible generation capacity, and may thus underestimate the value of load shifting to the grid. Improving on these avoided cost estimates is beyond the scope of this study; however, we can estimate the *maximum* cost level at which shift DR might be cost-effective by considering the cost of installing BTM batteries, which is shown in Figure 26. Whatever the avoided-cost level of load shifting, any load flexibility more costly than the battery threshold could be achieved more cheaply by purchasing BTM batteries instead. Therefore, we estimate the maximum economic shift potential as the potential available at the cost threshold for non-residential BTM batteries (since these represent the lowest BTM battery cost). Our maximum estimates of the economic shift potential are presented in Table 16. We do not present avoided cost estimates for this potential estimate, since we do not have a firm avoided cost estimate beyond what is in the ACC. The avoided GHGs would scale up from the values in Table 15 proportionally to the increased GWh of shift potential.

Table 16. Total technical shift DR potential, at cost equivalence with a non-residential BTM battery, in gigawatt-hours, by IOU in each forecast year.

Year	PG&E (GWh)	SCE (GWh)	SDG&E (GWh)	Total (GWh)
2025	5.7	5.2	0.83	12
2030	6.8	6.3	0.95	14
2040	13	11	2.0	26
2050	16	15	2.7	33

Based on our estimates at the two cost thresholds above, the economic shift potential in California ranges from 5.9 to 12 GWh in 2025, increasing to between 31 and 33 GWh by 2050. These numbers represent the virtual energy storage capacity that can technically be made available by enabling cost-effective load flexibility on the demand side in California. For comparison, the average daily energy consumption in CAISO was approximately 590 GWh in 2019 (CAISO 2022a), the most recent year not disrupted by the COVID-19 pandemic.

Figure 27 shows the economic potential for shift DR in each of the three IOU service territories in each forecast year, broken out by end use as stacked bars. The whiskers attached to each bar indicate the range of potential increase in economic potential up to the BTM battery threshold. This figure allows us to see the evolution in the economic shift potential for different end uses in more detail, as well as the variation in the resources across IOU service territories. As in the case of shed, there is variation in the relative importance of certain end uses among the IOUs, owing to differences in climate and customer types in each territory, with PG&E having a relatively large contribution from agricultural pumping and SDG&E having a relatively small industrial resource. Strong growth in electrified loads is evident across all three IOUs. Space cooling loads (both residential and commercial) and agricultural pumping also show modest growth, owing to the fact that the avoided-cost threshold increases significantly over the forecast period, allowing increasingly higher-cost resources to be captured in the economic potential. Most notable is the rapid growth in electrified loads, including LDEV and MHDEV charging, as well as space and water heating and home appliances.

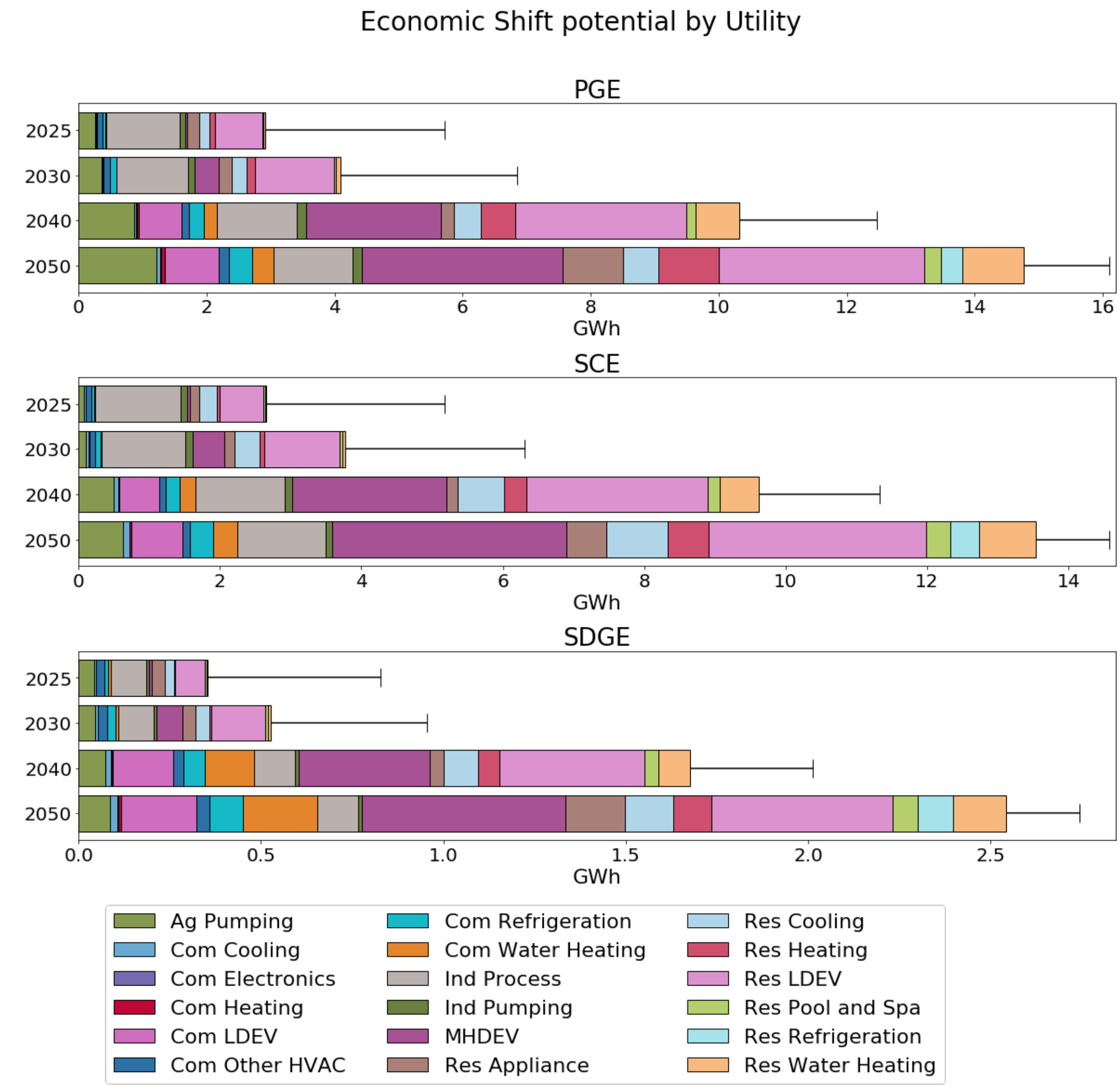

Figure 27. Estimated economic shift DR potential resources for each IOU, broken out by end use, in each forecast year. The economic potential in each year is taken to be the cost-conditional technical potential at each year's avoided-cost benchmark, as shown in Figure 26. We also show the potentially larger potential that is available up to the lowest BTM battery cost threshold as a horizontal whisker attached to each bar.

The resources reported here are the total quantity of load that can be shifted in a single shift DR event, which could be dispatched up to twice daily (once in the morning and once in the evening) in principle. There was an average of 20 GWh of curtailed VRE generation in CAISO in April, 2022 (CAISO 2022b), which was the highest monthly average reported as of this writing. The lower 2025 shift economic potential estimate of 5.9 GWh, if dispatched twice daily, would be adequate to utilize the majority of that curtailed generation, eliminating an equal measure of non-VRE generation in the mornings and evenings. The estimated maximum potential, 11.7 GWh, would be adequate to eliminate current curtailment levels entirely.

4.4.2. BAU Achievable Shift Potential

Figure 28 shows the supply curve of BAU achievable shed potential in each forecast year, broken out into end uses and sectors. This figure also shows the same cost benchmarks for avoided costs and for BTM batteries as in Figure 26. As was the case for shed, the limited contribution from space cooling means that the difference between the 1-in-10 and the 1-in-2 weather scenarios is small. Recall from Section 4.3.2 that the achievable potential is substantially reduced compared to the technical potential because of additional program administration and incentive costs and, more significantly, because of the impacts of customer enrollment probability at a given incentive level. New approaches to customer engagement or changes to program eligibility rules could increase the achievable potential.

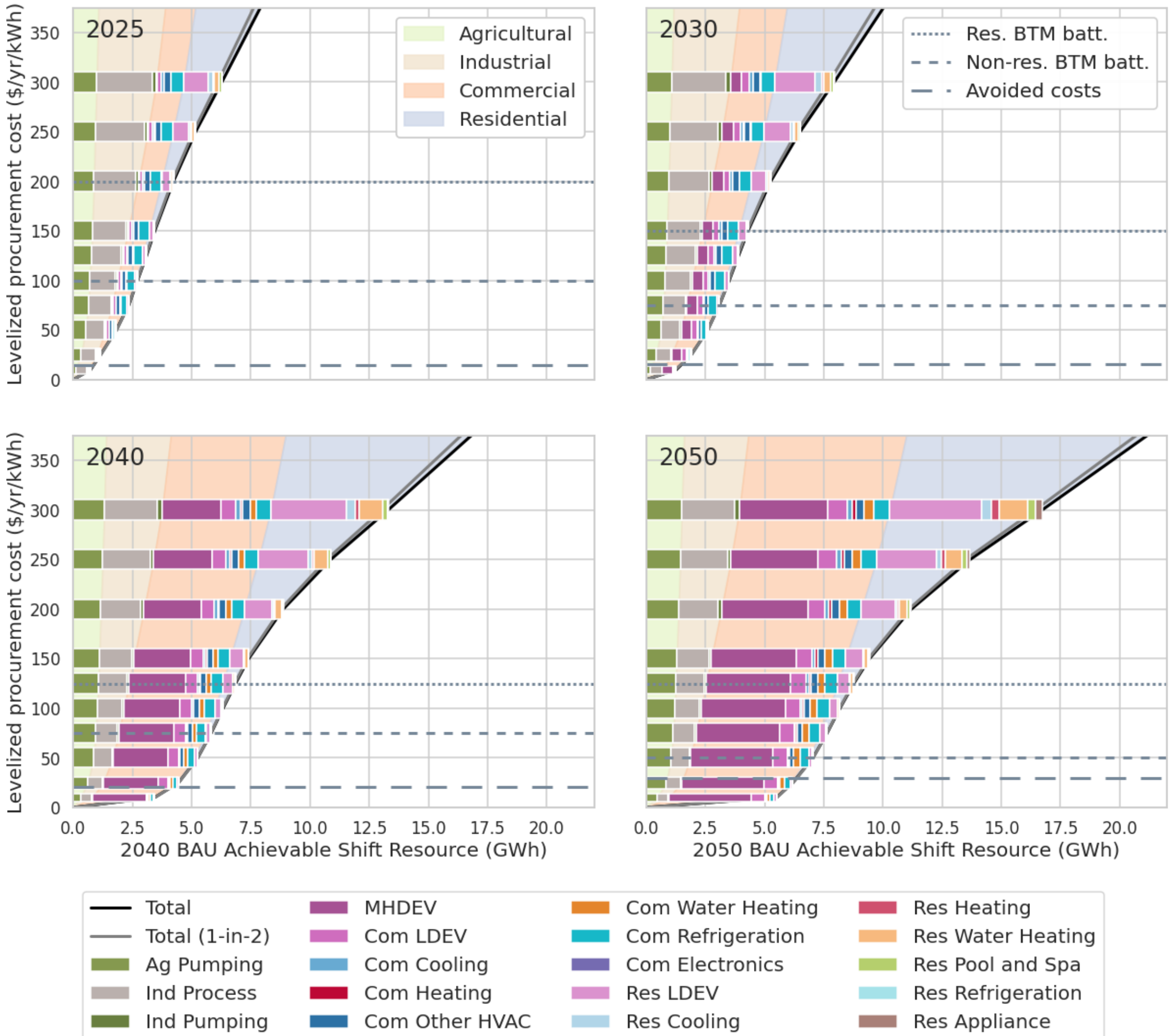

Figure 28. Supply curves for the BAU achievable potential of shed DR in California for each of the forecast years considered in this study. Meanings of the lines and shaded regions are as in Figure 21, except that the resource shown is shift DR, measured in GWh.

Table 17 presents the cost-effective BAU achievable shift potential in each service territory and overall. Table 18 presents the avoided system costs and emissions associated with this potential. The values are considerably smaller than we saw for the economic potential, owing to the large reduction arising from modeled customer enrollment at low costs. Given the low avoided costs for shift DR calculated from the ACC, there is not enough value available to incentivize widespread shift enrollment. We discuss other barriers to achieving the full economic DR potential, and potential pathways to overcoming them, in Section 5. Nevertheless, the BAU achievable shift resource is able to eliminate 360 ktCO2 by 2050, corresponding roughly to eliminating 82 MWh of natural gas generation operating for a full year, while avoiding nearly $190M in system costs.

Table 17. Total cost-effective achievable shift DR potential, in gigawatt-hours, by IOU in each forecast year.

Year	PG&E	SCE	SDG&E	Total
2025	0.31	0.36	0.05	0.72
2030	0.53	0.65	0.09	1.3
2040	2.0	2.1	0.38	4.4
2050	2.8	2.9	0.54	6.2

Table 18. Total annual GHG emission savings in ktCO2 (left) and annual value of shedding in 2020$ Million (right) to be achieved through total cost-effective achievable shift DR potential in the reference years.

Year	Annual avoided GHGs (ktCO2)	Annual avoided costs (Million 2020$)
2025	38	11
2030	71	21
2040	250	94
2050	360	190

As discussed previously, the avoided cost values from the ACC do not consider the value of flexible capacity and thus may underestimate the value of shift DR. As we did for the economic potential, we therefore also consider the BAU achievable shift potential at the non-residential battery-cost threshold in Figure 28, to place an upper limit on the cost-effective BAU achievable shift potential. The corresponding values are presented in Table 19. We do not present avoided cost estimates for this potential estimate, owing to our lack of a precise higher avoided-cost estimate, and the avoided GHGs scale proportionally from the values in Table 18.

Table 19. Total BAU achievable shift DR potential, at cost equivalence with a non-residential BTM battery, in gigawatt-hours, by IOU in each forecast year.

Year	PG&E (GWh)	SCE (GWh)	SDG&E (GWh)	Total (GWh)
2025	1.2	1.3	0.21	2.7
2030	1.4	1.4	0.25	3.1
2040	2.7	2.7	0.50	5.8
2050	3.2	3.2	0.62	7.0

The BAU achievable shift potential ranges between 0.72 and 2.7 GWh in 2025, growing to between 6.2 and 7.0 GWh by 2050. Figure 29 shows the BAU achievable shift potential at the avoided-cost threshold, in each of the IOU service territories for each forecast year, broken down by end-use category. The whiskers attached to each bar indicate the range of potential increase in economic potential up to the BTM battery threshold. The trends in the cost-effective achievable shift potential are similar to what we observed for the economic potential (Figure 27), with agricultural pumping having higher representation in PG&E owing to the larger agricultural customer base. Rapid growth in electrified loads is also evident, most notably LDEV and MHDEV charging, as well as commercial water heating. Agricultural pumping and commercial refrigeration loads also exhibit modest growth.

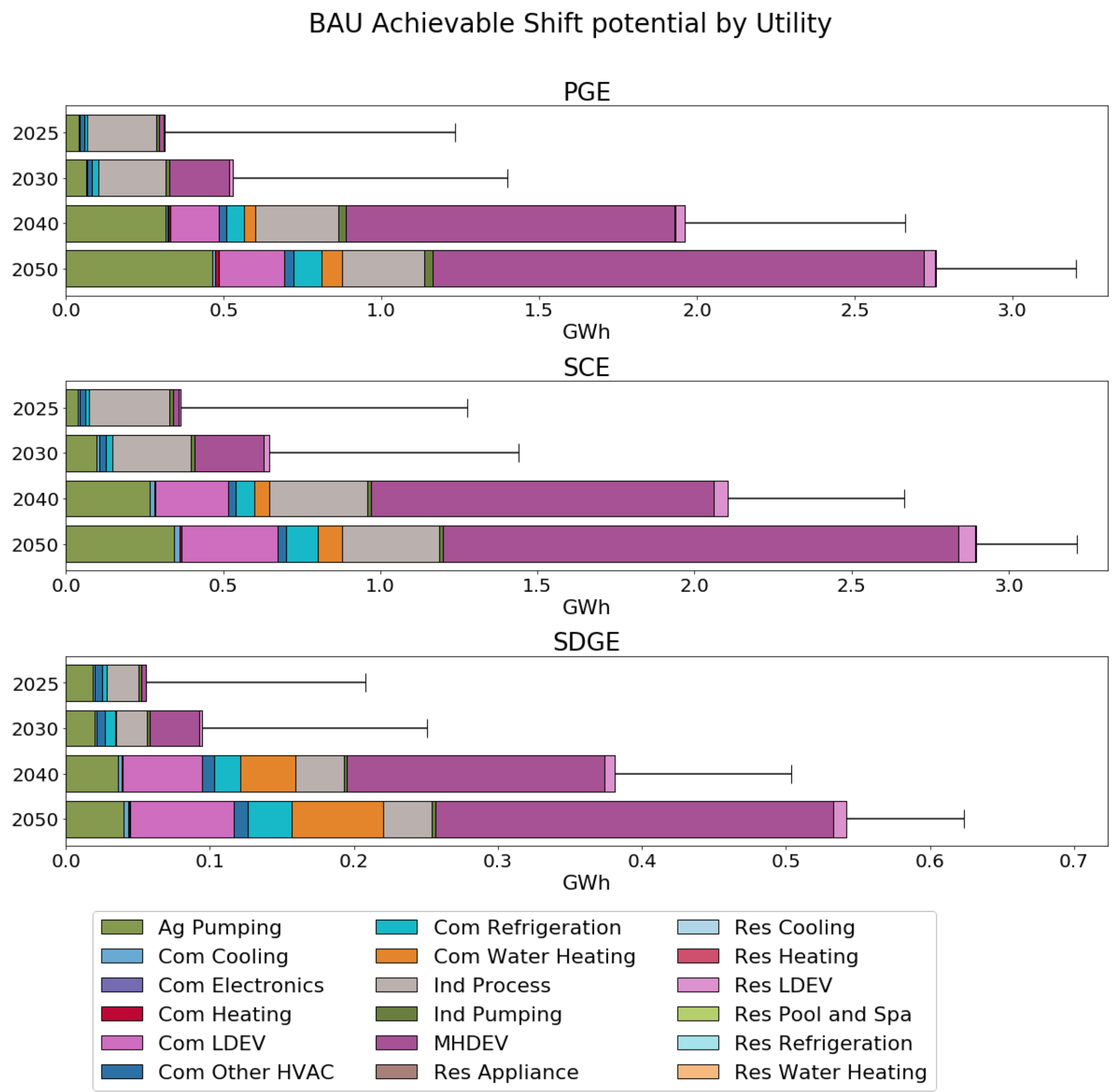

Figure 29. Estimated cost-effective BAU achievable shift DR potential resources for each IOU, broken out by end use, in each forecast year. The cost-effective potential in each year is taken to be the achievable potential at each year's avoided-cost benchmark, as shown in Figure 28. We also show the potentially larger potential that is available up to the lowest BTM battery cost threshold as a horizontal whisker attached to each bar.

Previous phases of the California DR Potential Study only estimated the quantity that we are presenting here as BAU achievable potential. As discussed previously, this study also comprehensively updates the customer load modeling, DR technology characterization, DR dispatch modeling, and customer enrollment modeling. It is interesting to compare our BAU achievable shift results to the most recent shift results from the Phase 3 report, to understand how the new modeling has impacted the DR potential estimates, just as we earlier compared our shed results to Phase 2.

At the battery-cost thresholds plotted in Figure 28, the Phase 3 study found just over 4 GWh of shift DR resource in both 2025 and 2030, somewhat more than the 2.7 and 3.1 GWh found in this study. There are numerous factors in the updated modeling that contribute to this change, as follows.

- First, as we discussed for shed DR, the Phase 4 load modeling includes only loads from IOU customers, unlike previous studies that scaled IOU loads up to the CAISO level. As a result, the quantity of shift DR available will be roughly 20% smaller than in previous studies, all else equal.
- As was the case with shed, the more detailed disaggregation of industrial process loads compared to previous studies allowed for a more realistic assessment of which loads can contribute to shift DR, leading to a modest reduction in the estimated resource.
- Where previous studies considered a single commercial HVAC end use, the present study disaggregates commercial heating, cooling, and other HVAC system loads (e.g., air handling and ventilation) into separate end uses. The disaggregation was also performed separately in different time periods throughout the day and year, as described in Section 3.3.3, impacting the amount of cooling load that was predicted at specific times. These changes considerably reduced the amount of flexible HVAC load that could be enabled to provide shift DR. In particular, the finer disaggregation of HVAC loads reduced the potential influence of TES systems in providing shift DR.
- Finally, the new model for customer enrollment in DR predicts somewhat lower enrollment at a given incentive than the model used in Phase 2.

4.4.3. The Shed Implications of Shift DR

As we have noted in the previous sections, the annual avoided costs we compute for shift DR are low, and they may undervalue shift to some degree since all of the generation capacity value in the ACC is assigned to peak hours, with no explicit value associated with flexible generation capacity. Shift DR, operationally speaking, just consists of a load reduction coupled with an offsetting load increase (Gallo et al. 2018), so it is necessarily true that all shift DR resources are also able to provide shed DR. Capturing the avoided capacity and other costs that are available from participation in shed programs provides an additional potential value stream for shift-enabling technologies. The Phase 3 study gave a rough estimate of the shed potential of shift DR, based on simple assumptions about the duration of the load-reduction period of a shift event. In the present study, since we estimate both shed and shift resources using the same load shapes and technologies, we are able to do a more rigorous calculation. In this section, we briefly estimate the potential shed resource that could be co-enabled when procuring shift DR.

To estimate the co-enabled shed resource, we start at the bottom of the shift supply curve and identify all of the individual combinations of cluster, end-use, and technology (i.e., the *site installations* described in Section 3.5.2) that contribute to the shift potential at that cost level in DR-Path. For each of these site installations, we then search the DR-Path results database and extract the quantity of shed DR that it could provide. This constitutes the shed resource that has been co-enabled by procuring the shift resource. Working our way up the supply curve, we repeat this process and sum the resulting shed resources to yield the total co-enabled shed resource at each point on the shift supply curve.

Figure 30 shows the co-enabled shed technical potential at different points along the shift technical potential supply curve in each forecast year. Reference lines are also plotted showing different ratios between the shed and shift resources. In 2025 and 2030, we see slightly higher than a 1:2 ratio there is slightly more than 1 GW of shed DR potential for every 2 GWh of enabled shift. This indicates that the technologies enabling shift in the supply curve are generally able to shift load in a four-hour window (two hours of load reduction and two hours of load increase), with the shed resource being slightly more than half the shift resource because shed DR is dispatched during peak periods when increased load is present compared to more the more ordinary loads during shift dispatches. In 2040 and 2050, the shed-to-shift ratio is slightly reduced, due to the changing set of end-uses and technologies that contribute, particularly the reduced importance of space cooling in providing shed DR.

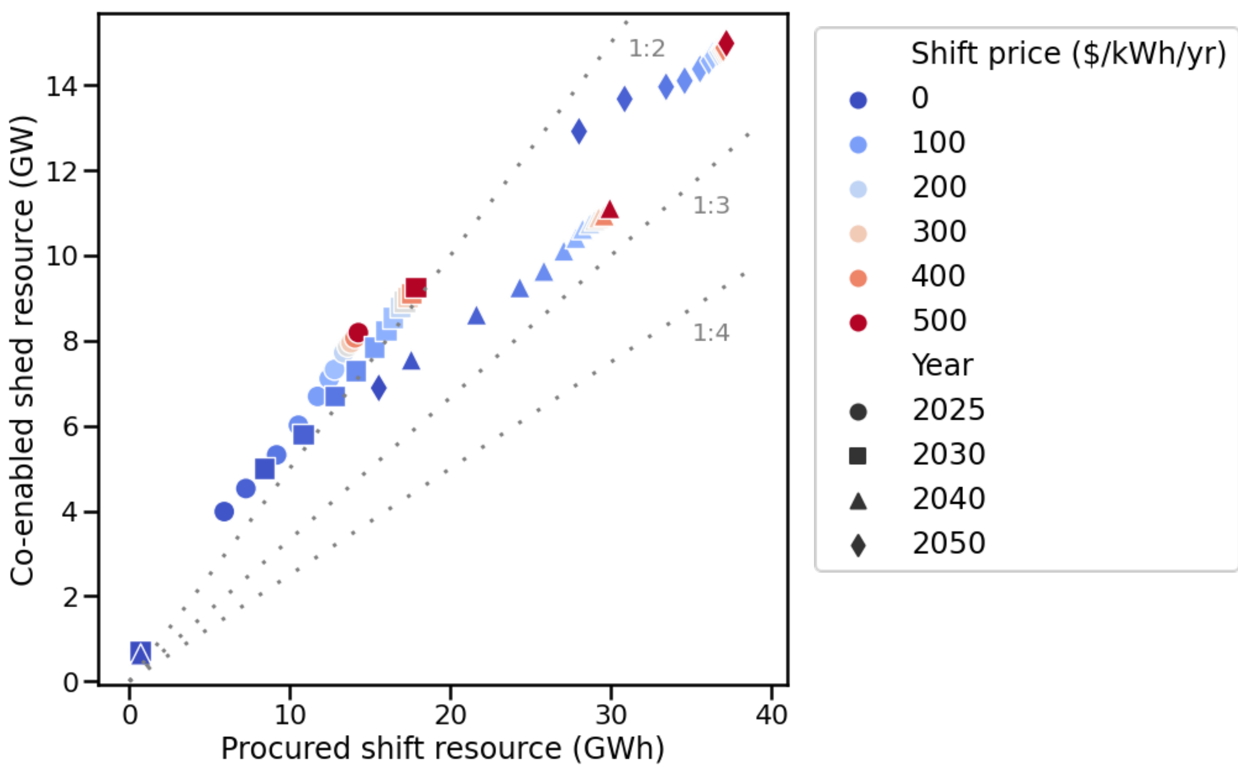

Figure 30. Shed DR resources that can be co-enabled through the procurement of shift DR, in each forecast year. Data points show the technical shift potential (horizontal axis) and the resulting cross-enabled shed resources (vertical axis), at different points along the supply curve, with procurement costs indicated by the color map. Different shapes indicate the various forecast years. Dotted lines indicate 1:2, 1:3 and 1:4 relations, for reference.

It is not clear whether all of the co-enabled shed potential could be captured in a real-world shift DR program, since customers who are willing to engage in load shifting may not be willing to also participate in shed events. For instance, a customer enrolling in a smart-thermostat program focused on load shifting may be willing to pre-cool their building on relatively cool spring days, when such a strategy can maintain comfort levels. On a hot summer day, on the other hand, pre-cooling in the afternoon before the evening peak may not be possible, since the air conditioning equipment may already be operating at maximum capacity during the pre-cooling window, and the customer may not be willing to forgo comfort in that scenario.

Nevertheless, the potential to provide shed service represents a significant additional value stream for shift resources. It is interesting to compute the added system benefit that could be provided if all of the co-enabled shed potential could be captured as a resource. To estimate this, we multiply the co-enabled shed resources from Figure 30 by the corresponding annual avoided costs of shed from Table 6 in each year to yield the total value of co-enabled shift in $/yr. Dividing this by the total kWh of shift resource at each point along the supply curve, we obtain the value of co-enabled shed per unit of procured shift in $/kWh/yr, and we add the resulting values to the annual avoided cost of shift from Table 8. This results in an enhanced value for shift at each point on the shift supply curve. We can then compute a benefit-cost ratio by dividing this value by the corresponding procurement cost. Figure 31 presents benefit-cost ratios for shift, with and without considering the added value of co-enabled shed, in each forecast year. In each panel, the blue curve is the benefit-cost ratio considering only the avoided costs from providing shift service (computed by dividing the avoided-cost values in Figure 26 by the corresponding technical potential supply curve). The orange curves present the benefit-cost ratio when the benefits of co-enabled shed are also included. Where the curves are greater than 1, the corresponding resource would be nominally cost effective, if all included benefits were captured. As a reference, the cost thresholds for residential and non-residential batteries are plotted as vertical lines.

Co-enabled shed adds significant value to the shift resources at each cost level, and significantly increases the procurement price at which shift DR is cost-effective, from values around $10-15/kWh/yr to values around $100/kWh/yr. Notably, the cost-effective procurement price level is approximately equal to the non-residential BTM battery cost in 2025 through 2040, and it exceeds the battery threshold by 2050. This implies that, by 2025, BTM batteries in non-residential[58] settings could be marginally cost-effective based on their value as DR resources *alone*, if they are used to provide both shed and shift services.

We emphasize that, as discussed above, it may not be realistic to capture all of the co-enabled shed value for a given DR resource; therefore, and the precise cost-effective level would depend on the details of a given shift-plus-shed DR program design. To be conservative, we therefore used the shift-only avoided cost threshold when computing the primary results for shift potential in the previous two sections. Nevertheless, it is clear that more value is potentially available from shed resources than is represented by the avoided-cost threshold, and the true value may be as high as the battery threshold. The horizontal whiskers in Figure 27 and Figure

[58] Residential-sector batteries, by contrast, never reach a cost-effective level as purely DR-enabling resources and would need to capture other value streams, such as providing resiliency

29 show the range of potentially cost-effective shift potential when considering value streams from providing both shed and shift services.

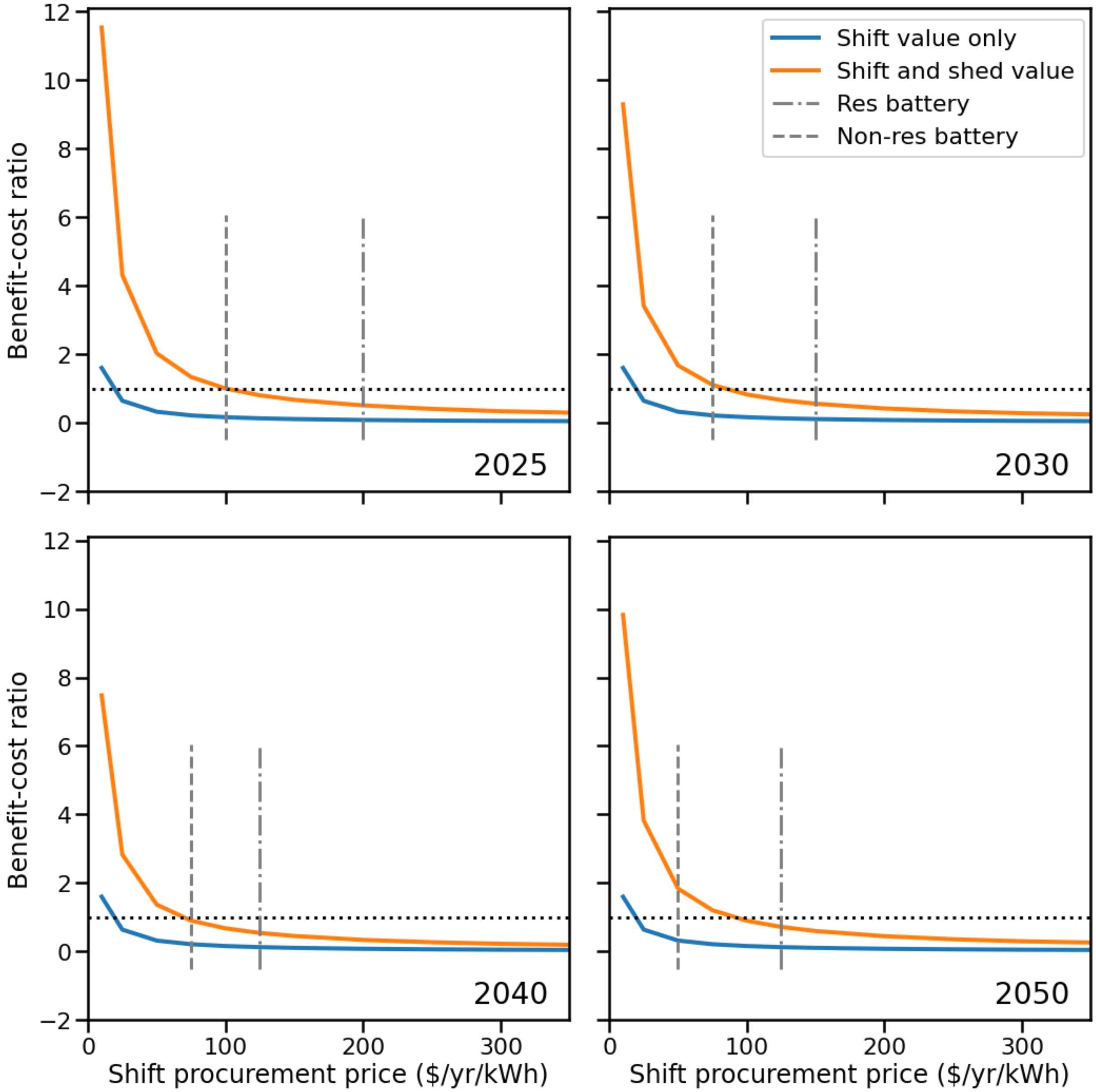

Figure 31. Benefit-cost ratios for shift DR, representing the total annual value of shift divided by the annual avoided costs from Section 4.2.2. Blue curves show the ratio considering the value of the shift resource alone, and orange curves depict the ratio when the full value of co-enabled shed DR is included. Vertical lines indicate the minimum annualized cost of residential and non-residential BTM batteries per unit of storage capacity.

4.5. The Evolving Landscape of Shed and Shift DR

Figure 32 presents a high-level summary of the main results of this study for shed and shift DR. Our results indicate that (a) dramatic evolution is expected in the size and the nature of the DR resources in California through mid-century, and (b) there is a substantial gap between the amount of DR that is available as economic potential and the amount expected to be captured as achievable potential under a BAU approach to DR programs. In this section, we consider the evolving landscape of DR in more detail, considering how the potential economic and BAU achievable resources change (and do not change) in terms of end-use contributions, key enabling technology, geographical distribution, and contributions from different customer types. Table 20 and Table 21, summarize the BAU achievable and economic DR potential for shed and shift, respectively, disaggregated by end use as in Figure 32. Table 22 presents the shift potential that is available up to the lowest BTM battery cost threshold in each forecast year (i.e., the quantity indicated by the whiskers in Figure 32), disaggregated by end use.

Aggregated DR Potential plots

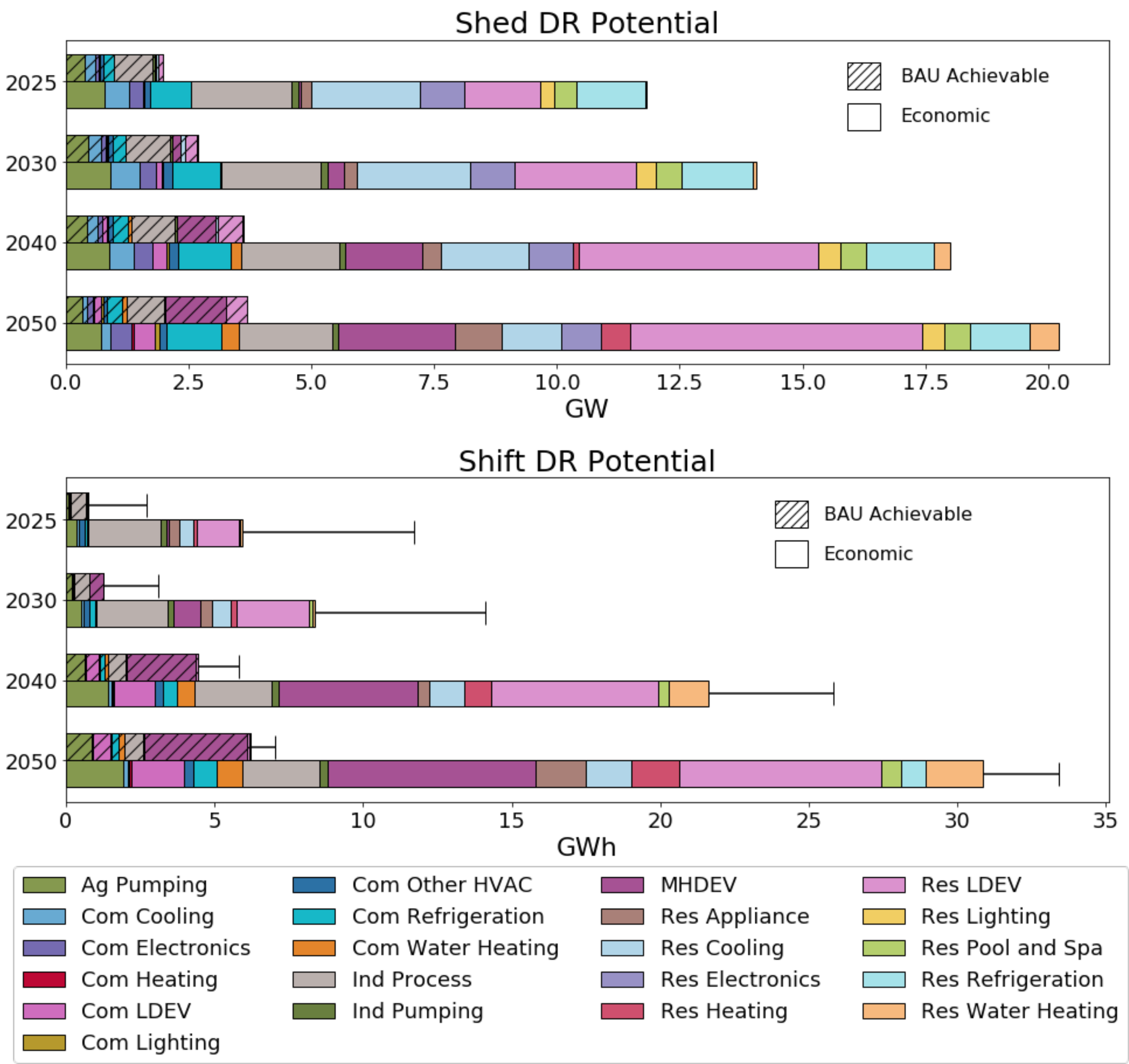

Figure 32. Summary of the economic and BAU achievable DR potential for shed (top) and shift (bottom) in each forecast year, disaggregated by end use. We also show the potentially larger shift potential that is available up to the lowest BTM battery cost threshold as a horizontal whisker attached to each bar in the lower plot.

Table 20: Economic and BAU achievable DR potential for shed DR in each forecast year, in GW, disaggregated by end use, as presented in Figure 32.

	2025		2030		2040		2050	
	BAU Achievable	Economic	BAU Achievable	Economic	BAU Achievable	Economic	BAU Achievable	Economic
Ag Pumping	0.38	0.78	0.45	0.90	0.44	0.89	0.34	0.72
Com Cooling	0.22	0.49	0.27	0.61	0.21	0.50	0.10	0.19
Com Electronics	0.08	0.30	0.09	0.33	0.10	0.36	0.11	0.41
Com Heating	0.00	0.00	0.00	0.00	0.00	0.01	0.02	0.06
Com LDEV	0.00	0.00	0.04	0.11	0.10	0.27	0.16	0.42
Com Lighting	0.01	0.02	0.01	0.04	0.02	0.06	0.03	0.09
Com Other HVAC	0.07	0.11	0.10	0.17	0.10	0.19	0.09	0.15
Com Refrigeration	0.22	0.82	0.27	0.99	0.30	1.1	0.30	1.1
Com Water Heating	0.00	0.02	0.00	0.02	0.07	0.23	0.11	0.36
Ind Process	0.80	2.1	0.90	2.0	0.89	2.00	0.75	1.9
Ind Pumping	0.04	0.13	0.04	0.13	0.04	0.12	0.80	0.11
MHDEV	0.02	0.04	0.18	0.34	0.80	1.6	1.2	2.4
Res Appliance	0.00	0.23	0.00	0.26	0.00	0.38	0.00	0.94
Res Cooling	0.05	2.2	0.08	2.3	0.04	1.8	0.00	1.2
Res Electronics	0.00	0.90	0.00	0.91	0.00	0.88	0.00	0.81
Res Heating	0.00	0.00	0.00	0.00	0.00	0.12	0.00	0.59
Res LDEV	0.09	1.5	0.24	2.5	0.51	4.9	0.43	6.0
Res Lighting	0.00	0.27	0.00	0.40	0.00	0.46	0.00	0.45
Res Pool and Spa	0.01	0.46	0.01	0.52	0.01	0.52	0.01	0.50
Res Refrigeration	0.00	1.4	0.00	1.5	0.00	1.4	0.00	1.2
Res Water Heating	0.00	0.02	0.00	0.05	0.00	0.34	0.00	0.61
Total	**2.3**	**12**	**2.3**	**14**	**3.2**	**18**	**4.1**	**21**

Table 21: Economic and BAU achievable DR potential for shift DR in each forecast year, in GWh, disaggregated by end use, as presented in Figure 32. Lighting and residential electronics end uses are not shiftable and have no associated resource.

	2025		2030		2040		2050	
	BAU Achievable	Economic	BAU Achievable	Economic	BAU Achievable	Economic	BAU Achievable	Economic
Ag Pumping	0.10	0.37	0.18	0.50	0.62	1.4	0.85	1.9
Com Cooling	0.01	0.05	0.01	0.07	0.02	0.12	0.03	0.16
Com Electronics	0.00	0.01	0.00	0.01	0.00	0.01	0.00	0.01
Com Heating	0.00	0.01	0.00	0.01	0.01	0.05	0.02	0.10
Com LDEV	0.0	0.0	0.0	0.0	0.44	1.4	0.58	1.8
Com Lighting	--	--	--	--	--	--	--	--
Com Other HVAC	0.04	0.18	0.04	0.21	0.06	0.25	0.07	0.30
Com Refrigeration	0.02	0.10	0.05	0.20	0.13	0.48	0.22	0.79
Com Water Heating	0.00	0.03	0.00	0.04	0.12	0.58	0.21	0.87
Ind Process	0.49	2.5	0.48	2.4	0.61	2.6	0.60	2.6
Ind Pumping	0.02	0.20	0.02	0.20	0.04	0.25	0.04	0.25
MHDEV	0.03	0.07	0.45	0.9	2.31	4.7	3.47	7.0
Res Appliance	0.00	0.37	0.00	0.38	0.00	0.4	0.00	1.7
Res Cooling	0.00	0.44	0.00	0.64	0.00	1.2	0.00	1.6
Res Electronics	--	--	--	--	--	--	--	--
Res Heating	0.00	0.12	0.00	0.18	0.00	0.92	0.00	1.6
Res LDEV	0.01	1.4	0.03	2.5	0.08	5.6	0.10	6.8
Res Lighting	--	--	--	--	--	--	--	--
Res Pool and Spa	0.00	0.03	0.00	0.08	0.00	0.37	0.00	0.67
Res Refrigeration	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.84
Res Water Heating	0.00	0.05	0.00	0.11	0.00	1.3	0.00	1.9
Total	**0.72**	**5.9**	**1.3**	**8.4**	**4.4**	**22**	**6.2**	**31**

Table 22: Summary of the technical and BAU achievable DR potential for shift DR, in GWh, at the BTM battery cost threshold in each forecast year (i.e., the quantity indicated by the whiskers in Figure 32), disaggregated by end use. Lighting and residential electronics end uses are not shiftable.

Year	2025		2030		2040		2050	
End Use	BAU Achievable	Technical	BAU Achievable	Technical	BAU Achievable	Technical	BAU Achievable	Technical
Ag Pumping	0.69	1.5	0.73	1.6	0.95	2.0	1.1	2.2
Com Cooling	0.04	0.08	0.03	0.09	0.05	0.12	0.04	0.16
Com Electronics	0.00	0.01	0.00	0.01	0.00	0.01	0.00	0.01
Com Heating	0.01	0.02	0.00	0.02	0.02	0.08	0.04	0.12
Com LDEV	0.12	0.35	0.23	0.69	0.47	1.4	0.60	1.8
Com Lighting	--	--	--	--	--	--	--	--
Com Other HVAC	0.19	0.50	0.19	0.21	0.21	0.26	0.19	0.30
Com Refrigeration	0.36	1.0	0.34	0.97	0.40	1.2	0.37	1.2
Com Water Heating	0.01	0.04	0.01	0.05	0.17	0.58	0.25	0.88
Ind Process	1.1	3.2	0.93	3.1	0.91	3.1	0.77	3.0
Ind Pumping	0.07	0.30	0.06	0.28	0.06	0.28	0.05	0.27
MHDEV	0.03	0.07	0.45	0.90	2.3	4.7	3.5	7.0
Res Appliance	0.00	0.37	0.00	0.41	0.00	0.59	0.00	1.7
Res Cooling	0.00	1.0	0.00	1.22	0.00	1.5	0.00	1.6
Res Electronics	--	--	--	--	--	--	--	--
Res Heating	0.00	0.37	0.00	0.40	0.00	1.1	0.00	1.7
Res LDEV	0.08	2.0	0.10	3.2	0.19	5.7	0.15	6.9
Res Lighting	--	--	--	--	--	--	--	--
Res Pool and Spa	0.00	0.27	0.00	0.27	0.01	0.56	0.01	0.77
Res Refrigeration	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.84
Res Water Heating	0.01	0.56	0.01	0.74	0.03	2.7	0.01	3.0
Total	**2.7**	**12**	**3.1**	**14**	**5.8**	**26**	**7.0**	**33**

4.5.1. The relative efficacy of different end uses

When considering the technical potential for DR, we found significant variation in the size of the DR resource that can be provided by different customer end-use categories, for both shed and shift DR. The size of the DR resource from a particular end use is driven both by the overall size of the end use load and by its inherent flexibility. For instance, an end use may have an especially large potential because it has a large demand coupled with a moderate level of flexibility, or because it has a smaller demand but a high degree of flexibility. By contrast, an end use with a smaller shed potential may simply have low demand, or it may be a larger end use with limited flexibility. These examples illustrate that there will be variation in the *efficacy* of different end uses as DR resources. Understanding the relative efficacy of different end uses can help in identifying "low-hanging fruit" for future DR programs, as well as research and development opportunities to improve the flexibility of end uses that have untapped potential in our current modeling.

Figure 33 illustrates the relative efficacy of different end use categories as shed DR resources, and how it evolves over time. In each panel, the colored shapes represent different end uses, where the color denotes the end use and the shape denotes the sector. Shapes are plotted on a two-dimensional plane, with the horizontal position indicating the fraction of the peak load that the end-use contributes, on average, during times when shed is likely to be dispatched, while the vertical position denotes the fraction of the economic[59] shed potential that the end use provides. The size of each shape indicates the total aggregate energy consumption from that end use. In each panel, a dotted line shows the 1:1 relation, where an end use has peak load contribution and shed potential that are exactly proportional. Shapes above this line are providing a disproportionately large shed resource compared to their peak-load contribution--i.e., they have a high relative efficacy--whereas shapes below the line are underperforming as DR resources relative to their peak load contribution. In addition, shapes near the upper left corner of each panel represent especially important sources of DR potential, in the sense of being both large and efficacious.

[59] It would also be possible to make charts such as this for the achievable DR potential. In that case, however, the results would be strongly impacted by the customer enrollment model, so that, for example, all residential end uses would appear to have low efficacy relative to other sectors. Our goal here is to understand the *capabilities* of different end uses to provide shed, not customer preferences, so we focus on the economic potential.

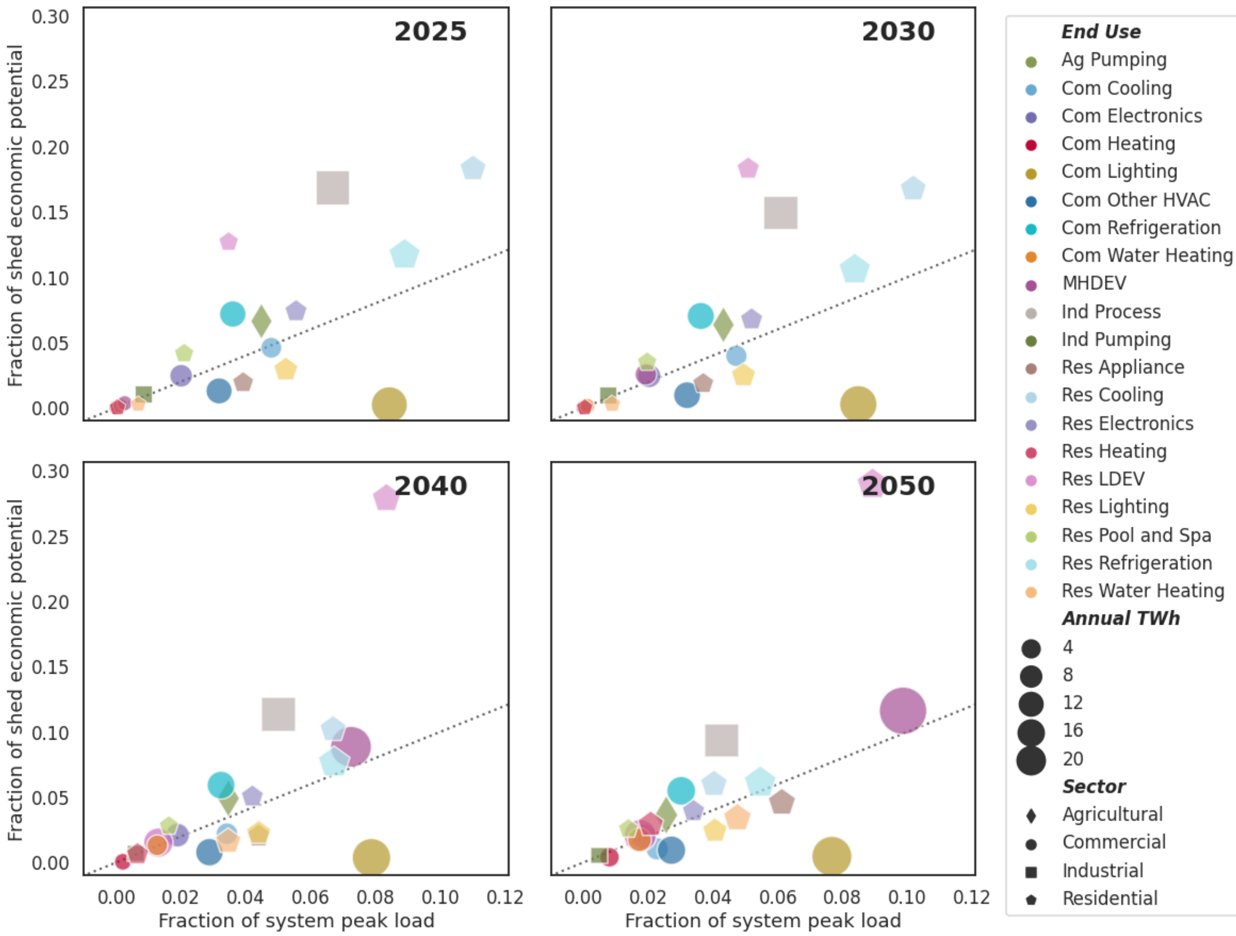

Figure 33. Scatter plots illustrating the relative efficacy of different end uses as shed DR resources, by forecast year. Colored shapes indicate different end uses, by sector. The horizontal and vertical position of each shape, respectively, denote the fraction of the system peak demand and the fraction of the economic shed potential for which each end use is responsible. Size denotes the total annual energy consumption from each end use. In each panel, a dotted line indicates a 1:1 relation.

Focusing first on the 2025 forecast year in Figure 33, we see several end uses that stand out as particularly important and efficacious, namely industrial processes and residential space cooling and EV charging. Refrigeration (both residential and commercial), agricultural pumping, and residential electronics and pool and spa loads are also able to provide a disproportionately large shed resource compared to their peak load contributions. By contrast, residential lighting and appliances, commercial HVAC system loads, and especially commercial lighting tend to underperform as shed resources relative to their peak load contribution. Other end uses, such as commercial space cooling and electronics and industrial pumping, can provide shed resources that are roughly proportional to their peak load contribution. Emerging electrified end uses (MHDEV and space and water heating) are relatively small and sit near the zero-point of the diagram.

Moving forward in time, we observe fairly dramatic changes in the relative efficacies. Most notable is the meteoric rise of residential LDEV charging, which dwarfs all other end uses in terms of shed potential and efficacy by 2040, indicating that residential EVs' potential as a resource for peak-load management far outweighs their contribution to peak load growth. MHDEV charging also grows dramatically as a fraction of both peak load and total shed resource, although its shed potential remains more nearly proportional to its peak load contribution. Other electrified loads also grow in importance, generally providing DR potential that is proportional to their peak load contribution, though residential water heating and appliances have slightly lower relative shed efficacies than other electrified end uses. Several other end uses remain stable and consistent as high-efficacy sources of shed potential, specifically industrial processes, agricultural pumping, and commercial and residential refrigeration loads. Meanwhile, residential and commercial space cooling loads see significant declines in both importance and relative efficacy over the forecast period.

Figure 34 shows plots of the relative efficacy of end use categories as shift DR resources. In this case, the vertical axes show the fraction of the economic shift potential that each end use represents, while the horizontal axis represents the fraction of the consumption occurring on the "high" side of steep ramps (either after an upward ramp or before a downward ramp). As was the case for shed, we see that several end uses represent particularly important sources of shift in the near term, particularly industrial process loads, residential EV charging, agricultural pumping, commercial refrigeration, and residential space cooling. Certain emerging end uses, such as residential space and water heating, are smaller but also relatively efficacious. By contrast, residential refrigeration and commercial electronics[60] are relatively low-efficacy. Other end uses generally yield a shift resource that is proportional to their ramp-adjacent consumption.

As time progresses, we again see rapid evolution in the most important and efficacious end uses, with residential EV charging undergrowing moderate growth in importance, while water heating and especially MHDEV charging both skyrocket from relatively low levels to become among the most important and efficacious sources of shift DR by 2050. Residential space heating, commercial water heating, and commercial EV charging also grow in importance, albeit more modestly. Meanwhile, industrial process loads, agricultural pumping, commercial refrigeration, and residential space cooling diminish somewhat in importance but remain highly efficacious. Interestingly, residential refrigeration becomes somewhat more efficacious over this period, owing to increasing penetration of smart refrigerators that can control the timing of defrost cycles. Other residential appliances also improve modestly in efficacy as more connected appliances enter the market.

[60] The commercial electronics end use category includes IT equipment in datacenters, which is assumed to be shiftable to some degree, along with a larger contribution office equipment, which is assumed not to be shiftable, explaining the low overall efficacy.

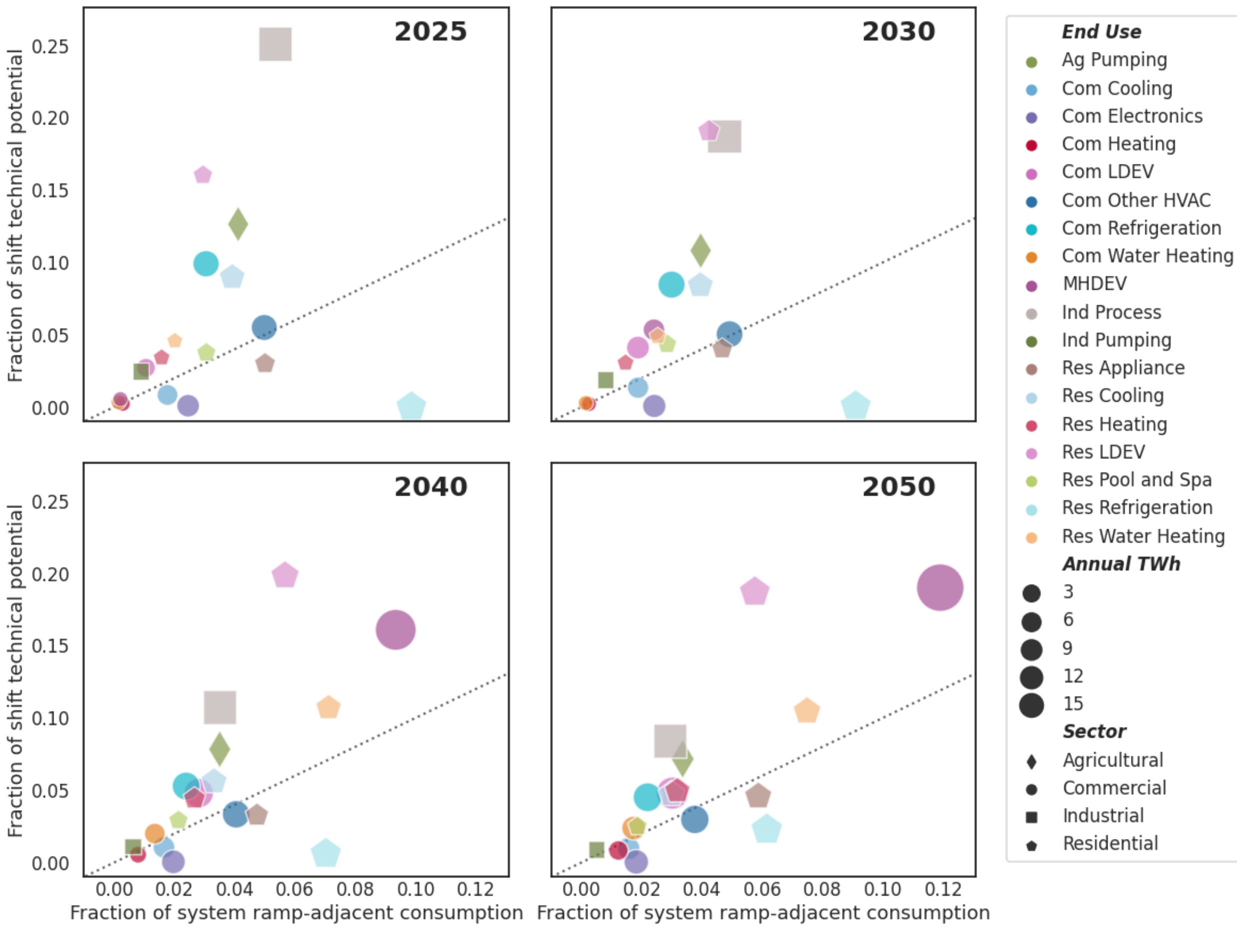

Figure 34. Scatter plots illustrating the relative efficacy of different end uses as shift DR resources, by forecast year. Data points are displayed as in Figure 33. The horizontal and vertical position of each shape, respectively, denote the fraction of the system energy consumption occurring at the high end of a ramp and the fraction of the economic shift potential for which each end use is responsible.

4.5.2. Key end use categories and DR-enabling technologies in detail

The previous section identified several end-use categories that are of particular interest for DR over the coming decades, either because of rapid evolution in their potential, or because they provide consistently strong performance over the full period. This section explores some of these key end use categories in more detail, examining the individual end uses and DR-enabling technologies that contribute to the potential in each case. Throughout this section, we will present diagrams showing the BAU achievable and economic potential from a given end use category in each forecast year, using stacked bar charts that disaggregate the potential according to the specific enabling technologies that are selected by DR-Path in the supply curve.

EV Charging

It is clear that EV charging is of outsized importance in the projections of future DR potential, both for shift and for shed. Figure 35 shows the shed DR potential for LDEV charging in both the residential and commercial sector, by enabling technology. A sizeable and rapidly growing resource is available both in the BAU achievable and the economic potential.

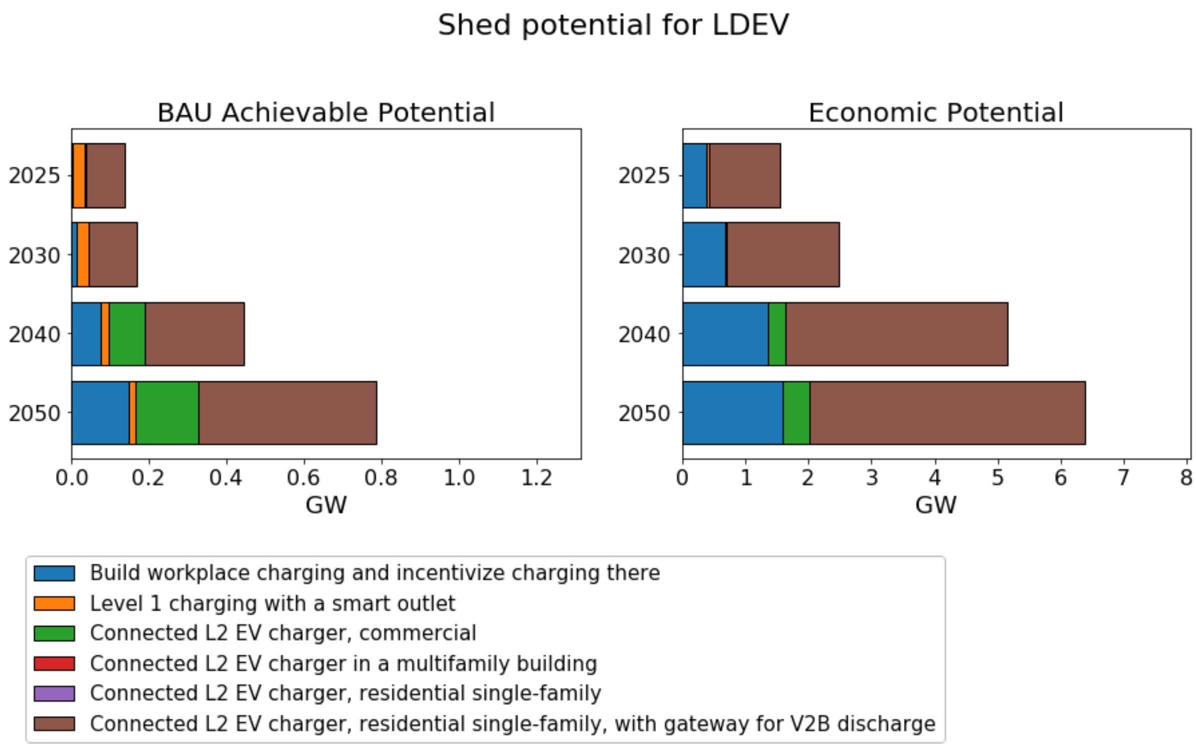

Figure 35. BAU achievable and economic shed DR potential for commercial and residential LDEV charging in each forecast year, disaggregated by the enabling technology selected by DR-Path as maximizing DR at the relevant cost level.

Perhaps the most intuitive DR-enabling technology for LDEV charging is a connected level-2 charging station that can start and stop charging in response to a signal. Interestingly, however, this is not the primary source of shed DR enablement in the model results. Instead, the enabling technologies responsible for the bulk of the potential are (a) a connected level-2 charger with the capacity for vehicle-to-building (V2B[61]) discharge to serve loads within the building from the EV battery and (b) a strategy of building additional EV charging stations at workplaces and incentivizing customers to charge there on peak days.[62] The latter approach may have implications for future distribution-system upgrades, which are important to consider; however, a recent study indicates that the overall infrastructure cost implications of such an approach would be similar to those for at-home charging (Elmallah, Brockway, and Callaway 2022).

These approaches both have higher incremental technology costs than household connected charging stations, but the deeper load shed possible from two-way charging, and the more

[61] This technology is not assumed to have the capability to discharge to the grid (V2G). We consider such export of energy to the grid to be outside the definition of “demand response” for the purposes of this study. Full V2G technology could potentially provide even larger benefits to the grid than we estimate here.
[62] This strategy would involve sending day-ahead notification to customers prior to peak days. This admittedly strains the definition of “dispatchable” DR somewhat, but it could deliver significant load reductions as shown.

sustained shed available from location-shifting, yield sufficiently large additional resources to justify the increased cost. Although we do not consider the possibility explicitly in this study, combining these two strategies could be particularly interesting, enabling an approach in which customers fill their EV batteries with renewable electricity while at work, then use that energy to power their homes at night, thereby both avoiding some curtailment of VRE and obviating the need for some grid-scale storage.

One-way connected charging stations in the commercial sector become modestly important later in the forecast period as EV penetration reaches high levels. We also considered the strategy of providing shed DR with level-1 charging via a connected outlet or power strip; this potential is very small compared to the level-2 technologies, and it shrinks with time as level 2 charging becomes more widespread.

Figure 36 shows the shift DR potential from LDEV charging. Incentivizing workplace charging is an important source of shift DR, as it was for shed. Unlike the case with shed, however, one-way residential charging is a more important enabling technology for shift DR than two-way V2B charging. This is because of an assumption in the model that any V2B discharge must be made up during the same charging session, which limits the duration of load shifting compared to one-way controlled charging. The significant value that we find in expanded access to workplace charging for both shed and shift DR is consistent with the recommendations of a recent study on the grid impacts of widespread EV adoption in the western United States (Powell et al. 2022).

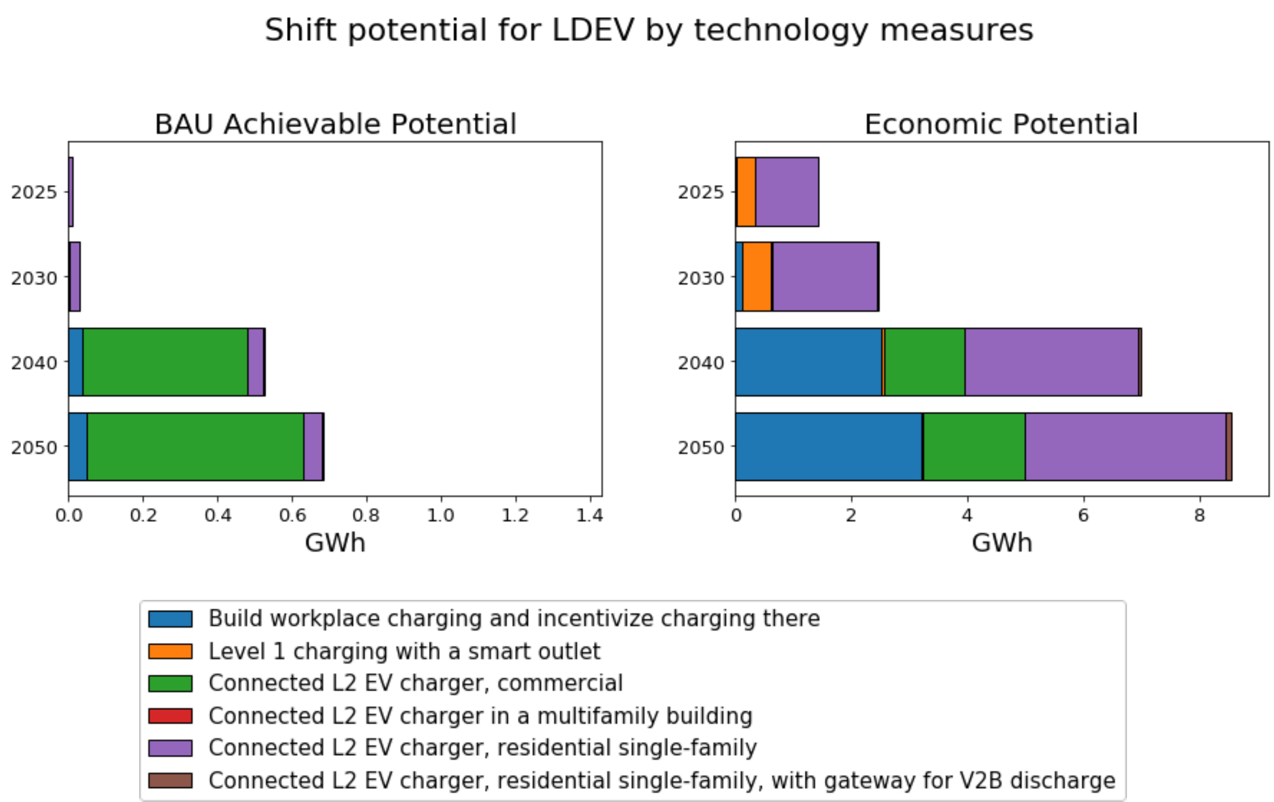

Figure 36. BAU achievable and economic shift DR potential for commercial and residential LDEV charging in each forecast year, disaggregated by the enabling technology selected by DR-Path as maximizing DR at the relevant cost level.

We also saw in earlier sections that MHDEV charging becomes a dominant DR resource, both for shed and shift, by midcentury. In the modeling for this study, all DR from such charging is assumed to be enabled by connected one-way charging infrastructure, which is assumed to be nearly universal for MHDEV. It is likely that two-way charging could enhance this resource, but given the current uncertainty about the nature of MHDEV charging infrastructure, we do not explicitly model this option here. It is worth noting that the modeling of MHDEV load shapes performed for this study using LBNL's HEVI-LOAD model (see Section 3.3.5) includes modeling of the load shapes for a wide array of different types of medium and heavy-duty vehicle categories (e.g., buses, freight trucks, refuse vehicles). Readers interested in the specific breakdown of the MHDEV DR resources by vehicle type can find this information in Appendix D, with the caveat that modeling of category-specific charging load shapes is highly uncertain at present.

Water heating

Figure 37 shows the shed DR potential from water heating broken down by enabling technology, and Figure 38 shows the same for shift DR potential. In both cases the potential is enabled by a mixture of technologies, including connected ("smart") water heaters, add-on controls compliant with the ANSI CTA-2045 standard, and, in the case of shed, direct load control (DLC) switches.[63] DLC switches are not considered for shift DR because they cannot shift load into the period prior to a load reduction, whereas the smart water heaters and add-on controls are all paired with thermostatic mixing valves that allow the set point of the water heater to be safely adjusted upward and increase load in particular periods prior to a load reduction.

[63] All of these technologies can apply to either electric resistance or heat pump water heaters, though in practice most new electrified water heating in California is anticipated to use heat pump technology.

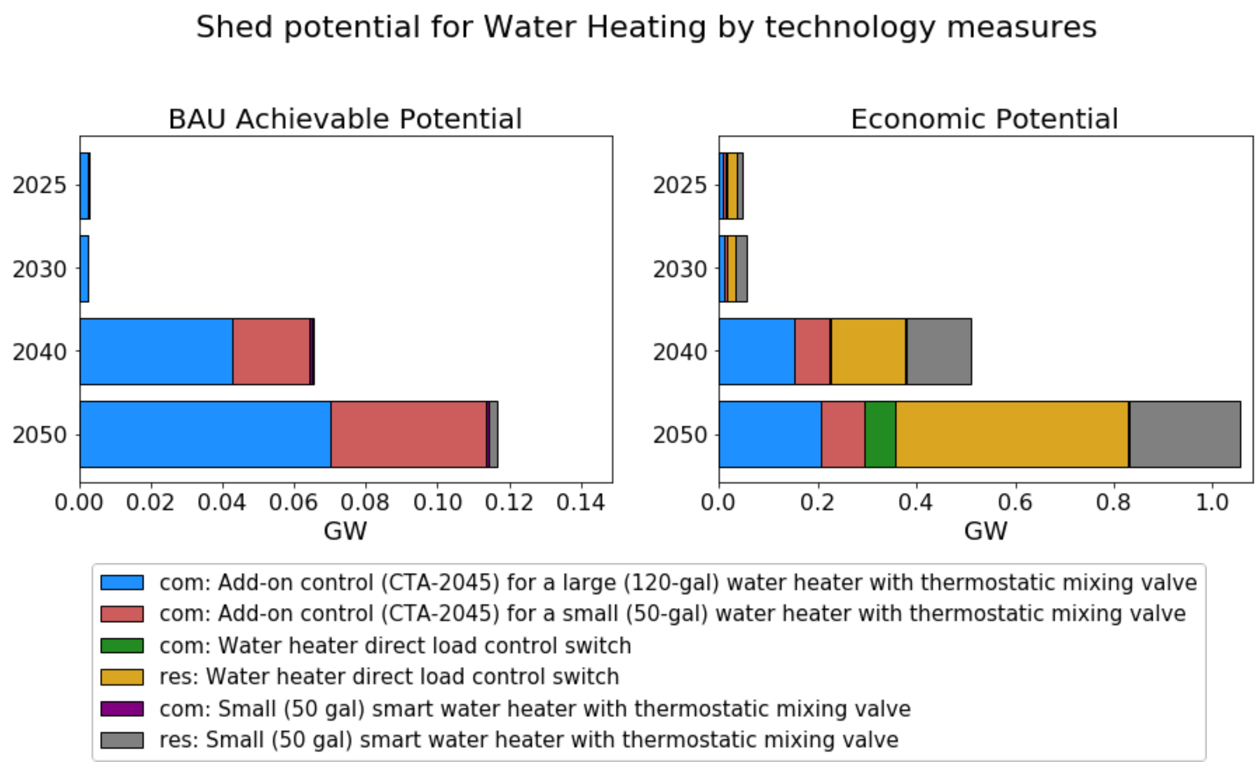

Figure 37. BAU achievable and economic shed DR potential for commercial and residential water heating in each forecast year, disaggregated by the enabling technology selected by DR-Path as maximizing DR at the relevant cost level.

It is important to note that the cost and performance assumptions used for modeling water heating control technologies in this study were very similar across these various technologies (see Appendix D). The specific breakdown of technologies shown here reflects very small differences that allow one technology to edge out another in the DR-Path model. In practice, the resources that would be enabled by connected water heaters versus CTA-2045 add-on controls are similar at a given cost, and either of these technologies would be a potentially viable path to enabling DR. Given the importance of connected water heaters and add-on controls, policies that encourage connected features or CTA-2045 control ports will be particularly important as California transitions to electrified water heating.

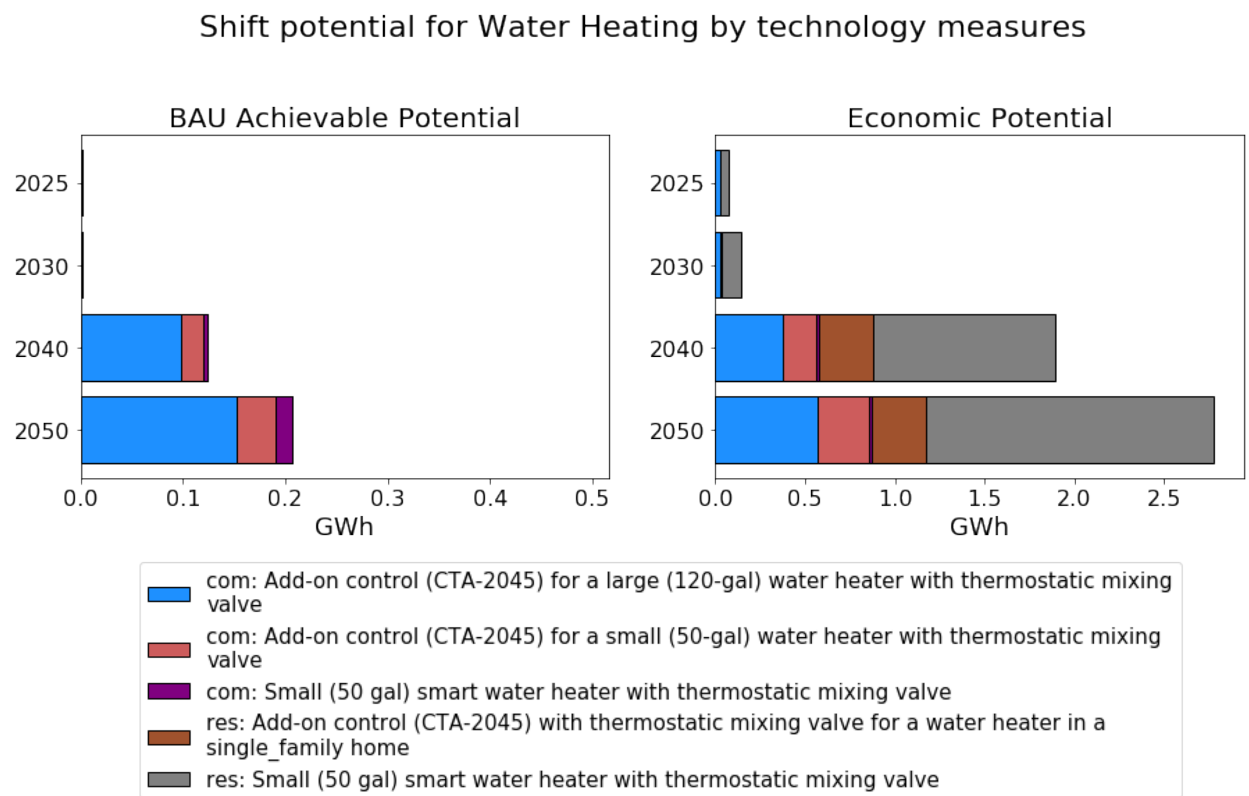

Figure 38. BAU achievable and economic shift DR potential for commercial and residential water heating in each forecast year, disaggregated by the enabling technology selected by DR-Path as maximizing DR at the relevant cost level.

Residential appliances

Figure 39 shows the BAU achievable and economic shed DR potential from residential appliances broken down by enabling technology, and Figure 40 shows the same for shift DR potential. In both cases, the potential is enabled by a mixture of technologies, including delay-cycle functions that can be set manually, internet connection allowing remote controllability, and, in the case of refrigerators, smart power outlets. It is important to note that refrigeration has been included here with other appliances, though it is split out separately in previous figures owing to its dominant size.

For shed, the most important technology is smart power outlets on residential refrigerators, which are assumed to turn off the refrigerator for up to two hours[64] during a shed event (corresponding to a 50% average load reduction in a four-hour event). Manual delay-cycle functions are also important in the near term, but are replaced by connected devices by midcentury. Notably, the growth of electrified clothes drying yields a significant new resource by 2050. Due to the low customer enrollment rates in the residential sector, the BAU achievable potential is sharply smaller than the economic potential for these end-uses, indicating an opportunity to develop new customer-engagement strategies.

[64] The two-hour limit is assumed to ensure food safety. This strategy is currently employed in California by the aggregator OhmConnect.

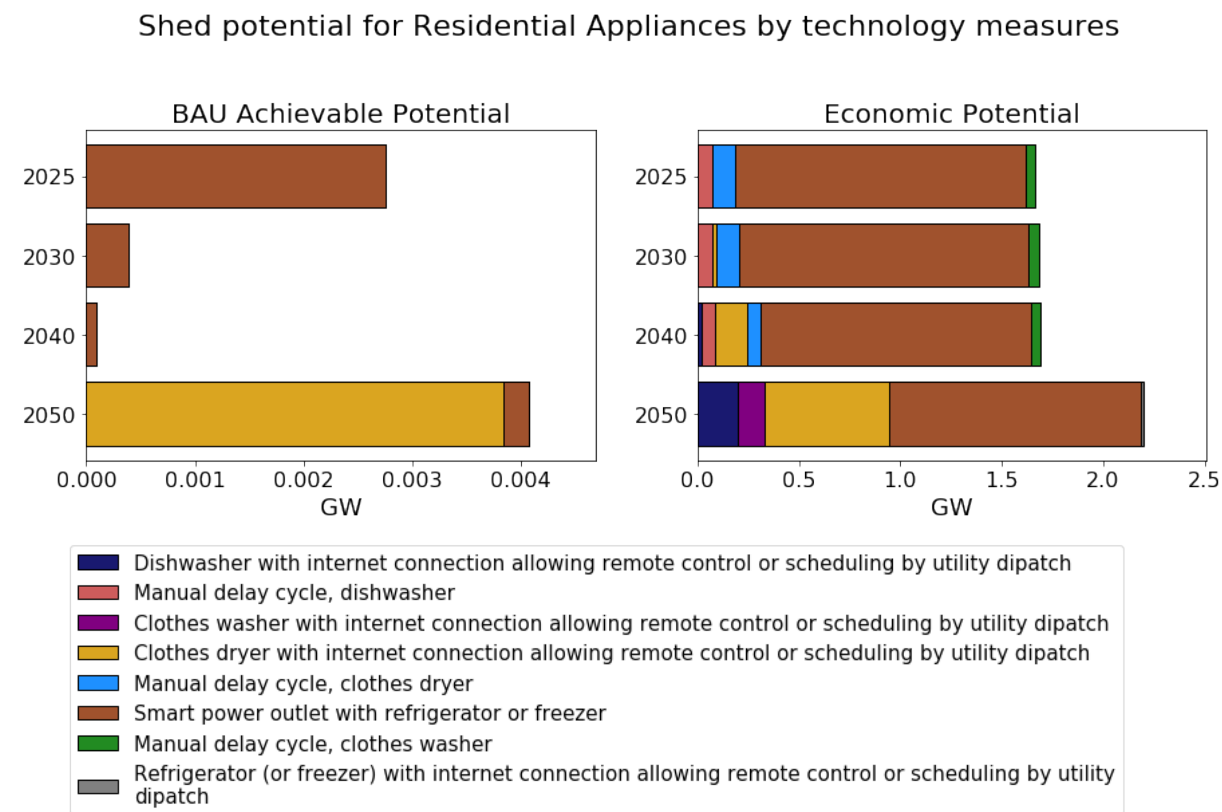

Figure 39. BAU achievable and economic shed DR potential for residential appliances in each forecast year, disaggregated by the enabling technology selected by DR-Path as maximizing DR at the relevant cost level.

For shift, manually delaying appliance cycles is the only viable approach through 2040, but after that, connected appliances become cost-effective within the economic potential, yielding a sharply higher potential. Notably, refrigeration appears as a shiftable load in this case, using a strategy of rescheduling defrost cycles to off-peak times (the smart plug technology used for shed, by contrast, cannot shift load). The assumption is that by 2050 there will be a cost decline in smart appliances and all appliances in the market will be connected, so the incremental cost of ownership would drop to zero so that connected appliances would become cost-effective in the economic potential. The low avoided-cost value of shift that we calculated from the ACC means that none of this shift potential appears in the cost-effective BAU achievable potential, indicating an opportunity for new customer engagement models.

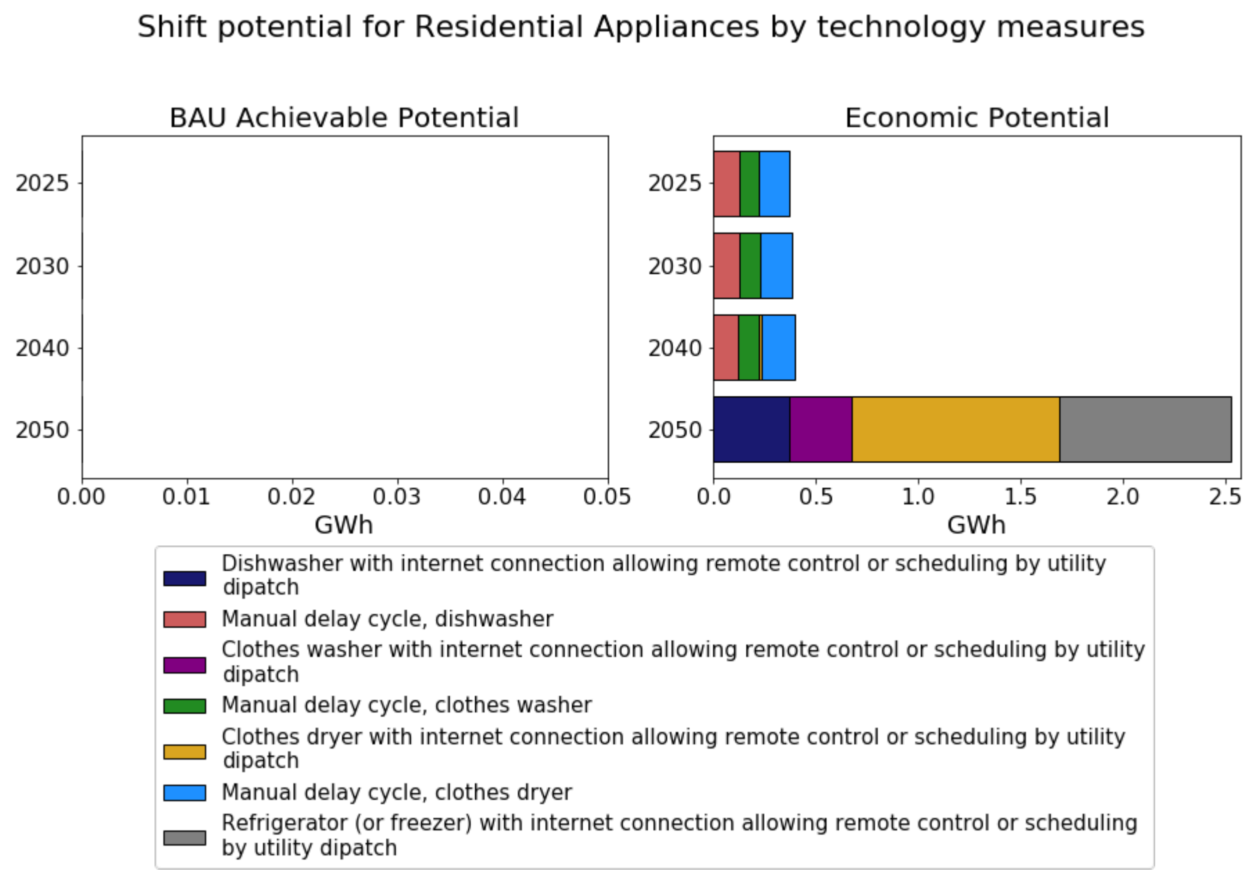

Figure 40. BAU achievable and economic shift DR potential for residential appliances in each forecast year, disaggregated by the enabling technology selected by DR-Path as maximizing DR at the relevant cost level.

Water pumping

Pumping loads within the scope of the Phase 4 Study

Figure 41 shows the BAU achievable and economic shed DR potential from water pumping for industrial and agricultural sectors broken down by enabling technology and Figure 42 shows the same for shift DR potential. Agricultural pumping provides the largest shed potential, enabled partially by DLC but increasingly by remote control with automated demand response (ADR). Agricultural pumping is also the dominant shift resource, and ADR is the only enabling technology since the DLC option cannot shift load. The resulting shift potential grows consistently throughout the forecast period as the price of the technology falls. In the industrial sector, pumping load is a steady, if smaller, source of shed and shift potential, primarily enabled by manual controls, with little to no contribution from ADR.[65]

[65] In this case, "manual" pumping controls refer to controls that require human intervention after communication from the utility or aggregator, rather than being controlled directly by a DR signal, although the actual turning on and off of the pump may be remotely controlled from, e.g., a water agency control center.

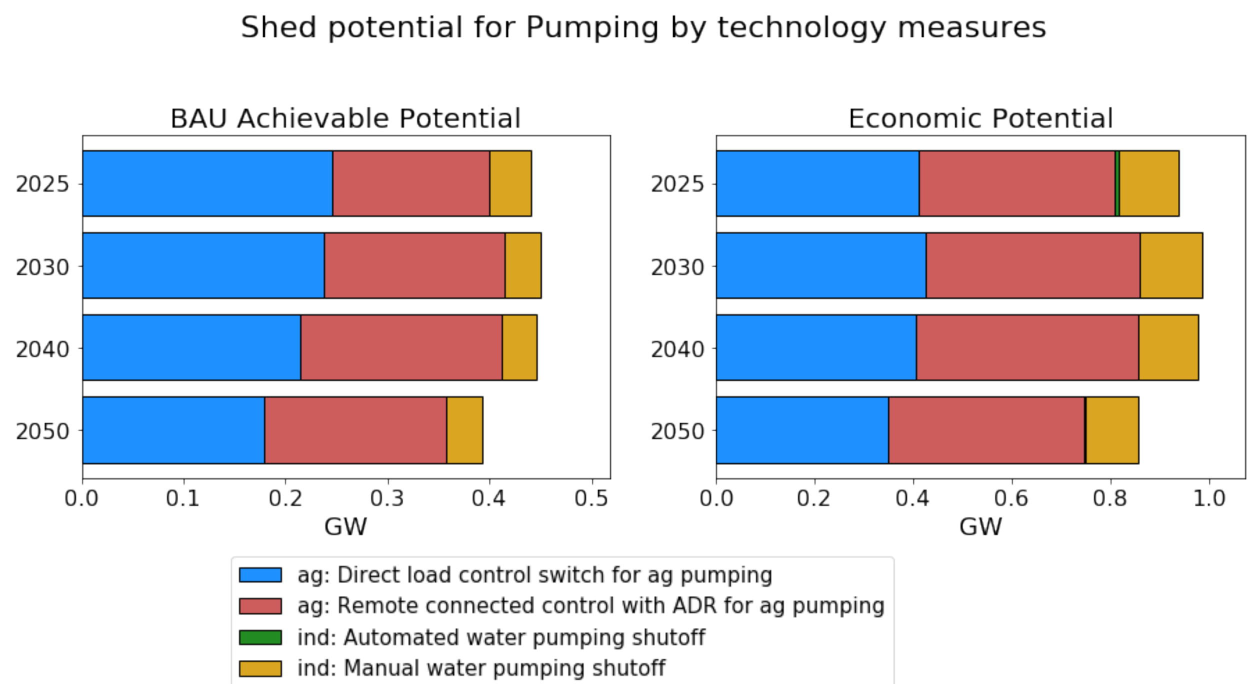

Figure 41. BAU achievable and economic shed DR potential for water pumping loads in each forecast year, disaggregated by the enabling technology selected by DR-Path as maximizing DR at the relevant cost level.

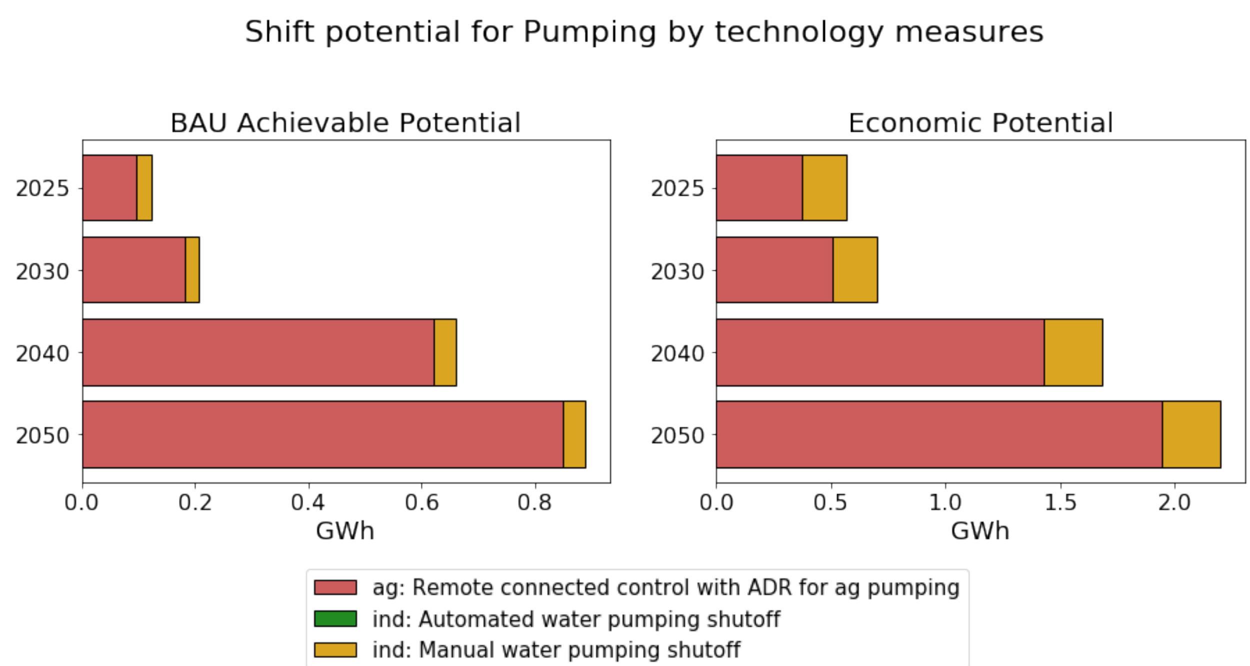

Figure 42. BAU achievable and economic shift DR potential for water pumping loads in each forecast year, disaggregated by the enabling technology selected by DR-Path as maximizing DR at the relevant cost level.

Water conveyance pumping loads

As discussed in Section 3.3.7 the major pumping loads for water conveyance within the state are not within the IOU customer base and therefore fall outside the scope of this study, including the State Water Project (managed by DWR), the Central Valley Project (managed by the federal Bureau of Reclamation), and the Metropolitan Water District of Southern California. Despite being outside the scope of this analysis, it is interesting to consider qualitatively the DR potential that these loads may be able to provide. To better understand this, we conducted interviews with experts at DWR and various water consultancies.

These large water delivery entities manage significant hydroelectric generation facilities in addition to their water conveyance operations. As a result, generation and pumping operations are directly exposed directly to the CAISO wholesale market, and pumping loads are likely to be scheduled to minimize electricity costs, with pumping reduced during high price periods, and maximized during low price periods, to the extent possible within operational constraints. As a result, these loads are unlikely to be significant sources of new dispatchable DR potential, since most of their available DR potential has already been captured as shape DR via response to the CAISO wholesale price.

The amount of pumping flexibility available for load shaping depends on the particular operational constraints of the system, which can be weather dependent. During normal or wet water years, water delivery requirements may restrict the amount of flexibility that is available, since water must be continuously delivered. In that case, it may be necessary to maintain pumping operations even during peak periods. During dry years, when water deliveries are reduced, more significant pumping flexibility may be possible, with the maximum amount of flexibility ultimately being limited by the need to maintain safe and adequate water levels within the canals and aqueducts making up the system.

Space conditioning

Figure 43 shows the BAU achievable and economic shed DR potential for space conditioning which include heating, cooling and ventilation (other HVAC) broken down by enabling technology, and Figure 44 shows the same for shift DR potential. There is consistent decline in the shed resource potential throughout the forecast period due to the evolving seasonality of the system peak. By contrast, the shift potential shows steady growth throughout the forecast period. The most prominent technologies which contribute to both shed and shift DR include PCTs (both residential and commercial) and commercial EMSs for HVAC in the commercial sector. It is interesting to note that residential smart thermostats remain important even as space cooling diminishes in importance, because they can also control space heating, which grows in importance in our forecasts. Commercial EMSs stay relevant by controlling both heating and air handling (“Other HVAC”) loads. DLC retains some significance in the commercial sector but is generally outweighed by PCTs and EMSs. Thermal storage is a potentially useful technology in shifting space cooling load, but it is too costly to enter the economic potential in a significant way here. It is evident from both figures, that while PCTs in residential buildings are an effective and significant DR enabling technology, the limited consumer enrollment in programs under BAU assumptions is a barrier to capturing its full potential.

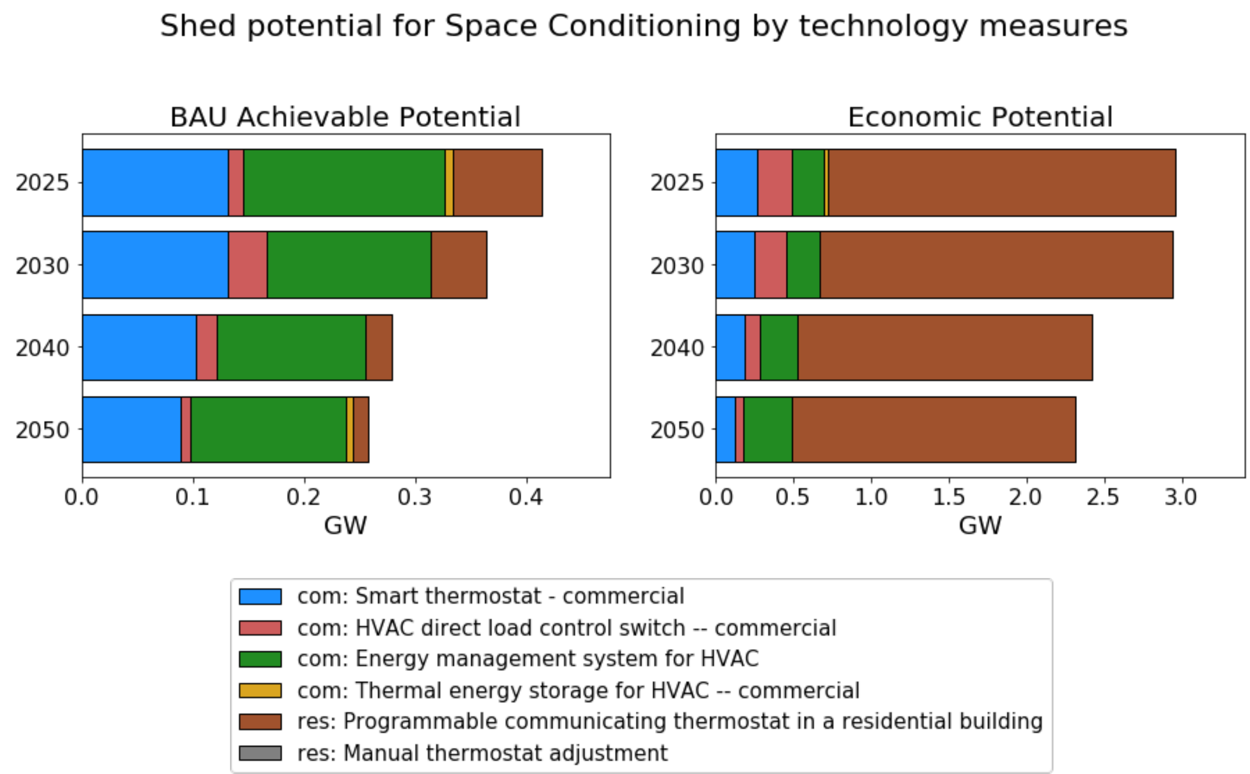

Figure 43. BAU achievable and economic shed DR potential commercial and residential space conditioning (heating and cooling) loads in each forecast year, disaggregated by the enabling technology selected by DR-Path as maximizing DR at the relevant cost level.

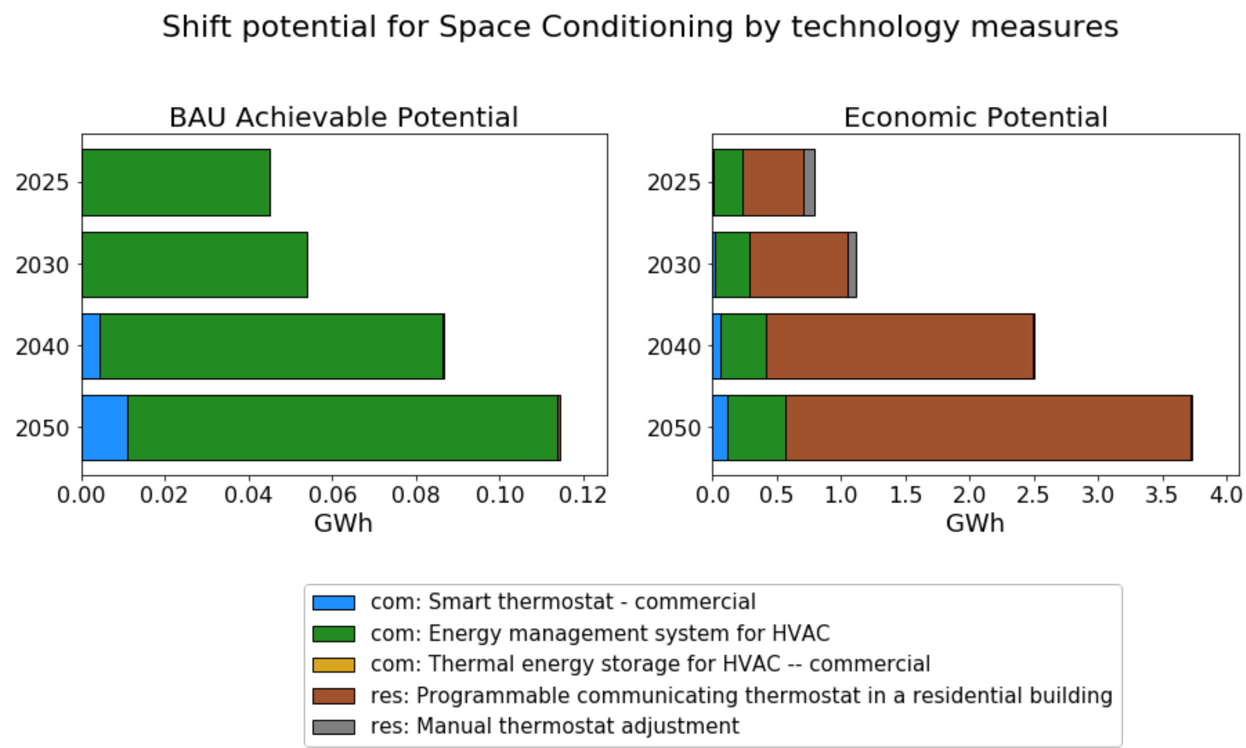

Figure 44. BAU achievable and economic shift DR potential commercial and residential space conditioning (heating and cooling) loads in each forecast year, disaggregated by the enabling technology selected by DR-Path as maximizing DR at the relevant cost level.

Commercial refrigeration

Commercial refrigeration was a consistently significant and efficacious source of DR potential both for shed and shift. Readers interested in the specific breakdown of the commercial refrigeration DR resources by DR enabling technology type can find this information in Appendix D. TES for commercial refrigeration is by far the largest technology measure which contributes to the shed and shift resource potential, suggesting that the investment and development of this technology measure will be important. Refrigerated warehouses connected with ADR control also contribute, but the resource they enable is significantly smaller.

Industrial process loads

Industrial process loads also provided a consistent source of DR potential for both shed and shift in each forecast year. In all years, the measure that enables nearly the entire resource is a manual "deep-cut" process shutdown, which represents a total shutdown or rescheduling of operations during DR events. Less extreme measures, such as auto-DR technologies or partial shutdowns also have the ability to provide DR potential, but the deep-cut measure is selected by the model since it maximizes the size of the DR resource.

As discussed in section 3.3.5 and Appendix A, in Phase 4 we disaggregated industrial process loads into several more granular end uses, including process cooling, process heating, electrochemical processes, machine-drive processes, and other processes. Readers interested in the breakdown of the industrial process DR resources into these end uses can find details in

Appendix D. However, we caution that the Phase 4 study did not include any efforts to model future changes in the size of these end uses, owing to a paucity of relevant forecasting studies on this topic. In reality, decarbonization of the industrial sector would be expected to yield significant increases in both process heating loads (for low-temperature process heating) and in electrochemical process loads for hydrogen production (to support high-temperature process heating). As we have seen in the case of space and water heating and EV charging, electrification of present fossil-fuel end uses can have dramatic impacts on the need for and the availability of DR. Understanding potential pathways to industrial electrification, and their potential impacts on the DR landscape, will be a critical area for future research.

Electronics

Residential and commercial electronics are a consistently important source of shed DR potential throughout the forecast period. Residential TVs and PCs, and residential and commercial office equipment, can provide economic shed capability when coupled with smart plugs or power strips but do not have any shift capability. IT equipment in commercial datacenters provides a small amount of both shed and shift DR when strategies are applied to reschedule batch data processing operations. Readers interested in the specific breakdown of the residential and commercial electronics DR resources by end use categories can find this information in Appendix D.

Lighting

Residential and commercial lighting have a small but consistent economic shed resource potential throughout the forecast period, but lighting cannot provide shift resources, since it must be provided at the time of use. Manual control (i.e., switching off lights) is the only cost-effective residential DR technology measure, with connected light bulbs being too costly throughout the forecast period. Shed in commercial lighting is primarily accomplished by networked lighting controls. Readers interested in the specific breakdown of the residential and commercial lighting DR resources by end use categories can find this information in Appendix D.

Pool and spa

Residential pool and spa is a consistently important source of both shed and shift DR economic resource potential. The most important technologies for the shed resource potential are a DLC switch for the pool pump and a smart plug for the spa heater, though connected pool pumps grow in importance throughout the forecast period as their price declines. A connected pool pump is the only technology capable of shifting load. Readers interested in the specific breakdown of the residential pool and spa DR resources by DR enabling technology type can find this information in Appendix D.

4.5.3. The geographic distribution of DR potential

In this study, CEC Title 24 climate zones were mapped to three aggregate climate regions (hot-dry, marine, and cold) for consistency with the approach taken in the EE Potential and Goals Study (Sathe et al. 2021) (See Appendix A for details of the mapping). Figure 45 presents the economic shed potential by climate region for each forecast year. This figure allows us to see the evolution in the economic shed potential for different end uses in more detail, as well as the variation in the resources across the climate zones. The stacked bars show the breakdown of the resource by end-use category. The 'All Climate' category captures clusters where there are not enough customers to meet the minimum customer count criteria laid out in Section 3.3.4 (which are primarily large industrial customers), as well as MHDEV, whose load forecasting we conducted without reference to climate. Charging of LDEVs drives much of the growth in the overall resource across all climate regions, but particularly in the marine climate region, which contains many of the state's large population centers. Commercial and residential space heating and water heating have a significant contribution in the cold climate region as expected. In comparison, in the hot and dry climate there is higher resource potential from commercial and residential space cooling and refrigeration, as well as agricultural pumping.

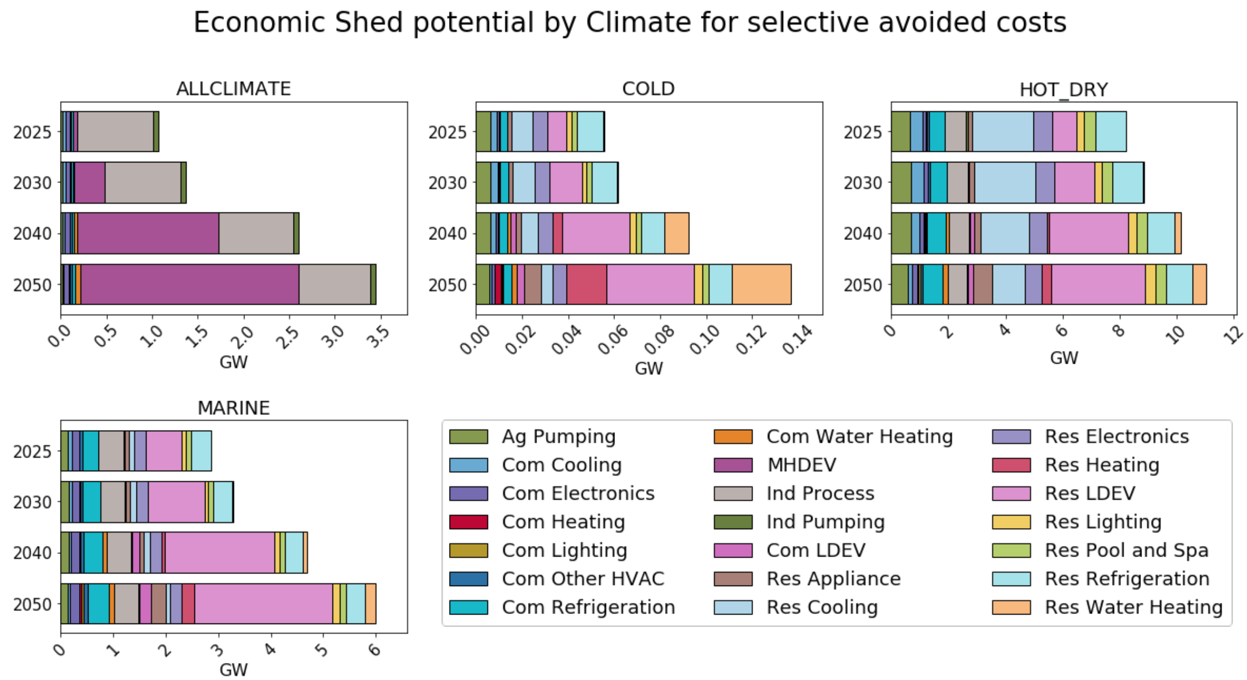

Figure 45. Stacked bar plots of economic shed potential for all end uses for each climate zone in CA by economic potential (x-axis) and year (y-axis).

Figure 46 presents the economic shift potential by climate region in each forecast year. Similar to the plot for the economic shed potential, the stacked bars show the breakdown of the resource by end-use category. We see similar variation in dominant end uses by climate zone as we saw for shed, with outsized LDEV charging resources in the marine-climate population centers, significant space cooling and refrigeration resources in the hot-dry climate region, and large space and water heating resources in cold climates.

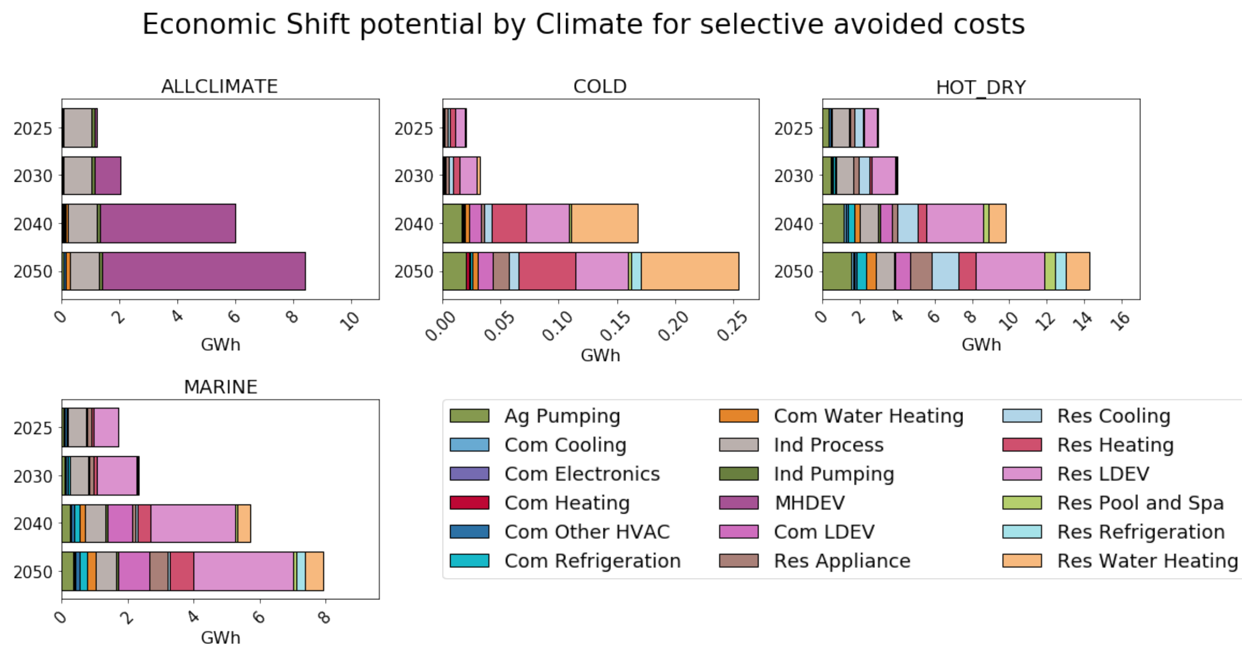

Figure 46. Stacked bar plots of DR shift potential for all end uses for each climate zone in CA by economic potential (x-axis) and year (y-axis).

Figure 47 shows the economic shed potential resource in each CAISO LCA, broken down by sector, and Figure 48 shows the economic shift potential. Every panel depicts a particular year in the forecast period. The total potential in each LCA depends strongly on the population. LA county has the highest shed and shift potential throughout the forecast period and is closely followed by the Bay area, with SDG&E service territory in third place. It is interesting to consider the varying breakdown by sector in different LCAs, with a significantly higher proportion of commercial-sector potential in the largest, most urbanized LCAs, compared to others with a higher proportion of residential-sector potential. There is a disproportionate contribution from agricultural loads in the unspecified-LCA category, which is reasonable given that this category is made up of outlying regions not in any LCA.

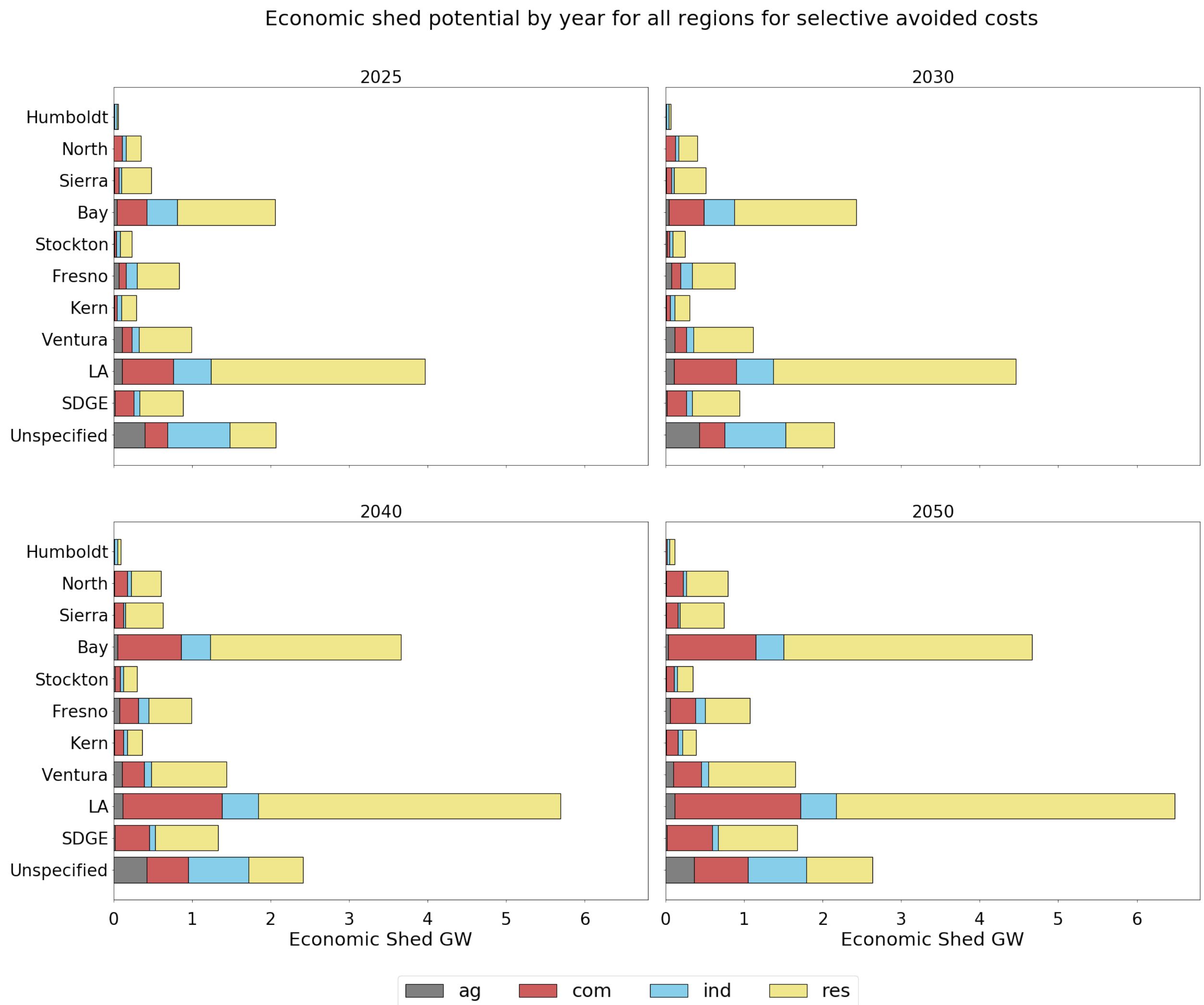

Figure 47. Stacked bar plots of economic shed potential for all sectors for all LCAs in CA by potential (x-axis) and year (y-axis).

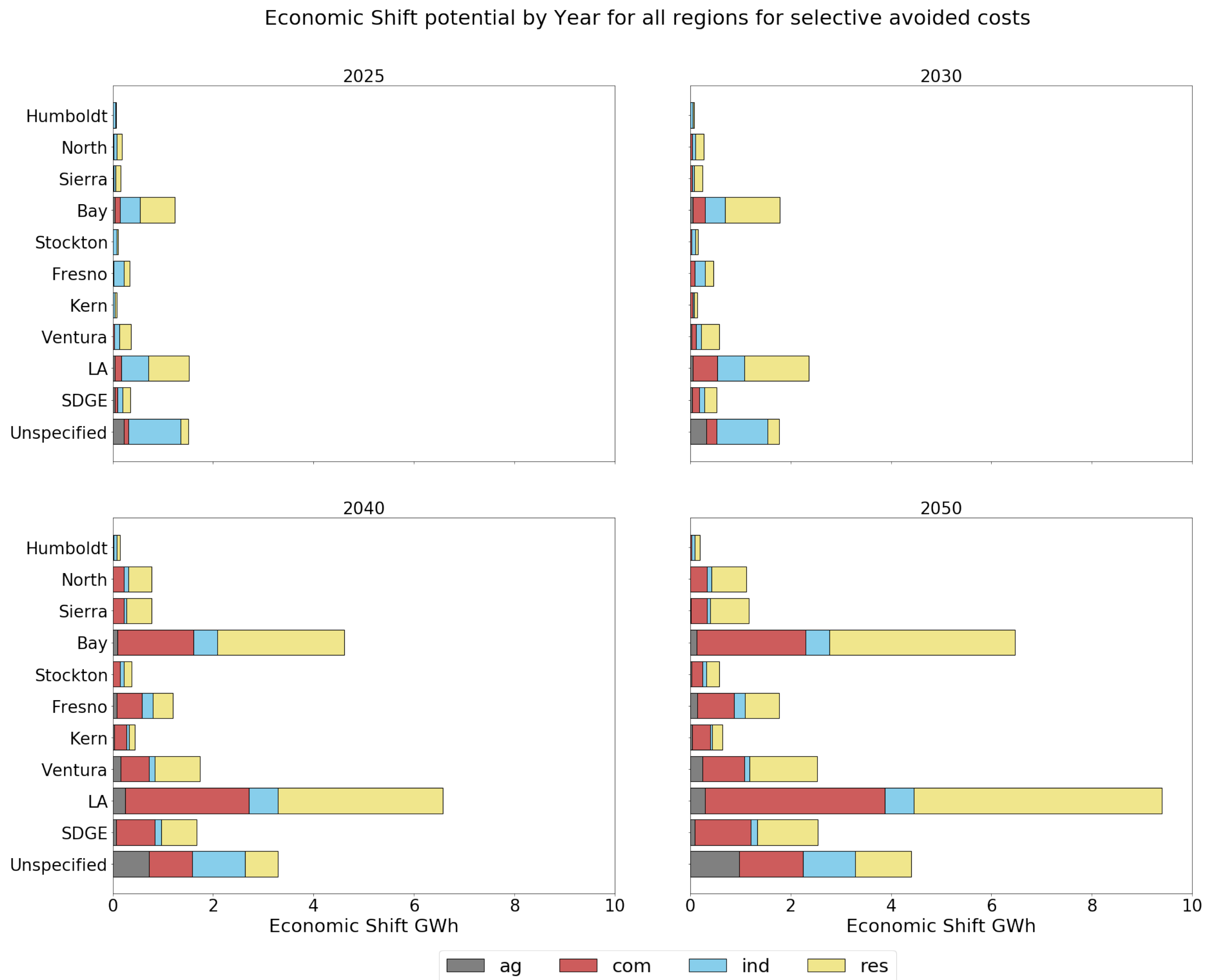

Figure 48. Stacked bar plots of economic shift potential for all sectors for all LCAs in CA by potential (x-axis) and year (y-axis).

4.5.4. The distribution of DR potential by customer type

To help illuminate which customers have the most potential to provide DR resources, in this section, we present the estimated DR potential across different types of customers. First, we examine the DR potential breakdown by building type or site utilization type. We then consider the relative efficacy of the prototypical load shape clusters we developed for this study (see Section 3.3.4) as sources of DR, to understand the degree to which customers' energy consumption patterns might affect their DR capabilities.

DR Potential by building type

Figure 49 presents the economic shed potential in each sector, broken down by building type, for each forecast year. This figure allows us to see the evolution in the economic shed potential for different building types in detail, and the variation in the resources across sectors. The total economic shed potential growth varies by sector; it increases annually for commercial and residential sectors and decreases annually for the industrial sector. Charging of MHDEVs drives much of the growth in the overall resource across the commercial sector followed by resource growth in office buildings, with dining and retail buildings remaining fairly stable, reflecting the stable contribution of refrigeration load. In the residential sector, there is consistent growth across both single-family and multi-family dwellings.[66] Industrial sector resources remain fairly stable by site type throughout the forecast period, with a slight reduction in the size of the resource stemming from a slight projected decline in industrial load in the state. Agricultural resources also remain fairly stable, with a slight decline in 2050 focused on crop-growing sites as the seasonality of the system load peak moves into the winter season, while irrigation preferentially occurs in the summer. The ‘agricultural other’ also has a significant and fairly stable potential. This building category includes forestry and logging, agriculture, fishing and hunting and uncategorized support activities for agriculture and forestry.

[66] There was insufficient data in PG&E service territory to distinguish between single-family and multi-family, so these customers are categorized as “residential unknown.”

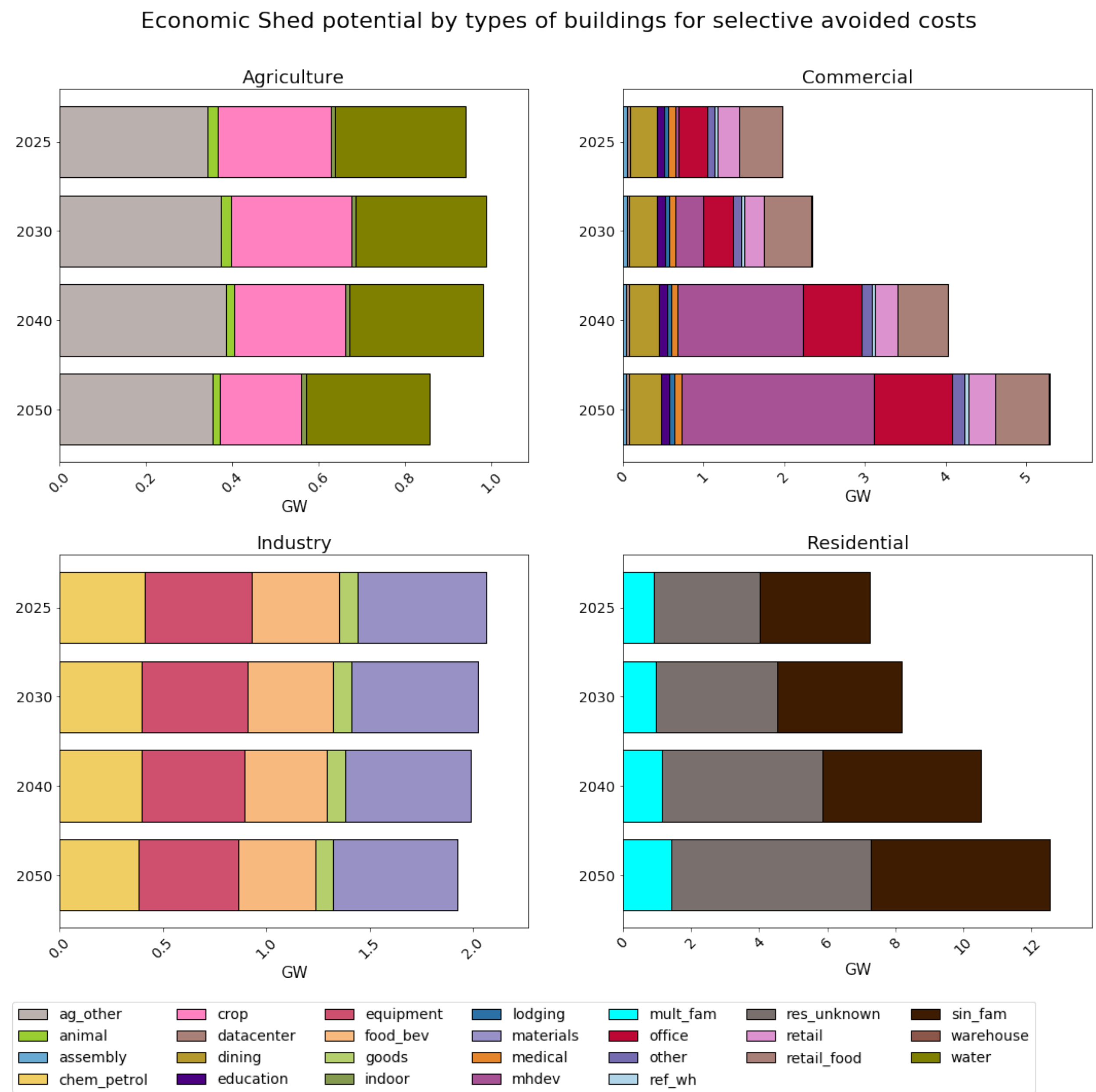

Figure 49. Stacked bar plots of economic shed potential by building types for all sectors and years in CA by economic potential (x-axis) and year (y-axis). The "res_unknown" building type represents residential buildings that could not be categorized as single-family or multi-family owing to a lack of relevant data in the PG&E service territory.

Figure 50 presents the economic shift potential, by sector and building type, in each forecast year. Similar trends by sector and building type can be seen as what we observed for shed DR, with the exception of the agricultural sector, which sees steady growth in potential, stemming from the decreasing cost of remote pumping controls, coupled with the relatively stable seasonality of shift need.

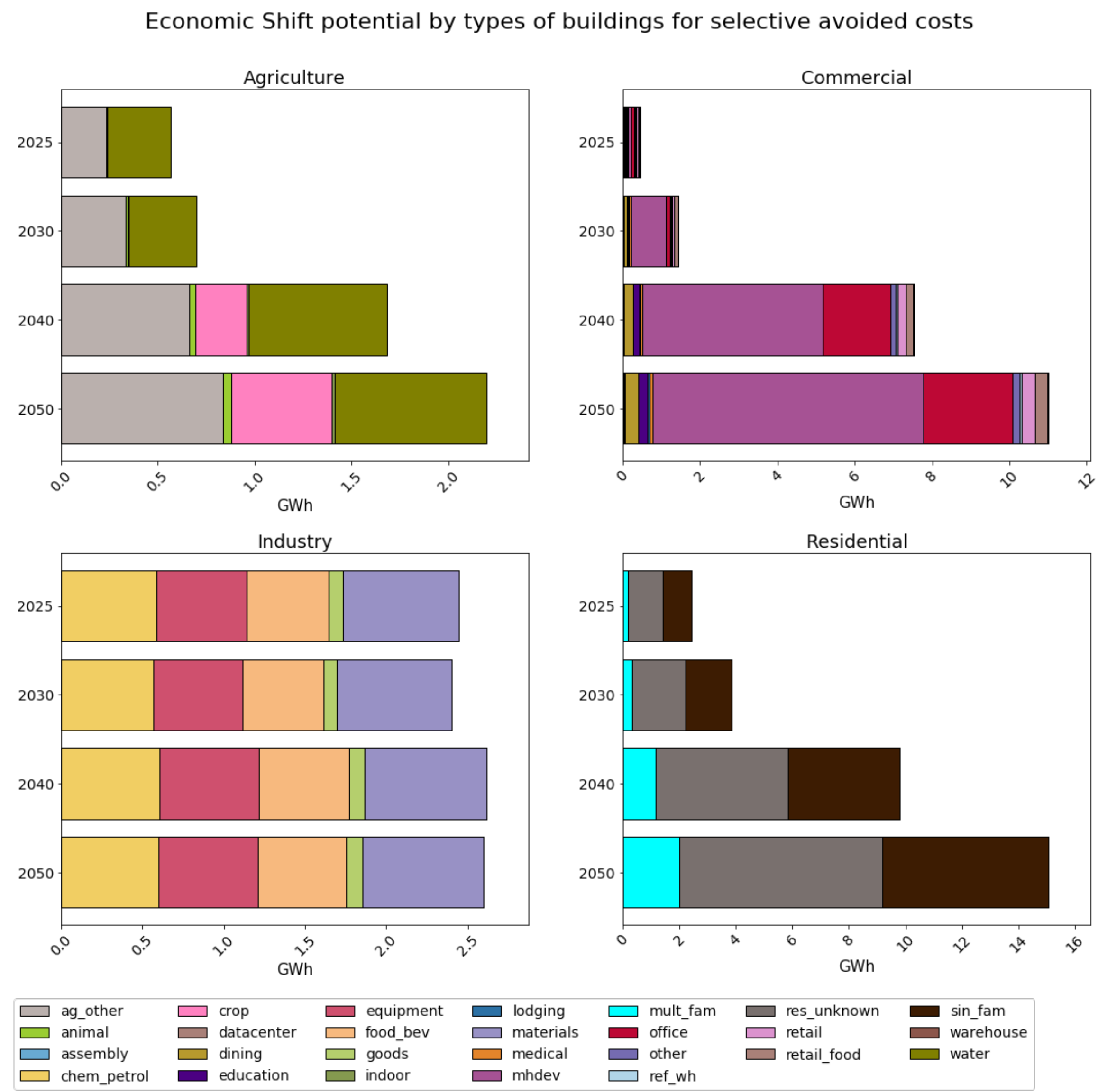

Figure 50. Stacked bar plots of economic shift potential by building types for all sectors and years in CA by economic potential (x-axis) and year (y-axis).

DR Potential by customer load shape

Now we consider the relative efficacy of the prototypical load shape clusters developed in Section 3.3.4 as DR resources in 2025. As a reminder, these load shape clusters were calculated only for commercial and residential buildings, so industrial and agricultural loads are not included here. Further, results are only presented for the 2025 forecast year because widespread electrification would be expected to modify customer load shapes significantly in later years, such that customers' present load shapes will be increasingly less predictive of future DR potential.

Figure 51 shows the relative efficacy of the various load shape clusters as shed DR resources in 2025. Here we have summed up the peak load impacts and economic shed resources from all of the granular customer clusters that include a distinct load shape cluster. The layout and meaning of the diagram are similar to the end-use plots shown in Section 4.5.1, with the horizontal and vertical axes representing the fraction of the peak load and shed resource that each load shape represents, respectively. The colored symbols represent the individual load shape clusters, with the size of each symbol indicating the total consumption by customers in each cluster. The symbols in the commercial sector appear relatively small because only a small fraction of commercial clusters contained sufficiently many customers to be subdivided into distinct load shape clusters. A large fraction of the commercial load is therefore not included here, but these diagrams show the impact of load shape on DR efficacy where it was possible to distinguish the load shape cluster.

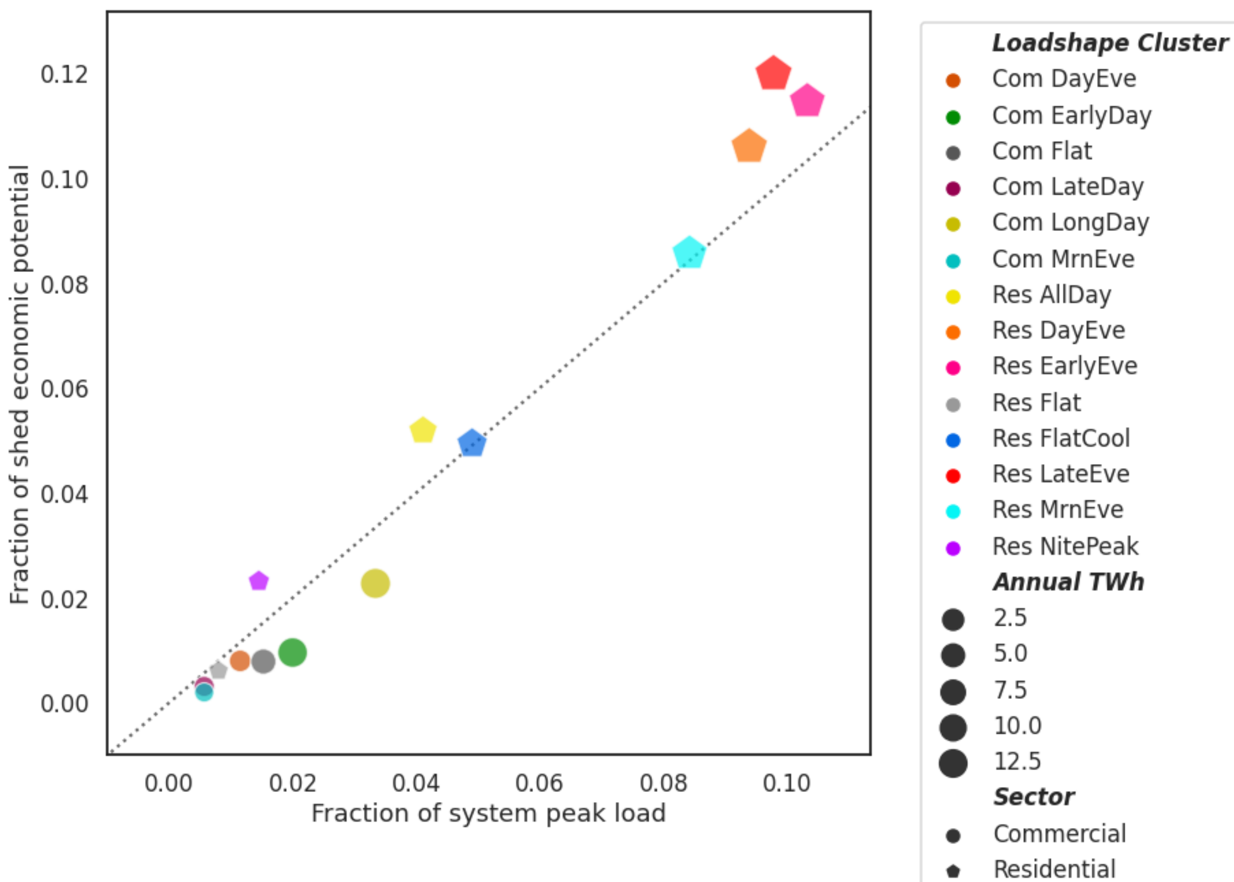

Figure 51. Scatter plots illustrating the relative efficacy of different customer load shape clusters as shed DR resources, in 2025. Colored shapes indicate different load shape clusters, by sector. The horizontal and vertical position of each shape, respectively, denote the fraction of the system peak demand and the fraction of the economic shed potential for which each cluster is responsible. Size denotes the total annual energy consumption from each cluster. In each panel, a dotted line indicates a 1:1 relation.

We can see in Figure 51 that residential customers tend to be generally more efficacious than commercial customers in terms of the economic shed DR potential they can provide, since the higher occupancy of residential buildings during the evening peak means that more flexible load is in use at that time, while the less-occupied commercial buildings are operating closer to their base consumption level. Beyond this sectoral trend, we can see that certain load shapes have larger or smaller shed DR efficacy. For instance, the residential LateEve and NitePeak load shapes have particularly high efficacy, reflecting the fact that they exhibit relatively high EV ownership and therefore significant flexible LDEV charging load. By contrast, the commercial EarlyDay and LongDay load shapes have relatively low efficacy, indicating that their hours of operation are not well aligned with the timing of shed DR need. By and large, however, the impact of load shape on shed efficacy is relatively weak, with most clusters providing shed resources that are roughly proportional to their peak-load contribution. This suggests that most customers can provide significant shed resources regardless of the details of their load shape.

Figure 52 shows the relative efficacy of the load shape clusters as shift resources in 2025. Most of the commercial and residential load shapes have relatively low efficacy in this case, contributing proportionally more load around steep ramps than they are able to contribute to the shift DR resource. This likely reflects the very high efficacy of industrial process loads (as seen in Section 4.5.1), which are not shown here, and which will suppress the relative efficacy of other resources. The variability across load shape clusters is also more significant here in the case of shift than what we saw previously for shed. Most notably, the residential NitePeak and LateEve load shapes are the most efficacious for shift DR, reflecting their relatively high EV ownership. By contrast, load shapes with early evening peaks (EarlyEve, MrnEve, DayEve) are less efficacious for shift, since they have limited load available to shift out of the later evening period.

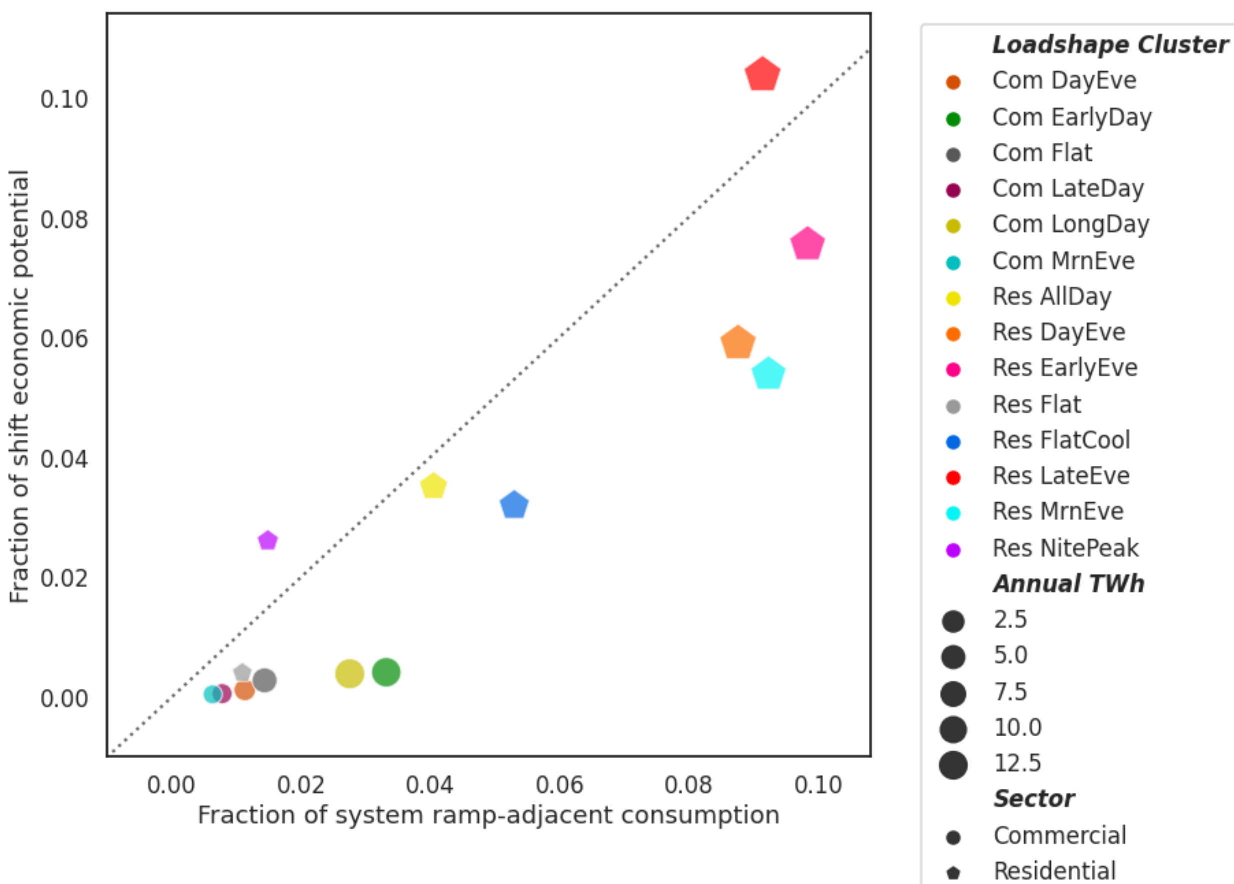

Figure 52. Scatter plots illustrating the relative efficacy of different customer load shape clusters as shift DR resources, in 2025. Data points are displayed as in Figure 51. The horizontal and vertical position of

each shape, respectively, denote the fraction of the system energy consumption occurring on the high side of a ramp and the fraction of the economic shift potential for which each cluster is responsible.

4.6. Shape DR potential from dynamic pricing approaches

4.6.1. Overview

In this section, we present the effective shed and shift resources that could be enabled via dynamic electricity pricing under a tariff that reflects the value stack tabulated in the ACC. As described earlier, customer response to dynamic pricing is most naturally categorized as a form of shape DR; hence we refer to the resulting effective shed and shift DR resources as "shape-as-shed" and "shape-as-shift" potential. The methodology for computing these potentials is summarized in Section 3.5.10 and detailed in Appendix B.

It is important to keep several caveats in mind in interpreting these results. First, since we lack information on customer enrollment rates for dynamic tariffs, we compute dynamic pricing potential under an assumption that 100% of customers are enrolled on such tariffs. Therefore, the best point of comparison to these results is the technical potential supply curves presented in Sections 4.3.1 and 4.4.1. Lower fractions of customer enrollment would scale down our estimated potentials accordingly. Second, in computing dynamic pricing results, we consider customer response via a generalized price elasticity of demand that would yield manual response in the absence of enabling technology, with a larger response if such technology is installed. Therefore, our results here include a zero-cost manual response, unlike the shed and shift supply curves, which require enabling measures to be in place (though some of these measures may be manually activated). Third, our estimates here are based on a particular dynamic tariff design, in which marginal avoided system costs are passed through to the customer as a price signal. Different dynamic tariff structures are possible, and these would be expected to yield different results. Finally, as noted in Section 4.2, the ACC calculations in 2040 and 2050 do not reflect expected evolution in the generation stack and thus are subject to a high degree of potential inaccuracy. Because of this, we do not attempt to compute dynamic pricing results in these years.

4.6.2. Shape-as-shed Potential

Figure 53 shows the shape-as-shed potential as a result of including all customers under a dynamic tariff for the years 2025 and 2030 at different levels of technology cost, under the low-elasticity scenario described in Section 3.5.10. Some of the noteworthy observations are listed below. For the results of the high elasticity scenario, refer to Appendix D.

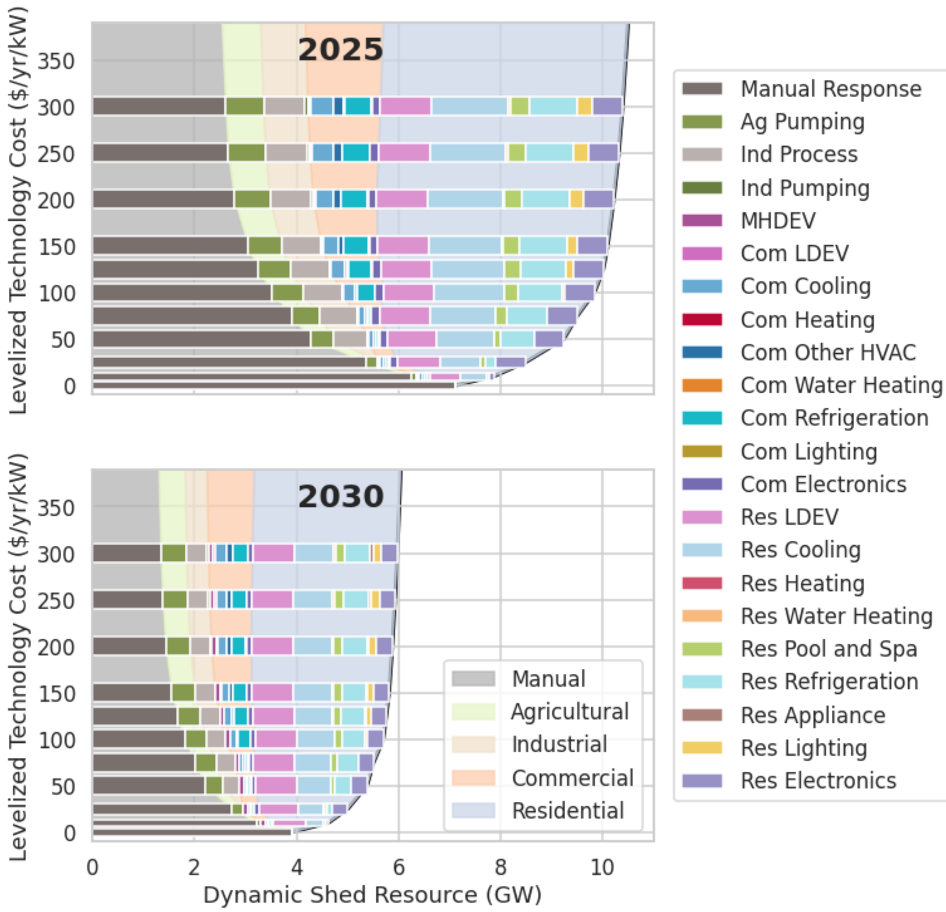

Figure 53. Shape-as-shed potential for the years 2025 and 2030 in the low elasticity scenario.

- The shape-as-shed potential in 2030 is much smaller than 2025. As described in Section 3.5.10, we use an elasticity-based approach to compute these values, and our assumption of typical electricity price during a shed event is equal to the marginal cost of shed as shown in Table 6. Note that the avoided cost of shed in 2030 is much lower than 2025, hence we would expect a much lesser customer response.
- We can capture a large fraction of the cost-conditional technical potential through dynamic pricing: In 2025, it roughly amounts to 75% of the cost-conditional technical potential as shown in Figure 22, and in 2030, despite the lower avoided costs, it is 40%.
- As we move up the supply curve, automation technologies replace manual response partially. However, manual response remains a significant component at all cost levels. At $0/kW/yr, we can see that it can provide about 7GW of potential in 2025 and nearly 4GW in 2030. At $350/kW/yr, we see that manual responses account for over 2GW of impact in 2025 and a little under 2GW in 2030.
- At costs above $0/kW/yr, we can see that the residential sector is the largest contributor to the shape-as-shed potential with the largest contributing end-uses being LDEV, space cooling and refrigeration. It is important to note that these are available as fairly low-cost resources. At similar low costs, we also see a small amount of residential electronics' potential to shed. The key enabling technologies for these end-uses are mentioned in

Section 4.5.2. We also see that at slightly higher cost levels, residential lighting, pool and spa start to offer small but consistent impacts.

- Other relatively consistent contribution to the shape-as-shed potential come from agricultural pumping, industrial processes, and commercial cooling and refrigeration

4.6.3. Shape-as-shift Potential

Figure 54 shows the shape-as-shift potential as a result of including all customers under a dynamic tariff for the years 2025 and 2030 at different levels of technology cost, in the high price-ratio scenario described in Section 3.5.10. Some of the noteworthy observations are listed below. For the results of the low price ratio scenario, refer to Appendix D.

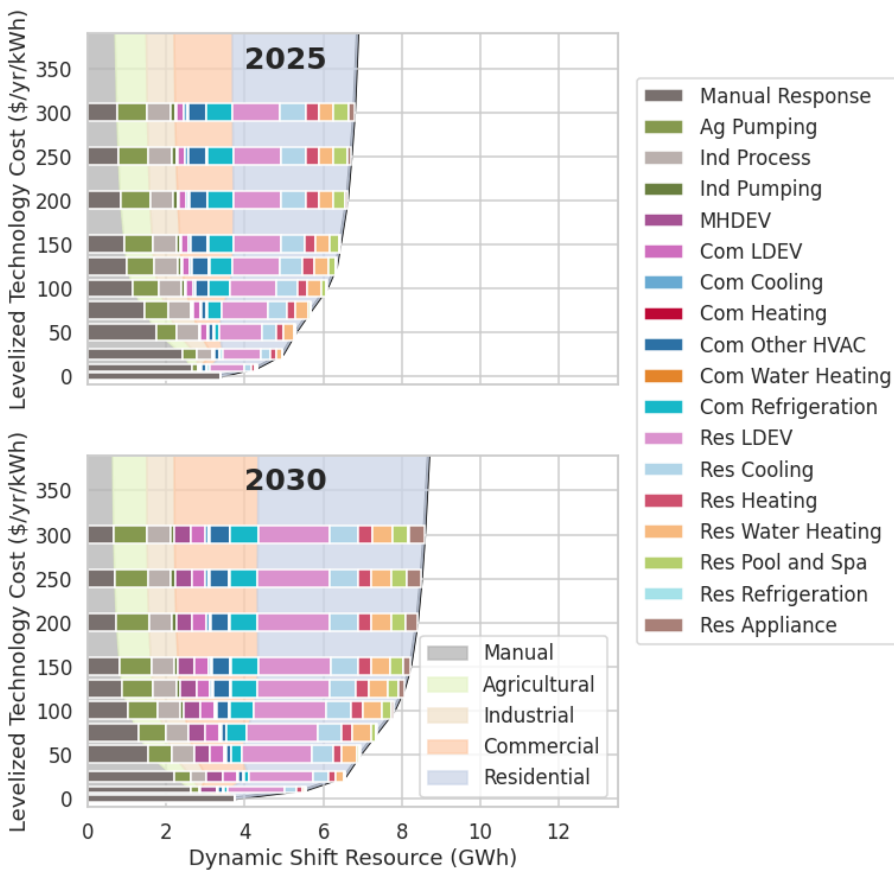

Figure 54. Shape-as-shift potential for the years 2025 and 2030 in the high price ratio scenario.

- The overall impact of dynamic pricing on shift DR potential in the high price ratio scenario at the highest cost levels shown is a little over 6GWh in 2025 and 8GWh in 2030. We see significant impact from manual response, providing some 3-4 GWh of effective shift at zero technology cost.
- The dynamic pricing approach can unlock a significant fraction of the technical potential for shift: in 2025, the dynamic pricing potential represents roughly 40% of the cost-conditional technical shift potential we saw in Section 4.4.1, and about 50% in 2030.

- We find that manual response is slightly smaller as a fraction of the maximum available potential in the case of shape-as-shift compared to shape-as-shed. This makes sense because automation is more helpful in load shifting since it requires repeated action.
- The residential sector again provides the largest shape-as-shift potential, although it is somewhat less dominant than we saw for shape-as-shed. Some of the end uses that show up specifically as low-cost shape-as-shift resources are LDEV charging (and MHDEV charging in 2030), residential space cooling, space heating, and water heating, commercial refrigeration, agricultural pumping, and industrial process loads.
- EV charging in particular can provide a particularly large automated response at low cost.

5. Discussion and Recommendations

Our results indicate drastic changes on the horizon for DR in California as the state transitions to a fully decarbonized energy system over the coming decades. Rapid growth in VRE generation and electrified loads will beget equally rapid evolution both in the need for DR and in the nature of the resource. As we saw in Section 4.1, the critical system peaks will transition from being concentrated in the summer season today to falling in both the summer and the winter by 2050. This migration will gradually erode the shed DR potential of space cooling loads, which have traditionally been a major source of shed. At the same time, substantial new sources of DR will become available from the new electrified loads, such as space and water heating, clothes drying, and especially LDEV and MHDEV charging.

The result is a dramatic increase in the potential for both shed and shift DR in California from 2025 through 2050. Over this period, the economic potential for shed DR nearly doubles, growing from 12 GW to 21 GW, while the economic shift DR potential undergoes a fivefold increase, growing from 5.9 GWh to 30 GWh in our primary estimate. Further, as discussed in Section 4.4, our primary estimate rests on avoided costs from the ACC, which does not explicitly place a value on flexible generation capacity, and so may underestimate the value of shift. Our estimate of the upper limit on economic shift potential, based on comparing to BTM battery costs, is 12 GWh in 2025, growing to 33 GWh by 2050. Improved valuation of shift DR in the context of other statewide modeling efforts (e.g., the ACC and IRP) will be an important component of unlocking its potential. Nevertheless, the potential impacts of these DR resources are considerable. In 2025, our primary estimates of shed and shift economic potential would avoid 220 and 310 ktCO2 of GHG emissions, respectively, each corresponding to eliminating a small natural gas generation unit for a full year. Avoided system costs for the economic shed and shift resources in 2025 amount to $1.8B and $88M, respectively (though we reiterate that the shift value may be an underestimate).

Importantly, however, these values represent *economic* DR potential--that is, the technical potential that can be enabled cost-effectively in principle. When estimating the potential that could be captured through programs based on historical enrollment rates--the *BAU achievable* potential--we find significantly smaller potential resources, with more than a fivefold gap between the economic and the BAU achievable resources for both shed and shift DR. It is evident that significant barriers exist at present to realizing the full potential of DR in California.

In the following section, we discuss the specific end uses and technologies that can serve as DR resources over the coming decades, and we identify particularly ripe opportunities to support or improve the enablement of future DR resources. We then consider specific barriers that exist to achieving DR potential at present, and we discuss approaches to overcoming them. Finally, we describe important future areas for DR research and development.

5.1. Key pathways for the future of California DR

The DR-Path model used in this study calculates a large number of future pathways to enabling DR, by coupling DR-enabling technologies with individual cluster end uses, and it selects the affordable pathways that maximize the DR resource to build a DR supply curve. In this process, certain pathways naturally come to the fore as being particularly important and impactful. Here we summarize the most important end uses and enabling technologies for the future of California DR.

5.1.1. Notable demand-responsive end use categories

Section 4.5 presents detailed breakdowns of the shed and shift potential available from various end-use categories over our forecast period from 2025 to 2050 and considers their relative efficacy as DR resources. We saw that certain end uses remained stable sources of DR throughout the period, while others underwent dramatic growth or notable decline. Still others appeared to underperform relative to their contribution to system load. We can summarize these findings by assigning the end uses to descriptive categories based on the roles that they may play in the California DR ecosystem over the coming decades: steady workhorses, rising stars, emerging performers, declining performers, and development opportunities.

Steady workhorses

Certain end use categories provide significant potential DR resources that are relatively stable throughout the forecast period. Given the evolving seasonality of DR need, especially for shed DR, capturing and maintaining these resources will be particularly valuable. These *steady workhorse*s of future DR potential include:

- **Industrial process loads.** Due to their consistent presence throughout the year, these loads can provide significant shed and shift potential even as the seasonality of DR needs evolves.
- **Agricultural pumping loads.** Although these loads have some seasonal variability, they are able to provide significant shed and shift resources throughout the forecast period, supported by emerging technologies for automated remote pumping control.
- **Commercial refrigeration.** Though they have not historically been a major target of DR programs, the year-round presence of these loads, coupled with their large size, make them an important source of future potential, especially when coupled with TES.
- **Residential space cooling (for shift DR).** Although the greatest need for shift occurs outside of the summer months, there is sufficient evening cooling load in the residential sector during shoulder seasons to provide a steady source of shift throughout the forecast period.

- **Residential refrigeration (for shed DR).** The consistent presence of refrigeration loads throughout the year makes this end use a steady and significant source of shed potential when coupled with connected outlets that can shut down refrigerators for a short period during shed events.
- **Residential and commercial electronics (for shed DR).** Coupling these loads (which include televisions, computers, and office equipment) with connected outlets or power strips can provide significant shed potential throughout the forecast period.
- **Residential lighting (for shed DR).** The coincidence of this end use with evening (and morning) net load peaks throughout the year makes it a steady source of shed potential, either when enabled by onboard communications (i.e., smart light bulbs) or through more mundane manual response.
- **Residential pool and spa loads.** These loads are also consistently present throughout the year, which allows them to remain significant sources of DR potential even as the timing of DR needs evolves, when coupled with connected pool pump technology or connected outlets controlling spa heaters.
- **Commercial air handling and ventilation.** These non-heating-and-cooling "other HVAC" loads represent a consistent, if modest, source of shed and shift DR throughout the forecast period when controlled by an EMS.

Rising stars

Possibly the most prominent change we see in the DR landscape through 2050 is the emergence of new electrified end uses that rapidly grow to become the largest and most efficacious available DR resources, sometimes by a wide margin. These *rising stars* of DR potential are:

- **MHDEV charging.** Due to their dramatic growth and their inherent flexibility, by 2050, these loads become the largest source of both shed and shift DR, by a wide margin.
- **Residential LDEV charging.** Already emergent as an important source of DR by 2025, these loads also grow dramatically as a source of both shed and shift through 2050, especially when coupled with enhanced flexibility measures such as V2B discharge or encouraging workplace charging.
- **Residential water heating (for shift DR).** Electric storage-tank water heaters have a natural thermal reservoir that can enable significant load shifting if coupled with appropriate controls and safety features. As water heating electrifies in California, it will become a major source of shift DR, second in importance only to EV charging.

Emerging performers

In addition to the rising stars, certain end uses also see significant growth in potential without coming to dominate the landscape, due to electrification and the growing availability of connected devices. These *emerging performers* are:

- **Commercial LDEV charging.** Although these loads are not as naturally coincident with times of DR need, their inherent flexibility presents a significant opportunity.

- **Residential water heating (for shed DR).** Because it does not coincide particularly strongly with the system peak, this end use's shed potential is less prominent than its shift potential. Nevertheless, it exhibits strong growth as a shed resource as electrification proceeds.
- **Residential space heating.** Widespread residential heating electrification is a driving force behind the migration of system peaks to the winter, which also makes space heating a prime candidate for shed DR. Shoulder-season heating also provides a substantial shift resource.
- **Residential appliances.** Growing penetration of connected appliances enables significant shedding or shifting through short-term load reductions or full rescheduling of cycles for dishwashers, clothes washers, and especially electrified clothes dryers**.**
- **Commercial water heating.** Although the load shape is not strongly coincident with times of system need for DR, widespread electrification of this end use yields significant growth in its DR potential.
- **Commercial space heating.** Although this end use is not particularly coincident with times of system need for DR, electrification makes it a growing, if modest, source of shed and shift DR.

Declining resources

Some historically prominent demand responsive end uses undergo a significant decline in importance as shed DR resources over our forecast period, due to the migration of peak hours from the summer to the winter. The *declining performers* are:

- **Commercial space cooling (for shed DR).** Due to the continuing shift of system peaks out of the midday hours, and the migration of such peaks out of the summer season, this end use is increasingly less able to provide significant shed capacity.
- **Residential space cooling (for shed DR).** Due to the migration of system peaks out of the summer season, this end use is less able to provide useful load shedding capacity as electrification proceeds, despite its strong coincidence with evening system peak times.

Development opportunities

Finally, there are certain end uses that provide limited resources in our study given present-day technologies. However, they are relatively large loads, and may have potential as future resources if appropriate advances are made in enabling technology. This includes certain end uses that were identified as steady or emerging resources above but whose responsiveness could be improved. These *development opportunities* are:

- **Residential lighting.** Although this end use is already identified as a steady workhorse for shed, its efficacy as a shed resource is relatively low, indicating that there may be significant untapped potential that could be unlocked by improved sensing and controls. Given the small size of individual light-bulb loads, on-board battery storage might also enable shift DR for this end-use, which is otherwise not capable of shifting.

- **Commercial lighting.** Indoor commercial lighting has reduced shed potential owing to reduced coincidence as the system peak shifts into the evening. In this study we have assumed that outdoor lighting, which has better peak coincidence, is incapable of providing shed due to safety considerations, but it may be worth considering whether sensors and controls could enable such a resource. As with residential lighting, the small absolute loads associated with individual lighting units may provide an opportunity to enable shift DR, or more significant shed, with on-board battery storage.
- **Commercial and residential electronics.** Although these are already identified as steady workhorses for shed DR, the small absolute loads associated with individual devices may present an opportunity to enable shift DR, or more significant shed, with on-board battery storage.
- **Residential refrigeration (for shift DR).** This end use emerges as a shift resource as connected refrigerators grow in penetration and enable the intelligent scheduling of defrost cycles outside of peak periods (already a feature in some present-day refrigerators). However, this strategy shifts only a small fraction of the available load. Communicating refrigerators with set-point control (which are not currently available on the market) could allow significant load shifting through pre-cooling strategies, especially for freezers, which can have arbitrarily low set-points in principle. On-board phase-change materials for thermal storage (featured in some present-day refrigerators in the developing world for resiliency to power outages) could also significantly increase the shift DR potential from this end use.

5.1.2. Notable DR-enabling technologies

The dramatic growth in DR potential we project in this study is enabled by a number of key technologies that will need to be deployed at scale if the potential is to be achieved. The most important such technologies are:

- **Flexible EV charging infrastructure.** Every strategy we considered for enabling LDEV charging flexibility was selected by DR-Path within the economic shed or shift resources, including fairly costly options such as V2B home gateways or building out additional workplace charging infrastructure to enable more daytime charging. MHDEV charging flexibility was also highly important, though it was assumed to be widespread in all future charging infrastructure. The extremely large size of the EV charging resource means that many pathways to achieving it are worthwhile.
- **Connected water heaters.** Shift DR from residential water heaters could be enabled either by water-heaters with built-in connected controls, or by add-on controls connected to a communications port adhering to the CTA-2045 standard. In either case, an important element of DR enablement is installing a thermostatic mixing valve to allow increasing the storage tank set point while maintaining a safe water supply temperature.
- **Connected outlets and power strips.** Connected outlets, plugs, and power strips proved useful in our modeling for enabling shed DR for a variety of end uses, including residential refrigerators, residential and commercial electronics, spa heaters, and level 1 EV charging. Incorporating these devices more widely into DR programs has the potential to unlock significant shed potential.

- **PCTs.** Despite the declining importance of space cooling as a shed resource over the forecast period, PCTs are expected to remain an important DR-enabling technology because of the stable contribution of space cooling to shift DR potential, as well as the rise of space heating as a potential shed resource.
- **Commercial EMSs.** As with PCTs, commercial EMSs are able to retain their importance despite the decline in space cooling for shed, due to their steady value for shift and the growth of electrified space heating.
- **TES for commercial refrigeration.** Although not in widespread use today, TES technology for commercial refrigeration was consistently selected as an important technology for enabling both shed and shift DR throughout our forecast period, due to the very large and consistent load it is able to address. This technology represents an important untapped area of DR enablement.
- **Automated agricultural pumping controls.** Automated communicating pumping controls for agriculture are a young but growing technology in California, which also have the potential to yield important non-energy benefits for farmers by automating operations. These controls provided a consistent low-cost pathway to both shed and shift DR throughout our forecast period.
- **Connected home appliances.** Connected home appliances, including refrigerators, dishwashers, clothes washers, and especially electric clothes dryers hold significant promise for enabling both shed and shift DR. They are relatively costly, but their market penetration is expected to grow due to the other customer benefits they provide, providing a low-cost pathway to DR enablement late in the forecast period.

5.1.3. Recommendations for facilitating future DR in California

There is clearly a wide range of technological pathways to enabling DR on California's future grid. Given the growing importance of demand-side flexibility, it will be important to follow many of them in parallel. To ensure that as many pathways as possible remain viable as decarbonization proceeds, there are certain directions and outcomes that will require policy support over the coming decades.

First, it is essential to ensure that electrification is coupled with flexibility: new EV charging, water heating, and space heating devices should incorporate connected communications technology to the greatest extent possible, or a significant opportunity to enable demand flexibility (and reduce the cost of decarbonization) will be missed. When it comes to EV charging infrastructure in particular, it appears that money is almost no object: even the costliest DR-enabling technologies we consider here appear to be cost-effective pathways to DR enablement, given the extreme size of the resource. Flexibility in EV charging, including two-way charging and increased access to public and workplace charging, should be aggressively pursued in tandem with the buildout of charging infrastructure in the state.

Regulatory requirements for connectivity in residential appliances (especially newly electrified loads such as heat pumps, water heaters, and clothes dryers) will also help to drive down the cost of enabling DR, thereby increasing the economic DR potential. Such requirements are already under development pursuant to the CEC's authority under SB 49 to set appliance load flexibility standards. To be effective in enabling DR, however, such regulatory efforts must specifically include requirements that the devices be *controllable* through an internet or other connection; merely being able to connect to the internet is not sufficient to enable load flexibility. The ENERGY STAR connected criteria (EPA 2021), which we used to inform the technology assumptions in this study (see Appendix C) are a useful example of existing load flexibility specifications for connected devices.

Appliance connectivity standards would only apply to new appliances, however, and the resulting connected devices would enter the building stock only slowly. In the near term, add-on controls will have significant value, in the form of either smart outlets and power strips or add-on controls adhering to the CTA-2045 standard where such communication ports are available. Policies to encourage the use of such devices for flexibility may be worthwhile for the immediate future.

In addition to connected appliances, two other emerging technologies showed significant near-term promise, namely, remote automated controls for agricultural pumping and TES systems for commercial refrigeration. Agricultural pumping has been recognized for some time as an inherently flexible resource with strong DR potential, but enabling reliable response has been a challenge. Development and demonstration of automated pumping controls has been the subject of a thorough study (Meyers and Hardy 2021) under the CEC's Energy Program Investment Charge (EPIC) program and is currently being deployed in a pilot dynamic pricing program in Valley Community Energy service territory. The importance of commercial refrigeration TES is somewhat less expected and points to the strong remaining potential for game-changing technological innovation to drive new sources of demand flexibility. Ongoing policy support for research and development programs, such as CEC EPIC, will be a crucial part of securing California's renewable energy future. A prime example today is the newly launched, EPIC-funded CalFlexHub project (M. A. Piette et al. 2022)[67] that aims to develop early-stage demand flexibility technologies and help bring them quickly to market.

Finally, it is important to consider how various DR-enabling end-use technologies measure up to BTM batteries, which are assets used exclusively for the purpose of shifting load in time. All else being equal, BTM batteries should be able to provide DR resources that are less dependent on customer preferences and settings, compared to end-use technologies whose primary purpose is providing end-use services (e.g., space heating and cooling), the delivery of which can be compromised if curtailed or shifted in time. However, batteries have historically been, and remain, quite costly and resource intensive compared to many DR-enabling technologies. If the levelized cost of BTM batteries were to fall below the avoided cost of DR, then installing batteries purely as a means to enable load flexibility would become attractive. In our supply curve plots (e.g., Figure 22 and Figure 26), the battery threshold never falls low enough to be equal to the avoided costs through 2050, suggesting that BTM batteries will not be cost-effective to install purely as shed or shift resources. However, if battery costs decline more rapidly than projected, they may become cost-effective at some point in the future. Moreover, as we saw in Section 4.4.3, if BTM batteries are used for *both* shed and shift, then they may be marginally cost-effective as DR resources, at least in non-residential settings. Regardless of the cost-

[67] calflexhub.lbl.gov

effectiveness of BTM batteries as stand-alone DR resources, existing batteries that have been installed for other purposes, such as resiliency, can yield significant DR value, as evidenced by the use of BTM battery virtual power plants for peak management in CAISO in 2022. DR thus has the potential to provide an additional value stream to BTM battery owners, potentially helping to grow the size of this resource.

5.2. Realizing the potential for DR in California

A main finding of this study is that a wide gap exists between the economic potential and the potential that is achievable cost-effectively in a BAU scenario for DR programs. This gap also varies significantly by sector: as shown in Sections 4.3 and 4.4, residential customers have the highest aggregate economic potential today and in the future, but their low historical enrollment rates mean that they have the lowest BAU achievable potential. To realize more of the available resource, it will be important to understand the barriers to customer enrollment and participation that exist today and to develop new models for customer engagement, particularly in the residential sector. In the following sections, we describe the existing barriers to realizing the DR potential that exists in the IOU customer base, and we discuss pathways to overcoming them.

5.2.1. Barriers to realizing DR potential

Complex DR program landscape in California

The number of possible options for participating in DR programs, as well as the complex rules around program participation, baselining, and settlement, serve as barriers to program participation. At the highest level, customers have a choice between participating in a supply-side CAISO program (often through a third-party aggregator) and/or a local IOU program. In addition, there are voluntary statewide programs, such as FlexAlerts (non-compensated conservation alerts called by CAISO), which some customers may confuse with DR events called by their IOU DR program (McGuire & Company 2014) . When deciding whether to participate in a program or which one to participate in, customers must understand whether they are eligible to participate, how they will be notified about events, and how their incentive payment (and non-performance penalty if applicable) will be calculated. The program marketing materials and customer education are often not sufficiently tailored for different customer segments to address their specific needs (Campbell and Patterson 2014) For CCA customers, there may be confusion about whether and how they can participate in DR programs run by the local IOU. This complex landscape requires effective program design and customer education. For larger customers, utility account representatives are an effective way to engage and educate customers about DR programs, but most customers do not have access to this resource. Furthermore, account representatives may be less conversant with DR programs as compared to energy efficiency programs; the representative workforce expressed that additional training will help identify customers suited for participation (Campbell and Patterson 2014). Another area for customer education is to help them understand how much load reduction is needed in order to fulfill their program commitment (Patterson, Sutter, and Elliott 2014) Through a series of evaluation studies conducted over the last decade or so by the IOUs, program administrators are learning how to improve program designs, marketing and customer education, but much work remains to be done in this area.

Customer structural barriers to load management

Some customers face “structural barriers” to participating in DR programs, meaning that they are not able to adjust their load in response to a DR event. This was found as the largest barrier in the statewide Critical Peak Pricing (CPP) program and Demand Bidding Program (DBP) (Campbell 2014; Patterson, Sutter, and Elliott 2014). These barriers can take many forms, either for technical or organizational reasons. Technical barriers include C&I customers’ inability to adjust their product or service schedules without incurring loss or risk to their revenue stream, or simply due to the critical nature of the company’s business operation. In the residential sector, customers may not be able to adjust load for life/safety reasons (e.g., medical equipment), or due to lack of technology access such as Internet access. Organizational barriers tend to occur in the C&I sector, where customers’ organizations may not be structured in a way to effectively implement load management. For instance, small businesses may not have the facilities management staff resources to implement either manual or automated DR strategies, and larger organizations may suffer from “split incentives,” in which the part of the organization that pays the cost of implementing DR measures is distinct from the part that benefits from the incentive payments. Low-performing sectors for DR also include small businesses and CARE customers (Research Into Action, Inc. 2013; Applied Energy Group (AEG) 2020) Organizations that do not have corporate energy goals and load reduction strategies are less likely to participate in DR programs (Campbell 2014).

Customer financial incentives

Among the many DR programs offered in CA, the financial incentive levels and structures vary significantly; so does customers’ perception of these incentives. Saving money by participating in events was found as an important driver of customer satisfaction in the CPP program (Campbell 2014), and customers in SDG&E’s AC Cycling/Summer Saver program found once a year incentive payment to be acceptable (Evergreen Economics 2016). In contrast, customers were less satisfied with the incentive amount in DBP (Patterson et al. 2014); customers in SDG&E’s Peak Time Rebate (PTR) program thought the bill credit was too low (Research Into Action, Inc. 2013) . Overall, for many customers, the possible financial benefits from participating in DR programs are not worth the effort to learn about or the risk of participating in programs. Especially in the small commercial and residential sectors, customers are more driven by bill savings (Evergreen Economics 2016) and are less well informed about DR programs and require larger incentives to overcome these barriers. The State has established new emergency DR programs such as the Emergency Load Reduction Program (ELRP), which compensates participants at as much as $2 per kWh of load shed during a called event, and the Demand Side Grid Support (DSGS) program. In addition, offering a technology product e.g., smart thermostat and installation at no cost was another effective incentive to attract participation (more than the incentives offer for each event) as found in SDG&E’s DR programs (Evergreen Economics 2016) (Gecils 2014)

When customers do participate in programs, they often don't receive immediate feedback about how their actions affect their utility bills or incentive payments, thus they do not develop the confidence that DR programs help them manage their energy expenses. Customers' interest in immediate and granular feedback manifested in multiple DR program evaluation results and recommendations (Campbell 2014; Research Into Action, Inc. 2013) This is complicated by both baseline inaccuracies and the variable nature of HVAC loads. On the other hand, Californians have shown over the years that they are very willing to take dramatic action to reduce load during grid emergencies, with no financial compensation, as described in Section 1. To an extent, a "gateway" program with no penalty such as the DBP, which ended in 2017 (Patterson, Sutter, and Elliott 2014) and the current ELRP program can help recruit customers with no previous DR experience and concerns about their bills. However, "economic" DR programs that provide relatively small payments for a handful of events per year do not send a strong enough signal to interest most customers, who often feel that it is their local utility's job to keep the lights on without regularly bothering them with notices and alerts.

Access to automation technology

In order to overcome some of the barriers listed above, many have looked to communication and automation technology to change DR participation from a manual process, which is limited to the customers' management resource (Campbell 2014), to something built into the control systems in buildings and industrial facilities. Automation technology has proven to be effective in some cases. For example, the statewide Auto-DR program enhanced participants' ability to participate in DR program events, engaged customers in curtailing more loads beyond automated response, and increased enrollment in other IOU DR programs and customer satisfaction (Campbell and Patterson 2014). The program was also found to reduce customers' operational costs by reducing their energy use, avoiding non-performance penalties or by qualifying for incentive payments. However, incorporating automation in program offerings also encountered challenges. One of the primary barriers to event participation found in the Auto-DR program was that the automated DR technology was not operational or did not operate as planned due to the lack of vendor quality control and other reasons.

Larger customers tend to have the facilities management staff and capital budgets to be able to effectively use automation, but access and effective use of automation technology for demand response could present more challenges to smaller businesses and residential customers. In some cases, the upfront cost of the controls is a barrier, including the cost to purchase and install, as well as the effort involved to properly configure and program the controls to respond to DR events. In commercial buildings, these controls also need ongoing maintenance as the building systems they are controlling change, software gets updated, network access changes, and DR programs evolve. While the increasing use of home automation technology has helped in the residential sector, the integration with DR programs has mostly been limited to connected thermostats for space cooling. These automation technologies also suffer from a lack of interoperability, meaning that each smart device often can only be automated through its manufacturer's cloud-based interface, which limits how devices can participate in DR programs. Communication standards, such as OpenADR, have the potential to improve interoperability, but the adoption of these standards by equipment manufacturers and DR aggregators has been slow.

5.2.2. The promise of dynamic electricity pricing

Dynamic electricity pricing, in which retail rates vary in response to real-time or forecast grid conditions, represents an alternative approach to capturing the value of load flexibility. In Section 4.6, we investigated the effective shed and shift DR resources that could be captured via a dynamic retail rate whose hourly variation mirrors the hourly avoided costs tabulated in the ACC. We found that with universal enrollment in a dynamic tariff, customer price response could capture some 40-50% of the technical potential for shed and shift DR in the form of shape DR, much of it being available at zero cost through manual customer response. In 2025, those zero-cost resources amounted to some 7 GW of effective shed and 3.5 GWh of effective shift, which would represent dramatic changes in the peaks and ramps occurring on the CAISO grid.

These findings rest on a set of assumptions about customer responsiveness based on existing studies of real-time pricing programs, but it is uncertain how well these assumptions will apply in the context of a highly dynamic tariff such as the one we considered in this study. Moreover, our modeling estimates the maximum potential that could be achieved under universal enrollment in dynamic pricing. Customer willingness to adopt such tariffs represents a significant unknown in the size of the dynamic-pricing resource that could actually be achieved. Finally, our estimates of the dynamic pricing potential are based on a particular assumed tariff design, in which avoided system costs passed through to the customer as a price signal. Other dynamic tariff structures would be expected to yield different results.

Through the CPUC staff proposal on the CalFUSE framework (CPUC Energy Division 2022) and the ongoing rulemaking (CPUC 2022a), the CPUC is taking significant steps toward making opt-in dynamic electricity pricing a reality. Currently ongoing dynamic pricing pilot programs in SCE and VCE service territory will provide important insights into the real-world potential of this approach to capturing flexible load resources.

5.3. Future directions for DR research

This study aimed to undertake a thorough consideration of the potential for shed and shape DR across the full spectrum of customer types and enabling technologies in California. There are nevertheless certain boundaries to the study scope that represent opportunities for future research. In this section, we briefly discuss two such areas.

5.3.1. Overcoming barriers to realization

Section 5.2.1 identified several barriers to realizing the DR potential identified in this study. Each of these barriers represents an area ripe for future research to better capture the DR resource and support the state’s energy transition.

Improving customer incentives and engagement strategies

Limited customer enrollment at a given incentive level is the primary cause of the large gap we have identified between the economic and BAU achievable DR potential in this study. Future research focused on improved approaches to engaging and enrolling customers has the potential to shrink this gap. Specific research efforts could work to determine optimal financial incentive levels for maximizing customer enrollment or could consider non-financial engagement and incentive structures such as gamification or social encouragement to boost customer willingness to enroll in DR programs.

Streamlining program structures

As discussed in the previous section, the complex landscape of DR programs in California can lead to customer uncertainty and confusion, which may suppress enrollment. Future research efforts could focus on identifying specific points of customer confusion and their root causes, as well as developing new program rules and designs that can provide clearer, more readily understandable pathways to customer enrollment and participation.

Addressing structural barriers to customer response

Certain customers may also be unable to provide DR due to structural barriers to participation that may be technological or organizational in nature. Future research could aim to address technological barriers by developing and testing new technologies that can enable load flexibility in applications that are currently inflexible. One example of such a technology, identified in this study, is TES systems for commercial refrigeration applications, whose development has opened up a significant new opportunity for load flexibility from an end use that was previously largely inflexible. Future research efforts could also identify organizational barriers in more detail and test new means of overcoming them, such as providing support to smaller organizations in developing energy management strategies.

Ensuring access to automation technology

In addition to the limitations of loads that are structurally inflexible, some customers face challenges related to the affordability, ease of use, or interoperability of automated controls. Research and development efforts focused on bringing down technology costs, improving user experience, and improving interoperability among various building systems have a long history, and these efforts will continue to be important in bringing a broader ecosystem of technologies to bear on driving demand flexibility in California.

Improving measurement methodologies

With widespread availability of customer AMI data and steady advances in analysis and modeling methodologies, it should be possible to improve the accuracy of baseline estimation over present-day approaches. Development of improved DR measurement methods through an open research process that can achieve broad consensus among utilities, aggregators, advocates, and the CAISO, has the potential to increase participation in DR programs and to compensate participants more fairly for their response.

5.3.2. Exploring shimmy DR

This study did not consider at all one of the four types of DR identified previously in the Phase 2 study, namely *shimmy* DR. Shimmy refers to DR that can respond quickly (within seconds) and reliably to a rapidly changing dispatch signal, in order to provide ancillary services (AS) to the grid such as frequency regulation or spinning reserves. The Phase 2 study estimated the potential for shimmy, which was modest and on the order of several hundred MW. The value for DR shimmy came from allowing batteries -- which would otherwise have been dispatched for frequency response and load following -- to be used to reduce renewables curtailment through net load shifting. Because of the relatively small market for AS, the challenges of providing them with demand-side modulation, and the ease with which the AS need can be met with traditional generation resources or utility-scale batteries, there has been little further study of the potential for shimmy DR in California.

As we have seen in the present study, however, the growth of EV charging and other electrified loads will rapidly transform the landscape of DR resources. It is possible that these new loads could similarly create new opportunities for shimmy. This seems particularly plausible in the case of managed EV charging (i.e., “V1G” charging), which should be able to be rapidly modulated in response to a signal, given appropriately enabled charging infrastructure. In a decarbonized future, where the main alternative AS capacity is provided by utility-scale batteries, EV charging could potentially be an economically favorable option. The round-trip losses in batteries (which need to maintain a balanced state of charge over time when providing frequency response and other ancillary services) represent an opportunity cost compared to charging or discharging at any given time. If EV owners are indifferent to the timing of their charging (provided that the charging is complete by the time the vehicle is needed), there may be less opportunity cost to shimmying EV charging than there is to providing AS with grid-scale batteries. This topic -- identifying energy neutral ancillary services alternatives to dedicated batteries -- may reward further research.

5.3.3. Industrial sector decarbonization

A recent US Department of Energy (DOE) roadmap outlined four key pillars to industrial decarbonization: EE; industrial electrification; low-carbon fuels, feedstocks, and energy sources; and carbon capture, utilization, and storage (DOE 2022). Each of these strategies has the potential to significantly impact the future electricity demand of the industrial sector as well as the DR potential associated with that demand. While this study includes forecasts for industrial loads based on the latest IEPR estimates, it does not consider the potential impacts of additional efforts in these areas of decarbonization.

In particular, this study forecasted the growth of electrified loads in buildings and for LDEV and MHDEV charging and found that these new loads had a dramatic impact on both the DR need and the DR potential in California. An important missing piece of the electrification puzzle is the electrification of present-day fossil-fuel end uses in the industrial sector. At the time of this study, there were no appropriate forecasts available of the expected load growth in this area. Given the large and steady DR resource from the industrial sector without electrification, however, it is likely that industrial electrification will have a significant impact on DR potential in

California. By and large, industrial electrification will consist of the electrification of industrial process heating, either via high-temperature heat pumps, electric resistance heating, or creation of electrolytic hydrogen as fuel, and many of these new loads may have inherent flexibility that make them highly valuable DR resources.

The detailed strategies and mechanisms that will yield full decarbonization of the industrial sector are not fully clear and remain an active and productive area of research today. It will be important to incorporate new findings on industrial electrification pathways into future DR potential research, to account for both the changes in system-level load they will cause, as well as the new demand-side resources they will create.

5.3.4. Dynamic electricity pricing

In this study, we also considered an alternative means to capturing DR potential via dynamic electricity tariffs that attempt to present customers with a price that reflects the full marginal cost of electricity consumption in real time. This approach has been proposed in a recent white paper from CPUC Energy Division staff (CPUC Energy Division 2022), in a concept known as CalFUSE, and it is the topic of an ongoing proceeding at the CPUC. Given the novelty of the proposed approach, research efforts are likely to be useful on a number of fronts.

First, it will be helpful to understand the potential impacts of such a tariff on customer bills, both for average bills and for month-to-month bill volatility. Bill impacts will depend in practice on the manner and degree of customer response to the time-varying price, which may be difficult to predict, but it will be helpful as an initial step to understand how customer bills would change compared to present-day tariffs if customers maintained their current behavior. It will also be interesting to consider different strategies for mitigating these impacts via strategies like subscription-based tariffs and the other transactive elements included in the CalFUSE framework.

It will also be important to thoroughly consider the potential effects of customer response to a dynamic tariff, both on customer bills and on the system-level load shape. Our analysis in the present study considered the effective amount of shift or shed DR that could be captured during times when they would be likely to be dispatched, under an assumed customer price elasticity of demand that was applied across all end uses and customer classes, under an assumed price ratio between the dynamic and present-day tariffs. This approach is necessarily highly approximate, glosses over what are likely to be large differences in responsiveness from different customer classes and end uses, and does not attempt to estimate the overall change in load shape or the customer impacts. A more thorough modeling effort to consider continuous customer price response to a time-varying tariff, perhaps considering strategies for response that are differentiated by customer type, end use, and enabling technologies, would significantly improve on our estimates here.

Such a modeling effort would require input assumptions on customer response strategies, price elasticities, and technological capabilities. Existing literature on customer responsiveness to dynamic pricing is limited, however, and much of it is not particularly recent, so the effects of recent advances in communications and automation may not be captured. Evaluation studies of other pricing programs, such as TOU or CPP, may contain information that could be generalized to the case of a fully dynamic tariff. A meta-analysis of such studies could provide useful insights. Pilot programs implementing dynamic tariffs (several of which are currently underway in California) should also proceed in parallel to provide updated information on customer responsiveness and willingness to enroll in dynamic tariffs.

Finally, significant technological research and development will be needed to realize the promise of dynamic pricing. Devising the means to collect data on real-time grid conditions, compile them into a dynamic price signal, and broadcast the signal to customers in a way that can be understood and responded to is an initial hurdle, though much progress has been made in the development of CEC's MIDAS price server. Real-time data-collection needs are particularly acute for understanding local conditions on the distribution system, since real-time data may not be readily available in many cases and there is not presently a means for transmitting such data to entities outside the utility. Further, for optimal responsiveness, it will be essential for customers to have technologies that can automatically respond to the time-varying price signal. Many of the technologies considered in the present study are able to respond to a utility dispatch but may not have the capacity to respond on a continuous basis to a time-varying signal. Advances in MPC and development of new technological strategies for price response will be crucial for maximizing the value of dynamic pricing. Significant work in this area is currently underway in LBNL's CalFlexHub project for the CEC (M. A. Piette et al. 2022), but the relevant technological space is vast, and expanded efforts are likely to yield dividends.

6. Conclusion and Future Directions

We have described the analysis and findings from Phase 4 of the California DR Potential Study, which considered the potential for shed and shift DR in California through 2050. Phase 4 provides a substantially improved and updated picture of the potential DR resource in California. More recent customer and load shape data provides an updated picture of customer loads. Updated load modeling in the LBNL-Load software dramatically expands the scope of the study in terms of building types and end uses, expands the modeling of electrified loads, and extends the time horizon of the study to 2050. In addition, a novel approach to load shape clustering unlocks new insight into how customer behavioral features interact with DR potential. In the DR-Path model, an updated technology characterization and a new customer enrollment model provide a more accurate and up-to-date window into the cost of procuring DR from different customers and end uses. These updates aim to more thoroughly characterize the DR landscape as it evolves under the combined effects of growing VRE generation and electrification in California.

We find that profound changes are in store for DR needs and resources on the California grid over the coming decades. Electrification of transportation and heating, will have significant impacts on the nature of the need for DR in California, as well as on the available resource. The system net load peak is projected to shift to the winter, and periods of need for shed DR evolve from being tightly clustered in the summer months at present to being clustered primarily in the winter by 2050, with only a scattering in the summer months. This change in the seasonality of peak periods will have significant implications for the nature of the available shed DR resource. Over the same period, the daily morning and evening ramps in the net load become considerably steeper, heightening the need for shift DR.

At the same time, the rapidly growing new loads from electrification will create new opportunities for DR. Charging of MHDEVs and residential-sector LDEVs are set to become the most important sources of DR in California, by a wide margin, by 2040, while other electrified loads--particularly residential space and water heating--also emerge as significant potential sources of DR. Meanwhile, certain prominent sources of DR, such as industrial process loads, maintain their historical importance, while others, such as space cooling, go into decline as they become less coincident with times of system need.

Over the same period, advances in communicating control technologies will open new pathways to enabling DR resources to support the California grid. Cost declines and growing penetration of PCTs, connected power outlets, and connected appliances enable significant new resources across a variety of end-uses in the residential sector. In the commercial sector, TES systems for refrigeration, currently emerging on the market, show the potential to unlock a significant new resource whose lack of seasonal variability makes it a steady source of DR even as system loads evolve. Remote communicating controls for agricultural pumping provide a new approach to enabling a significant flexible end use. Most importantly, communicating technologies for new electrified loads, especially communicating EV charging infrastructure and water heating controls, are the key to converting the new loads into DR resources. Co-deployment of DR-enabling technologies with electrified end uses will be critical to achieving the DR potential that these end uses represent.

The result of these technological trends is a rapidly growing potential for both shed and shift DR in California, with significant implications for system costs and emissions. The economic shed resource grows from 12 GW in 2025 to 21 GW in 2050, representing considerable load reductions compared to the record CAISO peak of 52 GW. The 2025 resource represents $1.8B in potential avoided system costs, growing to $3.1B by 2050. The economic shed resource evolves even more drastically, growing from 5.9 GWh in 2025 to 31 GWh in 2050, with $88M in avoided system costs in 2050 growing to $920M by 2050, based on valuation estimates for load shifting from the ACC. Because these estimates do not place explicit value on the flexible generation capacity that shift DR provides, they may underestimate the true cost-effective levels of shift DR. If this value stream could be captured (or if shift resources could also capture value by participating in shed DR), the 2025 shift DR resource could be as high as 12 GWh, growing to 33 GWh by 2050. These resources are substantial compared to the 590 GWh of average daily energy consumption in CAISO as of 2019.

Capturing these large economic potentials for shed and shift poses a challenge, however, given historical enrollment rates in DR programs. When customer incentives, program costs, and enrollment trends are considered, the cost-effective BAU achievable potential amounts to less than one-fifth of the economic potential, for both shed and shift, throughout the forecast period. Improving on this will require new approaches to customer engagement and streamlined pathways for customers and aggregators to access the relevant markets and be compensated appropriately for the value they bring to the grid. In response to the grid emergency and rolling blackouts of 2020, new models are already emerging, such as the ELRP, MAP, and DSGS, and these new models have already demonstrated their value in helping to avert rolling blackouts in 2022.

Another interesting new approach to engaging customers in DR is to communicate the value of demand modifications directly to customers, in near-real time, via a dynamic tariff structure like CPUC Energy Division's proposed CalFUSE framework. We estimated the effective shed and shift resources that could result from customer response to such a tariff, finding that universal enrollment in a dynamic tariff (and universal willingness to respond) could capture some 40-50% of the technical potential for shed and shift, with considerable resources available even without investment in enabling technologies. Further study of this approach will be important, to better understand customer willingness to enroll and respond to such a tariff.

Dynamic tariffs such as the CalFUSE proposal may not be effective if commercially available end-use control technologies are not developed with capabilities to respond to such signals. To help adapt these communicating control technologies to achieve California's demand flexibility goals, the CEC has initiated a research program called CalFlexHub. CalFlexHub is a 3.5-year program designed to enable scaled adoption of equitable, advanced, interoperable, and load flexible technologies via lab and field research and analysis activities (M. Piette et al. 2022).

DR has an essential role to play in supporting California's renewable future. Maximizing the potential resources that are captured will require a sustained and coordinated effort from policymakers, regulators, IOUs, program administrators, aggregators, researchers, evaluators, implementers, and technology firms. Regulators and the CAISO can set targets for load flexibility and create the program rules and market structures that connect that flexibility with its value to the grid and society. Within those structures, utilities, program administrators and aggregators can devise new models for engaging customers and capturing the DR resources they are able to provide, while technology firms can develop new ways to enable flexible loads in the building stock and bring them to market to capture untapped or underutilized potential. Meanwhile, evaluators and researchers can verify the effectiveness of these approaches and develop pilot programs and studies to open additional pathways. It will be particularly important to ensure that electrification proceeds in tandem with load flexibility, and this will depend on statutory policy, regulatory standards, appropriate incentives, and ongoing outreach and education to customers and the workforce of installers. Through such collaborative efforts across the full ecosystem of electricity demand management it will be possible to make the potential for DR a reality and ensure a cleaner, more affordable, more reliable, and more rewarding power system for California ratepayers.

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