Overview of Phase 4 of the California Demand Response Potential Study

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ABSTRACT

The California Demand Response (DR) Potential Study is an ongoing effort to assess the current and future DR resource in California in the context of the state's renewable energy goals. This paper provides an overview of Phase 4 of the study, which aims to provide a thoroughly updated and expanded picture of DR in California compared to previous studies. Leveraging interval consumption data for some 400,000 utility customers, along with novel methods for clustering and end-use disaggregation, the study will construct a detailed picture of customer electricity demand in the state through 2050, including growth in electrified end uses, light-duty electric vehicles, and new loads such as electric trucks and buses, all of which present both challenges for the grid and opportunities for new DR resources. Combining the load forecast with an updated database of DR-enabling technologies, the study will assess the cost of achieving DR through a comprehensive set of technological pathways, resulting in a detailed, bottom-up supply curve for future DR resources, as well as an assessment of the potential greenhouse gas savings from development of new DR resources. The Phase 4 study focuses on the potential for shed-type DR, for mitigating peak demand events, and shift-type DR, to alleviate the steep ramps arising from the California duck curve. The study will examine specific pathways to obtaining these resources, including consideration of new approaches such as dynamic electricity tariffs, considerations for low-income and disadvantaged communities, and synergistic effects that may be achievable through integrated energy efficiency and DR programs.

Introduction

Demand response (DR) is widely recognized as a valuable resource in power systems, for improving system reliability and reducing system costs and emissions (Faruqui et al. 2007; Wang et al. 2017; Joung and Kim 2013). Historically, DR programs have primarily focused on managing extreme system peak loads by dispatching participating customers to reduce load in lieu of dispatching peaking generation resources, but growing deployment of variable renewable energy (VRE) generation in many power systems has the potential to profoundly change the timing and the nature of the DR resources that can provide the most value to the grid (Seel et al. 2018; Murthy, Satchwell, and Gerke 2022). In California, rapid expansion of solar photovoltaic (PV) generation has created a new set of grid-management challenges for the California Independent System Operator (CAISO), in the form of the "duck curve" (CAISO 2016), which is characterized by steep ramps in the net[1] system load around sunrise and sunset and a frequent need to curtail solar resources during daytime hours to accommodate the flexible fossil resources

[1] The net system-level load is the total ("gross") demand on the system minus generation by non-dispatchable VRE resources such as solar and wind.

needed to manage the ramps. The role of DR is evolving significantly in response to these challenges.

In part to address this changing landscape, in 2015, the California Public Utilities Commission (CPUC) initiated the California DR Potential Study to explore the nature of the future DR resource in the state. Phase 1 of the study (Alstone et al. 2016) introduced a novel modeling framework, DR-Futures, which leveraged the detailed energy-consumption data made available by the near-universal penetration of advanced metering infrastructure (AMI, commonly referred to as smart meters) in California to construct a detailed, bottom-up picture of the potential DR resource across a fine-grained set of customer classes, electrical end uses, and enabling technologies. The Phase 2 study (Alstone et al. 2017) expanded the scope beyond traditional DR for peak management to consider more novel forms of DR that may be valuable in the future. Phase 2 identified four categories of DR that have since come into common use in discussions of the future of DR: *shape*, *shift*, *shed*, and *shimmy*.

- *Shape* refers to "load-modifying" DR that reshapes customer load profiles through response to time-of-use prices response or behavioral campaigns.
- *Shift* refers to DR that encourages the movement of energy consumption from one time of day to another. Shift could smooth net load ramps associated with daily patterns of solar energy generation.
- *Shed* represents the traditional type of DR that curtails loads to provide peaking capacity and support the system in emergency or contingency events.
- *Shimmy* involves using loads to dynamically adjust demand at timescales ranging from seconds up to an hour to provide ancillary grid services such as frequency regulation.

A key finding from Phase 2 was that shift DR would be of particular value to the future California energy system, possibly supplanting traditional shed DR, given the capability it provides for managing the steep diurnal ramping events that are expected in the context of the duck curve. The Phase 3 study (Gerke et al. 2020) therefore focused on a deeper assessment of the shift DR potential in California. Shift DR can provide similar grid services to energy storage resources such as batteries; therefore, the Phase 3 study estimated the quantity of DR expected to be available at a lower or equivalent cost to behind-the-meter (BTM) batteries. The study found that, as of 2020, there was 5.3 GWh of virtual storage from shift DR that was cost-competitive with BTM batteries, enough to utilize the typical quantity of daily solar generation that was being curtailed at that time. This cost-competitive shift resource was projected to grow only slowly, however, and to be outstripped by growth in VRE generation by 2030. Thus, the key recommendations of the Phase 3 study focused on strategies for growing the size of the shift DR resource. Since the completion of the Phase 3 study, the emergence of occasional severe peak-management challenges in CAISO (such as rolling blackouts in 2020) has also led to a renewed interest in increasing the shed DR resource (CAISO, CPUC, and CEC 2021).

In this paper we present an overview of Phase 4 of the California DR Potential Study, which takes an updated look at the future shed and shift DR resources in California as well as the potential for capturing these resources using dynamic electricity pricing approaches (which can be considered as a form of shape DR).[2] Building on the analytical framework from the previous studies, Phase 4 will update the analysis of DR potential and expand its scope. Working with a

[2] Shimmy DR was found in the Phase 2 study to have a fairly limited market and applicability; hence, it is not considered in Phase 4.

new set of AMI data for a larger set of customers, the study will consider a dramatically wider diversity of customer types and end uses than considered previously, and it will extend its forecast horizon through 2050, with a more thorough consideration of the effects of fuel-switching from fossil fuels to electricity in buildings and transportation. To better capture potential synergies between DR and energy efficiency (EE), the study will also integrate its approach to technological forecasting approach with the modeling performed for the CPUC's 2021 EE Potential & Goals Study (Sathe et al. 2021), hereafter referred to as the EE P&G study. To better inform resource planning and program development, the Phase 4 study will also provide shed and shift DR forecasts to the CPUC's integrated resource planning (IRP) process, and it will consider emerging approaches to achieving DR through dynamic electricity tariffs.

Findings from Phase 4 of the DR Potential Study will be released in a final report expected in late 2022. In this paper, we present the key updates to the DR-Futures modeling framework for Phase 4. We then consider the potential implications that these modeling updates may have on the understanding of future DR Potential that will emerge from the Phase 4 study.

Overview of the DR-Futures Modeling Framework

The DR Potential Study rests on an analytical modeling framework developed specifically for the study and 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:

- **LBNL-Load** is a bottom-up load-forecasting module that capitalizes on the customer AMI data to project future end-use load shapes for a diverse set of customer clusters.
- **DR-Path** starts from the forecasted load shapes to assess a large number of 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.

For example, LBNL-Load models the space cooling loads for residential and commercial customer clusters. DR Path uses these modeled loads to estimate the quantity of space cooling load that is present at times when there is a need for shed or shift DR on the grid, and it then considers pairing this load with a range of possible enabling technologies and program participation incentives in each customer cluster to compute the amount of responsive load that can be captured at a given cost. The LBNL-Load and DR-Path modules are described in full detail in the Phase 2 (Alstone et al. 2017) and Phase 3 (Gerke et al. 2020) study reports. In the remainder of this section we describe the updates to these models and the underlying data that were undertaken for the Phase 4 study, including areas of integration with the EE P&G study, and we discuss potential implications in the context of the Phase 4 study.

Data Updates for the Phase 4 Study

The DR Potential Study leverages AMI data from the three California Investor-Owned Utilities (IOUs)[3]. Phases 1 through 3 used data from 2014; Phase 4 updates the modeling effort with a new dataset reflecting consumption in 2019. Data were requested and collected through a two-stage data request process. The first stage included demographic data for every single account that was active in 2019; a total of 13.6 million customers. This data included the customer's ZIP code, NAICS[4] code, tariff, CARE[5] status annual energy consumption, peak power consumption, DR Program enrollment, and information about participation in incentive programs for distributed energy resources. Combining this information with various public datasets, we were able to map additional characteristics like the customer's climate region, flags for whether or not they are on a time-of-use (TOU) rate or located in a disadvantaged community (DAC),[6] the building type or industrial sub-sector the customer belongs to, whether or not they had an electric vehicle (EV), and the presence and capacity of rooftop PV systems.

In the second data request, 2018-2019[7] AMI data was requested for a sample of 3% of accounts in the demographic data. To ensure that this sample adequately represented the full diversity of customer types in California, including niche categories that may have unique consumption patterns, customers were grouped based on their sector, building type (or sub-sector), size (small, medium, or large based on peak energy use), location, and other characteristics. Those groups were then stratified based on total annual energy use and sampled. Additionally, all customers that consumed more than 10 GWh in 2019 were requested, as well as all customers with a separately metered EV. AMI data was requested for 2% of residential customers and of customers whose sector or building type did not fall into a category of interest or could not be specified.[8] The remaining request allowance was such that we were able to request approximately 17% of commercial, industrial, and agriculture accounts. Ultimately, AMI data for 411,000 accounts were requested, with approximately 60% of those being residential, 30% commercial, and 10% industrial, agriculture, and other. Although we obtained a small fraction of accounts, our sampling strategy was such that the data collected represented about 35% of all the electricity consumption by California IOU customers.

LBNL-Load Modeling Updates

LBNL-Load uses customer-level hourly load data to build a detailed, bottom-up picture of the grid-system load in California. First, the model processes individual customer load data to correct for behind-the-meter PV generation and estimate temperature-dependent heating and cooling loads. Then it groups the customers into a highly granular set of customer clusters, aggregates customer data within each cluster, and uses statistical methods to disaggregate individual end use load shapes. Finally, the model projects future load growth at the cluster level

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[3] Pacific Gas and Electric (PG&E), Southern California Edison (SCE), and San Diego Gas and Electric (SDG&E)

[4] NAICS is the North American Industry Classification System, which is used to classify business establishments.

[5] CARE is California Alternate Rates for Energy, a low-income electricity rate subsidy program in California.

[6] Disadvantaged communities defined according to California's CalEnviroScreen tool, using criteria set by California SB 535 (California OEHHA 2017).

[7] Data were requested for 2018 and 2019 to allow for a more thorough modeling of temperature-driven effects on customer load, but the final modeled load shape data focuses only on 2019.

[8] Such customers were assigned a sector or building type of "other" and make up a very small proportion of the total customer sample.

based on existing population forecasts and climate policy constraints, and it develops an aggregate forecast of load at the grid-system level.

Individual customer load data modeling

Significant data preprocessing was required to transform the raw customer AMI data into a usable time series of customer energy demand. After basic cleaning and reformatting, the first preprocessing step was to account for behind-the-meter PV generation at customer sites. The System Advisor Model from the National Renewable Energy Laboratory (Blair et al. 2018) was run with input data from the National Solar Radiation Database (NREL 2022) to construct 2019 PV generation estimates for each customer with rooftop PV, based on IOU-provided links to public PV installation data (Energy Solutions 2022). This modeled profile was then adjusted to ensure consistency with the customer's hourly export data, which represents the amount the customer was generating in each hour in excess of their demand. The modeled PV generation was then added back to the customer AMI data to yield an estimate of the total load behind the meter for each customer.

Residential and commercial customer load then was disaggregated into temperature-dependent and non-temperature-dependent loads using the temperature regression framework developed for the phase 2 study (Alstone et al. 2017). New developments for phase 4 included developing independent parameters for weekdays vs. weekends, different seasons, and times of day, to account for variation in usage patterns, as well as time lags to account for building thermal inertia.

Finally, customer demand profiles were modified to account for the significant Public Safety Power Shutoff (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. 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 applied to local temperatures during the event.

Development of load shapes for customer clusters

Having processed and corrected the individual customer load shapes, we then constructed clusters of similar customers to develop representative load shapes for different customer types. For Phase 4, in order to group customers with similar behavioral patterns, we developed a novel approach to clustering customers according to similarity in their load shapes. The customer data collected for Phase 4 also supported clustering customers on a more granular set of building types than were able to be considered in previous studies, as listed in Table 1. Customers were assigned to clusters according to their sector, IOU, local capacity area (LCA)[9], climate region[10], building type, site size, load shape cluster, and CARE and DAC status. Each of these groups were then separated into kWh bins, (e.g. quintiles) to form the final clusters. During the initial

[9] Local capacity areas are geographic regions in CAISO used for grid planning purposes, which are defined by having significant load and transmission constraints

[10] California's sixteen climate zones were mapped to three climate regions (hot-dry, marine, and cold) to be consistent with the EE P&G study

load shape sampling, customers were assigned two weights based on the data sampling strategy: one for the number of customers it represented, and one for the total energy it represented. These weights were used to determine the final count of customers in the cluster and to scale the sampled time series to produce a final cluster load shape.

In total, 5,422 clusters were created to represent the entirety of California IOU customers. Cluster load shapes were then disaggregated into the end uses described in Table 1 using the temperature regression approach described above for heating and cooling load, combined with representative load shapes and saturation data for the other end uses. As noted in Table 1, the set of end uses that were disaggregated represents a substantial increase from previous phases of the study, which will allow for a more comprehensive assessment of the DR potential in California. More complete details on the Phase 4 clustering and disaggregation methodology are included in a separate paper in these proceedings (Murthy et al. 2022).

Table 1. Sectors, building types, and end uses modeled in the DR-Futures framework. Building types and end uses in red represent newly added categories in Phase 4.

Residential Sector		**Commercial Sector**		**Industrial/Ag 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 • PCs • Water heating • Misc. • EV level 1 • EV level 2 • Rooftop PV	• 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

Load forecasting

Data from California's 2021 Integrated Energy Policy Report (IEPR) (Garcia et al. 2022) were used to forecast baseline changes in energy use (EV and non-EV), customer count, and self-generation to 2025 and 2030. All energy use multipliers were applied equally to all hours of the year. We then added end-use specific modifications to the baseline load forecasts, including reductions due to adoption of EE and growth due to electrification of fossil end uses through 2030; these impacts were estimated using forecasting outputs from the EE P&G study, which defines measure-specific energy impacts for each relevant utility, climate region, and building type. This represents a key new point of integration between the DR Potential Study and the EE

P&G study. Energy impacts for each measure were allocated across all relevant clusters and end uses proportional to the baseline energy consumption of the given cluster and end use combination. In addition to projecting the growth of existing loads, we also added a projection of hourly loads from the charging of medium and heavy-duty EVs (MHDEV, i.e., electric trucks and buses) based on preliminary forecasts from the CEC's HEVI-Load model, currently under development at LBNL.

Loads were further forecasted to 2050 using the PATHWAYS model used for California's 2021 SB100 Joint Agency Report (Gill, Gutierrez, and Weeks 2021). This long-term forecast represents a significant expansion of the forecasting scope for the DR Potential Study, which has previously limited its consideration of DR potential to the 2030 time horizon. Loads were further forecasted to 2050 using the PATHWAYS model used for California's 2021 SB100 Joint Agency Report (Gill, Gutierrez, and Weeks 2021). This long-term forecast represents a significant expansion of the forecasting scope for the DR Potential Study, which has previously limited its consideration of DR potential to the 2030 time horizon. The PATHWAYS model forecasts load for statewide baseline electricity use as well as additional electricity demand expected from electrification of vehicles and building end-uses. The baseline load growth rate from 2030-2050 was applied to all non-EV end-uses in our model, while the light-duty EV (LDEV) and MHDEV forecasts were used to scale up EV demand. We then added the additional demand forecasted from residential and commercial space heating, water heating, and cooking, and residential clothes drying to those end uses. Customer counts were forecasted linearly based on the average growth rate forecasted from 2020-2030 in IEPR. Similarly, self-generation was forecasted linearly using the 2029-2030 growth rate, since the IEPR forecasts show the early 2020s having much faster growth than the latter half of the decade.

System load aggregation

Because the initial customer sampling was carefully designed to include all customer classes, the resulting customer clusters provide a complete representation of the hourly loads from California IOU customers. Summing up the loads across all clusters thus yields a forecast of the expected future demand on the California grid, with a detailed breakdown of 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 at times of system need. Figure 1 shows the aggregated hourly system-level demand for an average day in summer, winter, and shoulder seasons,[11] subdivided into the individual end-uses modeled in LBNL-Load.[12] Overplotted on the gross end-use-level demands are the grid-system[13] gross load (which is the gross electricity demand less rooftop PV generation as projected by LBNL-Load) and net load (which is the net load less grid-scale VRE generation as projected based on the most recent CPUC integrated resource planning process).

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[11] 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.
[12] In fact, some of the end-uses plotted in Figure 1 are disaggregated more finely in the LBNL-Load modeling (e.g., home appliances includes dishwashers, clothes washers, clothes dryers, and cooking appliances); some end-use groups have been reaggregated in the figure for the sake of readability.
[13] Loads shown are for California IOU customers only. 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.

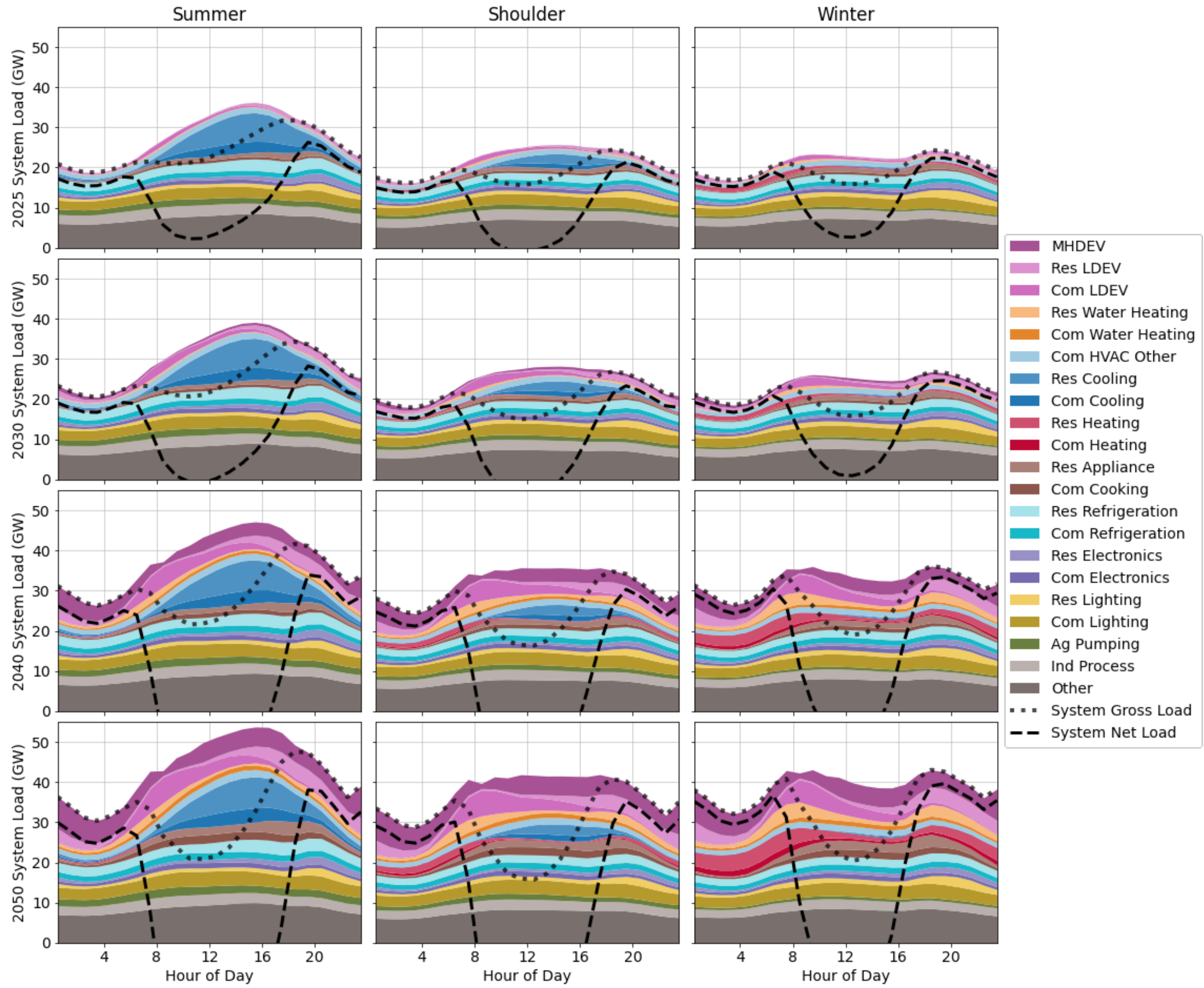

Figure 1. Future system-level load shapes from LBNL-Load modeling as updated for the Phase 4 study. Panels show average hourly gross demand over a day in summer, winter, and shoulder seasons, disaggregated into individual end uses. Overplotted are the gross system load (gross demand net of rooftop PV) and the net system load (gross load net of grid-scale VRE generation). Forecasts are shown for the 1-in-10 weather scenario.

Several features are worth noting in Figure 1. 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. (Of course, in practice, such consistent excess VRE generation would not simply be curtailed; rather, batteries or other storage would be built to capture the excess and serve overnight loads. From the perspective of estimating DR potential, however, a dispatchable grid-scale battery is no different from traditional dispatchable resources: if DR can eliminate the need for some peaking or ramping capacity—battery or otherwise—it can serve to reduce system costs. Therefore, the seemingly naïve net load plotted here is the correct one to consider when estimating the potential of DR to support grid operations.) 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, despite the fact that the gross load and gross demand continue to have pronounced summer peaks.

To illustrate the shift more clearly, Figure 2 shows the modeled CAISO[14] system-level gross (gray) and net (blue) hourly load from LBNL-Load in 2019 and in each forecast year. The yellow shaded region shows the summer season, and orange points indicate the top 250 net-load hours of the year, during which shed DR would be 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 move to non-summer months, and, by 2050, although some peak hours still occur in summer, a clear majority fall outside the summer months.

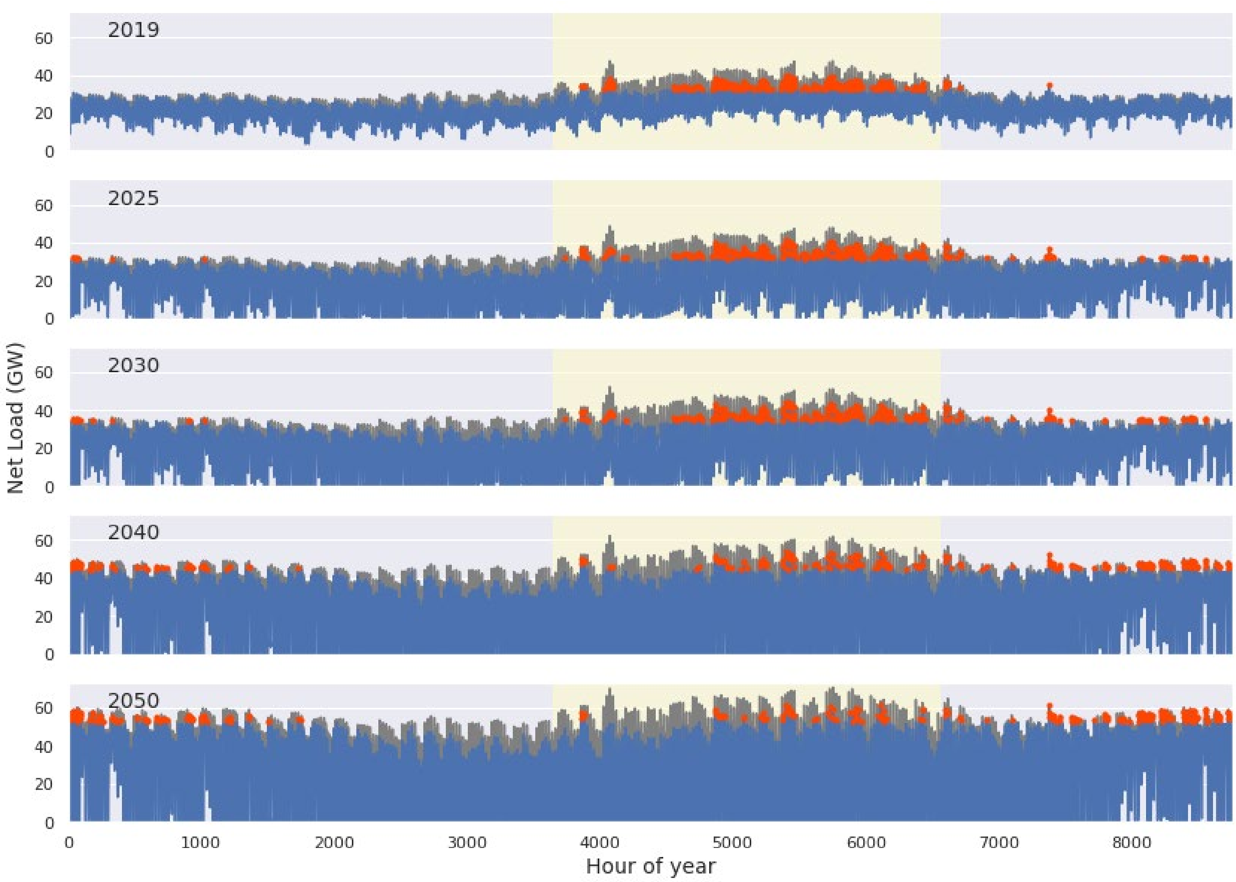

Figure 2. Modeled system-level hourly gross load (gray) and net load (light blue) for each year modeled in LBNL-Load, as estimated from aggregating the cluster load shapes from the Phase 4 study. Orange dots indicate the 250 highest net load hours of the year, which are the hours in which shed DR is most likely to be needed. The yellow shaded region indicates the summer months of June through September.

[14] Here, the gross and net loads have been scaled up from the loads shown in Figure 1, to account for ~20% of CAISO load that is not from from non-IOU customers and not explicitly modeled in LBNL-Load.

DR-Path Modeling Updates

The DR-Path model leverages the cluster end-use load shapes from LBNL-Load, along with a database of DR-enabling technologies and a model of customer enrollment probabilities, to construct a detailed picture of the various pathways to achieving DR resources in California. Figure 3 provides a schematic depiction of the DR-Path calculation framework. First, using the LBNL-Load forecast of CAISO system load, combined with a projection of future VRE generation, the model estimates the likelihood that DR will be needed in each hour. Applying this to DR dispatch model to each cluster (gray circle), the model then computes the weighted-average quantity of DR that is technically available from each cluster end use (green circles). These end uses are coupled with a database of DR-enabling technologies (blue circles) that can enable different amounts of flexibility for different costs. An enrollment model then determines the percentage of customers who would be expected to enroll in a DR program at a given incentive (red circles), yielding 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). The model then selects the pathways that maximize the overall DR resource at a given procurement cost. Repeating this 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.

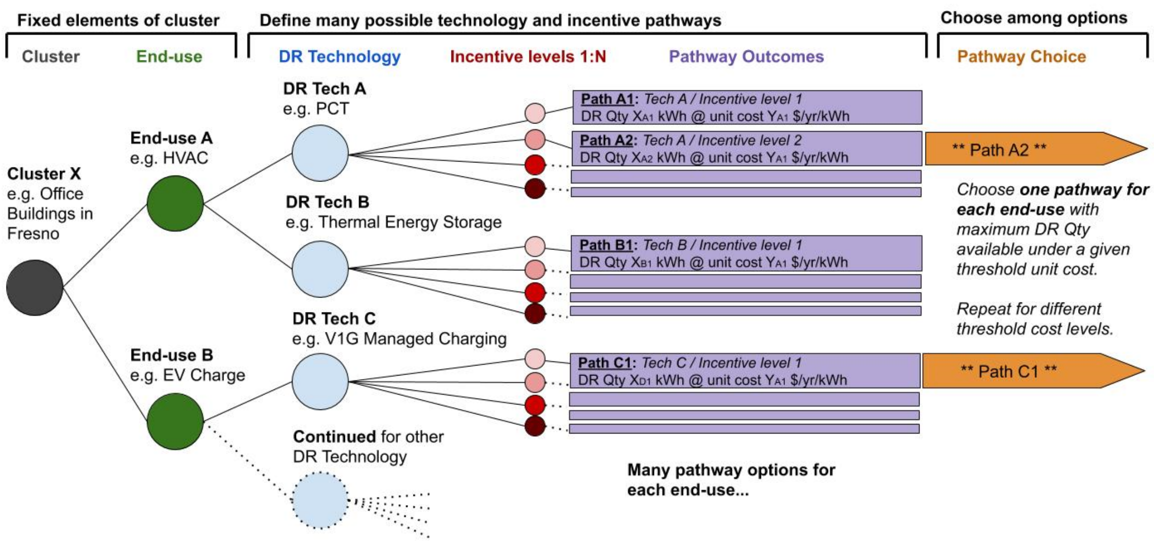

Figure 3. Schematic diagram of the calculation procedure in DR-Path, combining cluster end uses with technologies and a customer incentive/enrollment model to select optimal future DR pathways.

The DR-Path framework has been developed incrementally throughout the previous phases of the DR Potential Study. In Phase 4, we have added several upgrades and new features; these are detailed in the remainder of this section.

Technology characterization updates

DR-Path relies on a database of DR-enabling technologies that are paired with the individual cluster end uses to estimate DR potential and cost. In light of the expanded set of building types and end uses in Phase 4, we undertook a substantial update to the technology dataset. We developed an extensive list of DR-enabling measures for potentially demand-responsive end uses in the sectors and building types highlighted in Table 1. Previous phases of the study included controls technologies such as (among others) programmable communicating thermostats (PCTs), commercial energy management systems, connected EV charging infrastructure, thermal energy storage 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. In addition, in lights of the expanded end-use modeling, we also characterized new controls technologies, such as connected appliances and water heaters, connected power strips and outlets, and thermal energy storage for commercial refrigeration. For these 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.[15]
- *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.

The majority of the cost data, price trend projections, and saturation forecasts for residential and commercial technologies were derived from a recent report detailing cost data and projections for technologies that can enable demand flexibility in buildings (Nubbe et al. 2021). Performance data in the residential and commercial sectors draw substantially from the ENERGY STAR Connected Criteria (EPA 2021), which provide realistic performance parameters for present-day technologies. Behind-the-meter battery costs were derived from the Electricity Annual Technology Baseline from the National Renewable Energy Laboratory (NREL 2021). For DR-enabling technologies that can also provide EE benefits (e.g., PCTs), present-day saturations and projections to 2030 were derived from forecasting outputs from the EE P&G study, a key point of integration between these two studies. Remaining gaps in the data were filled via interviews with industry experts and by market research and informed estimates performed by the authors.

Updated customer enrollment model

The incentive/adoption layer of DR-Path (red circles in Figure 3) estimates the fraction of customers who would enroll in a DR program for a given financial incentive.[16] 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, whose parameters were not readily modifiable. To better reflect present-day

[15] Importantly, to estimate the cost of obtaining DR, we considered only the costs of DR-enablement—e.g., the incremental cost of upgrading a standard appliance to a connected one, or the annual software platform costs for participation in a DR program—not the total underlying costs of equipment or maintenance.
[16] Note that in our enrollment modeling we consider only the incentives offered to customers for enrolling, or remaining enrolled, in a DR program, and not any incentives offered for participation in individual DR events.

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 via fractional regression using DR program enrollment data provided by one of the IOUs[17] for the Phase 4 study. To eliminate vacant buildings from our sample, we excluded electricity customers who did not satisfy minimum electricity consumption requirements from the dataset.[18] We then calculated the per-kW incentive offered by taking the following steps. First, we reviewed the sign-up bonus and/or retention incentive (i.e., the credits earned by maintaining the DR program participation regardless of the actual load shifting or reduction) that IOU and third-party program providers provide to their participants. Next, we estimated the total bonus by annualizing the sign-up bonus over 3 years and adding the expected annual retention incentive. Finally, we divided the total incentive estimates for each customer by their peak annual kW load. In the case of electricity customers who were not enrolled in any DR programs, we treated them as having declined the maximum incentive that they would have been eligible to receive by enrolling in one of the programs for which they were eligible. Using these incentive and participation data as inputs, we conducted fractional regression analyses to predict the enrollment probabilities as a function of sector, climate region, CARE rate status (for the residential sector), building type, building size, and per-kW enrollment incentive. The result is an adoption probability curve, as a function of enrollment incentive, for each modeled customer class. Figure 4 shows the curves for three example customer classes. Note that for each customer class, a fraction of customers are willing to enroll for zero incentive, with an increasing fraction enrolling as incentives grow.

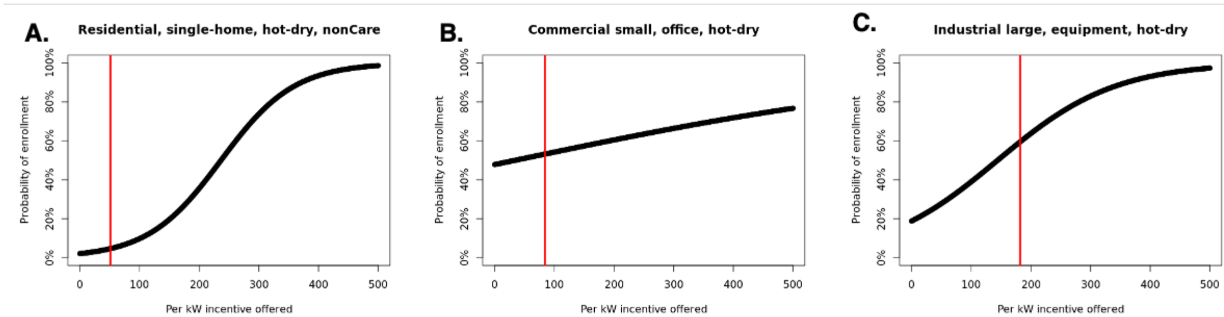

Figure 4: Estimated enrollment probability for each level of per-kW incentive offered for example residential customers (left), medium-sized commercial customers (middle), and large-sized industrial customers (right). Red lines indicate the maximum annual per-kW incentive offered by current IOU and third-party programs.

Discussion and Conclusion

Phase 4 of the California DR Potential Study will provide a substantially improved and updated picture of the potential DR resource in California. New, more recent customer and load

[17] All three IOUs provided program enrollment data for this study; however, much of the data did not have an appropriate level of detail or an accessible format for this study; therefore, we estimated the model for a single IOU and extrapolated to the others.

[18] To exclude electricity customers with no consequential electricity consumption (i.e., vacant buildings), we used 10% of the minimum of electricity allocated for the lowest consumption tier in residential tariffs (≥417kWh), 1% of the CA average commercial electricity consumption (≥621kWh), and 0.1% of the CA average industrial electricity consumption (≥322kWh) for the electricity consumption thresholds.

shape data provides an updated picture of customer loads, and an updated LBNL-Load drastically 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 in LBNL-Load will provide 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 will accurate and provide up-to-date insight into the cost of procuring DR from different customers and end uses. All of these updates aim to more thoroughly characterize the DR landscape, which is likely to evolve rapidly under the combined effects of growing VRE generation and electrification in California.

Findings from Phase 4 of the DR Potential Study will be made public in a report planned for release in late 2022; here, we have described the key updates to the methodological framework that underpins the study. Even in the absence of final model results, based on the updated methodology presented here, it is possible hypothesize about the main changes that may emerge. The changes to the system net load shape through 2050, as modeled with LBNL-Load (see Figures 1 and 2) will have profound impacts on the nature of the need for DR in California, as well as on the available resource. The 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 size and 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 and shift earlier and later, respectively. This evolution may alter the set of end uses that can most effectively provide shift DR.

Inspection of Figure 1 shows that the change in peak timing is driven by the growth of electrified loads such as EV charging and water heating. Many of these loads are highly flexible, and an opportunity exists to install networked controls at the time of electrified device installation, to unlock the DR potential that these loads represent. In this sense, the emerging new system peak contains the keys to its own mitigation. Existing flexible loads that have a significant presence throughout the year—such as commercial refrigeration or lighting—may also have an increased role to play. By contrast, space cooling, which has been the traditional workhorse of shed DR, seem poised for a substantially smaller role, given its increasingly reduced coincidence with the system peak.

The specifics of which end uses will be the most viable as future DR resources in the will depend on the cost of outfitting them with enabling technologies—such as networked controls for EV charging, smart appliances, or thermal energy storage for commercial refrigeration—as well as on the willingness of the relevant customers to enroll in future DR programs. The thoroughly refreshed treatment of these questions in DR-Path, coupled with the dramatic expansion of the load modeling scope in LBNL-Load, will paint a thorough and detailed picture of the complex and evolving interplay between DR resources and DR needs that is expected to play out in California over the coming decades, against the backdrop of growing VRE generation and electrification. The Phase 4 California DR Potential Study will thus serve a critical guidepost for setting appropriate DR targets to support California's renewable future.

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References

Alstone, Peter, Jennifer Potter, Mary Ann Piette, Peter Schwartz, Michael A. Berger, Laurel N. Dunn, Sarah J. Smith, et al. 2016. "Interim Report on Phase 1 Results. 2015 California Demand Response Potential Study: Charting California's Demand Response Future." California Public Utilities Commission. https://www.cpuc.ca.gov/WorkArea/DownloadAsset.aspx?id=10632.

———. 2017. "Final Report on Phase 2 Results. 2025 California Demand Response Potential Study: Charting California's Demand Response Future." California Public Utilities Commission. https://www.cpuc.ca.gov/WorkArea/DownloadAsset.aspx?id=6442452698.

Blair, Nate, Nicholas DiOrio, Janine Freeman, Paul Gilman, Steven Janzou, Ty Neises, and Michael Wagner. 2018. "System Advisor Model (SAM) General Description (Version 2017.9.5)." NREL/TP-6A20-70414. Golden, CO: National Renewable Energy Laboratory. https://www.nrel.gov/docs/fy18osti/70414.pdf.

CAISO. 2016. "Fast Facts: What the Duck Curve Tells Us about Managing a Green Grid." https://www.caiso.com/Documents/FlexibleResourcesHelpRenewables_FastFacts.pdf.

CAISO, CPUC, and CEC. 2021. "Final Root Cause Analysis: Mid-August 2020 Extreme Heat Wave." http://www.caiso.com/Documents/Final-Root-Cause-Analysis-Mid-August-2020-Extreme-Heat-Wave.pdf.

California OEHHA. 2017. "SB 535 Disadvantaged Communities." Text. OEHHA. 2017. https://oehha.ca.gov/calenviroscreen/sb535.

Energy Solutions. 2022. "CaliforniaDGStats." 2022. https://www.californiadgstats.ca.gov/.

EPA, U.S. 2021. "Connected Criteria for Partners." 2021. https://www.energystar.gov/products/smart_home_tips/about_products_connected_functionality/connected_criteria_partners.

Faruqui, Ahmad, Ryan Hledik, Sam Newell, and Hannes Pfeifenberger. 2007. "The Power of 5 Percent." *The Electricity Journal* 20 (8): 68–77. https://doi.org/10.1016/j.tej.2007.08.003.

Garcia, Cary, Anitha Rednam, Heidi Javanbakht, Stephanie Bailey, Ingrid Neumann, and Quentin Gee. 2022. "Final 2021 Integrated Energy Policy Report, Volume IV: California Energy Demand Forecast." CEC-100-2021-001-V4. Sacramento, CA: California Energy Commission. https://efiling.energy.ca.gov/GetDocument.aspx?tn=241581.

Gerke, Brian, Giulia Gallo, Sarah J. Smith, Jingjing Liu, Peter Alstone, Shuba V. Raghavan, Peter Schwartz, Mary Ann Piette, Rongxin Yin, and Sofia Stensson. 2020. "The California Demand Response Potential Study, Phase 3: Final Report on the Shift Resource through

2030." DOI 10.20357/B7MS40. Lawrence Berkeley National Laboratory. https://eta.lbl.gov/publications/california-demand-response-potential.

Gill, Liz, Aleecia Gutierrez, and Terra Weeks. 2021. "2021 SB 100 Joint Agency Report." CEC-200-2021-001. Sacramento, CA: California Energy Commission. https://www.energy.ca.gov/publications/2021/2021-sb-100-joint-agency-report-achieving-100-percent-clean-electricity.

Joung, Manho, and Jinho Kim. 2013. "Assessing Demand Response and Smart Metering Impacts on Long-Term Electricity Market Prices and System Reliability." *Applied Energy*, Sustainable Development of Energy, Water and Environment Systems, 101 (January): 441–48. https://doi.org/10.1016/j.apenergy.2012.05.009.

Murthy, Samanvitha, Brian F. Gerke, Sarah J. Smith, Aditya Khandekar, Cong Zhang, Richard E. Brown, and Mary Ann Piette. 2022. "A Multi-Level Load Shape Clustering and Disaggregation Approach to Characterize Patterns of Energy Consumption Behavior." In *2022 ACEEE Summer Study on Energy Efficiency in Buildings*. Pacific Grove, CA: ACEEE.

Murthy, Samanvitha, Andrew J. Satchwell, and Brian F. Gerke. 2022. "Metrics to Describe Changes in the Power System Need for Demand Response Resources." *Smart Energy* (submitted).

NREL. 2021. "Electricity Annual Technology Baseline (ATB) Data Download." https://data.openei.org/submissions/4129.

———. 2022. "National Solar Radiation Database." 2022. https://nsrdb.nrel.gov.

Nubbe, V., K. Lee, A. Valdez, E. Barbour, and J. Langevin. 2021. "Grid-Interactive Efficient Building Technology Cost, Performance, and Lifetime Characteristics." Lawrence Berkeley National Laboratory. https://escholarship.org/uc/item/44t4c2v6.

Sathe, Amul, Karen Maoz, Tyler Capps, Rebecca Legett, Debyani Ghosh, Divya Iyer, Micah Turner, et al. 2021. "2021 Energy Efficiency Potential and Goals Study, Draft Report." San Francisco, CA: California Public Utilities Commission. https://pda.energydataweb.com/api/view/2531/2021%20PG%20Study%20DRAFT%20Report%202021_Final.pdf.

Seel, Joachim, Andrew D. Mills, Ryan H. Wiser, Sidart Deb, Aarthi Asokkumar, Mohammad Hassanzadeh, and Amirsaman Aarabali. 2018. "Impacts of High Variable Renewable Energy Futures on Wholesale Electricity Prices, and on Electric-Sector Decision Making." https://doi.org/10.2172/1437006.

Wang, Fei, Hanchen Xu, Ti Xu, Kangping Li, Miadreza Shafie-khah, and João. P. S. Catalão. 2017. "The Values of Market-Based Demand Response on Improving Power System Reliability under Extreme Circumstances." *Applied Energy* 193 (May): 220–31. https://doi.org/10.1016/j.apenergy.2017.01.103.