Title

2015 California Demand Response Potential Study - Charting California's Demand Response Future: Interim Report on Phase 1 Results

Authors

Alstone, P
Potter, J
Piette, MA
et al.

Publication Date

2016-04-01

Peer reviewed

LBNL-2001115

BERKELEY LAB

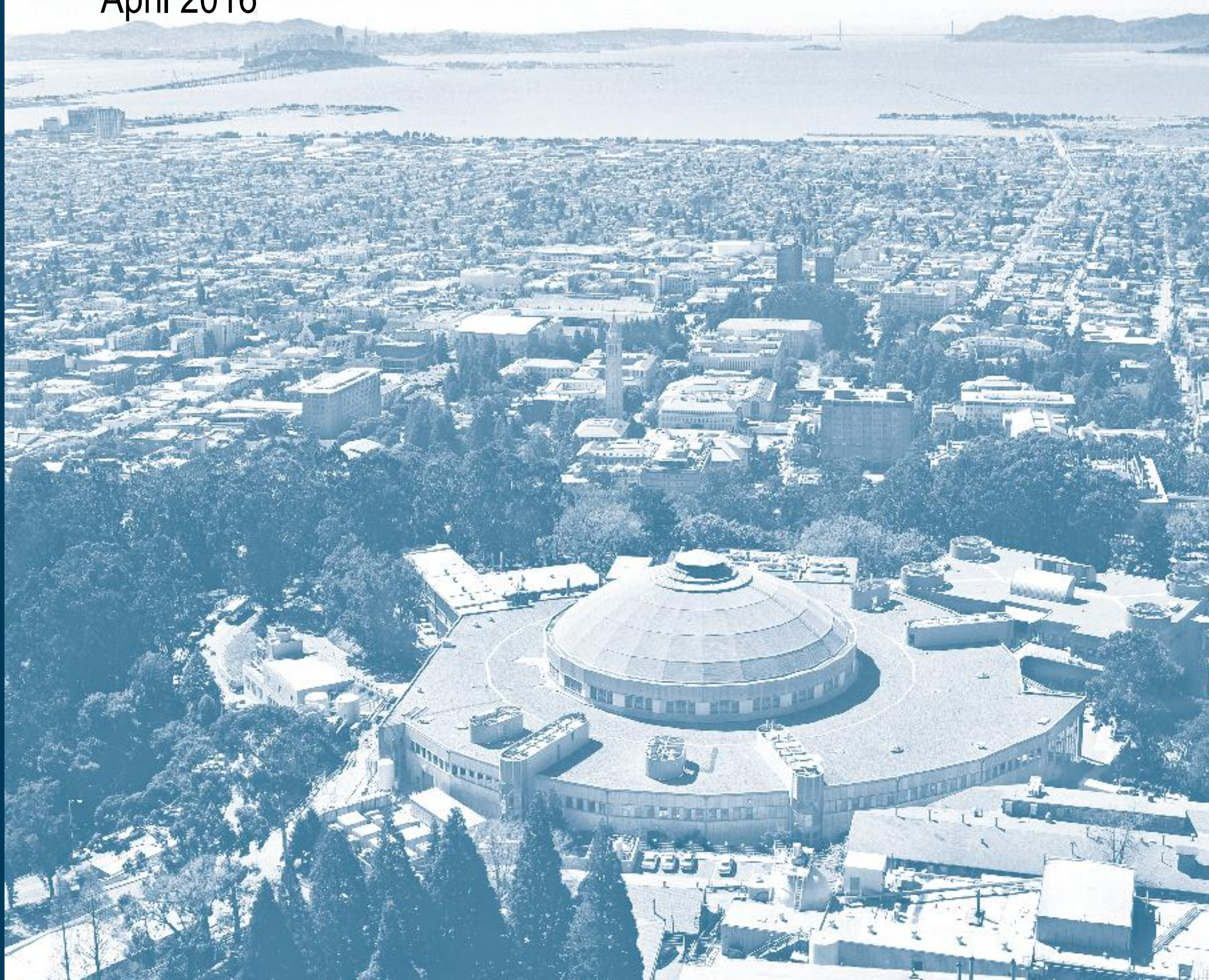
Lawrence Berkeley National Laboratory

2015 California Demand Response Potential Study – Charting California's Demand Response Future: Interim Report on Phase 1 Results

Peter Alstone, Jennifer Potter, Mary Ann Piette, Peter Schwartz, Michael A. Berger, Laurel N. Dunn, Sarah J. Smith, Michael D. Sohn, Arian Aghajanzadeh, Sofia Stensson, Julia Szinai

Energy Technologies Area

April 2016



Disclaimer

Acknowledgments

This work was supported by the Assistant Secretary for Energy Efficiency and Renewable Energy, Building Technologies Office, of the U.S. Department of Energy under Contract No. DE-AC02-05CH11231. The work described in this report was funded by the California Institute for Energy and Environment, which is funded by the California Public Utilities Commission (CPUC), under CPUC Contract No. 13IA5025 UC-CIEE Subaward No. POCP04-L01.

Interim Report on Phase 1 Results

2015 California Demand Response Potential Study

Charting California's Demand Response Future

Peter Alstone, Jennifer Potter, Mary Ann Piette, Peter Schwartz,
Michael A. Berger, Laurel N. Dunn, Sarah J. Smith, Michael D. Sohn,
Arian Aghajanzadeh, Sofia Stensson, Julia Szinai

April 1, 2016

DISCLAIMER

ACKNOWLEDGEMENTS

This work was supported by the Assistant Secretary for Energy Efficiency and Renewable Energy, Building Technologies Office, of the U.S. Department of Energy under Contract No. DE-AC02-05CH11231. The work described in this report was funded by the California Institute for Energy and Environment, which is funded by the California Public Utilities Commission (CPUC), under CPUC Contract No. 13IA5025 UC-CIEE Subaward No. POCP04-L01.

We would like to thank the individuals listed below who provided guidance, assistance, and critical review to the project. We appreciate their substantial contributions to this work. Any remaining errors and omissions are our own.

Thank you to the following CPUC staff for their contributions to this study:

CPUC Energy Division, Demand Response Customer Generation and Retail Rates
Simon Baker, Nathan Barcic, Bruce Kaneshiro, Jean Lamming, Robert Levin, Rachel McMahon, Joy Morgenstern, Maryam Mozafari

CPUC Office of Ratepayer Advocates (ORA)
Sudheer Gokhale

CPUC Office of the Commissioners
Matthew Tisdale

Thank you to the following individuals at LBNL and the University of California for technical assistance and project administration:

California Institute for Energy and Environment (CIEE), University of California
Carl Blumstein, Ken Krich, Eric Lee

Energy Institute at Haas, Haas School of Business, University of California at Berkeley
Andrew G. Campbell

LBNL Building Technology and Urban Systems Division
Norman Bourassa, Jessica Granderson

LBNL Energy Analysis and Environmental Impacts Division
Charles Goldman, Pete Cappers, Joe Eto, Kristina LaCommare, David Lorenzetti, Andy Satchwell

LBNL Energy Storage and Distributed Resource Division
Douglas Black, Jonathan Coignard, Jason McDonald, Janie Page, Sam Saxena. Michael Stadler, Rongxin Yin

Thank you to our project partners from Nexant Consulting who worked with us in the design phase of our DR Potential Approach, specified and fit the propensity score model, and developed the residential TOU analytic approach for estimating load impacts:

Nexant Consulting, Inc.
Josh Bode, Adriana Ciccone, Jon Cook, Ankit Jain, Steve George

Thank you to the following additional individuals in external and partner organizations who provided input, review and guidance to the project:

SLAC National Accelerator Laboratory
Sila Kiliccote, Emre Can Kara

Energy and Environmental Economics, Inc. (E3)
Lucy McKenzie, Ana Mileva, Zachrey Ming, Arne Olson

Brattle Group
Ahmad Faruqui, Ryan Hledik

Navigant Consulting
Debyani Ghosh, Greg Wikler,

CPUC DR Potential Study Technical Advisory Group (TAG)
Kenneth Abreau, PG&E
Fabienne Arnoud, PG&E
Rick Aslin, PG&E
Barbara Barkovich, CLECA
Serj Berelson, Opower
Eric Borden, TURN
Jennifer Chamberlin, Joint Parties
Fred Coito, DNV-GL
Paul DeMartini, Newport Consulting
Chris Ann Dickerson, DAWG
Kent Dunn, Comverge
James Fine, EDF
Debyani Ghosh, Navigant
John Goodin, CAISO
Marcel Hawiger, TURN
Don Hilla, CFC
Eric Huffaker, Olivine
David Hungerford, CEC
Mike Jaske, CEC
Xian (Cindy) Li, CPUC ORA
Mona Tierney Lloyd, EnerNOC
Alex Lopez, Opower
David Lowrey, Comverge
Carol Manson, SDG&E
Mark Martinez, SCE
Ali Miremadi, CAISO
Neda Oreizy, PG&E
Sam Piell, PG&E
Jill Powers, CAISO
Heather Sanders, SCE
Nora Sheriff, CLECA
Mike Ting, Itron
Greg Wikler, Navigant
Gil Wong, PG&E

Table of Contents

List of Figures

List of Tables

List of Abbreviations

AMI	Advanced metering infrastructure
AS	Ancillary services
BAA	Balancing authority area
BAU	Business-as-usual
BEV	Battery electric vehicle
CAISO	California Independent System Operator
CBECS	Commercial Buildings Energy Consumption Survey
CEC	California Energy Commission
CEUS	Commercial End-Use Survey
CPUC	California Public Utilities Commission
DLC	Direct load control
DOE	U.S. Department of Energy
DR	Demand response
DRAM	Demand response auction mechanism
DRRC	Demand Response Research Center
DSM	Demand-side management
EE	Energy efficiency
EIA	Energy Information Administration
EUI	Energy use intensity
EV	Electric vehicle
GW	Gigawatt
HVAC	Heating, ventilation and air-conditioning
IOU	Investor-owned utility
ISO	Independent system operator
IT	Information technology
JASC	Joint Agency Steering Committee
kW	Kilowatt
kWh	Kilowatt-hour
kW-yr	Kilowatt-year
LAP	Load aggregation point
LBNL	Lawrence Berkeley National Laboratory
LED	Light-emitting diode
LLNL	Lawrence Livermore National Laboratory
LMP	Locational marginal price
LSE	Load-serving entity
LTPP	Long-term procurement plan
MECS	Manufacturing Energy Consumption Survey
MW	Megawatt
NAICS	North American Industry Classification System
NEM	Net energy metering
NOAA	National Oceanographic and Atmospheric Administration
O&M	Operations and maintenance
OIR	Order instituting rulemaking
OpenADR	Open automated demand response
PAC	Program administrator cost
PDR	Proxy demand resource
PCM	Production cost modeler
PCT	Programmable communicating thermostat
PDR	Proxy demand resource
PG&E	Pacific Gas and Electric Company

PHEV	Plug-in hybrid vehicle
PV	Photovoltaic
R&D	Research and development
RA	Resource adequacy
RASS	Residential Appliance Saturation Survey
RDRR	reliability demand response resource
RECS	Residential Energy Consumption Survey
SCADA	Supervisory control and data acquisition
SCE	Southern California Edison
SDG&E	San Diego Gas & Electric
SONGS	San Onofre Nuclear Generating Station
Sub-LAPs	Sub-load aggregation points
TAG	Technical Advisory Group
T&D	Transmission and distribution
TOU	Time-of-use
TPP	Transmission planning process
TRC	Total resource cost

1. Executive Summary

1.1. Study overview and motivation

Demand response (DR) is an important resource for keeping the electricity grid stable and efficient; deferring upgrades to generation, transmission, and distribution systems; and providing other customer economic benefits. This study estimates the potential size and cost of the available DR resource for California's three investor-owned utilities (IOUs), as the California Public Utilities Commission (CPUC) evaluates how to *enhance the role of DR* in meeting California's resource planning needs and operational requirements. As the state forges a clean energy future, the contributions of wind and solar electricity from centralized and distributed generation will fundamentally change the power grid's operational dynamics. This transition requires careful planning to ensure sufficient capacity is available with the right characteristics – flexibility and fast response – to meet reliability needs. Figure 1 shows a snapshot of how net load (the difference between demand and intermittent renewables) is expected to shift. Increasing contributions from renewable generation introduces steeper ramps and a shift, into the evening, of the hours that drive capacity needs. These hours of peak capacity need are indicated by the black dots on the plots. Ultimately this study quantifies the ability and the cost of using DR resources to help meet the capacity need at these forecasted critical hours in the state.

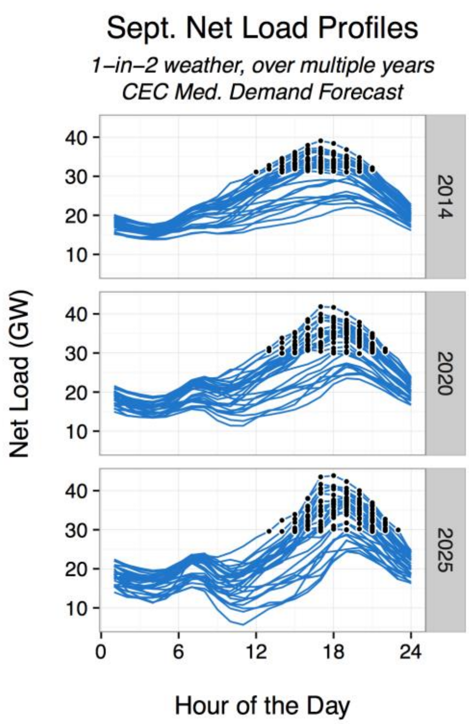


Figure 1: Net load profiles for September in a consistent weather case with growth in renewable generation.

1.2. Scope

Our study incorporates advanced metering, customer demographics, technology and other data to estimate how DR can cost-effectively meet California's electricity grid's fast-changing needs in 2020 and 2025. This Phase 1 report details how DR can meet the system and local peak capacity needs that drive California's resource adequacy (RA) requirements. Phase 2 of our study will broaden the scope to cover more advanced technology options that can enable fast-response DR and help meet California's future capacity and ancillary services needs.

Our study geographically covers the service areas of the three major California, investor-owned utilities' (Pacific Gas and Electric Company (PG&E), Southern California Edison (SCE) and San Diego Gas & Electric Company (SDG&E)) service areas. We worked with staff from each organization to obtain the customer electricity load data needed to support this work. A broader stakeholder group contributed technical expertise as well to inform our study. This technical advisory group (TAG) included representatives from the utilities, DR aggregators, regulatory agencies, advocacy organizations, and others who provided important input that informs our approach and methods.

In Phase 1, we developed a framework for characterizing the cost, performance and availability of dispatchable DR technology options as well as load reductions from time-of-use pricing. The end-uses and dispatchable enabling technology included in the model for this report are listed in Table 1 below.

Table 1: Summary of enabling technology options included in Phase 1 results.

Sector	End-Use	Enabling Technology Summary
All	Battery-electric & plug-in hybrid vehicles	Level 1 & Level 2 charging interruption
	Behind-the-meter batteries	Automated DR (Auto-DR).
Residential	Air Conditioning	Direct load control (DLC), programmable communicating thermostats (PCT).
	Pool Pumps	DLC
Commercial	HVAC	Depending on site size, energy management system Auto-DR, DLC, and/or PCT.
	Lighting	A range of luminaire, zonal & standard control options.
	Refrigerated warehouses	Auto-DR
Industrial	Processes & large facilities	Automated and manual load shedding & process interruption.
	Agricultural & municipal pumping	Manual, DLC & Auto-DR
	Data centers	Manual DR
	Wastewater treatment	Automated & manual DR

1.3. Methodology Highlights

The methods developed for this study make use of advanced metering infrastructure (AMI) data to support new approaches to estimating load profiles and DR availability. At the outset, one of the most important goals of this research was to forecast demand response availability and associated costs in a manner that includes the regional, demographical and behavioral differences between customer groups. Such an approach allows our analysis to uncover the links and nuances between unit costs, candidate technologies, and likelihood of adoption across California's DR landscape.

Our "bottom-up" modeling framework leverages large, customer-level electricity use and demographic datasets provided by each of California's investor-owned utilities (IOUs). The approach extends the methods used in past DR potential studies, which were often limited by having only state-level data. First, our tool groups customers in similar cohorts, which we refer to as 'clusters'. Each cluster represents an aggregation of real customer consumption and demographic information. Each cluster's consumption time series is disaggregating into its constituent end uses, and these end-use baseline load shapes are forecasted to the study years. Second, our tool forecasts likely DR pathways, given existing and emerging technologies, cost projections, and adoption information for the selected forecast years. The resulting pathways represent the likely set of possible futures, given technology adoption and DR products participation. Finally, our tool aims to present the distilled results of our analysis through DR cost versus capacity supply curves. These supply curves provide a visual representation and tool for interpreting the available DR resource in our forecasted scenarios and weather years.

Our modeling framework combines TOU pricing with dispatchable DR availability. Starting with a non-TOU baseline load, we estimate a modified baseline that includes the effects of TOU. This modified baseline is the basis for estimating the availability of dispatchable DR.

When defining the cost of DR technology systems, we use the cost perspective of a DR aggregator who must pay for any incremental need for technology at a site, along with paying for incentives, program administration, marketing and any financing costs. The aggregator can receive revenue from wholesale market participation (in Phase 1, this is constrained to revenues from the day-ahead energy market, which are not expected to contribute significantly to buy down the DR systems' cost). The costs are presented in "levelized" terms—the expected average annual long-run cost, amortizing the initial cost of technology over its lifetime using a 7% weighted average cost of capital. In cases where technology is pre-existing at a site (e.g., if a customer installs a programmable communicating thermostat, or there is pre-existing control hardware from a previous DR program), we reduce the initial costs accordingly based on the expected fraction of sites with that pre-existing stock.

In Phase 1 we developed three core analytical capabilities:

1) LBNL-Load: An end-use, load-forecasting approach that capitalizes on IOU-provided demographic data for the full set of more than 11 million utility customers, and hourly load data for 300,000 customers across the three IOUs. Using these data, we developed approximately 1,500 representative customer clusters characterized by a typical demographic profile, location and hourly, end-use load estimates.

2) DR-PATH: A DR capability analysis model that estimates the potential hourly DR contributions to support system reliability across a diverse set of future pathways. The possible pathways consider the predicted end-use load (from LBNL-Load), technology capabilities, market design parameters, and expected participation rates-derived from the demographic variables.

3) DR-VALUE: An economic analysis framework that estimates the effective RA capacity credit from available DR resources. The DR-VALUE outputs are organized around supply curves that illustrate the quantity of competitive DR across a range of costs.

1.4. Demand Response Pathways for California

To forecast the DR in California we define three potential DR market and technology trajectory scenarios: 1) business-as-usual (BAU), 2) medium, and 3) high. These three scenarios can be compared to the "base" scenario, which describes the DR market and technology characteristics of the baseline time for this study circa 2014-2015. The BAU scenario represents steady incremental progress to improve technology performance and market adoption. The medium and high scenarios explore what is possible with moderate and more aggressive technology and market transformations. Table 2 summarizes the assumptions that define the trajectory of cost, performance, and propensity to adopt DR for the three years we model and report on: 2014, 2020, and 2025. Note: 2014 was chosen as the base year because it was the last full calendar year for which smart meter hourly data were available.

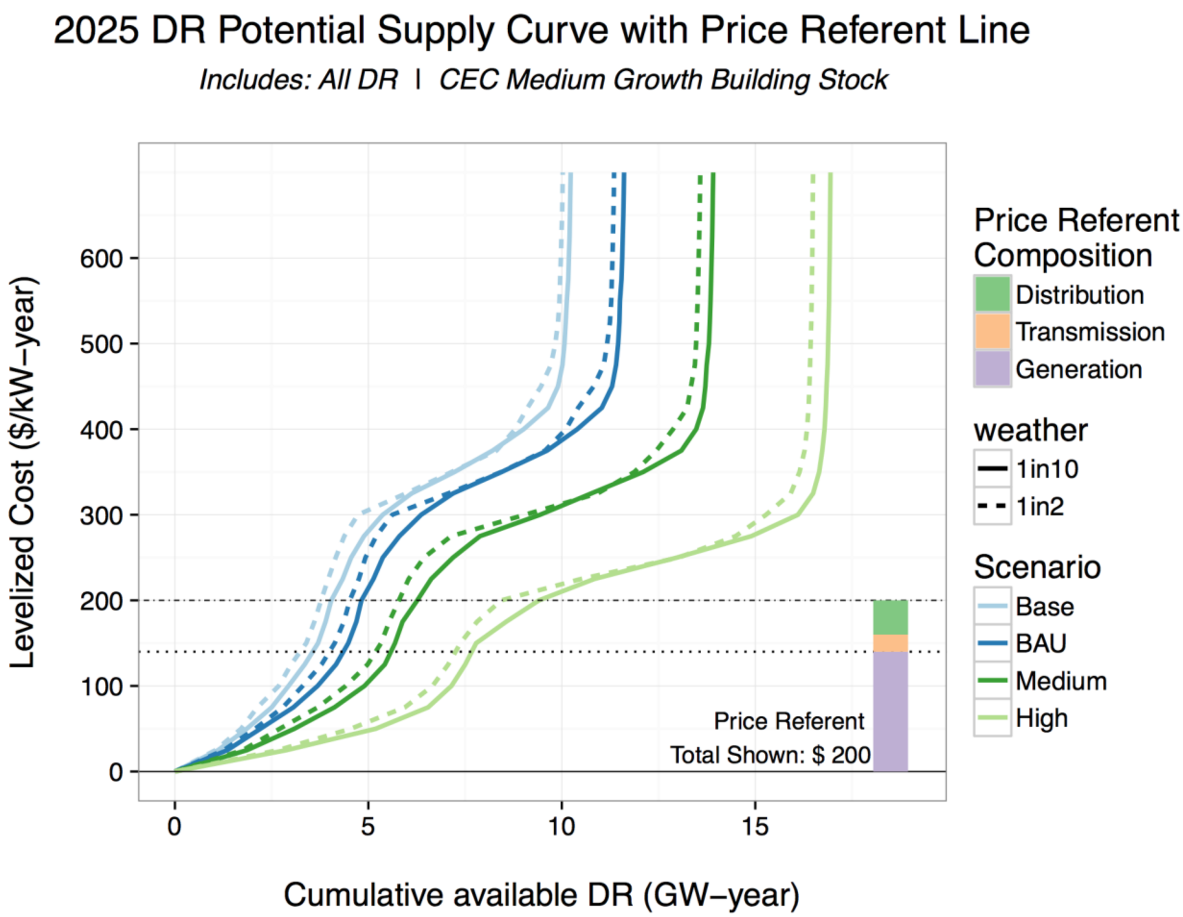
Table 2: Summary of scenario-defining model parameters

Parameter	Description of Parameter	Scenario	2014 Value	2020 Value	2025 Value
Cost	Full cost of DR enabling technology relative to the base cost.	BAU	1.00	1.00	1.00
		Medium	1.00	0.95	0.90
		High	1.00	0.85	0.70
Performance	Quantity of DR service (kW or end-use load fraction) available relative to base performance.	BAU	1.00	1.05	1.10
		Medium	1.00	1.10	1.20
		High	1.00	1.20	1.40
Propensity	Likelihood to enroll and participate in DR relative to base propensity.	BAU	1.00	1.05	1.10
		Medium	1.00	1.15	1.30
		High	1.00	1.25	1.50

In this report, we focus our discussion around the medium DR pathway to maintain consistency in narrative. Our findings indicate that on a medium pathway like the one we define, DR contributions to California's net load capacity needs could more than double by 2025, reaching a total contribution of 6 gigawatts (GW). Compared to an expected 40 GW net load peak, that quantity of DR would represent 15 percent of the net load capacity need. The DR resource mix includes both "load-modifying" and "supply-side" DR resources, terms that are defined by the CPUC rulemaking guiding this study. Of the 6 GW DR resources forecasted in the medium scenario, we expect 4 GW of dispatchable-supply DR, and 2 GW of load-modifying DR from time-of-use (TOU) price load impacts that reduce capacity procurement needs by 2025. For reference, the current-day mix of DR includes approximately 2 GW of dispatchable DR (based on utility program filings) and 900 megawatts (MW) of time-varied price impact (based on our assumptions about the depth of load impacts from current-day TOU pricing).

Our resulting DR supply curves show the available DR quantity for a range of potential levelized cost values (the y-axis). The curves' shapes combine information about the DR technology capabilities, the correlation between site loads and system needs, the enabling technology cost, and the likelihood of enrollment and participation in DR programs or aggregator offers. Figure 2 shows a supply curve with all of the DR categories that the study includes together, combining contributions from supply-side controllable loads (i.e., conventional DR which uses dispatch signals to modify end-use services), behind-the-meter battery storage that can make any load appear to be flexible from the perspective of the grid or system operator, and load-modifying TOU pricing.

Figure 2 includes a price referent line at $200/ kW-year (i.e., $200 per kW of capacity available over the course of the full year) to facilitate our discussion of results. However, the resulting analysis can be presented using any price referent of interest. The price referent defines the limit for cost-effective DR based on the current California practice of valuing DR against the cost of constructing and operating a combined-cycle natural gas turbine and the associated costs to support the transmission and distribution (T&D) systems required to serve load with central generation. The supply curve framework readily allows quick estimates to compare alternative price-referent levels. . If there is a higher willingness to pay (because of local constraints) or a lower willingness to pay (from shifts in the alternative competing technology or misalignment between DR ability to provide service to the bulk power system), it is possible to estimate the quantity of DR at alternative referent points by moving up and down the supply curves to establish a new target price. For example, significant quantities of DR resources are available at the referent price of $100/kW-year: 4.4 GW in the medium scenario, which is 75% of the 5.8 GW resources available at a referent price of $200.



Note: Levelized cost (y-axis) refers to annualized cost per unit of DR capacity, including technology costs, financing, marketing, and administration. Line colors indicate which DR market and technology scenario is used, and the line type distinguishes between a typical "1-in-2" weather case and an extreme "1-in-10" weather case.

Figure 2: Potential DR for 2025, with price referent at a total of $200/kW-year including generation, transmission and distribution capacity.

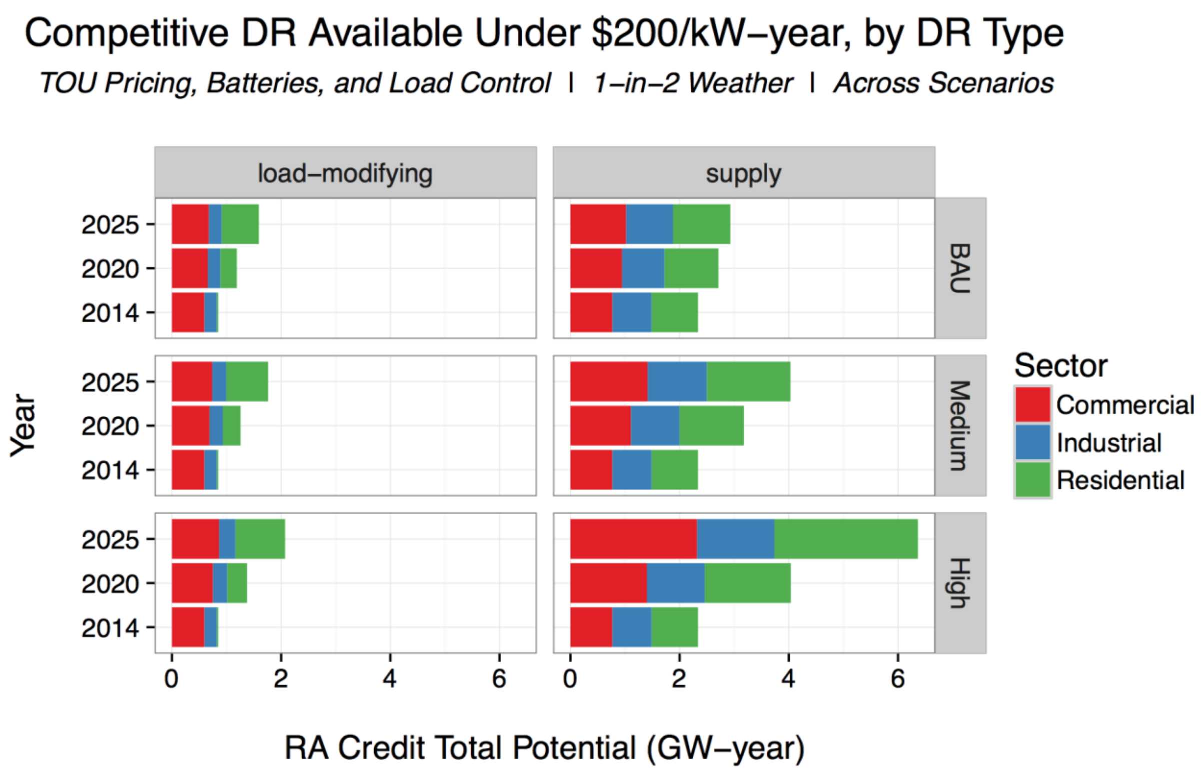
The analysis considers various future DR scenarios, such as a "frozen" DR market with today's cost, market uptake, and performance characteristics held constant with future weather (e.g., a more extreme 1-in-10 weather year). In more severe weather scenarios, when DR is particularly valuable to maintain system reliability, there is also more DR available to meet capacity needs because weather-sensitive loads like heating, ventilation and air-conditioning (HVAC) have a DR capacity resource that scales with load under these weather conditions.

1.5. Key Findings

Overall Resource Size: Our research suggests that California could achieve approximately 6 GW of DR by 2025 at a levelized cost of less than $200/kW-year. These 6 GW are described in our "medium DR" scenario, which we believe is achievable with continued progress in policy, markets, and technology. In the "high" scenario, which could be achieved with more aggressive support for technology research and development (R&D) and higher levels of DR participation, we predict approximately 8 GW of DR is achievable under the referent price above. The results are summarized graphically in the supply curves shown in Figure 2 for 2025, and in a compact summary for the $200/kW-year price referent level in the bar graphs in Figure 3 across multiple years. We expect that DR resource potential will grow over time partly as a result of structural changes in the California building stock (more load from population and economic growth) and shifts in DR markets and technology.

Bifurcation: One way to segment the available DR to meet California's capacity needs is to classify the DR resource base as "load-modifying" or "supply" measures. This DR bifurcation is core to the CPUC rulemaking that this study informs. The defining characteristic of supply DR is participation in the wholesale energy or AS markets. Load-modifying DR's distinguishing feature is that it is a nonparticipant in these two markets. This interim report's results include only one load-modifying measure: expected load impacts from TOU pricing. Supply DR is defined based on a range of possible DR enabling technologies. Although our model shows the apparent size of the load-modifying resource to be smaller than the supply resource, it is notable that **TOU pricing is the most cost-effective option we included in the study, and could contribute substantially to overall DR potential**[1]. Our section discussing the results describes how load-modifying and supply DR should be viewed as two parts of the DR resource base. Shifts in the underlying baseline load (load-modifying DR) can reduce system needs for capacity, but also incrementally reduce the ability of effected loads to participate in wholesale electricity markets as dispatchable DR (i.e., the load impacts from load-modifying DR can reduce the quantity of supply DR available). In general, however, the net combined effect of load-modifying and supply resources at a particular site is undiminished when load participates in both pathways. This highlights the need for careful consideration of the interplay between these resources when creating market and policy plans, since only counting supply DR in isolation without reference to the scale of the complementary load-modifying resource could lead to misaligned incentives and under-counting of the full DR contribution.

[1] Time of use pricing is particularly cost effective because there are no site-level technology enablement costs and while the load reduction at any given site is typically small, the breadth of participation if the rates are default or mandatory (what we include by 2025) provides a substantial statewide effect. The costs for TOU are based on customer-level average incremental additional costs required to set up and maintain periodic communication with customers about rates and strategies for response.



Note: ***Customer sectors are stacked bars depicting cumulative DR potential (GW-yr) falling beneath the $200/kW-year price referent.***

Figure 3: Cost-competitive DR displayed by DR type (load-modifying and supply) by year, scenario and each customer sector.

Diverse technology options: A wide range of DR-enabling technology could provide grid service in the future. Our study shows that although there are meaningful differences among technology options in the expected average DR cost, there are also significant (and often larger) differences in the effective cost of DR between sites that have identical enabling technology but different underlying baseline load profiles. Figure 4 illustrates the relative contributions of technology categories to the medium DR scenario in 2025, under a $200/kW-year price referent. Each technology category is a combination of sector and end-use under control with a range of applicable technology, and the combined average DR cost and quantity in the group based on targeting the highest-quantity DR options available below the specified price referent. We included the price-based, load-modifying DR options that were the most cost-effective DR in the study, followed by a set of conventional and emerging supply technologies. We identify substantial contributions to DR available from HVAC loads in the commercial and residential sectors along with the industrial-process DR that has been a mainstay of incumbent DR programs. There are also emerging DR technology options like commercial lighting, electric vehicles (plug-in and battery), and behind-the-meter storage that are represented in this scenario.

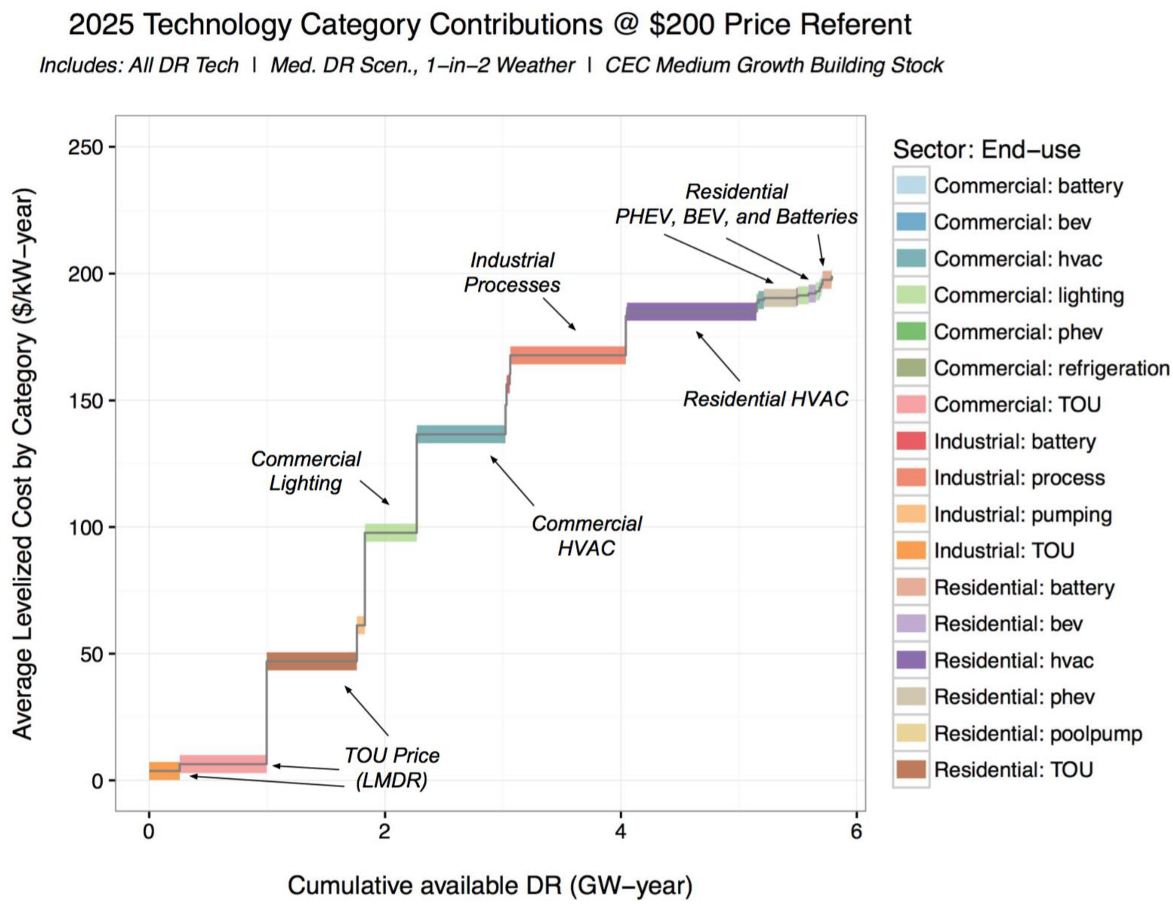


Figure 4: The 2025 technology category contributions below the $200/kW-year price referent. The average levelized costs for each technology category (y-axis) and their contributions to cumulative DR (GW-yr) are shown for the medium DR scenario, 1:2 weather year for all DR technologies.

Targeting DR: Within the categories of technology potential like those shown in Figure 4, there is a large diversity in site-to-site resource potential and cost. In the example of residential HVAC the mean cost for that resource category in Figure 4 is $190/kW-year, but the cost of DR varies over a wide range from site to site, with some sites well below $100/kW-year and others near the price referent used to develop the supply stack, $200/kW-year. Figure 5 shows the potential for residential programmable controllable thermostats (PCT) and how the costs depend strongly on soft-cost contributions (e.g., incentives, administrative and marketing costs). The average cost of DR using PCTs varies based on incentive levels that were included as pathways in the model. The supply curves combine numerous sets of those pathways to identify the available capacity at a range of levelized cost thresholds. Since the model represents a diverse set of customers, there are low DR costs in some cases and much higher DR costs in others. For example the DR from a PCT is more cost effective from a large home that has a larger air conditioner for one PCT, versus a smaller home with less air conditioning. Targeting where to focus DR investment on a site-to-site or portfolio category basis could help improve the overall cost-effectiveness of PCTs as a technology category, as is the case with many of the DR technology options in the study. Visibility into load-reduction opportunities combined with modern data-driven marketing could help unlock DR potential across a range of sectors and technology options.

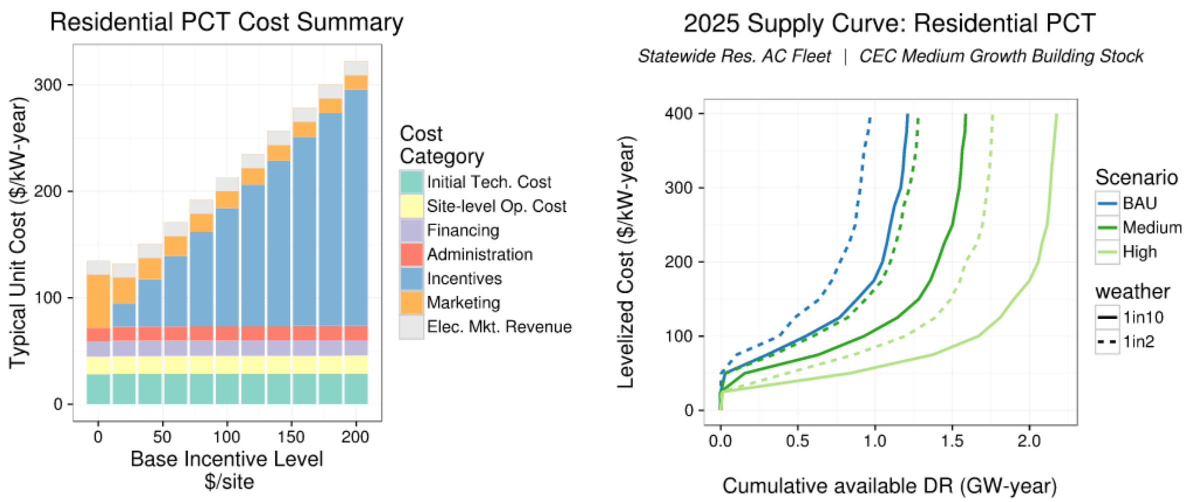


Figure 5: Panel A - Cost contributions to residential programmable communicating thermostat (PCT) DR across a range of possible incentive levels. Panel B - A set of supply curves showing the technology-specific contribution of residential PCT to overall DR Potential for 2025.

1.6. Megatrends

The results of our study should be viewed in the context of several key mega-trends in energy systems: rapid scale-up of renewable generation, energy storage technology advances and fast-changing information technology capabilities and cost. In response to the imperative to reduce climate pollution, recently enacted state policies (e.g., SB 350) will lead to rapid changes in generation and load on California's electric grid (e.g., **tripling of renewable energy by 2025** compared to 2015). The conventional generation fleet was designed and planned to meet demand profiles with a distinct base load and diurnal and seasonal demand cycles driven by weather (like the demand profile in Figure 1 for 2014). With substantial investment in renewables (and ignoring export capabilities), the net load is strikingly different, creating new opportunities and needs for supporting the next-generation grid with new technology and pricing options that can provide reliability services.

Batteries for energy storage have the potential to disrupt the market for capacity on the grid. Driven by device applications and electric vehicles, performance of lithium-ion batteries is rapidly improving, while costs are falling. Our model shows how behind-the-meter batteries could compete if the full system cost were paid for with RA capacity credit. There are also value streams from a range of other potentially available sources. Compared to load-control DR, behind-the-meter batteries offer unique additional services: backup power for critical loads during grid outages, energy arbitrage in response to time-varying price, and generic peak-load management. Combined with the potential for cost breakthroughs that accelerate beyond the trend we use in our forecasting, **battery storage could reset the price referent,** replacing conventional generation or marginal T&D capacity. If the portion of cost allocated to capacity service for batteries were cut in half by a breakthrough in technology cost or multi-value-capture retail offering, the potential DR at a $200/kW-year price referent would be double or more compared to our reference scenario—more than 15 GW in the high DR scenario out of a peak of almost 40 GW.

To set some context, DR is inherently an **information and control technology** approach to providing grid reliability, and is one of several linked information technology (IT) layers that defines the power system—from critical peak-day marketing messages over email to real-time linked supervisory control and data acquisition (SCADA) and electricity dispatch systems. All of these systems have capabilities that depend on the underlying IT, and the ubiquity of connectivity and rapidly falling cost of computing hardware make many consumer-electronics IT applications technically feasible and widely adoptable (e.g., Wi-Fi-enabled thermostats and other connected appliances). Notably, this public-interest study employing detailed bottom-up technology potential models is possible only because large data sets from advanced meters are now available. These meters are already the backbone for settlement for some DR products. As the period of record grows, site data offer a potentially rich information resource for long-term planning, monitoring and verification and retail market transformation.

Similar to the battery case we simulated an **"internet-of-things" (IoT)** breakthrough that could occur (e.g., embedded connectivity and advanced marketing drives the incremental technology cost towards zero, and reduces the administration and marketing costs by half). This modestly shifts the supply curve intersection with the price referent levels we show for discussion purposes (i.e., increases in apparent cost-competitive DR from 5.8 GW to 6.4 GW in the medium scenario with 1-in-2 weather at a $200/kW-year price referent), but leads to substantially more DR available at very low price referent levels.

Ultimately, the scale of DR potential in California will depend on how the policy environment, market design and technology R&D progress over the coming years. Next, we describe recommendations in the context of the emerging next-generation grid DR landscape.

1.7. Recommendations and Opportunities

Based on the process of developing our analytical framework and the findings of our work in Phase 1, and building on team expertise in DR markets, we offer a set of recommendations and opportunities below. These are listed in summary form here and in more detail in the main report. In Phase 2, we plan to use our modeling framework to quantify and explore these areas of opportunity in greater depth.

Beyond widgets - Although there are important strides to be made in DR sensing and control hardware costs, many of the DR costs we identified are "soft" costs related to administration, marketing, incentives, etc. These soft costs can be reduced if DR is integrated with other energy service offerings (e.g., energy efficiency, electrification of heating and transportation, and distributed generation) in mutually supported portfolios.

Open standards – California has made great strides in developing and promoting common standards for DR automation (e.g., OpenADR), and continued support for these is critical for enabling low-cost pathways to DR enabling the evolution of the IoT approaches that use onboard, or built-in device connectivity to support DR.

Open data sets by customer segment and cluster – Given the data privacy and security concerns and legal framework in California, there is a lack of demand-side data available and a missed opportunity to promote research, technology development, public interest policy analysis, and market assessment. It would be useful to explore how to make the data sets from this project available in an anonymized form to facilitate greater understanding California's DR potential and to support the kinds of targeting opportunities that our results identify.

Expand the DR Industry and Improve Customer Outreach and Awareness – California has more than three decades of success in growing an energy-efficiency marketplace. Our experience with DR is growing, but we need to educate, enable, and evaluate customers, account managers, aggregators, policy makers and evaluators regarding DR opportunities and concepts.

Building Codes – California policy makers and IOUs need to continue to explore how to best develop and foster building codes to lower the cost of DR automation and ensure that the intention of the code results in successful compliance.

Multiple Product Participation – This Phase 1 study has a limited set of DR products included in the evaluation. We anticipate that in Phase 2 we will explore the opportunities for multi-attribute grid service provision. Some of the most cost effective DR is likely to be the DR that can be used in multiple programs or markets as the cost of enabling the DR resource can be covered by multiple value streams.

Long-term Market Transformation - Market transformation overcomes market barriers to to shift entire sectors into a more efficient product mix, and has been successfully used to advance energy efficiency in California. A similar perspective is needed to explore how to most aggressively promote a long-term commitment to DR.

DR, Load Shape Comparisons and Peak Demand Benchmarking – Many large commercial building owners know the energy use intensity (EUI) of their building but peak demand intensities and load shape data are much less often available. Making energy consumption benchmarks that effectively communicate the multidimensional attributes of consumption beyond kWh could help lead to institutional and operational awareness of DR.

Continuously improving TOU and load shaping strategies – The net system load profile is changing fast, and there are clear opportunities to mitigate the need for capacity at low cost with smart TOU rates and pricing strategies. It will be important that the evolution of pricing strategies for reshaping the load (e.g., CPUC rulemaking and Joint Agency Steering Committee (JASC) work streams) are coordinated with DR goals and strategies given the linked nature of load modifying and supply DR availability as we describe above.

1.8. Next Steps and Plans for Phase 2

This report summarizes the DR Potential Study Phase 1 results. In Phase 2, which is scheduled to be complete in August 2016, we plan to extend our framework and analysis to include a full set of DR products for supporting the next-generation grid. This will include defining fast-DR product sets that meet broader system needs and improving our inputs and analytical framework.

Additional enabling technology options: In Phase 2, we anticipate working with stakeholders in the TAG to refine our existing set of enabling technology inputs (possibly including new end-use categories like plug loads or large appliances), fortify them with fast and advanced DR capabilities and costs, and develop new potential pathways for a broader set of technology.

Additional load-modifying approaches: We plan to improve and extend our approach to modeling load-modifying DR, aligning our approach to TOU pricing with ongoing Joint Agency Steering Committee (JASC) efforts across a range of rate design scenarios from that work, incorporating critical peak-day load-modifying approaches (based on both price and behavioral notifications), and incorporating the best available information about the "load-modifying" value of dispatched DR that serves distribution system capacity needs.

Additional DR Products: In Phase 1, we addressed energy and reliability DR products with specific characteristics built around today's markets. In Phase 2, we will introduce flexible products that can provide ramping services or fast DR for AS and determine the value they provide to a grid system that has increasing levels of renewables. We will explore how DR can fit into the power system as a distributed energy resource, forecast what value it can provide as a tool to integrate renewable resources, and the cost-effectiveness of various DR resources during the next 10 years.

Multi-product economic analysis: Our Phase-1 approach to modeling DR economics was based on collapsing the resource to a single effective capacity cost that is not linked to other value streams and that is compared to a market price referent. In Phase 2, we plan to work with E3 to integrate our analysis with existing models for multi-market participation of DR in advanced grid service products. We expect to develop new capabilities for using an equilibrium operations and investment model for the California grid (RESOLVE) to estimate the value of ramping and fast DR, and to validate and improve our Phase 1 capacity credit allocation approach in collaboration with E3 and based on their experience in developing the RECAP model. The Phase 2 approach will provide a way to estimate DR's potential value for both capacity and other grid needs in combination and in dynamic competition with a mix of conventional generation and grid-scale storage.

2. Introduction

2.1. Background, Motivation and Scope

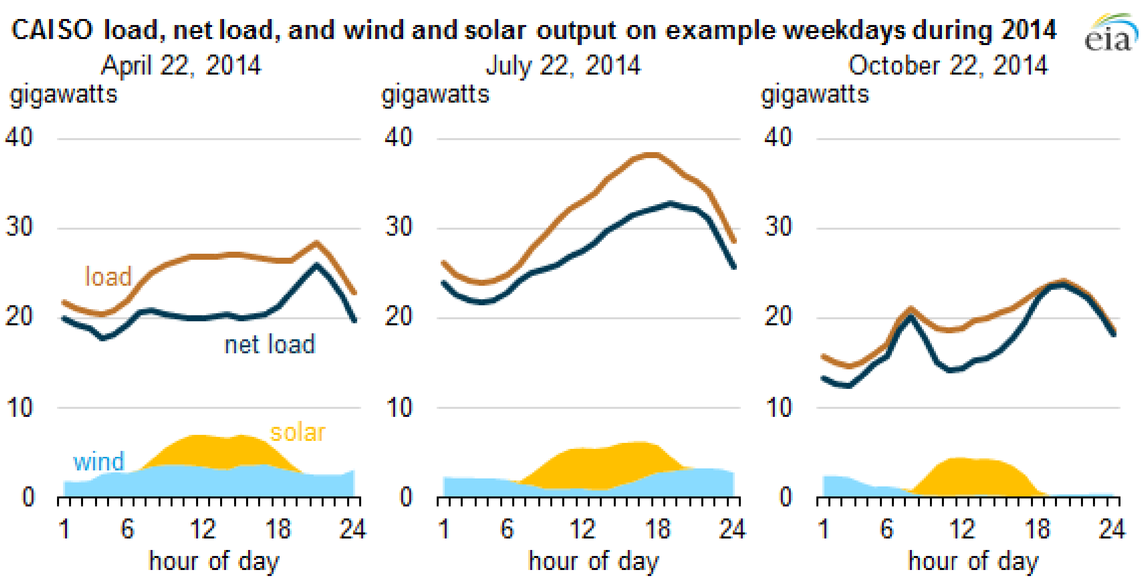
Demand response (DR) is an important resource for keeping the electricity grid stable and efficient; deferring upgrades to generation, transmission, and distribution systems; and providing other customer economic benefits. The California Public Utilities Commission (CPUC) is evaluating how to *enhance the role of DR* in meeting California's resource planning needs and operational requirements. The CPUC recently bifurcated the investor-owned utility (IOU) DR program portfolio into two categories: 1) load-modifying resources, which reshape or reduce the net load curve; and 2) supply resources, which are integrated into the California Independent System Operator (CAISO) energy markets (D.14-03-026). The definitions and operational requirements for each will have important implications for whether feasible DR options can participate and provide value across a range of grid services. The CPUC's decision provides a general framework for the future of DR in California.

This 2015 California DR-potential study is part of the CPUC "Order Instituting Rulemaking (OIR) to Enhance the Role of Demand Response in Meeting the State's Resource Planning Needs and Operational Requirements" (13-09-011). The purpose of this rulemaking was to initiate action to determine the feasibility of bifurcating current DR programs into demand-side and supply-side resources, ultimately enhancing the role of these programs in meeting the state's long-term clean energy goals.

The CPUC's decision also outlined the 2015 California DR Potential Study requirements: to assist the CPUC in setting DR goals and policy based on potential size of the available DR resource, needs, and value. This chapter summarizes the study goals; describes previous related studies; and outlines the methodology used to identify the technical, economic, and market potential for DR in California to the year 2025.

The DR-potential study will investigate the range of DR options and opportunities available to California. DR's current role is to assist in meeting system peak demand, particularly in the summer or in reliability emergency conditions. However, existing and emerging needs for flexibility to integrate renewable energy could be met by DR that is enabled by advancing technologies and innovative market designs. These "flexible DR" resource needs are exemplified by the long-duration, multi-hour, net-load ramps with low minima (i.e., the "duck" curve, see Figure 6) that increase in magnitude as more distributed and utility-scale solar supplies power during daytime hours. The study scope also includes load following, regulation, and broad grid support. The examples shown in Figure 6 are for 2014, the year from which we take demand data to develop the DR estimates in our study. As renewable generation capacity expands, we expect that more peak hours will shift into the evening, with steep downward and upward ramps in morning and afternoon net load. There is little precedent in conventional grid operation for these ramps. In addition, minimum net loads could strain grid operators' ability to keep on line the generation that is required for maintaining reliability unless other resources are utilized. This situation could lead to curtailment of renewables.

The trajectory of the California power system is toward larger fractions of energy provided by wind and solar energy, an increase in new loads such as electric vehicles (EVs), and the potential for greater availability of dedicated energy storage. There have also been dramatic increases in the capabilities of "Smart Grid" information technology systems, with high-resolution visibility and control and new analytic and operational capabilities. A foundation of our study is identifying "system needs" and new ways that DR's technical capabilities can meet those needs. We compare DR to alternative approaches such as traditional ancillary services (AS) from generators, grid infrastructure expansion, and grid-scaled dedicated energy storage technology, and we take into account realistic customer preferences and market dynamics.



Source: Based on CAISO data and CAISO / EIA reports.

Figure 6: Changing system needs in CA for ramping to meet net load have been described as a "duck" curve because of the graph's shape (here, most evident in the net load curve from October 2014).

2.2. Lawrence Berkeley National Laboratory's History of Demand-Response Research

This study builds on research performed during the past decade for the state of California as well as for the U.S. Department of Energy (DOE) by Lawrence Berkeley National Laboratory's (LBNL's) Demand Response Research Center (DRRC). The DRRC was organized in 2003 to conduct research and development to assist the state of California in developing and evaluating DR technologies and policies.

The DRRC developed and evaluated an open automated DR communication system (OpenADR) with support form the California Energy Commission that is used extensively in California and throughout the world. It is now a formal national smart grid standard with certification through the OpenADR Alliance, which has more than 130 members. The formal standard allows for vendors, utilities, scheduling coordinators, and aggregators to use a common language of DR signals, allowing for an open market for innovation in DR automation. Such a standard is intended to reduce the costs of DR by allowing common software to embedded in customer end-use control systems.

In 2013, the DRRC was part of a DOE-funded research team to estimate the value that can be provided to the United States by DR and storage resources participating in energy, capacity, and AS markets in the year 2020 (Olsen et al. 2013). A key part of this past work was developing a method to estimate the capabilities of loads to respond to grid service needs. The past study investigated the loads within the Western Interconnection, and current research is investigating loads within the Eastern and Texas Interconnections.

The DRRC also recently completed a study evaluating the feasibility of demand-side resources to participate in the CAISO wholesale market as a proxy demand resource (PDR). This pilot concentrated on understanding the issues related to direct participation of third parties and customers in PDR, including: customer acceptance, market transformation challenges (wholesale market, technology), technical and operational feasibility, and value to ratepayers (Kiliccote et al, 2015). This study is an important benchmark of the current status of PDR.

LBNL has also performed several scoping studies on the market potential for DR, including a methodology for estimating commercial and industrial customer DR potential, a study of DR's ability to integrate variable renewable generation, and a study of barriers to DR participating in AS.

2.3. How Demand Response Fits into California Public Utilities Commission Goals and Other Proceedings

The transition to bifurcating DR is occurring in the context of other important and related policymaking efforts at the CPUC and California Energy Commission (CEC).

Loading order: In 2003, the principal energy agencies in California established a loading order, putting as high priorities energy efficiency (EE), DR, renewables and distributed generation. This order effectively prioritized decreasing electricity demand before developing more generation, and using renewable and distributed generation before fossil-fueled generation. In 2012, the CPUC reinforced the loading order with a ruling that standardized the planning assumptions across all three IOUs. The CPUC noted an ongoing preference for DR and EE by explicitly noting that "The loading order applies to all utility procurement, even if pre-set targets for certain preferred resources have been achieved."

Planning processes: Three important planning processes could incorporate DR and assist in replacing, or delaying the need for investment in, alternatives to meet the requirements for a reliable and efficient grid: resource adequacy (RA) planning, the long-term procurement plan (LTPP), and the transmission planning process (TPP). These are summarized below:

- RA: In 2004, the CPUC adopted an RA policy framework establishing RA obligations for all load-serving entities (LSEs) within its jurisdiction. The intent is to demonstrate that each LSE has procured sufficient capacity resources, including reserves, to serve its aggregate system load and local reliability needs on a monthly basis. Each LSE must show RA that is sufficient to meet 115% of its total forecasted load.
- LTPP: LTPP by LSEs is a 10-year look-ahead at system, local, and flexible needs, comparing anticipated demand against existing generation and new resources, and excluding retirements.
- TPP: CAISO's TPP is an annual planning process to direct investment in transmission system additions and upgrades in support of a range of system goals.

Valuing DR: The ability to count DR toward RA and the manner in which DR is incorporated in long-term planning are critically important for establishing value streams that incentivize investments in DR technology, programs, marketing, and incentives. A set of DR working groups has been convened to guide the joint parties Joint Proposal (in R.13-09-011), with work on load-modifying DR, supply resources, and a DR auction mechanism (DRAM). These working groups' reports and outcomes inform the current study's inputs and assumptions.

On December 9, 2014, the CPUC issued Decision (D.) 14-12-024. Most important to our study, this CPUC decision approved and outlined a study to assess the DR potential in the service territories of the three largest utilities in California: Pacific Gas and Electric Company (PG&E), San Diego Gas and Electric (SDG&E), and Southern California Edison (SCE).

In its 2014 decision, the CPUC established a four-year timeline to assess the potential for DR, during which working groups are to create recommendations for categorization and valuation of DR programs.

On November 19, 2015, the CPUC issued Decision 15-11-042, which clarified the commission intent to proceed with bifurcation and defined the pathways for valuation of supply and load-modifying resources (specifically that load-modifying resources only provide capacity value through being embedded in CEC load forecasts that are used to set procurement targets). This strict bifurcation is set to be enforced as of 2018. The decision also approved a set of updates to the cost-effectiveness protocols used to evaluate utility DR activity. Our study incorporates both DR resource categories (supply and load-modifying) in a harmonized framework to help inform the continued development of DR markets and programs.

2.4. Previous Research and Comprehensiveness

For each end-use resource in this study, we have developed an hourly load profile incorporating available information on the magnitude, distribution, and timing of energy consumption for 2020 and 2025. Our approach builds on methods we developed in previous studies funded by the DOE and CEC, including a study that LBNL conducted to develop DR availability profiles and constraints for 13 end-uses in California for the year 2020. These DR profiles were used in a production cost model developed by Lawrence Livermore National Laboratory (LLNL), for the CEC's study on energy storage and DR for renewable integration (Edmunds et al, 2013). LBNL provided hourly profiles for regulation products in the AS market and five-minute load-following products in the energy market for LLNL's simulations. LBNL also developed a DR estimate for contingency reserves and defined a flexible product. Additional DR products developed in our past research include capacity products and DR for managing high ramps associated with renewable generation. This current study's methods and approach have evolved from these recent projects.

In previous work, we estimated the magnitude of energy used for each balancing authority area (BAA) using the Transmission Expansion Planning Policy Committee (TEPPC PC1 reference case). We estimated the magnitude of energy used by each sector within BAAs using Itron's predictions of monthly energy use by sector. Figure 7 shows a map of the BAAs for California. Commercial end-use load profiles were obtained from the California Commercial End-use Survey (CEUS) conducted by the California Energy Commission (California Energy Commission 2006). For residential loads, we used residential end-use forecast data from the CEC (California Energy Commission 2012). The research presented in this study aims to improve on prior estimates by incorporating empirical load data provided by utilities. Section xx describes additional details of our methodology.

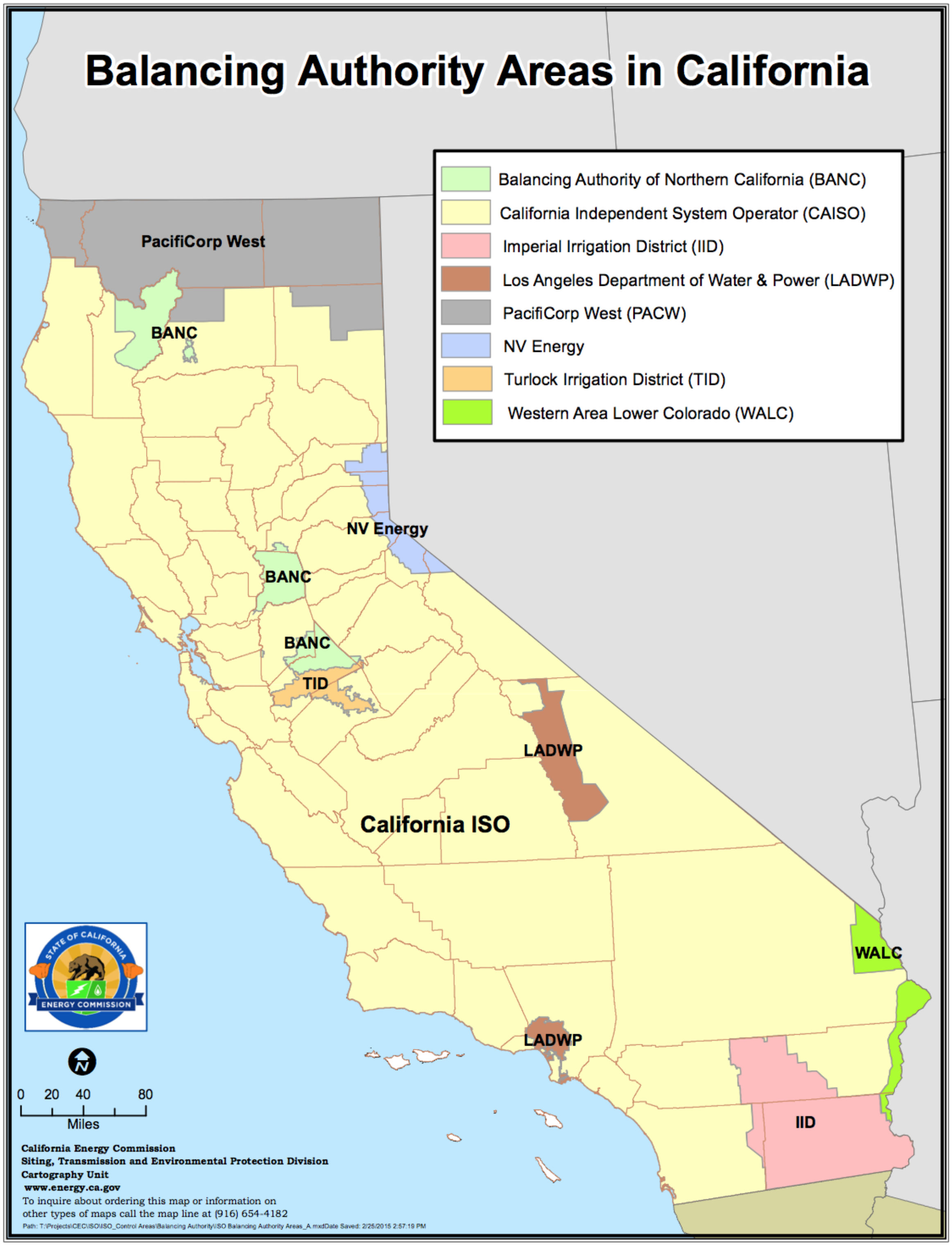


Figure 7: Balancing Authority Areas in California

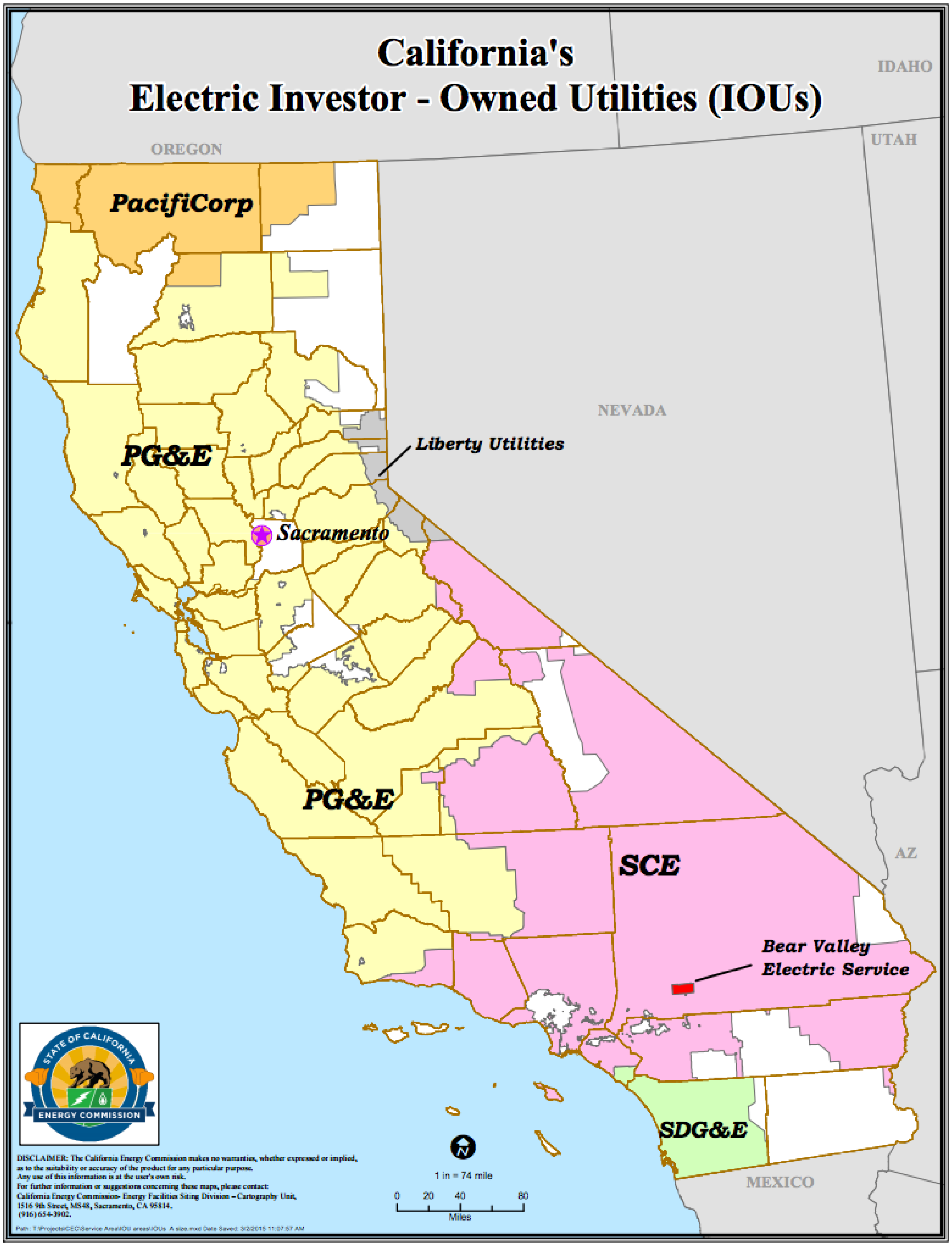


Figure 8: California's Electric Investor Owned Utilities

2.5. Approach and Comparison to Energy Efficiency Studies

This research is the first study to comprehensively evaluate the technical potential, availability and cost-competitive potential of DR in California. We have organized and integrated new economic and market value concepts for DR. This includes new research on the characteristics of DR to ensure it is more concretely valued than has been conducted in the past. California has a strong history of conducting related research on the potential for energy efficiency. This research will extend this tradition into the DR realm, but with changes to the approach and methodology.

One of the challenges of estimating DR's potential in a framework that is useful for planning and policy development is the manner that DR differs from energy efficiency, with regard to measure lifetimes and "durability." Specifically, in efficiency potential studies, each efficiency measure has an assumed lifetime during which it provides a relatively predictable stream of energy benefits from fixed equipment under regular operation. DR products, however, involve a set of strategies and actions taken by customers, or automatically by devices, in response to a system event or signal. These dispatch events may occur frequently or rarely depending on how particular sites participate in day-ahead and real-time electricity and ancillary services markets managed by the CAISO. This temporal variance in DR provision of grid services makes it vastly different from energy efficiency analyses. There are also differences in the durability of resources from year to year. Energy efficiency load reductions last for the full useful lifetime of equipment, while customer commitments to load curtailment are often renewed on a periodic basis (e.g., annually). Therefore, with respect to "measure lifetimes," DR technology attrition includes control equipment failure along with enrollment-related factors like the opt-out rate and effects of move-outs. In the model we developed we employ an estimated lifetime for automation technology to characterize the investment horizon for controls in developing DR levelized costs that includes our best estimate of these combined effects.

This study's approach deviates from energy-efficiency potential studies in several ways. As discussed above, DR measure lifetimes often differ from energy-efficiency (EE) measures, where an end-use can be installed in a site and the savings begin accruing as soon as the end-use become operational. Many EE programs have incentives that are paid through upstream, midstream, or downstream payments. For DR technologies, few of these characteristics apply. Rather, customers are recruited and offered the program via customer account managers, aggregator outreach, direct mail, phone calls, and in some cases, door to door. The DR programs typically have constraints on how often the program will be dispatched, and the customer load availability (i.e., whether the end-use in operation) is uncertain. If the DR program requires automation for signal and dispatch, then installation and provisioning of the technology adds another layer of complexity that is not involved with EE end-uses.

A growing number of integrated demand-side management measures provide both EE and DR capabilities, such as programmable communicating thermostats, or advanced lighting controls or building automation systems associated with space conditioning that enable DR communication.

In EE programs, a utility can commit to a buydown of specific end-uses by their make and model, which are clearly defined by Energy Star standards. Policy at both the state and federal level provides guidance on building codes, lighting, and appliance standards that facilitate adoption of EE technologies. The framework for DR programs and standards is not as well defined. DR enabling technologies, dispatch requirements, qualifying loads, and program rules lack the standardization that EE maintains.

Additionally, because of bifurcation, DR is increasingly seen as a distributed energy resource, that needs to have the flexibility for dispatch across a number of hours through the year. However, the benefit streams for DR are not equal in all hours, nor is the resource available all the time since the program administrators typically constrain the number of events that will be called to increase participation in the programs. End-uses such as HVAC units that are enrolled in the programs are often not running year round or at all hours. These factors complicate how to assess the value and quantity of DR available throughout the year. We note this is an area where the state-of-the-art for EE programs is advancing as well; the same advanced meter data that supports our study can also improve the estimates for EE benefits.

Because of these vast differences between EE and DR, we determined that in order to conduct a holistic DR Potential study, we needed to deviate from the methodology employed in EE potential studies. Existing DR evaluation methods did not fit in that framework. Our team developed a framework that creates supply curves of enabling technologies and end-uses for the DR products in order to determine the potential DR in California. Rather than following the EE framework that looks at the annual technical, market and economic value streams, our approach allows us to examine DR availability on an hourly basis, using hourly load profile customer data, and end-use load profiles to determine the amount of DR available for each hour of the year. Because the value of DR is based on the hourly availability, this methodology gives us the ability to determine how much supply is available for each hour and to weight its value based on overlap with times of system need for specific DR products. For our study, we do away with the references to technical, market and economic potential, and rather, introduce the following:

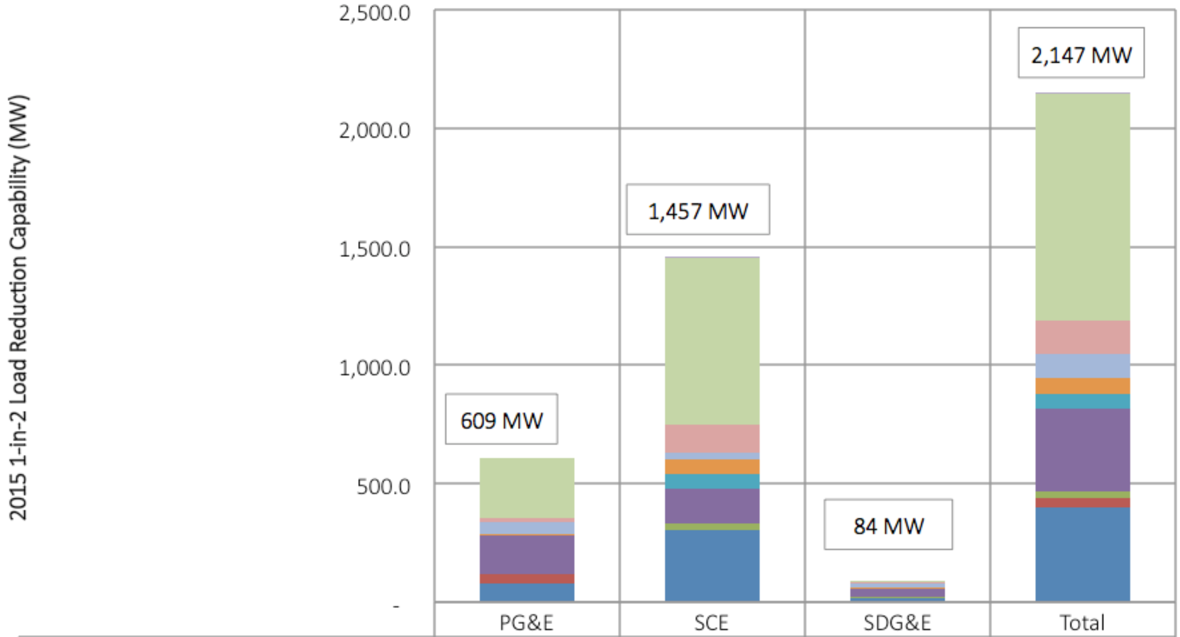
- **End-use Load Forecasts and Technical Baselines**- Segmentation, disaggregation and forecasts of end-uses over a range of customer clusters that represent the population and building stock. These establish the expected baseline gross load disaggregated by end-use across a diverse building stock.
- **Supply Curves of DR Potential**- Development supply curves that synthesize of the costs, availability, sheddability and quantity of DR coincident with system net load needs.
- **Economic Valuation of Cost-competitive DR**- Determination of the value of DR can provide compared to alternative sources of reliability and capacity. The competitive

quantity of DR is based on analysis of the supply curve in the context of the price of alternative technology.

This study is intended to be comprehensive in scope, considering all possible types of DR resources (e.g., capacity, energy, and ancillary services) for California. **For this interim Phase 1 of the study, we address two DR Products from the energy and reliability market, PDR and RDRR, respectively.** These are designed to map to existing CAISO products. We also include a version of the PDR product with binding 20-minute dispatch requirements to estimate the quantity of DR that is available for dispatch that has faster response needs and can better-serve local capacity planning (where dispatch requirements are more strict than for system RA, since the resource diversity is inherently lower in local capacity areas than on the full system).

2.6. Existing DR in California by IOU

Figure 9 shows the existing DR capability by IOU and customer sector in California for 2015. These data show that the IOUs currently provide about 2.1 GW of DR according to the administrative and market settlement frameworks for defining the size of the resource. In the Results section below we comment on how these values compare with the DR in the LBNL model for 2014, which is an important benchmark comparison for our model.



	PG&E	SCE	SDG&E	Total
Non-Res - Real time pricing		2.5		2.5
Non-Res - Interruptible rates	252.1	707.8	1.0	961.0
Non-Res - Demand bidding	21.0	114.5	2.6	138.1
Non-Res - Critical peak pricing	51.5	29.8	20.9	102.2
Non-Res - Air conditioner load control	2.7	64.3	3.1	70.1
Non-Res - Agricultural pump control		59.4		59.4
Non-Res - Aggregator programs	165.7	147.2	34.7	347.6
Residential - Peak time rebates		27.0	5.3	32.3
Residential - Critical peak pricing	36.9			36.9
Residential - Air conditioner load control	78.9	304.5	17.0	400.3

Figure 9: Total DR resource based on filings for 2015. Source: Utility Monthly reports on interruptible load and demand response programs. Filed with the CPUC (A.11-03-001).

3. Methodology

The DR Potential Study model includes three modules that produce results for the years 2020 and 2025, under various scenarios and weather inputs. The first module, the Load Forecaster (LBNL-Load), produces baseline end-use load profiles for customers in every sector (residential, commercial, and industrial) for the years 2020 and 2025. These baselines are fed into the second module, Demand Response Technology Pathways (DR-PATH), which incorporates the capital and programmatic costs, performance and capabilities of available DR enabling technologies and end-uses, and organizes those services into supply curves of available DR for the top 250 hours of the year as those peak hours are when DR would most likely be dispatched/needed. These supply curves are then modified in the Demand Response Economic Evaluation module, which considers non-monetary DR costs and benefits. These modules are illustrated in Figure 10.

We issued three data requests to PG&E, SDG&E, and SCE asking the utilities to provide raw data and reference material to support the analysis. Data collected from the utilities included AMI load data, demographic and billing data, DR program information, program evaluation reports, load research and RASS data, and customer population information that was all used to support our research. For forecasting context and demand response empirical inputs, we incorporated data from publicly available sources, such as the California Energy Commission, CA Department of Finance, NOAA, California Independent System Operator, and the California Public Utilities Commission, and previous LBNL research to help inform the analysis. More information about inputs to each of the modules can be found in their corresponding Appendices (Appendix B).

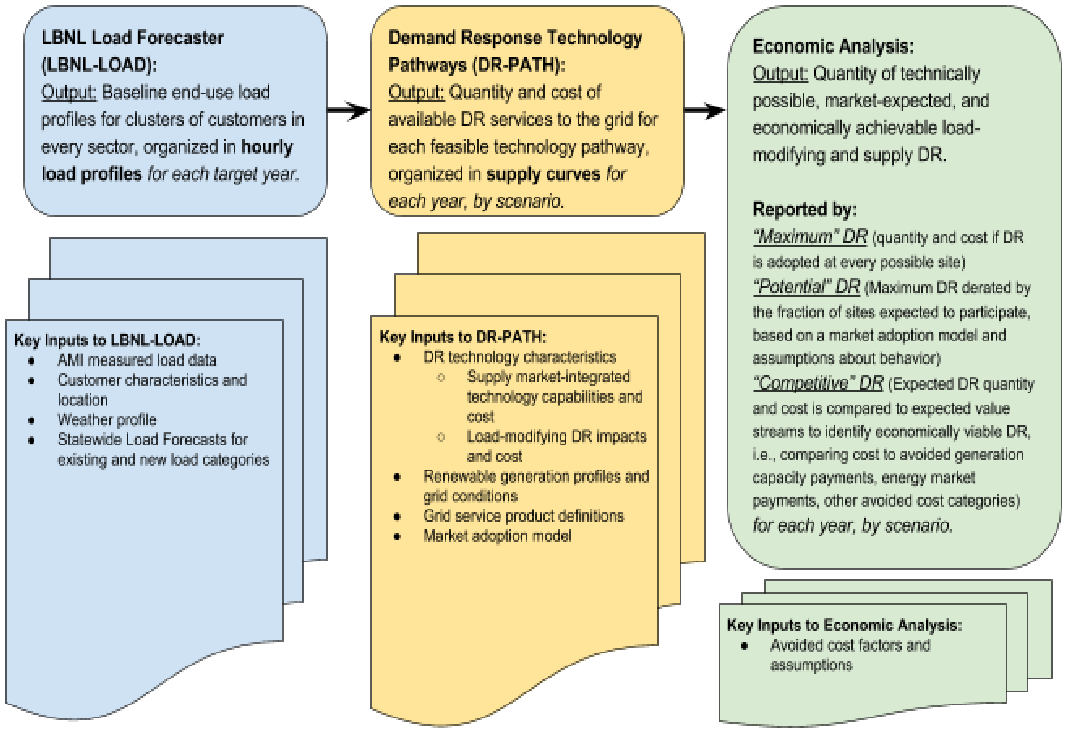


Figure 10: Overview of three modules for forecasting demand response potential.

3.1. Load Forecaster Module

The Load Forecaster module (LBNL-LOAD) is a model, which utilizes detailed demographic and electricity usage data for consumers across California to create bottom-up end-use load forecasts. A full description of the LBNL-Load inputs, methodology, and results are provided in Appendix B.

As shown in Figure 11, LBNL-LOAD consists of four processes. First, customers in each utility are grouped together according to Sub-LAP[2] (see Figure 12), sector, building or rate type, and energy use level to form customer clusters. This process is demonstrated in Figure 13. Hourly load is known for a sample number of customers in each cluster, and this data is used to estimate the cluster's aggregate load profile. These total load profiles are then disaggregated to end-use loads using a set of assumptions along with consumer end-use surveys and industry data. Finally, the resulting end-use loads are forecasted to the desired year (2020 or 2025) for a given electricity demand and weather scenario.

2 California's Independent System Operator (CAISO) has defined 23 Sub-Load Aggregation Points (Sub-LAPs), which are geographic areas that divide the electric grid. Sub-LAPs are the common unit at which day ahead load forecasting is done, and affect how loads can be aggregated into market bids.

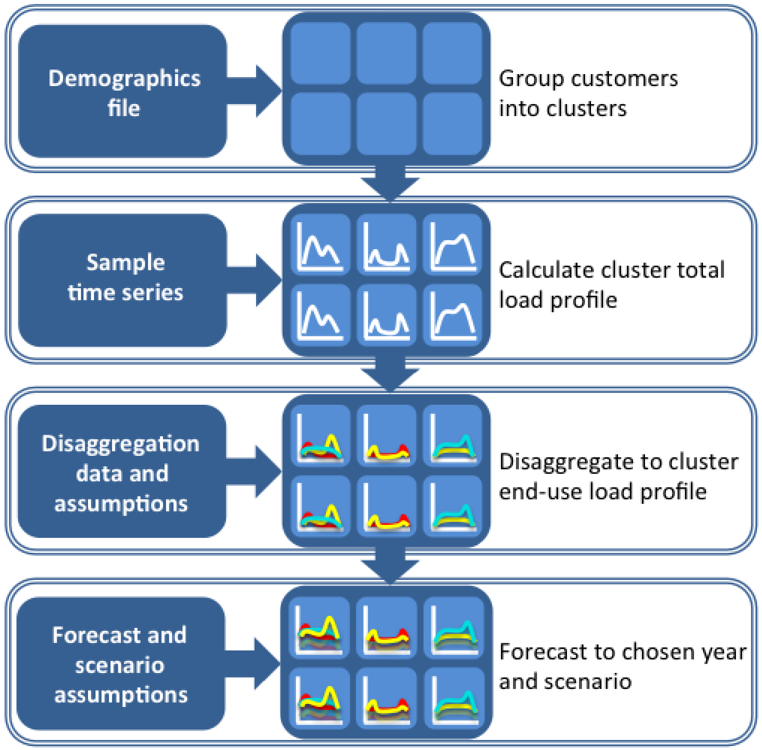


Figure 11: Overview of LBNL-Load methodology.

Figure 12: California Sub-LAPs (CAISO, 2010).

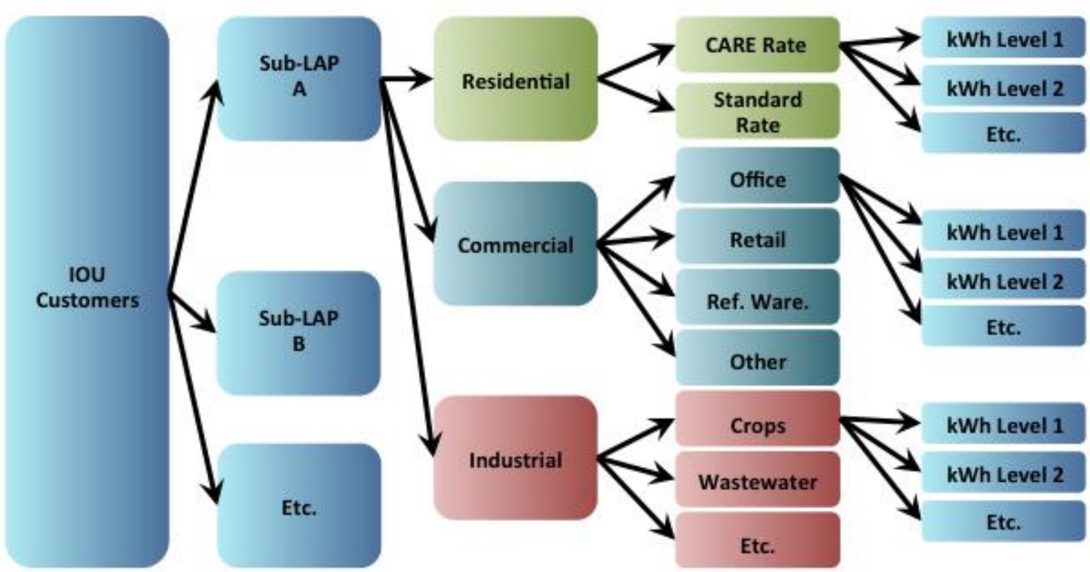


Figure 13: Criteria for grouping customers into clusters.

Table 3: Characteristics of clusters with respect to customer counts by sector.

	Sector	Number of Clusters	5th percentile Customer Count	95th percentile Customer Count	Median Customer Count
1	Commercial	445	20	12,000	1,400
2	Industrial	715	4	1,800	79
3	Residential	226	2,100	190,000	23,000

We defined 1386 clusters in the residential (226), commercial (445) and industrial (715) sectors. The number of customers in each cluster depends on how many similar customers are in each group. For residential clusters, there are typically many customers in each group. In 2014, the median number of customers in residential clusters is 23,000, the 5th percentile is 2,000, and the 95th percentile is 190,000. For commercial clusters the median is 1400, and for industrial the median is 80. Table 3 summarizes the customer count characteristics of clusters. The clusters include growing customer counts through time.

3.2. Demand Response Technology Pathways Module

The Demand Response Technology Pathways Module (DR-PATH) estimates the potential of future end-uses to provide grid service with DR across a range of technology and market pathways. The input to the model includes end-use load baseline forecasts (from the LBNL-Load module), a database of assumptions about the cost and performance of DR technology, attributes of the market and value frameworks, and supporting datasets. Using a set of algorithms (documented in Appendix C), the model calculates the expected cost and quantity of DR available for each end-use in each cluster included in the baseline load. For each LBNL-Load scenario (combination of year, weather, and demand level), the DR-PATH module creates multiple DR-level scenarios experiencing varying technology costs, technology capabilities, and customer propensities to enroll. DR-PATH has **five broad steps to develop estimates for the cost and quantity of DR available:**

1) **Compare the dispatch, telemetry, and load control performance** attributes of each potential DR technology (in the context of the possible sites) with the requirements for DR products.
2) For DR technology system - product matches, **estimate the flexibility potential** for qualified loads and develop an estimate of the RA capacity value for sites that participate through that combined technology and market pathway, adjusted based on assumptions for performance increases if appropriate. This analytical system is an abstraction of the cyber-physical bridge between building systems under control and grid operations, as

shown in Figure 14. The flexibility for each end-use under control is estimated to be equal to the instantaneous load in each hour times a shed factor that defines the continuous fraction of load that can be shed over a sustained period (the duration of the period defined by the grid product).

3) DR's value for offsetting capacity depends on how the DR resource lines up with times of system need on the grid. The approach for defining these periods of need in DR-PATH is based on the estimated system wide net load peaks, including any expected load and intermittent renewable generation. We estimate the **quantity of capacity credit** each DR technology system should be awarded by finding the weighted average shed capabilities during the peak hours of need for the system. In the study we use the top 250 hours of system load to define these hours of need, and assign weights proportionally to the relative magnitude of load hours within that set (i.e., the weight in each of the top 250 hours is based on the system net load in that hour compared to the other 250, with a minimum threshold weight defined so that the top hour in the year gets approximately 4x the weight of the 250th hour). The assumptions and framework for translating hour-to-hour flexibility into capacity credit is critically important for defining the quantity and cost-effectiveness of DR resources, and in Phase 2 we will explore alternative frameworks and assumptions for assigning capacity credit as well to strengthen the approach.

4) Define a set of possible incentives pathways, and compute an **estimated enrollment probability ("propensity score")** for the customer based on the offer and their demographic profile (site type, energy use profile, etc.)

5) Estimate the full **cost of DR technology** from the perspective of an aggregator who pays for technology at the sites, including initial and operating hardware and labor costs, financing premiums, administrative and marketing costs, and incentive payments.

A full description of DR-PATH inputs, methodology, and results can be found in Appendix C.

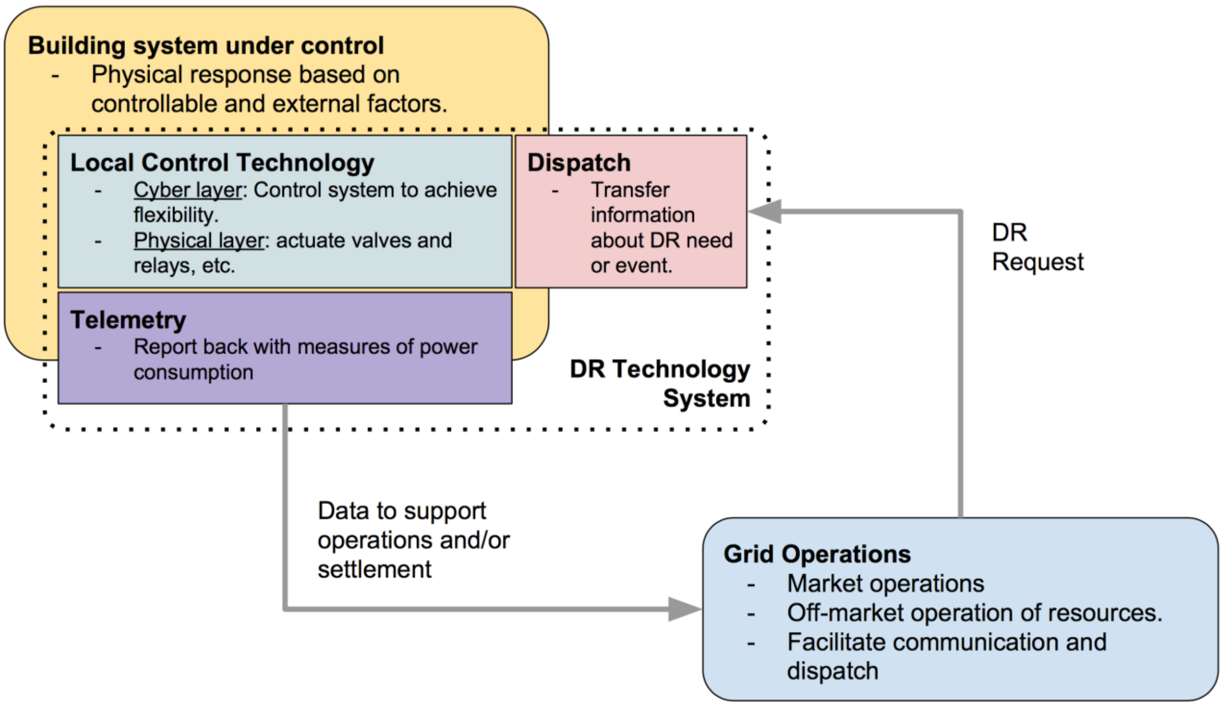


Figure 14: Interactions between the DR technology system, grid operations, and the building systems under control. The dotted area represents the behaviors considered in DR-PATH.

The structure of the DR-PATH model is based on estimating a wide range of possible pathways that each end-use can take for providing DR—a "tree of possible outcomes". This is illustrated in Figure 15 below. For each scenario/year/weather case we estimate the available DR along each possible pathway, including the expected quantity and unit cost of providing DR along the range of possible pathway options. The end-uses defined by LBNL-LOAD with baseline load profiles are fixed in the model, and there are many combinations of technology, markets, and incentive pathways defined for each.

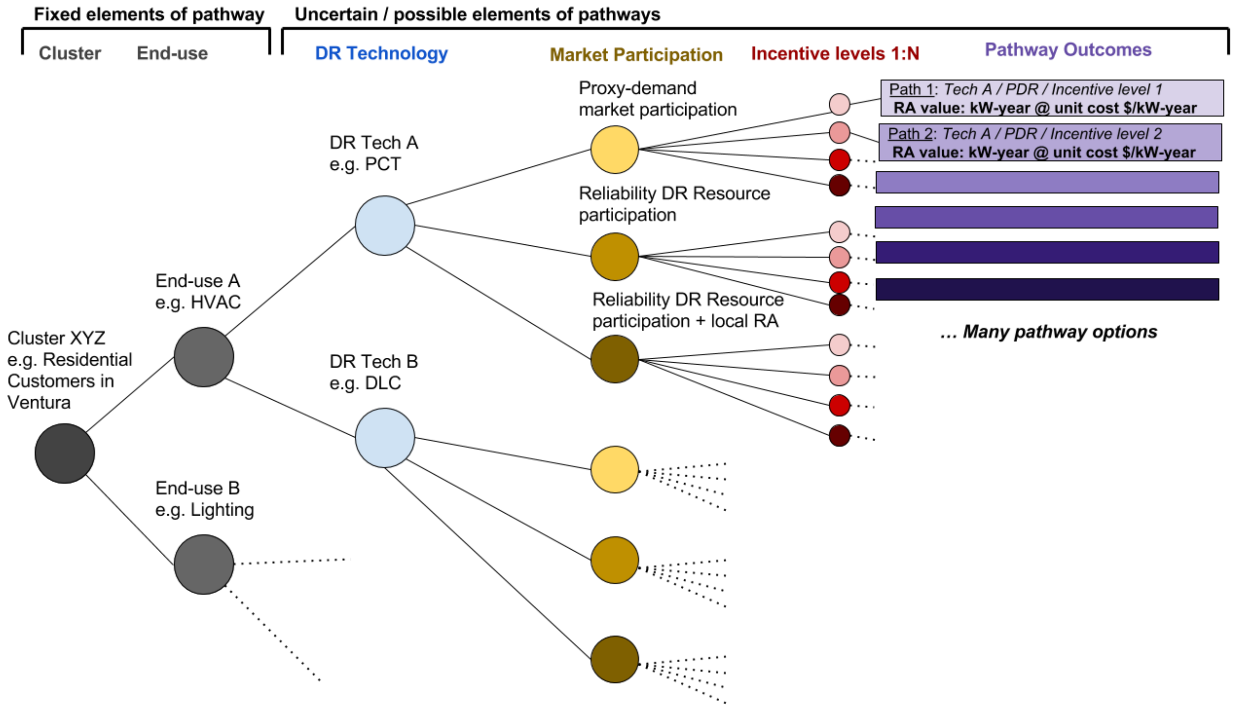


Figure 15: DR-PATH model structure

3.2.1. Propensity Scores

A propensity scoring approach is used to estimate DR enablement and enrollment rates in DR-PATH. In this framework we assume that the parameters used in recruiting customers include the number of events called, incentive levels, targeted end-uses, and marketing.

The approach employed here to estimate participation rates takes five general steps, the details of which are explained in the following Appendix H:

1. Estimate an econometric choice model based on who has and has not enrolled in DR programs. The econometric model estimates the pre-disposition or propensity of customers to participate in DR based on their characteristics.
2. Incorporate information about how different offer characteristics influence enrollment likelihood. Consider: "What is the incremental effect of incentives? How do requirements for on-site installation affect enrollment rates?'' The two questions above have been analyzed using California specific data for residential customers. In each case, a

regression model describes the relative contribution of each of the above factors on participation rates.

3. Incorporate information about how marketing tactics and intensity of marketing influence participation rates. Consider: What is the effect of incremental acquisition attempts? Is there a bump in enrollment rates when phone and/or door-to-door recruitment is added to direct mail recruitment?
4. Calibrate the models to reflect actual enrollment rates attained with existing mature programs.
5. Predict participation rates using specific tactics and incentive levels for programs with and without installation requirements. We provide enrollment estimates for low, medium, and high marketing levels, where specific marketing tactics are specified for each scenario.

All estimates reflect enrollment rates for eligible customers. For example, if 25% of eligible customers can be enrolled but only 40% have central air conditioners, the attainable penetration rate for AC load control is 10% (25% x 40%). The assumptions about marketing tactics underlying the enrollment projections are not prescriptive. Utilities or aggregators can attain the enrollment levels in a number of ways. Appendix H provides a conceptual overview of the probit models that underlie the approach taken here and background to understand how coefficients can be extracted from aggregate level tests.

3.2.2. Technology Input Summary

The DR-PATH model includes/considers performance and cost data for 56 DR enabling technologies we have identified for Phase 1, which are summarized in Table 1. A demand response enabling technology consists of the mix of load control and communications hardware and software that makes loads flexible. Each of the 56 instances of enabling technology are characterized by control and communications options that affect the performance of the technologies in terms of their response time and shed capabilities.

The costs for each of the technologies are separated into upfront costs and operating costs, and differ based on factors including customer sector, end-use, size, and control technology. The DR enabling technologies cost and performance data comes from a variety of sources, including other DR potential study reports, LBNL studies and institutional experience, academic literature, industry and stakeholder feedback, and available market data. The primary enabling technologies modeled were for HVAC, lighting, pumping, and process end-use loads, across the residential, commercial, industrial and agricultural sectors.

Table 4: List of enabling technology options included in the study for Phase 1.

Sector	End Use	Commercial Class/Sector	Enabling Technology Component
Commercial	HVAC	Small, Medium, and Large (separate technology spec for each)	Direct load control switches (DLC)
			Programmable communicating thermostats (PCT)
			Automated demand response (ADR)
	Lighting	Small, Medium, and Large (separate technology spec for each)	Office Luminaire
			Office Zonal
			Office Std.
			Retail Luminaire
			Retail Zonal
			Retail Std.
	Refrigerated warehouses	All Commercial	Automated demand response (ADR)
	Commercial Battery Storage	All Commercial	Automated demand response (ADR)
	Commercial Battery Electric Vehicles	All Commercial	Automated demand response (Level 2 Chargers, Public)
			Automated demand response (Level 2 Chargers, Fleet)
	Commercial Plug- in Hybrid EV	All Commercial	Automated demand response (Level 2 Chargers, Public)
			Automated demand response (Level 2 Chargers, Fleet)
Residential	HVAC	All Res.	Direct load control switches (DLC)
			Programmable communicating thermostats (PCT)
			Direct load control switches (DLC) (50% cycle)
			Programmable communicating thermostats (PCT) (50% cycle)
	Pool Pumps	All Res.	Direct load control switches (DLC, FM telemetry)
			Direct load control switches (DLC, Wi-Fi telemetry)
	Residential Battery Storage	All Res.	Automated demand response (ADR)
	Residential Battery Electric Vehicles	All Res.	Automated demand response (Level 2 Chargers)
			Level 1 Chargers IoT Automated
			Level 1 Chargers, Manual
	Residential Plug in Hybrid EV	All Res.	Automated demand response (Level 2 Chargers)
			Level 1 Chargers, IoT Automated
			Level 1 Chargers, Manual

Sector	End Use	Commercial Class/Sector	Enabling Technology Component
Agricultural / Industrial	Pumping	Agricultural	Direct load control switch (DLC)
			Automated demand response (ADR)
		Waste Water Treatment Pumping	Manual Process Interrupt
			Automated demand response (ADR)
	Process	Industrial	Manual Process Interrupt
			Manual Process Interrupt (day-ahead, deep cut)
			Semi-Automated Process Interrupt
			Automated demand response (ADR)
			Industrial Battery (ADR)
		Data Centers	Manual demand response
		Waste Water Treatment	Manual Process Interrupt
			Automated demand response (ADR)

3.2.3. DR Products

DR is capable of meeting a range of needs in the electricity system that can be organized as a set of grid service products. The DR products identify what end-uses are capable of providing the system need (based on the technical potential), notification and response requirements, and the types of customer response factors (e.g., response signal, automated or manual response). For this study of the California market, we organize the analytical framework according to the following (referencing Figure 16). More details on DR products as a framework is presented in Appendix D.

Bifurcation categories:

- **Supply DR** – DR that participates in one of the Independent System Operator wholesale electricity markets as a pathway to payment for grid service and other additional payments (listed below).
- **Load modifying** - retail market and programmatic approaches to reshaping load with critical-day prices or behavioral signals, permanent load reshaping from time-of-use pricing, or active DR service to support distribution system capacity. Permanent or dispatched load shifting can offset the need to procure conventional or more costly distributed resources.

Supply DR Dispatch categories:

- **Short-run (seconds to minutes) load-following** – contribute stability and provide frequency and voltage support – through regulation and spinning reserves markets (Phase 2).

- **Medium-run (minutes to hours) ramps and curtailment** - reduce reliance on unscheduled import / export (area control error) and avoid overbuilding flexible conventional generation to match a net load with steep ramps – through economic participation in non-spinning reserves and the energy market (day-ahead energy market participation in Phase 1).
- **Emergency dispatch** – availability to respond in case of system or local capacity shortfalls in extreme weather conditions or during times of system failure (reliability / emergency resources included in Phase 1).

Additional payments available

- **System capacity** - Qualifying resources receive payments for forward capacity obligations and ultimately avoid the need for procurement of additional conventional peak capacity. To receive credit resources must participate in energy or ancillary services markets where the capability to reduce peak system net loads is measured for settlement in those markets and assessment of performance (included in Phase 1).
- **Local capacity** – This category is similar to system capacity, but also supports local transmission system operation with local services that avoid the specific need for new transmission. In load pockets there are procurement obligations for local capacity. Qualification to provide local capacity is subject to geographic constraints and additional requirements for dispatch speed (included in Phase 1).
- **Flexible capacity** – These capacity resources are able to support multi-hour net load ramps. (Phase 2)

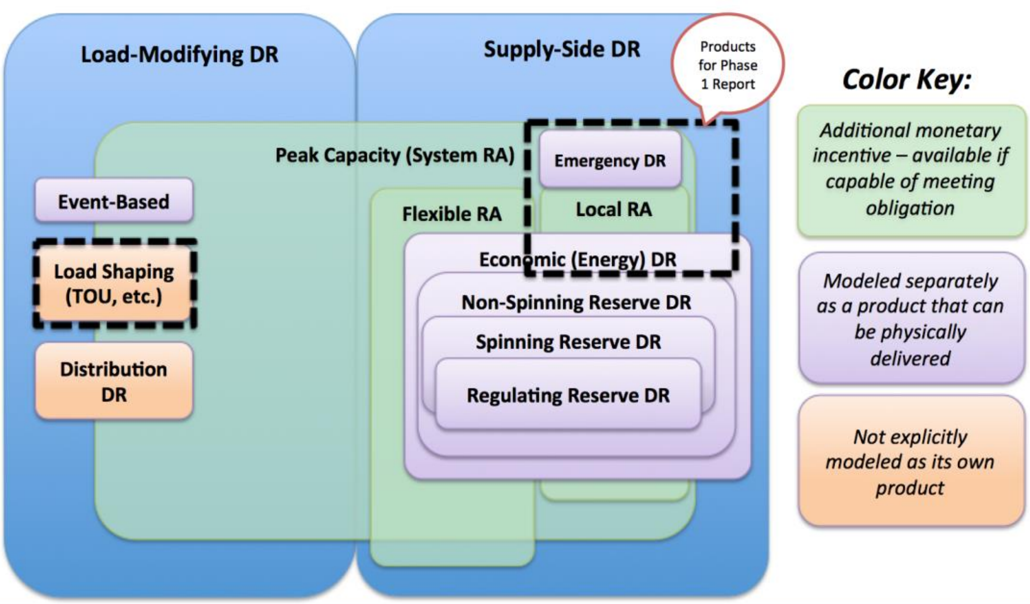


Figure 16: Nested Grid Support Products. DR products Classification by Resource Adequacy Capacity Credit, Supply-side & Load-Modifying DR, illustrating grid support products' interrelationship.

3.2.4. DR Product Market Factors

DR products serve as the foundation of our modeling framework for valuing the available DR resource, and are defined in our analytic framework in terms of product or program rules and requirements (i.e., constraints on technology system performance). Table 5 below lists some of the market characteristics that are relevant for two of the products we are including in Phase 1. Details on the implementation of these in the model are included in Appendix C. **This study considers the following DR market products and concepts for Phase 1:**

- Economic Energy Market Participation (aka: Proxy demand resource (PDR))
- Emergency & Reliability Resources (aka: Reliability Demand Response Resource (RDRR))
- Local & System Resource Adequacy capacity credits
- Load Modifying demand response is evaluated as Time-of-Use tariff

Table 5: *Key features of RDRR and PDR.*

Parameter	Emergency & Reliability Resources (aka: Reliability Demand Response Resource (RDRR))	Economic Energy Market Participation (aka: Proxy Demand Resource (PDR))
Minimum load curtailment* * Not binding in our model, we assume portfolios will achieve this	0.5 MW (500 kW)	0.5 MW Non-Spinning Reserve market 0.1 MW day-ahead & real-time energy
Bid Type	At 95%+ of price ceiling	Economic bid > Net Benefits Test price
Response time for day-ahead energy market	18 hours	18 hours
Metering & settlement	AMI sufficient for market participation unless a very large customer over 10 MW	Using AMI
Sustained run time	Up to 4 hours sustained service	Up to 4 hours sustained service
Dispatch type	Discrete (full on/off) dispatch allowed.	Dynamic within ramping constraints
Maximum dispatch for discrete loads	50 MW	N/A
Availability	Must be available for up to 15 Events and/or 48 hours per term during a 6-month summer & winter from June to September & from October to May.	May be called frequently (several times a month or year)

Our product factors are based on current and expected near-future electricity market designs. Demand response that is bid into the energy market at competitive prices can be thought of as operational or day-to-day DR. It may be called relatively frequently (several times a month or year) depending on the economics of the energy and/or ancillary services market in which it participates. Current CPUC and CAISO rules define an economic market participation product called Proxy Demand Resources (PDR). These PDRs can participate in Day-Ahead (DA) Energy, Real-Time Energy, and Non-Spinning Reserve markets like a generator resource and are valued for RA if they meet certain criteria for performance. RDRR is a wholesale DR product that enables emergency response DR resources to integrate into CAISO market & operations. It is bid into CAISO Day-Ahead Market near the price cap for dispatch in response to a reliability event for Real-Time, "reliability energy" delivery. An RDRR may participate in the Day-Ahead and Real-Time markets like a generator resource, but may not submit Energy Self-Schedules, may not Self-Provide Ancillary Services, and may not submit RUC Availability or Ancillary Service bids.

3.2.5. Capacity credit

The value of DR for offsetting capacity and getting additional payments for meeting Resource Adequacy obligations depends on the overlap in timing of DR availability and times of system need on the grid. Ultimately the need for capacity is driven by the long-run peak load that needs to be carried by the system. The approach for defining these periods of need in DR-PATH is based on identifying critical hours of value using the top 250 estimated system wide net load hours, as shown in Figure 17 below. The net load is the combination of the expected gross demand and intermittent renewable generation. Capacity estimates are calculated using a weighted average of the available DR through the year in those peak hours, with the relative weight for each of the top 250 hours based on the net load relative to other peak hours. We plan to revise and improve on this method in Phase 2 when additional DR value pathways are included in addition to RA capacity credit.

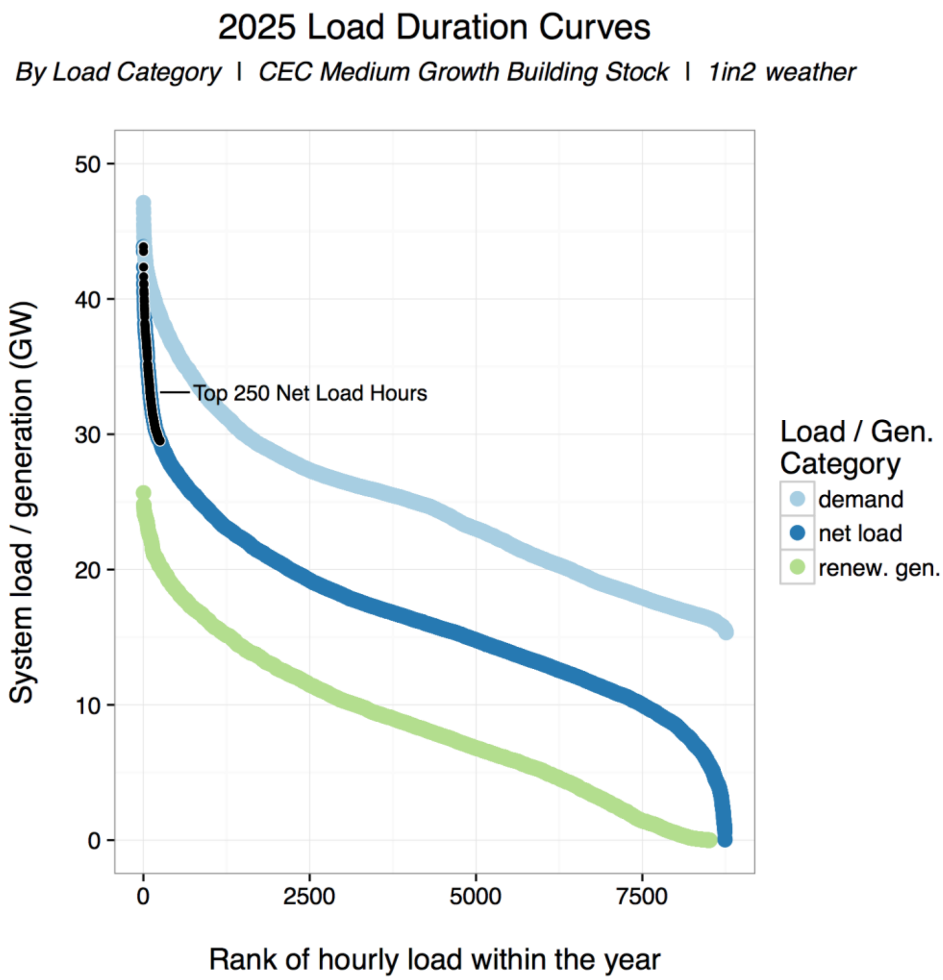


Figure 17: Load duration curves estimated with 2025 building stock and renewables, for the 1-in-2 weather case. The top 250 net load hours are indicated with black points overlaid on the net load duration curve.

The framework and assumptions we have used for assigning capacity weight are critical for the outcomes of the model. We chose to use an approach based on "the top X hours" in Phase 1 to have a simple and transparent framework for assigning credit that is linked to the core driver for capacity needs: meeting long run peaks with generation, transmission, and distribution capacity. It was also important that the metric could be re-calculated within each model run based on specific overlap between the expected demand, DR availability, and renewable generation profiles. We developed the assumption of 250 hours as a benchmark value for defining peak load hours in consultation with the CPUC and our partners in this study, E3 and Nexant. These represent approximately 3% of the load hours, but could account for over 10 GW in additional peak capacity needs, e.g., see Figure 17, showing nearly 15 GW in of marginal peak load in the top 250 hours for the 1-in-2 weather year.

While we use 250 hours to calculate RA credit for DR, this does not imply the resources will all be dispatched for the full period. RA credit is assigned based on the availability to respond (or load reshaping) during those hours of possible need that drive alternative capacity investments. Actual dispatch will depend on the combination of weather-driven system needs, bidding behavior in the market, unplanned equipment failures, and other drivers. We do not model or forecast when dispatch events will happen.

Our estimates for the contributions of renewables in future years are based on current-day operations data for utility-scale solar and wind that are reported publicly on the CAISO OASIS service. These are paired with the coincident estimates for weather in each weather case (the basis for estimating the weather-sensitive portion of the end-use load profile for the case). In the analysis, for each year and weather case, the generation from the statewide fleet of utility-scale solar and wind renewables are estimated based on the expected growth in generation capacity for renewables. We base the expected trajectory of renewable energy generation on current RPS requirements as interpreted by the CEC (listed below), which were most recently updated with SB350 to put California on track for 50% renewable electricity in 2030. The current (circa 2015) baseline is approximately 20%, which is a mix of utility scale solar and wind, geothermal, biomass, and small hydroelectric power. About half of that is the utility-scale renewables in the CAISO data. To achieve a ~40% RPS by 2025, the fleet is increased by a factor of four. The trajectory is reflected in Figure 18, which shows the implied growth in renewable generation over the source of our study periods based on the assumptions we made about the portfolio of future renewable energy investment (similar to todays grid-scale solar and wind power) and pace of development.

Table 6: CEC defined trajectories for renewables in California

CEC Defined Renewables Trajectories	Time Period
An Average of 20%	2011 - 2013
25%	By End of 2016
33%	By End of 2020
40%	By End of 2024
45%	By End of 2027
50%	By End of 2030
No less than 50%	In each Multi-Year Compliance Period Thereafter

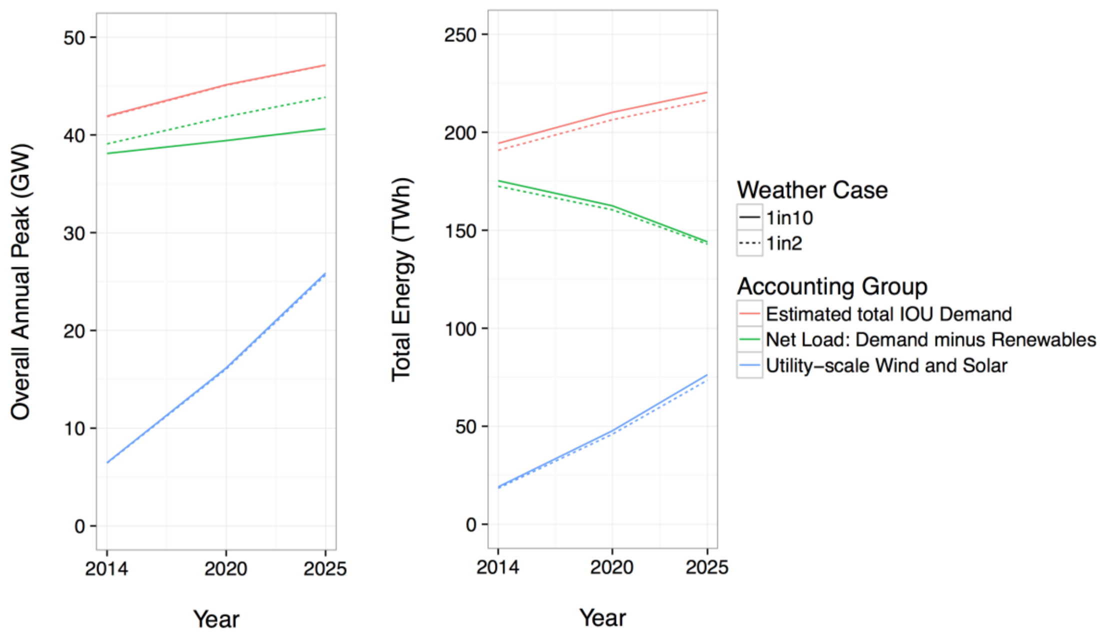


Figure 18: Peak demand/capacity & total energy use of demand, renewables & net load for years & weather cases included in study.

A key dynamic in the evolving power grid is shifts in the timing of system peaks both seasonally and hour-to-hour within peak days. As a point of comparison we provide a series of annual and daily net load profiles for 2014 and 2025 in Figure 19 and

Figure 20. The black dots show the top 250 net load hours. In the typical year circa 2025 we expect these hours occur sporadically throughout the year and with seasonal concentration that depends on the particular weather.

Ultimately, the value of DR in the market (i.e., the quantity that is paid for) is determined through administrative processes that define how DR is measured and settled, which may or may not match exactly with model-based estimates we use to weight the value of capacity. This is an important dynamic to consider when comparing the results of this model to administrative estimates, which use a range of measurement and verification processes to establish baselines, test resource size, and/or conduct ex post analysis.

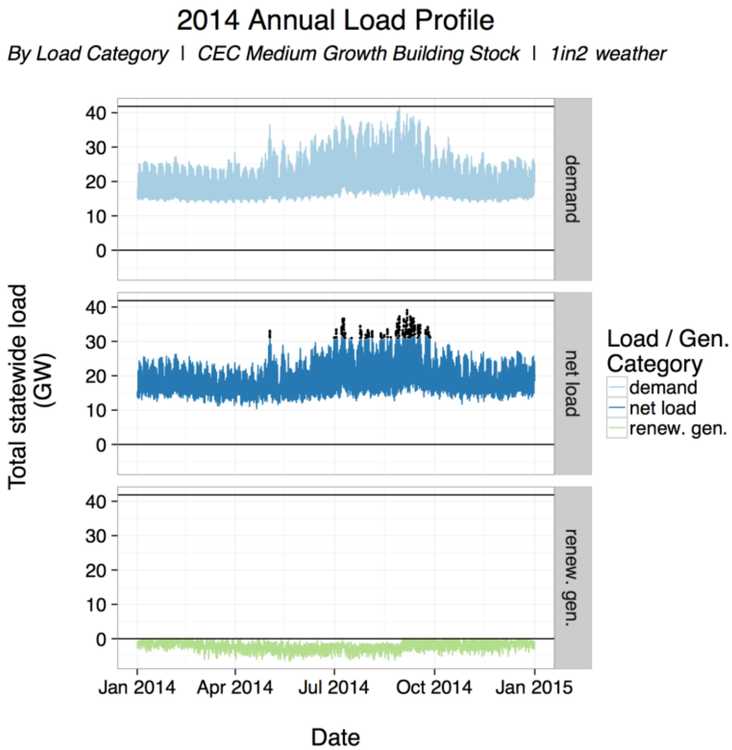
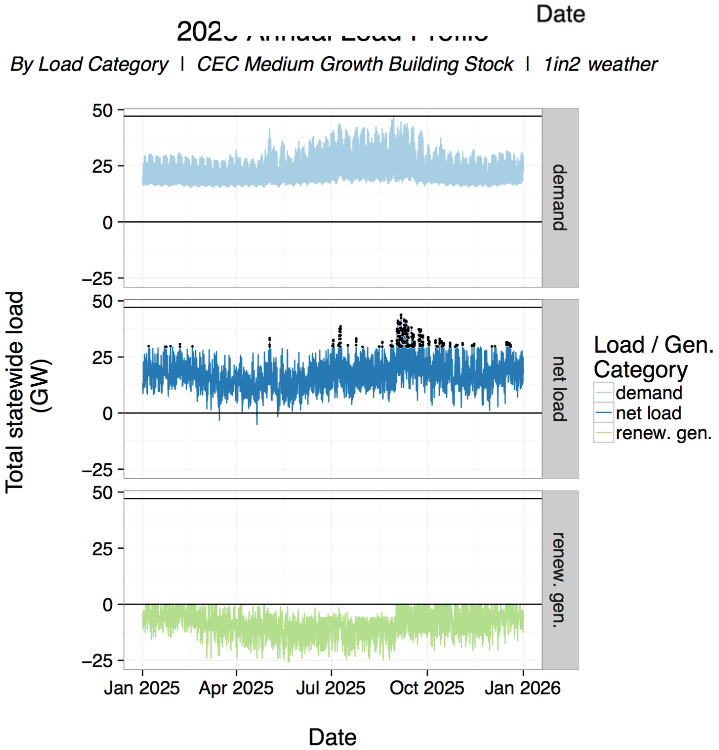


Figure 19: For 2014 and 2025, annual load profiles with the hours of peak system net load (top 250) indicated with black dots. This is using the 1-in-2 weather case and CEC Medium growth building stock assumptions.



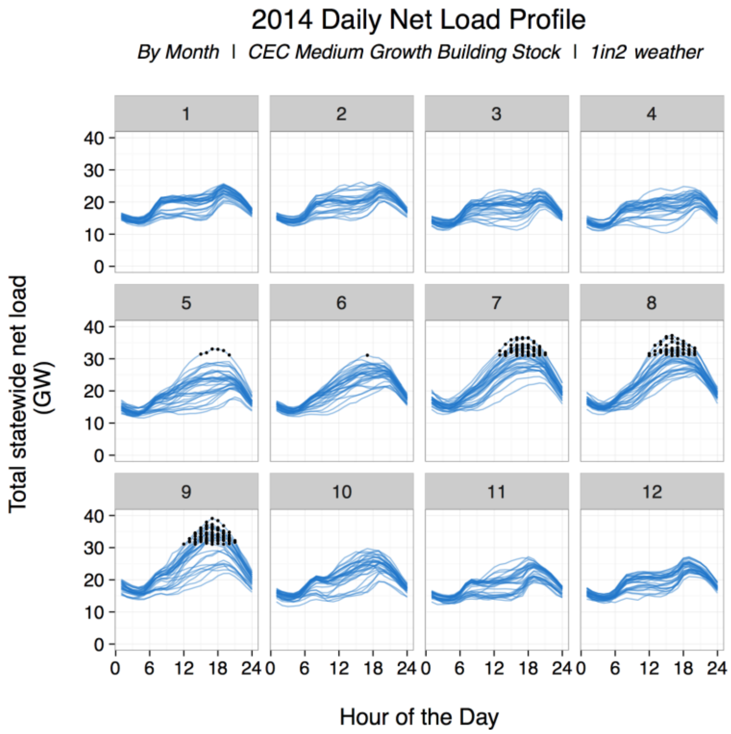
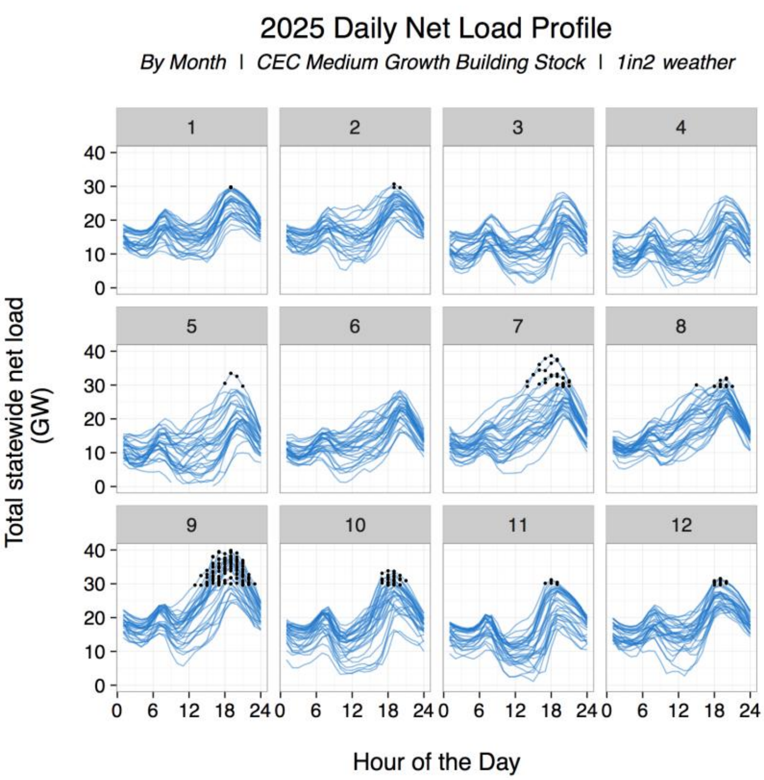


Figure 20: For 2014 and 2025, daily Net load profiles with the hours of peak system net load (top 250) indicated with black dots. This is using the 1-in-2 weather case and CEC Medium growth building stock assumptions.



3.3. Demand Response Economic Evaluation Module

With the available DR technology and market pathways defined and estimated by DR-PATH, we develop an economic evaluation analysis to summarize the results.

The organizing principle for our evaluation framework is supply curves for DR resources (e.g., see Figure 2). The DR supply curves show the quantity of DR available across a range of potential levelized cost "price referent" values (the y-axis). The shape of the curves combine information about the capabilities of DR technology, the match between site loads and system needs, the cost of technology enabling, and the likelihood of adoption of and enrollment in DR programs (with respective methods described in detail in the body of this report and appendices).

The core analytical tool that we use to develop results is a two-step process of operations on the "tree" of potential pathways: first pruning pathways that do not meet some criteria; then, assigning weights to the remaining pathways.

To develop a supply curve for an independent case (e.g., a particular year, weather case, building-stock trajectory, and DR technology and market scenario) we first isolate the available pathway outcomes based on those criteria broadly. Then we advance through a series of cost caps to trace a supply curve. Starting with zero, we prune pathways that have levelized costs over the cost cap, and find the pathway for each end-use that provides the maximum available RA credit. This traces a boundary around the feasible cost-quantity space given the assumptions and inputs for the upstream models, and represents the sets of maximum available DR resources across the a range of cost options.

The supply curve framework allows comparisons to alternative price-referent levels to be estimated quickly. Whether there is higher willingness to pay because of local constraints or lower from shifts in the alternative competing technology or misalignment between DR ability to provide service to the bulk power system and also locally, it is possible to estimate the quantity of DR at alternative referent points by moving up and down the supply curves to establish a new cost ceiling.

The fleets of technology, geographic areas, or market pathways that contribute to the supply curve across cost levels can further be explored using secondary analysis of the synthesized supply curves.

Appendix E contains a full description of Economic Evaluation inputs, methodology and results.

3.3.1. Demand Response Potential Scenarios

We define three feasible DR market and technology trajectory scenarios in this study: 1) business-as-usual (BAU), 2) medium, and 3) high. These each represent a trajectory over time relative to the "base" scenario—the DR market and technology characteristics circa 2014-2015 when we framed and developed the methodology for this study. The BAU scenario represents the steady incremental progress that has unfolded during the past decade toward improving technology performance and finding new ways to market and administer DR programs. The medium and high scenarios show what is possible with moderate and more aggressive market transformations, respectively. Table 7 below summarizes the assumptions that define the trajectory of cost, performance, and propensity to adopt DR for the three years we model and report on: 2014, 2020, and 2025. Note: 2014 was chosen as a benchmark year because it was the last full calendar year for which smart meter data was available when we received raw data from the IOUs, in the third quarter of 2015.

Table 7: Overview of forecasted scenarios for assumed technology cost, technology performance, and technology adoption.

Parameter	Description of Parameter	Scenario	2014 Value	2020 Value	2025 Value
Cost	The full cost of DR enabling technology relative to the base cost.	BAU	1.00	1.00	1.00
		Medium	1.00	0.95	0.90
		High	1.00	0.85	0.70
Performance	The quantity of DR service available relative to base performance.	BAU	1.00	1.05	1.10
		Medium	1.00	1.10	1.20
		High	1.00	1.20	1.40
Propensity	The likelihood to enroll and participate in DR relative to base propensity.	BAU	1.00	1.05	1.10
		Medium	1.00	1.15	1.30
		High	1.00	1.25	1.50

The concepts around these factors are as follows:

- **Demand Response Technology Performance** – This factor is related to the depth of DR shed that is possible, for example, through advances in controls or building energy management strategies. Future DR systems will have larger magnitude reductions or faster response times. Our scenarios consider results from pilot studies and DR economic studies to explore how DR may evolve in the next decade. In the adjustment from scenario-to-scenario, the magnitude of the DR quantity is adjusted but not the speed of dispatch.
- **DR Technology Costs –** This factor captures expected reductions in the cost of DR technology systems. The reductions in cost can come from integrated demand-side management that reduces allocated costs for technology that serves a portfolio of multiple needs.
- **Customer Propensity to Adopt DR technologies** – This factor adjusts the likelihood of customers to adopt DR technologies relative to the baseline estimate that is based

on eligibility, incentives, marketing and customer characteristics. We evaluate DR markets and explore assumptions to frame what we know about markets today and how future markets may evolve.

The scenario factors are all defined in terms of expected variations from the base case by 2025, which represents data from 2014. There is a linear application of the factors through time, i.e., in 2020 the adjustment only partially applied. We note that the performance of behind-the-meter batteries is not adjusted from scenario-to-scenario, and that rational caps on performance and propensity are enforced (you can't shed more load than what is under control, and you can't be more than 100% likely to adopt DR, etc.).

3.3.2. Economic Valuation Adjustments

We use a series of adjustments to the economic evaluation framework that include:

- True-up RA value for comparison to generators: We base our structural adjustments to RA value on the sets of CPUC-approved cost effectiveness protocols, incorporating appropriate values that are not intrinsically accounted for in the RA capacity-based approach we take for estimating DR potential. The protocols include performance adjustments to capture the DR benefits to overall system needs. These strive to make an equivalent comparison between DR and generators (the characteristics of which defined the structure of electricity market design). T&D loss adjustment ensures DR is evaluated on a "generator bus equivalent" since line losses are avoided by meeting capacity needs locally. Avoided operating reserves are similarly accounted for.
- Adjusted for scenarios: The performance ratios within the BAU, Medium and High scenarios include technology performance improvements for forecasting DR Potential in 2020 and 2025. The performance improvements are implemented as increases in the shed factors for each technology.
- Adjustments for year-to-year trajectory: From 2015-2025, the performance for some technologies is expected to improve beyond 2015 levels, which require additional adjustments outside of those performance adjustments made within the scenarios.

Additional adjustments and valuation inputs for determining the benefits for PDR and RDRR are required to appropriately estimate the value of DR in the sub-LAPs and IOU territories. The application, or exclusion, of the various cost-effectiveness protocols, (factors), and the values we used in the model are mapped in Table 8 below.

Appendix C and Appendix D provide details on the DRPATH model methodology for estimating the DR costs and value.

Table 8: 2015 C/E protocol factor mappings, explanations & application of these factors for the valuation of DR supply curves & products.

Data to estimate Supply Curves & Economic Valuation	Data Sources & Notes
Availability, dispatch trigger speed, and controllability of DR resource [A & B Factors]	Implicitly calculated for each cluster & end-use in model, based on a weighting function approach.
Avoided transmission capacity costs ($/kW-year)	2020 & 2025 values provided by NEM Public Tool. PG&E- $19.39; SCE- $23.34; SDG&E- $21.34
Avoided distribution capacity costs ($/kW-year)	2020 & 2025 values from the NEM Public Tool. PG&E- $67.70; SCE- $30.10; SDG&E- $52.24
T&D right time-right place adjustment [D Factor]	We assume that DR capacity leads to reductions in the need for T&D capacity on a 1:1 basis (i.e., a "D-factor" of 100%, with no additional adder or subtractor). We do not have sufficient information about investments in IOUs territories to determine whether locational DR sufficiently defers T&D investments, and the high value of locational-specific DR for distribution system support is not included in the Phase 1 scope.
Avoided energy and ancillary services' cost ($/kWh-year) by each Sub-LAP	Avoided energy & ancillary services costs based on expected hourly dispatch for DR. Time & weather dependent avoided costs estimated based on input data year with historical data from CAISO with ex ante estimates for the frequency of dispatch and average LMP during dispatch hours. We only simulate the day-ahead energy market in Phase 1.
Payments &/or avoided costs for flexible capacity & other advanced DR products. [F Factor & similar]	Excluded in Phase 1; Completed in Phase 2 in integrated investment optimization approach.
Geographic adjustment of capacity value for Sub-LAPs in local capacity constrained areas [G Factor]	Based on CPUC-provided factors from cost effectiveness protocols, by local capacity area: SDG&E-110%; SCE-for Local dispatch in Big Creek- Ventura or L.A. Basin, G Factor will be 105%; PG&E- 100%. These G-factors do not adjust the cost or performance of DR but are used as indicators to identify areas where there is a resource need. The G-factor can adjust the price referent value for DR in evaluating the availability within those areas.
System-level avoided cost of peak capacity ($/kW-year)	Avoided capacity costs & capabilities to model alternative price referents for sensitivity analysis & to benchmark model against other scenarios for future avoided cost. 2025 capacity costs modeled at $140-175/kW-year.

Data to estimate Supply Curves & Economic Valuation	Data Sources & Notes
Avoided GHG costs	GHG price based on the expected future price in California markets. Added to energy prices ~$13/MWh These are small compared to the energy market prices during peak dispatch hours, and the contribution of energy market revenue towards paying for DR technology is itself small as well. The real value DR provides for GHG is making it less costly to meet GHG goals by facilitating renewables integration, with minimal actual payments from GHG mitigation.
Avoided Line Losses	Line losses are assumed to be approximately 10%, with specific factors for each utility area based on typical losses (PG&E: 10.9%, SCE: 8.4%, SDG&E: 8.1%).
Avoided Operating Reserves	Reduced need for operating reserve margins in generation capacity: 15% additional capacity value added.

3.3.3. Demand Response Valuation Price Referent

An important step in summarizing the expected DR potential in our analysis framework is choosing a price referent. This is the expected price of alternative resources or investments that would otherwise need to be procured to meet system capacity needs (e.g., compared to the all-in costs of a new generator, plus the capacity values for T&D). With a price referent, one can interpret the supply curves to estimate the quantity of demand response that is cost competitive. DR that is available at a unit cost below it is considered cost competitive.

We considered many price referents while developing this study, and it is clear that different price referents will be appropriate in different contexts, depending on the locational value of resources, surplus or tightness in the forward capacity market, or deployment of significant non-conventional capacity alternatives (e.g., storage batteries) that may define the price referent in the future grid. In this report, we use a value of $200/kW-year for discussion purposes. It is comprised of capacity values that were developed in collaboration with the CPUC staff and with input from a range of experts and stakeholders. These values are developed based on the recent public tools, including the 2014 California Net Energy Metering Public Tool, E3's avoided costs calculator, and the 2015 Cost-Effectiveness protocols. The price referent is an approximate sum of the following values, rounded to $200 to underscore the uncertainty and variability in the estimate for future marginal average unit cost:

- System-level avoided cost of peak capacity ($/kW-year): There are a range of price referent benchmarks available, including specifically for the California context, $143 /kW-year data, from 2015 CE Protocols and $175 kW-year from the *2014 California Net*

Energy Metering Public Tool. In other electricity markets the cost of capacity varies widely.

- Avoided distribution capacity costs ($/kW-year): 2020 & 2025 values from NEM Public Tool. PG&E = $67.70; SCE = $30.10; SDG&E = $52.24.
- Avoided transmission capacity costs ($/kW-year): 2020 & 2025 values provided by NEM Public Tool. PG&E = $19.39; SCE = $23.34; SDG&E = $21.34.

There is significant debate about the ability of DR to support T&D operations in a way that offsets capacity needs for those systems. If ongoing distributed resource planning policy reforms are successful, there could be clear accountable value from supporting those systems with DR that also meets generation capacity needs. Our $200/kW-year discussion price is purposely in between the expected cost of marginal generation capacity ($140-175) and the combined expected cost of generation, transmission, and distribution capacity ($200-$250). It can be thought of as the combination of the lower-end of generation capacity cost ($140) with nearly complete integration with T&D to provide value there as well. Or, it is a high generation cost combined with little distribution value and only capacity value for transmission planning.

We note again here that with the supply curves developed for this study any price referent can be considered across the supply cost levels that are included, since at each cost point we compute DR capability that satisfies that point as a constraint on maximum cost.

3.4. Load Modifying Demand Response

In the decision to bifurcate DR, a clean line is drawn between DR that participates directly in operational markets through the ISO and DR that does not (load-modifying). We group these load-modifying DR resources in three categories for the purposes of this study:

1. **Structural load shaping** (e.g. time of use pricing)—annually fixed approaches to pricing and other programs that encourage energy efficiency investments and behavioral changes to reduce peak demand or reshape hour-to-hour expected ramps (included in Phase 1).
2. **Day-ahead dispatch (e.**g. critical peak day pricing)—day-to-day adaptive approaches to reduce peak demand or reshape ramps on a day of particular need or in response to real-time system prices or needs (Included in Phase 2, not in Phase 1)
3. **Distribution system service**s (e.g. reactive power support by distributed PV)—DR that is dispatched by a utility or based on SCADA rules for supporting operation of the grid at the sub-transmission level, beyond the control boundary for system operators. (Not addressed in this study.)

The reductions from LMDR are broad and shallow, but can add to a large total resource. As more price-responsive devices that could respond to price come online, including those meant for enabling supply DR, we expect the load impacts attributed to LMDR will increase from the amplified ability of devices and machines to respond to time-variant pricing (importantly, these technology interaction effects are not included in the Phase 1 model but we expect to include in Phase 2). This would tend to reduce the quantity of remaining load to shed in peak hours (thus also reducing the apparent resource available to bid into wholesale markets for the DR technology) but on net does not eliminate the absolute size of the DR resource when you consider the combined effect of load-modifying and supply pathways for the technology.

While the resource size for load-modifying and supply DR is thus tightly linked, the administrative approach for valuing the two resources is often separate (load-modifying DR is valued through the absence of need to procure grid services through markets, e.g. as expressed in capacity procurement needs from long-term load forecasts, while supply DR is a participant in those markets). To ensure that the full size of both resource types is accurately counted it will be important to make regulatory frameworks and market settlement designs that account for the linked nature of the resource base and do not penalize technology options that contribute to both. In the discussion that follows our results we elaborate on this dynamic.

Time-of-use pricing is the only load-modifying DR approach we include in Phase 1. Others will be added in Phase 2. The response of customers to time-varying rates is estimated using expected shed (or growth) factors in response to the price set consumers face. For TOU we forecast a 3% load reduction for commercial and industrial customers, with a deeper reduction from the residential sector as described below. Our model uses previous studies on TOU price elasticity to estimate load impacts for the residential sector in 2025 (see Appendix F). We assume that TOU will be opt-out by 2025 for the residential sector, and TOU adoption is estimated at 90% for residential customers. Commercial and industrial customers are already on mandatory TOU rates in California.

Residential response to time-based pricing is primarily driven by end-uses that are temperature dependent, most notably air conditioning. For a given group of customers, the percent load change is highly dependent on the temperature conditions for a given day as well as the penetration of AC amongst those customers. Therefore, this study aims to develop estimates of load modification as a function of AC saturation and average daily temperature. These results were generated for low income and non-low income customers in summer, winter, and shoulder months. To understand how residential customers will respond to time varying rates, this study used empirical estimates of demand elasticity for a range of temperature conditions and calibrated them for a range of AC saturation levels. The key assumptions, data sources, and methodology are described in Appendix F.

This study relied on estimates of price responsiveness from the SMUD SPO study's analysis of customers who were defaulted onto time of use (TOU) pricing. It was assumed that the price responsiveness (which is expressed in the form of elasticity) of these customers was representative of all California residents, though the values needed to be adjusted to account for a variety of AC saturation levels, which is described in more detail in Appendix F.

4. Results: California's Demand Response Potential

Our research suggests that California could achieve approximately 5-10 GW of DR by 2025 at a levelized cost under $200/kW-year, depending on the trajectory of DR markets and how DR is measured with respect to year-to-year expected differences due to weather. For example 6 GW are identified in our "medium DR" scenario with 1-in-2 weather, which we believe is achievable with continued progress in policy, markets, and technology. In the high scenario, which would involve more aggressive progress and support for technology R&D and higher levels of DR participation, we expect it is possible to achieve approximately 8 GW of DR under the price referent in 1-in-2 weather year. In the more extreme 1-in-10-weather year—when DR is particularly valuable to maintain system reliability—there is also more DR available to meet capacity needs because weather-sensitive measured like HVAC have a DR capacity resource that scales with the load.

The medium and high scenario results will be the focus of the written interpretation for the remainder of the report. The high scenario should be viewed as a scenario that would require more significant market transformation and support to be achievable. Figure 21 below shows DR potential supply curves for 2025 across the scenarios defined in our model, and for both the 1-in-2 and 1-in-10 weather cases. In the lexicon of our study, the full "width" of a supply curve before the unit-cost slope turns to vertical is the referred to as the "**DR potential"** for a given scenario and model case. The "**competitive DR"** is the quantity that is below a given price referent threshold, a subset of the potential.

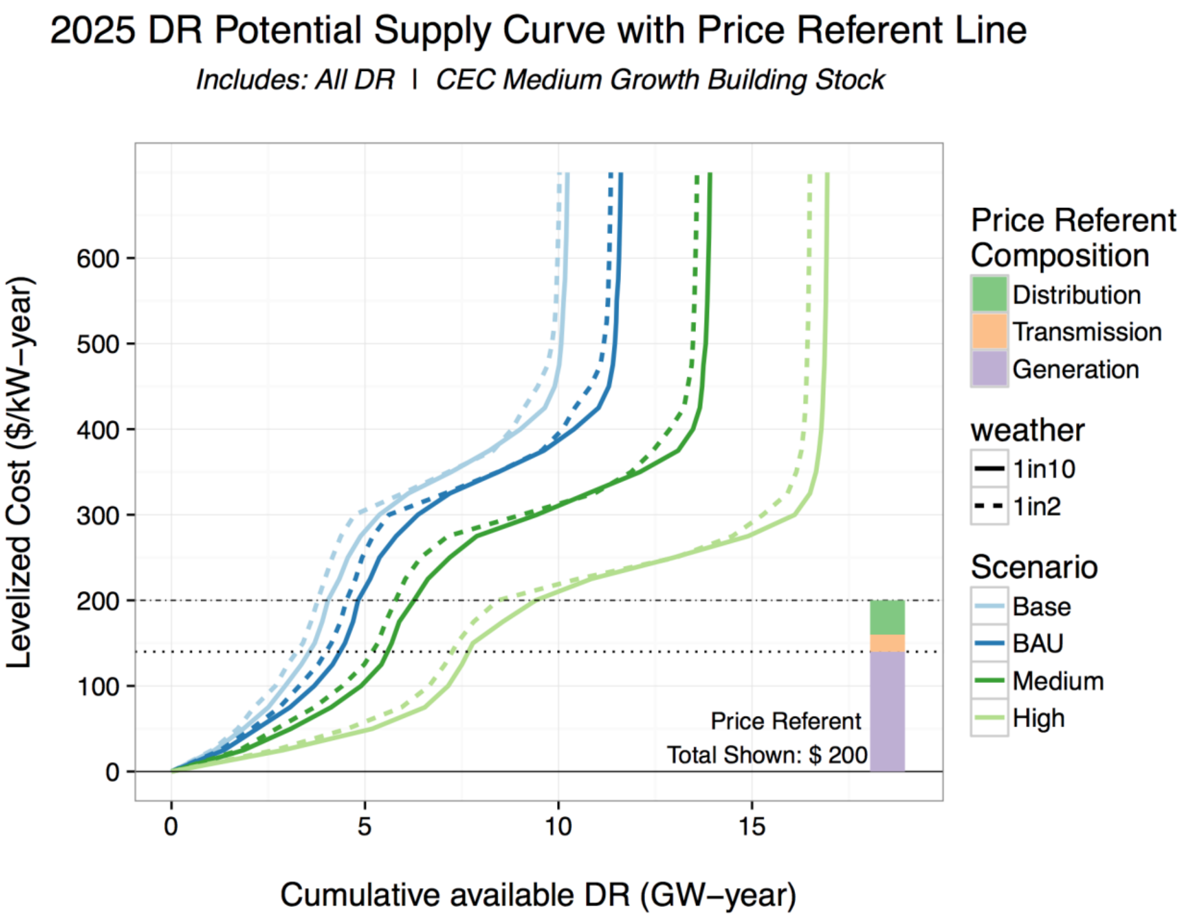


Figure 21: Potential DR for year 2025, with a price referent indicated at $200/kW-year with stacked bar graph showing a potential set of relative contributions to the total, and dotted lines at $140 and $200/kW-year. Levelized cost (y-axis) refers to the annualized cost per unit of energy, with consideration for technology purchase, maintenance and repair, and amortization.

The DR supply curves reflect the calibrated amount of DR available assuming expected levels of enrollment and adoption of DR technologies. The Figure 21 represents all forms of DR, including supply-side controllable DR, battery storage, and load shaping TOU pricing, and the price referent line of $200/kW-year delineates the amount of cost competitive DR available. The cumulative DR available in GW-year on the supply curve that intersects with the price referent line, or falls below it, is determined to be cost effective for each of the scenarios.

Table 9 provides MW-year values for the cost competitive demand response for each of the scenarios by year of our forecast. The business-as-usual scenario is built on assumptions that forecast limited improvements in the performance of DR technologies, customer enrollments, or costs reductions, and results in 2.4 GW of DR growth over the next ten years. This BAU scenario includes default TOU rates for residential customers, which accounts for 1.8 GW of the cost competitive DR in 2025. The remaining DR under the BAU scenario implies little growth from supply side resources, but does account for maintenance of the existing the fleet of resources and replacing decommissioned technologies.

The medium scenario assumes a more aggressive approach to DR potential growth and results in 5.8 GW of cost competitive DR by 2025. The high scenario, our most aggressive set of assumptions, provides 8.4 GW of cost competitive DR from TOU and supply side resources. In the report we focus our description of the analysis around the medium DR pathway to maintain a consistent narrative.

Table 9: Summary of RA credit for controllable loads in CA that are cost competitive with conventional resources, includes TOU & supply side DR. Total costs for competitive resources fall below price referent of $200/kW-year, under medium growth scenario. Forecasted RA credit is assumed with "1 in 2" weather. Results for 2014, 2020 & 2025.

Scenario	*Year*	*Below $200/kW-year (MW yr)*
BAU	2014	3,200
	2020	3,900
	2025	4,500
Medium	2014	3,200
	2020	4,400
	2025	5,800
High	2014	3,200
	2020	5,400
	2025	8,400

4.1. Load Modifying vs. Supply Demand Response Resources

The DR available to California comes from both load-modifying and supply resources, and in our model we include both (note: the only load-modifying DR included in the results for Phase 1 is time-of-use prices). We expect that TOU pricing contributes 850 MW today (i.e., the load reductions from TOU pricing result in lower needs to procure capacity obligations in that quantity) and that there is additionally 2.3 GW of available supply DR in the current day under $200/kW-year. Our 2014 benchmark value is reasonably close to the total DR that is currently accounted for by utilities in the current programs (2.1 GW in 2015, see Figure 9), but with a different mix of resources than what is currently accounted for. The supply resource mix predicted by our model is approximately evenly split between commercial, industrial, and residential customers in 2014, while in current programs there is much more industrial DR (the BIP program).

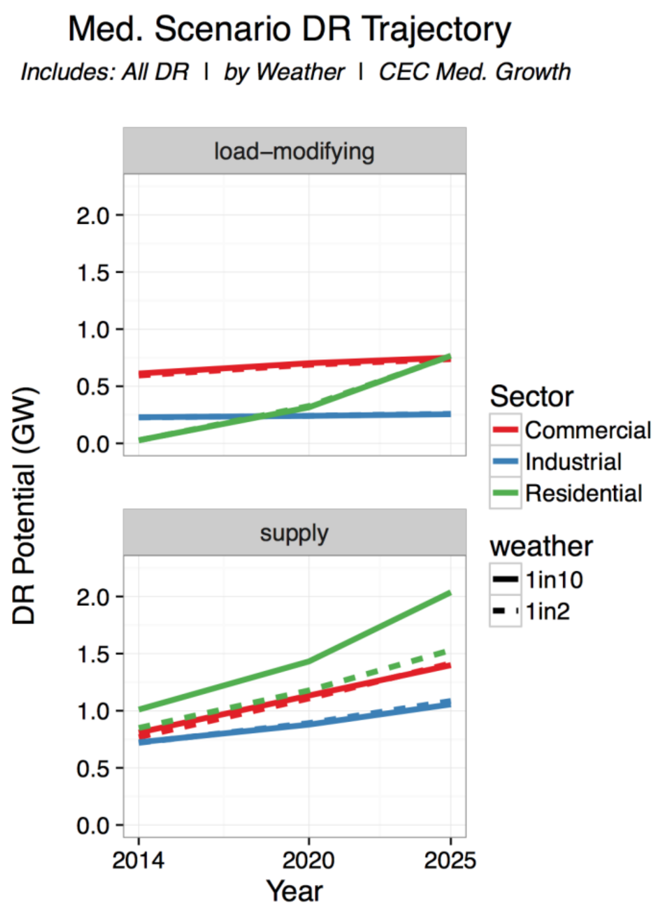


Figure 22: Summary of RA credit for controllable loads in California that are cost competitive with conventional resources, includes TOU and supply side DR. Total costs for competitive resources fall below price referent of $200/kW-year, under medium growth scenario. Forecasted RA credit is assumed with "1 in 2" weather. Results for 2014, 2020 & 2025.

We forecast growth in potential across all of the sectors, The growth in load-modifying DR to 1.8 GW (medium DR scenario) comes primarily from our expectation that by 2025 there will be default TOU rates in the residential sector (increasing participation from near 5% in 2014 to near 90% in 2025), and from improvements in the administration and marketing of TOU programs that lower costs and increase load reductions. Supply DR could grow more, up to a range from 3-6 GW by 2025 between the BAU and high scenarios, with an expected 4 GW in the medium scenario. This non-linearity in supply DR potential comes from technology options like dedicated behind-the-meter storage that are not economic in the medium scenario but with cost reductions achievable in the high scenario enter the resource base, a dynamic we will describe in the next section.

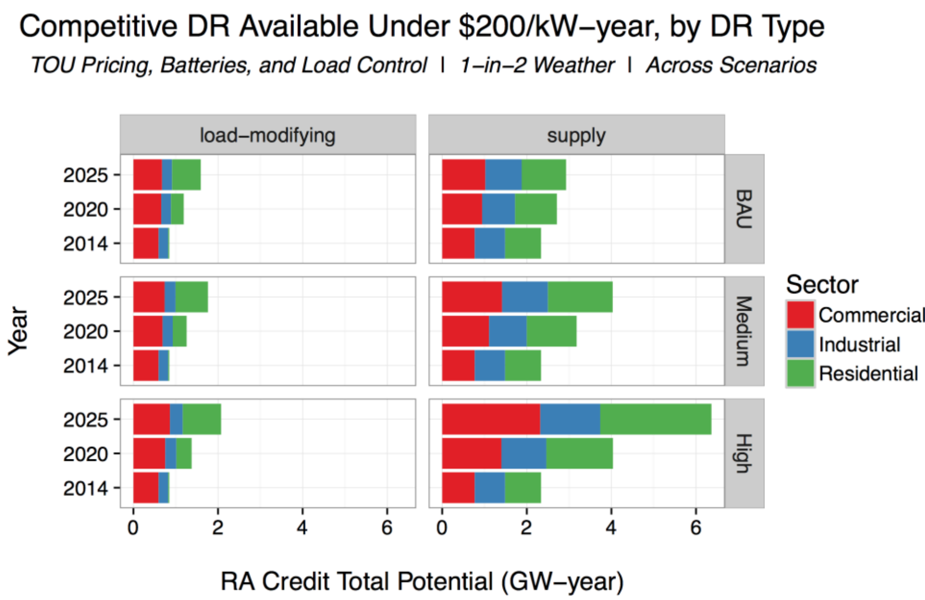


Figure 23: Summary of DR available below $200/kW-year, displayed by DR type (load-modifying vs. supply) and for each of the three main DR scenarios (BAU, Medium & High). Each sub-plot shows the expected contribution from each sector for each of the years 2014, 2020, & 2025.

Table 10: DR reported for Competitive RA in MW-yr for years 2014, 2020 & 2025, for BAU, Medium & High scenarios under a 1:2 weather year. RA totals are reported by DR type; load modifying or supply side DR.

DR Type	Scenario	Year	Cost-competitive RA Value under $200/kW-year (MW-year)
TOU Pricing (Load Modifying)	BAU	2014	850
		2020	1,200
		2025	1,600
	Medium	2014	850
		2020	1,300
		2025	1,800
	High	2014	850
		2020	1,400
		2025	2,100
Supply Market	BAU	2014	2,300
		2020	2,700
		2025	2,900
	Medium	2014	2,300

DR Type	Scenario	Year	Cost-competitive RA Value under $200/kW-year (MW-year)
		2020	3,200
		2025	4,000
	High	2014	2,300
		2020	4,000
		2025	6,400

4.1.1. Contributions of technology to total DR potential across price levels

We have evaluated a broad range of end-uses and technologies available for enabling DR. The study includes 57 unique end-use and enabling technology combinations. The end-uses could have a range of technology pathways, as described in Appendix C in detail, and each pathway resulted in a different shed capability. The results in the following figures aggregate the technology pathways to the end-use, which effectively captures the range of DR potential for each end-use, accounting for all possible enabling technology options and DR load reduction from controlling that end-use. As a result, we are able to report on the DR potential at the end-use by sector.

Our research indicates that in 2025, approximately 5 GW of cost competitive DR, that is, under the $200/kW-year price referent, is achievable with the main contributions from the following end-uses and enabling technologies:

- Commercial HVAC and residential AC
- Residential, Commercial, and Industrial TOU rates
- Industrial process load interruption
- Commercial lighting

The Figure 24 illustrates the contribution of cumulative DR from each end-use and the respective costs for acquiring that mix of technologies. Targeted investments in cost effective end-uses for each sector could substantially increase the pool of DR resources. Investing in resources with levelized costs of $175 kW-year would more than double the current level of DR at 2.1 GW.

In Figure 24, we can see that residential batteries, the salmon colored bars that fall above the price referent, represent approximately 7 GW of DR potential, but that amount of DR is only achievable at estimated costs of $400/kW-year. While these advanced DR resources have substantial ability to participate in the supply side markets, the costs for the technologies is vastly higher than cost competitive end-uses.

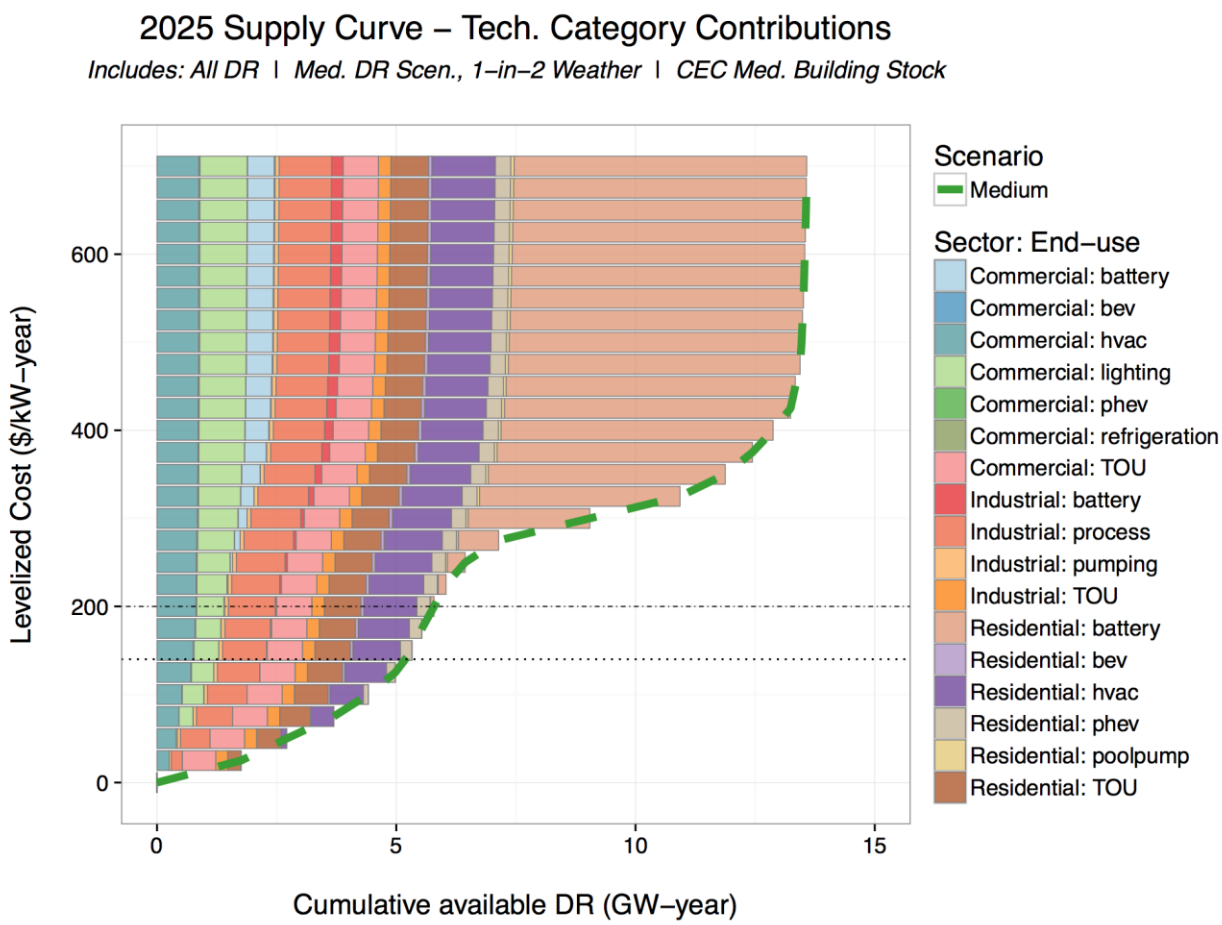


Figure 24: 2025 Supply Curve Technical Category Contributions figure depicts end-use and technology contribution to cumulative available DR (GW-yr) for the medium scenario, 1:2 weather year, under a medium building stock growth scenario. Levelized costs in $/kW-year (y-axis) and DR in GW/yr (x-axis) illustrate the quantity of DR by each end/use technology that are obtainable for each unit of costs (in $/kW-year). Mix of technologies are stacked vertically along y-axis for each unit of cost and illustrate cumulative DR available at each price unit and representative mix of end-uses/technologies.

Figure 25 provides additional insight into our findings on the fraction of DR that is available from each sector by end-use category at various price levels. Our study focuses on numerous end-uses, some of which were not visible in Figure 24 because the end-uses with larger numbers of eligible sites or higher loads, like HVAC, overshadow end-uses with lower saturation levels, like refrigerated warehouses, that still provide cost effective service. Many end-uses can provide costs competitive DR that are not obvious in the previous graphic.

Commercial refrigeration, commercial and residential battery electric vehicles, and industrial process and pumping all contribute significant amounts of DR load reduction below the price referent. In the industrial sector, process and pumping are inclusive of wastewater, data centers, agricultural and manufacturing industries, and are grouped below by the controllable end-use, rather than by industry type. The plots for industrial end-uses clearly indicate that large fractions of available DR potential is costs effective.

In Figure 25, our results indicated, with the exception of battery fleets and residential pool pumps, each end-use can provide 50%-75% of the identified end-uses' total available DR under the price referent, if targeted.

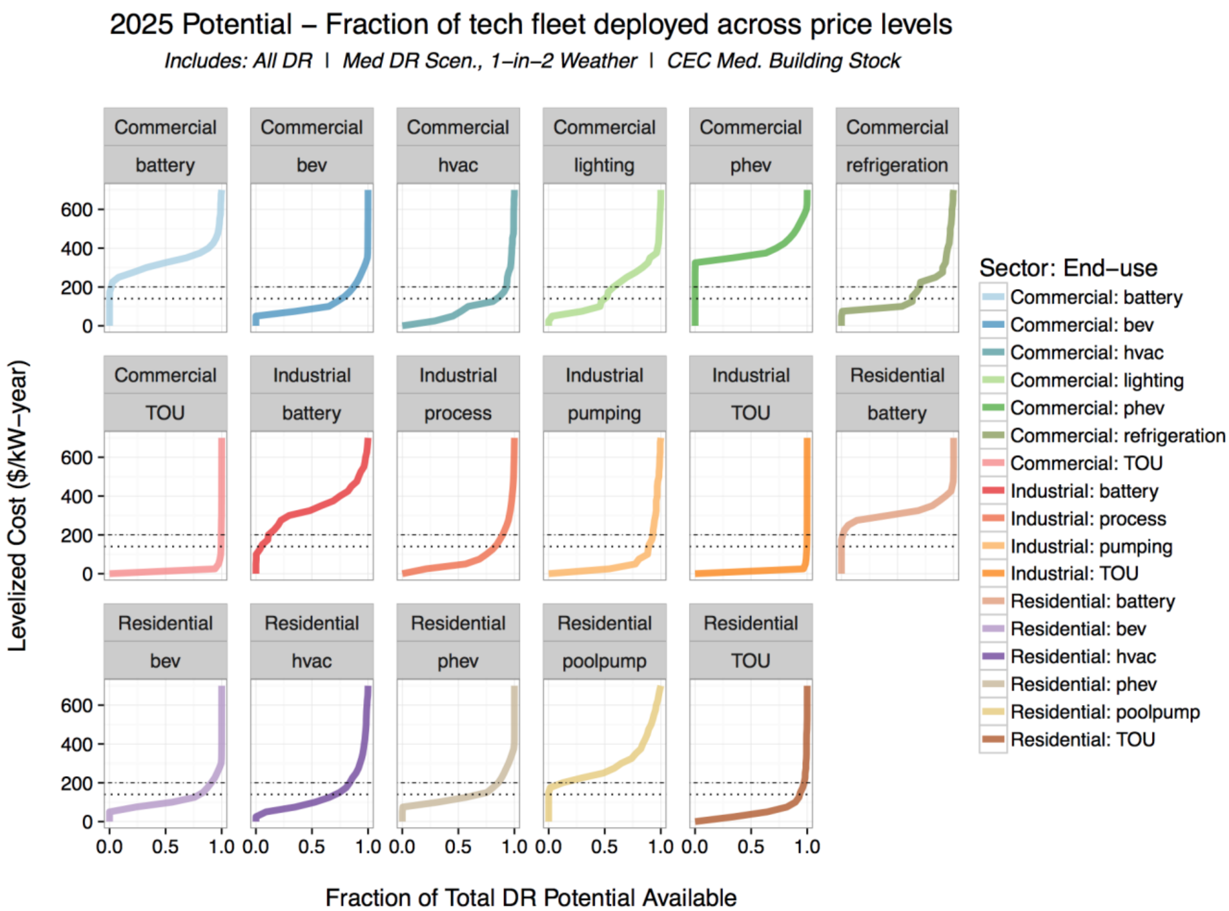


Figure 25: 2025 Potential DR depicts disaggregated supply curves to illustrate percentage contributions from each sector/end-use to total DR Potential, under medium scenario and 1:2 weather year. Each box represents a sector and end-use, with levelized costs in $/kW-year on y-axis, and fraction of total DR available on x-axis. The dotted line represents the price referent of $200/kW-year.

Figure 26 depicts a sector by end-use average supply curve of each technology categories' contribution to the cumulative available DR below the $200/kW-year price referent. Our analysis ranks the technology categories by the average levelized costs within the category (defined as the combination of a sector and end-use, with many specific DR technology options for controlling the end-uses) and their respective contributions to overall cost competitive DR potential.

This curve is particularly helpful for determining what types of DR, based on average costs, provide the greatest contributions to the DR fleet at different price referent levels. This may be helpful for approaching DR program recruitment through targeted marketing. One way to target DR participation that results in high returns on investment could be to identify customers within each sector that have:

- Eligible end-uses with strong coincidence between end-use load baselines and times of system need
- Large potential load reduction, i.e., typically customers with high annual kWh
- Characteristics that show a propensity to participate, such as utility program participation or other demographic factors

Rather than approaching all customers with an offer of DR, a targeted approach to recruiting customers with end-uses that are most cost competitive is efficient. For example, based on our results, targeting Commercial HVAC is in general more cost effective than Residential AC, on an average costs basis. However, the Residential AC end-use is capable of providing more cumulative DR than Commercial HVAC, and the distribution in customer-to-customer cost for DR within the technology are such that it is possible to target a set of very cost-competitive opportunities within the customer base.

Figure 26 highlights another important finding; industrial, commercial and residential TOU pricing is the most costs effective DR available. While this is load-modifying DR and doesn’t participate in operational markets, the impacts from this resource are broad and inexpensive during the top 250 hours (RA), and serve as an important resource for achieving long term DR goals.

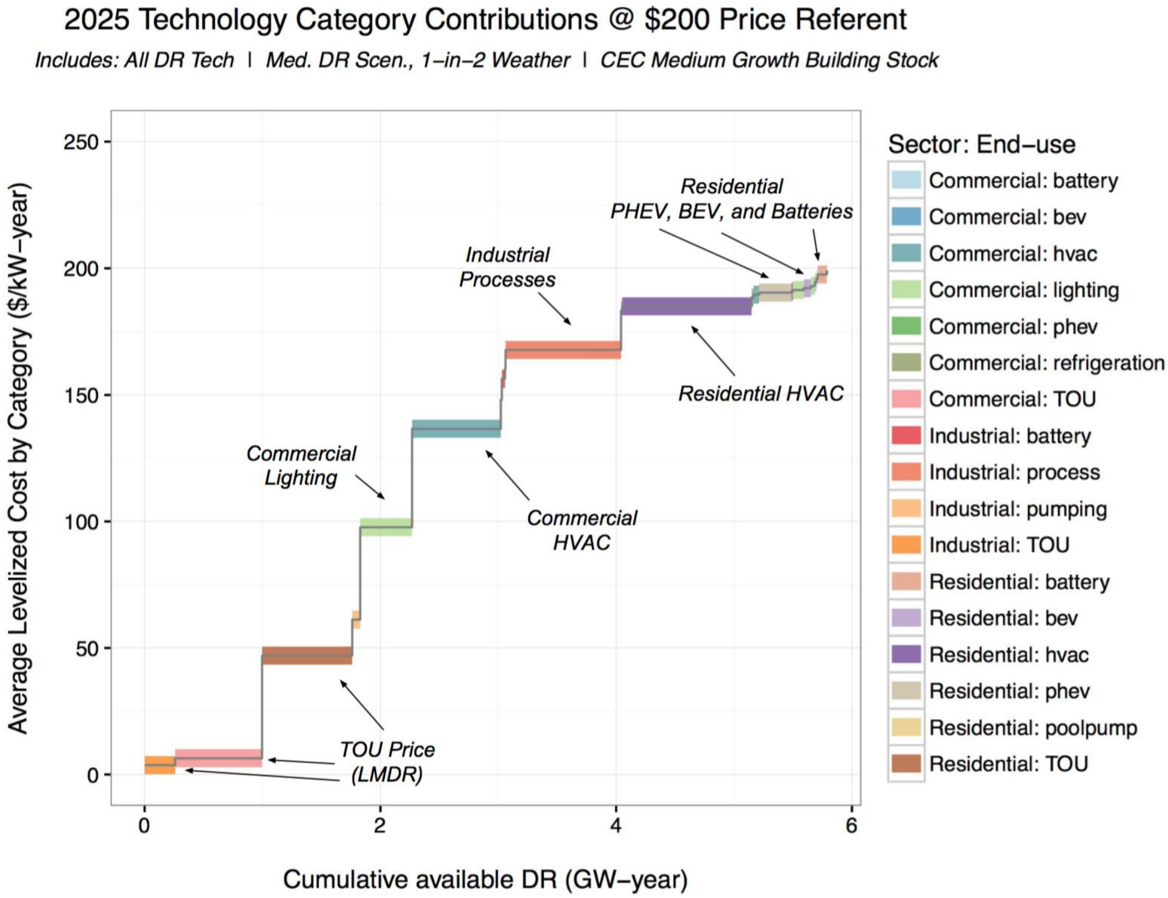


Figure 26: The 2025 technology category contributions below the $200/kW-year price referent. The average levelized costs for each technology category (y-axis) and their contributions to the cumulative DR (GW-yr) are shown for the medium DR scenario, 1:2 weather year, for all DR technologies.

The demand response potential for California comes from a wide range of technology options, and below we provide some detail on instructive examples that could be core contributors to the demand response resource base in the future: mass market DR like Residential AC, expanding the capabilities of large facilities with automation, and the new opportunities from behind-the-meter batteries. A full list of contributing technology to the disaggregated supply curve in Figure 26 is shown in Table 11. Note that because our algorithm for building supply curves chooses the maximum available capacity under a particular price referent threshold, the average cost of technology contributions is often near the threshold. There are also significant quantities available at lower cost, but with sometimes smaller potential quantity than just below the price referent. Additionally, in cases where there are two competing technology for the same end-use (e.g., DLC vs. PCT for residential AC cycling) one may dominate in the analysis because its expected cost is structurally defined to be slightly lower than the other. In reality there are diverse factors that also contribute to the cost but are not included in the modeling framework we use. Thus we do not recommend interpreting the detailed technology vs. technology results as being definitive answers for "which is lower cost", but rather the mix of end-uses and technology types is instructive for understanding how portfolios of DR technology could meet future grid needs.

Table 11: Summary of supply curve contents for Figure 26, showing the contribution by technology to the medium scenario DR potential for 2025, in a 1-in-2 weather case, under a $200 price referent.

Technology Name	Sector/End-use Category	Expected Avg. Cost ($/kW-year)	Total Qty. (MW)	Implied Total Cost ($M/year)
TOU Pricing	Industrial: TOU	4	260	$0.96
TOU Pricing	Commercial: TOU	6	740	$4.70
TOU Pricing	Residential: TOU	47	760	$36.00
Ag Pumping (ADR, Internet dispatch)	Industrial: pumping	61	68	$4.20
Com. Lighting (luminaire)- Med site	Commercial: lighting	98	440	$43.00
Com. HVAC (med. EMS & ADR)	Commercial: hvac	140	750	$100.00
Waste Water Pumping (ADR)	Industrial: pumping	150	9	$1.40
Ind. Battery (ADR)	Industrial: battery	160	27	$4.20
Com. AC (DLC, 50% control)- Med site	Commercial: hvac	160	5	$0.74
Ind. Process (ADR)	Industrial: process	170	980	$160.00
Com. AC (DLC, 50% control)- Small site	Commercial: hvac	180	9	$1.70
Res. AC (PCT)	Residential: hvac	180	1,100	$200.00
Ind. Process (Manual, day-ahead)	Industrial: process	190	1	$0.13
Com. Ref. Warehouse ADR	Commercial: refrigeration	190	16	$3.00
Com. AC (PCT, 50% control)-Small site	Commercial: hvac	190	47	$9.00
Res. PHEV (Level 1 IoT auto)	Residential: phev	190	270	$52.00
Res. AC (DLC)	Residential: hvac	190	13	$2.40
Res. Pool Pump (DLC, Internet dispatch)	Residential: poolpump	190	9	$1.60
Com. Lighting (luminaire)- Med site	Commercial: lighting	190	83	$16.00
Res. BEV (Level 1 IoT auto)	Residential: bev	190	61	$12.00
Com. Lighting (luminaire) –Lrg site	Commercial: lighting	190	29	$5.60
Com. BEV (Level 2 Automated - Fleet)	Commercial: bev	190	4	$0.83
Com. HVAC (med. EMS & Manual)	Commercial: hvac	190	1	$0.13
Com. Lighting (luminaire)- Small site	Commercial: lighting	190	13	$2.50
Com. Battery (ADR)	Commercial: battery	200	9	$1.70
Com. Lighting (zone)- Small site	Commercial: lighting	200	1	$0.18
Com. Lighting (zone)- Small site	Commercial: lighting	200	1	$0.27
Res. Battery (ADR)	Residential: battery	200	75	$15.00
Com. Lighting (luminaire)- Small site	Commercial: lighting	200	4	$0.83
Ag Pumping (Base switch, non-ADR)	Industrial: pumping	200	<1	$0.08
		TOTAL	**5,800**	**$680**

Mass Market Residential HVAC

Residential central air conditioning (AC) is the HVAC technology we included in the model and generally consists of a supply fan and a compressor conditioner and is a ubiquitous load across much of California with intrinsic thermal storage opportunities that are key to enabling DR. For DR applications, a residential central air conditioning unit can be controlled either via DLC (the legacy DR approach), which turns off the compressor for a selected period of time, or via adjustment to the setpoint temperature of a PCT, which controls the compressor and the fan of the entire central AC unit.

Unlike DLC switches, PCTs can turn off the entire AC unit (not just the compressor), by adjusting the setpoint or signaling the device to turn off, which allows for greater shed. Most DR administrators elect to offer program participant varying degrees of AC cycling within their programs, such as 50% cycling which equates to 30 minutes of cycling each hour.

The 2010 Statewide RASS survey conducted by Gilmore Research group reports that 46% of customers in the collective IOU territories have a programmable thermostat, while an estimate 26% have a programmable communicating thermostat (PCT). It is expected that PCTs will continue to grow in popularity among consumers and adoption of this technology, for non-DR purposes, and for DR specifically, will promote greater participation in DR programs and opportunities.

Residential PCTs are also instructive for showing the cost components for a DR technology system, which go far beyond the cost of hardware. The figure below shows our estimate for the relative cost contribution to the total cost of DR across several categories. The baseline cost is initial costs of hardware at the site, financing costs associated with the initial purchase, and operating costs for maintaining communications and other maintenance costs. In the case of a PCT at typical incentive levels (on the order of $50/site/year), these make up less than half of the total cost for DR, with the rest falling into what could be considered “soft” costs categories—costs for administering the retail and wholesale DR operations, incentive payments that are made beyond the cost of equipment installation and maintenance, and costs to market and acquire customers. The revenues from participation in day-ahead energy markets are minimal and do not result in significant buy-down of the effective cost for RA. The site-to-site variation in cost of service and the contribution of Residential PCTs to the overall statewide DR potential is shown in the supply curve in Panel B. These are a significant resource, providing 1.2-1.5 GW of DR (depending on the weather) in the medium scenario (approximately 20% of the total).

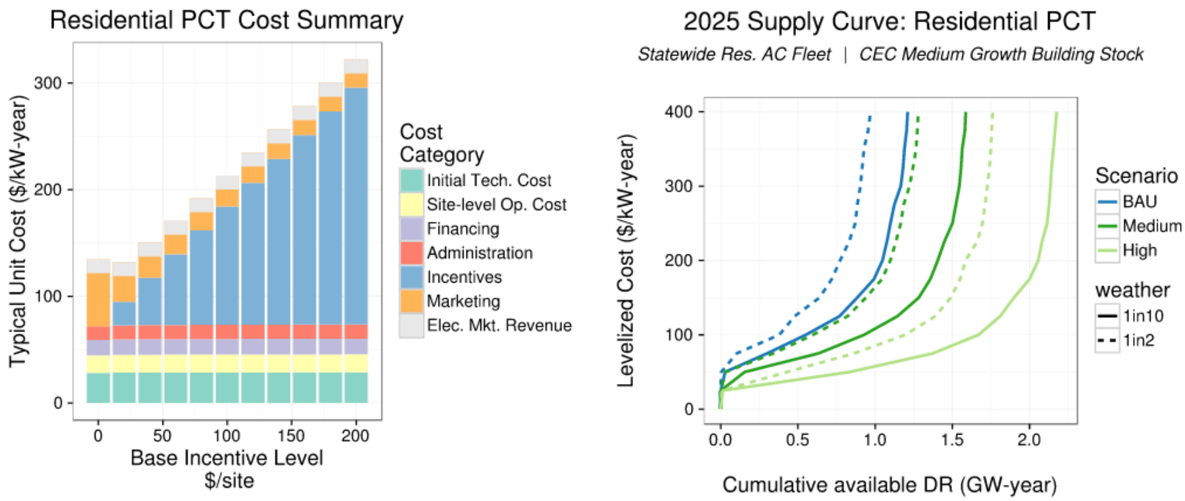


Figure 27: Panel A - The cost contributions to Residential PCT DR across a range of possible incentive levels, Panel B - A set of supply curves showing the technology-specific contribution of Residential PCT to the overall DR Potential for 2025.

The opportunities for growing the resource base of PCT can come from several approaches:

- Reducing the DR aggregator cost of hardware installation by finding effective ways to leverage background market uptake of the technology (i.e., purchases driven or influenced by non-DR uses) could further reduce the cost of equipment and potentially also customer acquisition with integrated marketing.
- There are significant opportunities for soft cost reductions, particularly in identifying optimal approaches for structuring incentive offers. With millions of potential customers there are clear opportunities as well for using data-driven approaches like A-B testing (incorporating randomization into program operations to uncover consumer response to different marketing, incentives, and dispatch strategies), and others.
- Targeting on a site-to-site basis could help improve the overall cost-effectiveness of Residential PCT as a technology category. As is the case with many of the DR technology options in the study, there is a broad distribution in the effective cost of DR from site-to-site as shown in the supply curves (some sites contribute DR at less than $50/kW-year while others have effective costs of $400/kW-year or more). Visibility into load reduction opportunities, combined with modern data-driven marketing could help unlock DR potential in this sector.
- If electrified space heating becomes more common in California, PCT will have year-round DR capabilities to offer.

Automated Industrial processes

For customers at large production facilities—such as factories, food processing plants or metal product manufacturing sites—utilities pay an incentive to have the ability to interrupt a process and either partially or completely shut down load during a contingency event. This "Base Interruptible Power" program is core to the current base of DR for California and we anticipate will continue to provide important reliability resources to the grid. In traditional BIP, programs are managed directly by utilities with their large industrial customers, who are dispatched through a phone call, typically providing 30 minutes advanced notice, or through an AutoDR system. Once notified, customers either manually shut down their facility processes or automatically shed load through an AutoDR signal. There are also facilities with semi-automated controls, where some elements of the industrial process still need to be switched off manually during a DR event (Ghatikar et. al, 2012).

In the future the ability to use fast, automated demand response could provide additional value beyond the system capacity needs that are currently met with industrial facility DR. The technology detailed in Figure 28 below is an example: fully automated DR at industrial facilities. The costs of DR from large facilities is often dominated by the incentive payments made to compensate for the loss in firm service that is involved with participating in DR programs and markets. Unlike the Residential PCT example, there is little weather sensitivity to the overall available supply from industrial processes (any differences in the supply curves is incidental to the modeling process), but similar to residential customers there are significant differences between the most cost-effective sites and the typical site. In the medium scenario the first 500 MW of DR is available for less than $75/kW-year, but the next 500 MW requires costs of up to $200/kW-year.

The results we show for industrial DR diverge from the current resource base for BIP and large facilities, showing a lower expected potential in the current day than what is accounted for in DR regulatory filings (700 MW of cost-competitive industrial supply-market DR below $200/kW-year predicted in the model for 2014 vs. ~1 GW of comparable industrial DR in utility filings). There are several factors that could explain this: The first and most important is that the approach we used to model DR broadly is data-driven using a generalized approach rather than case study driven. Our approach treats industrial facilities based on their observable characteristics and benchmarks DR capabilities based on historical performance. However, a detailed case-study approach is called for in the case of very large facilities that have significant available DR under the right circumstances and offer conditions. It was not the intention or goal of this study to model the detailed institutional and technological dynamics at play in individual large facilities that could participate in DR, but we used the best available data resources to benchmark them with broadly applied methods. Further discrepancies could arise from differences in the resource potential we estimate based on the coincidence between site load and the net load peaks across many hours versus the highly limited dispatch performance testing that is used to benchmark facilities administratively. If facility benchmarks are established on particularly "good" DR days, the administratively determined DR quantity could be higher than what it would be with repeated measurements across many days. Finally, there is a known contribution of unknown scale from backup generation to DR performance at many large facilities that is not included as a resource in our study.

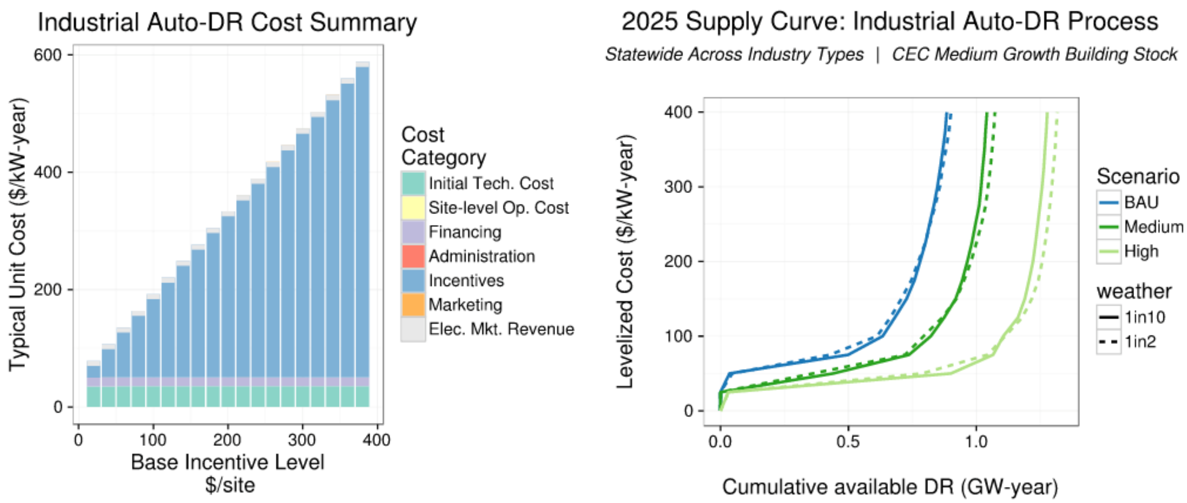


Figure 28: Panel A - The cost contributions to Industrial Auto DR across a range of possible incentive levels, Panel B - A set of supply curves showing the technology-specific contribution to the overall DR Potential for 2025.

Thus the opportunities for growing the resource base of large industrial load can come from several approaches:

- Identifying opportunities for multiple market participation, particularly for processes that are fully automated and have wide bands of potential operating states—those that could provide ancillary services and other advanced DR largely with existing equipment and without full facility shut-down required (maintaining the ability to also shut down for meeting capacity needs).
- Targeting on a site-to-site basis based on alignment between the site-wide load and system net load could help improve the overall cost-effectiveness of Industrial DR as a technology category, But unlike mass-market DR the customer characteristics at large industrial facilities are highly specialized. A case-study and detailed assessment approach is more appropriate than using data-driven methods for specific targeting, since the details of the sites are both lost in the relatively small sample sizes and more difficult to interpret based on remote data approaches. As new approaches to automation are proven, best practices sharing within industrial sectors should be shared and replicated.

Behind-the-meter battery storage

Locally sited, "behind the meter" energy storage can make any load appear flexible to grid operators. Batteries that are equipped with the right telemetry, control, and intelligence can provide a wide range of services to both local load (increased reliability, power quality correction, reduction in demand charges, etc.) and the grid (through demand response and other grid services). Battery storage is a rapidly evolving technology that promises to become dramatically more cost competitive over the next decade as economies of scale in manufacturing for batteries are reached (lithium in particular) and innovation on soft costs of installation and operation.

In the main results we include lithium-ion behind-the-meter batteries that are sized to be roughly appropriate for meeting many of the secondary value-streams available to them, but show the full cost of the battery system as the cost for DR capacity. This is in a sense the "worst case" scenario for cost contributions. The figures below show that the vast majority of the cost we represent are for the hardware purchase, installation and financing. Breakthroughs in the cost of batteries could lead to significant reductions in the cost for using them to provide DR, and could shift the resource from one that is only marginally a contributor to the supply curve below $200/kW to a significant and large resource.

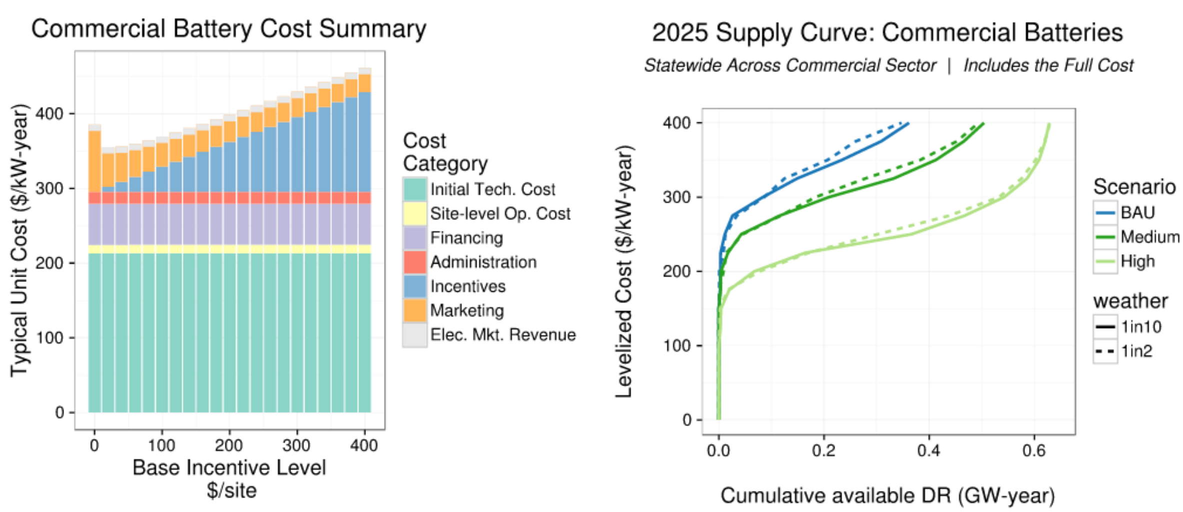


Figure 29: Panel A - The cost contributions to Commercial-sector sited batteries across a range of possible incentive levels, Panel B - A set of supply curves showing the technology-specific contribution to the overall DR Potential for 2025.

4.2. Geographic DR: Potential by Investor Owned Utility Service Territories, Sub-LAPs, and Local Capacity Areas (LCAs)

Our research has developed results that identify DR potential by IOU service territory, Sub-LAPs, and Local Capacity Areas (LCAs). This research indicates that SCE is the utility with the most potential DR and its corresponding Sub-LAPs and LCAs. Based on our results, indicated in Figure 30, SCE is has a cost competitive DR potential of 3.5 GWs by 2025 under the medium scenario. As of 2015, SCE reported current DR load reduction to be 1.46 GW. Our results indicate that SCE has a potential to add 2 GWs to the current totals, through supply side DR and load-modifying DR. In order to achieve this level of DR, the contributions from the residential sector will need to increase from the current level of 332 MW to 1.7 GW in the next 10 years. Assuming TOU becomes the default rate plan for residential customers, this will be achievable.

PG&E reported a total of 609 MW of DR load reduction capability in 2015. Based on our findings, PG&E could expect 2.5 GW of cost competitive DR in 2025 under the medium scenario. The vast majority of this potential DR comes from untapped resources in the residential and commercial sectors. In 2015, PG&E reported 114 MW from residential DR programs. By 2025, the potential cost competitive DR from the residential sector could be over 1 GW, which is an increase by a factor of ten.

SDG&E also has growth opportunity for DR potential from current levels. In 2015, SDG&E reported 84 MW of DR load reduction ability. Our study finds a cost competitive DR potential of approximately 500 MW by 2025. The DR potential growth comes from all customer sectors, all of which need to triple in order to meet such a target.

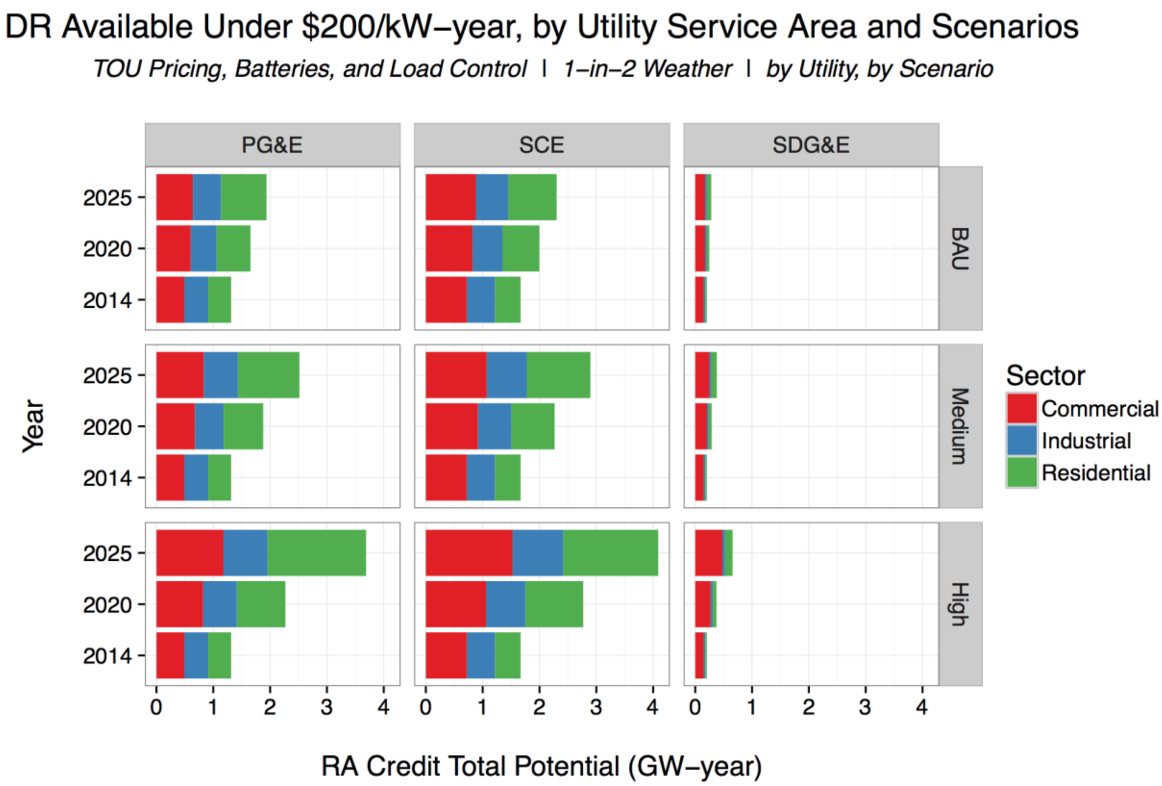


Figure 30: Cost competitive DR for each IOU service territory, by year, scenario and for each customer sector. The customer sectors are stacked bars depicting the cumulative DR potential (GW-yr) that fall beneath the price referent of $200/kW-year.

Our analysis examines the potential DR that is cost competitive by Local Capacity Area LCA)[3]. LCA is defined by CAISO as a geographical boundary represent sub areas of load pockets for which local generation capacity requirements can be evaluated. However, these areas are a part of the interconnected electric system and each Local Capacity Area (LCA) may include sub areas that overlap. To meet local capacity requirements, faster-than-typical dispatch response may be required of DR resources. A 20-minute requirement was initially rejected by CPUC for RA compliance year 2016 and is under consideration by the CPUC for RA compliance year 2017. In this section the results for LCA show the full resource based without a limitation on faster dispatch. In the next section describing the results by DR market product, we include the effect of a 20-minute dispatch requirement on tightening the available resource.

Figure 31 below illustrates the quantity of potential DR in each of the LCAs that falls under the price referent. The location of resources in our study has resolution at the Sub-LAP (and in some cases Zip Code) level and we are using a set of geographic definitions by Sub-LAP (provided by

3 For more information on Local Capacity Areas and the sub areas included therein, please see https://www.caiso.com/Documents/Final2014LocalCapacityTechnicalStudyReportApr30_2013.pdf

CAISO) to define which LCA each DR resource is located. All DR that was modeled in this study was included in the figure: TOU pricing, batteries, and supply side controllable DR. The LA Basin LCA has the greatest potential for DR, followed by the Greater Bay, Sierra, and San Diego, and Big Creek/Ventura LCAs. DR potential in the LCA and sub areas is driven by population concentration and load, and those areas with larger populations have greater DR potential.

It is important to note that here and elsewhere in the report, our results for DR potential and competitive quantities of DR assume there is sufficient time to build infrastructure and recruit customers in advance of the need for capacity. We do not model how quickly DR resources could scale up in the short run, and thus in cases where needs unexpectedly emerge (e.g., a need for additional local capacity within the year due to a loss of a large power plant or transmission line) our result should not be interpreted as the quantity of DR that could scale up quickly to meet a need on the order of months later. Rather, the results are the long-run available resource.

Figure 31: Quantity of cost competitive DR (GW-yr) by Local Capacity Area, customer sector, and year under the medium scenario and 1:2 weather year. The bar charts detail each sector's contributions to the annual GW potential within each LCA.

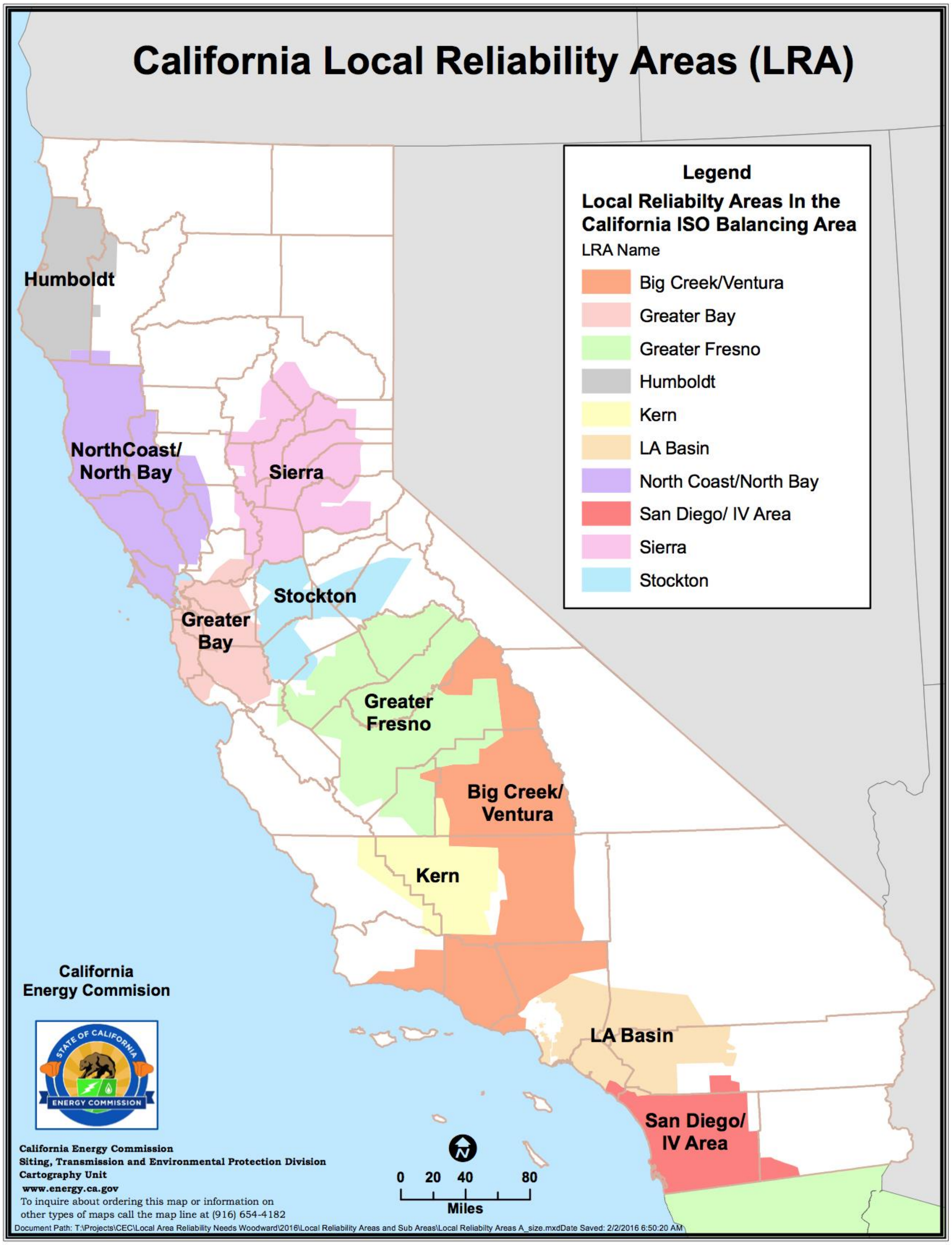


Figure 32: California Local Reliability Areas (from CEC)

The supply curve in *Figure 26* illustrates how the DR potential for the LCAs under the medium scenario is realized. A majority of the 13 GW in overall potential falling within the LA Basin LCA. An important result from the analysis is that the San Diego LCA has a notable increase in DR potential available above $300/kW-year but lower availability at low price referent values based on the mix of building stock and load coincidence with system needs. This indicates that San Diego has a number of available resources for system-level DR, but they are not cost competitive.

It is important to note that our analysis does not include "local net loads" for the capacity planning areas, and if there is significant divergence between the time of need for system RA and local constraints, the local DR resources could have higher capacity value for meeting those local needs.

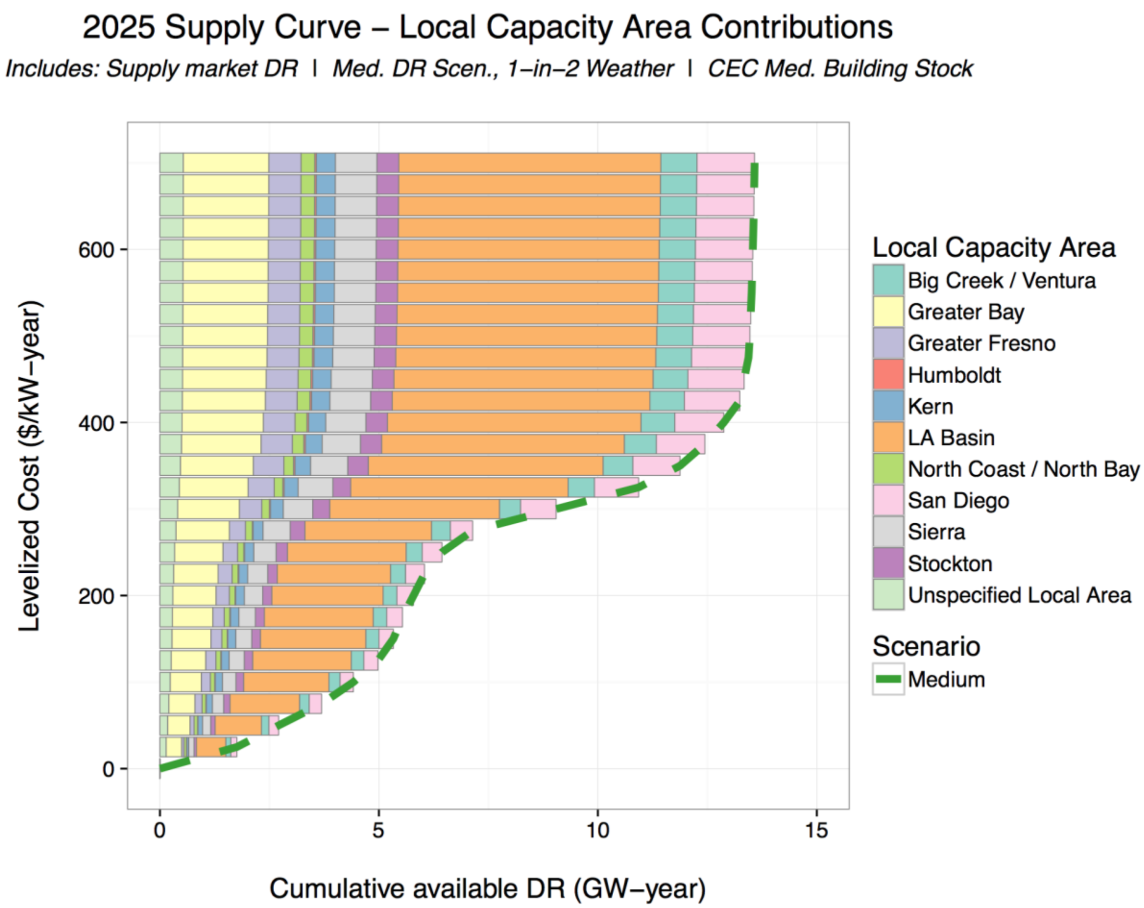


Figure 33: Supply Curve Local Capacity Area Contributions depicts LCAs contribution to cumulative available DR (GW-yr) for high scenario, 1:2 weather year, under a medium building stock growth scenario. Levelized costs in $/kW-year (y-axis) and DR in GW/yr (x-axis) illustrate quantity of DR obtainable for each unit of costs (in $/kW-year). Mix of LCAs stacked vertically along y-axis for each unit of cost and illustrates contributions of each LCAs to cumulative DR at each levelized price.

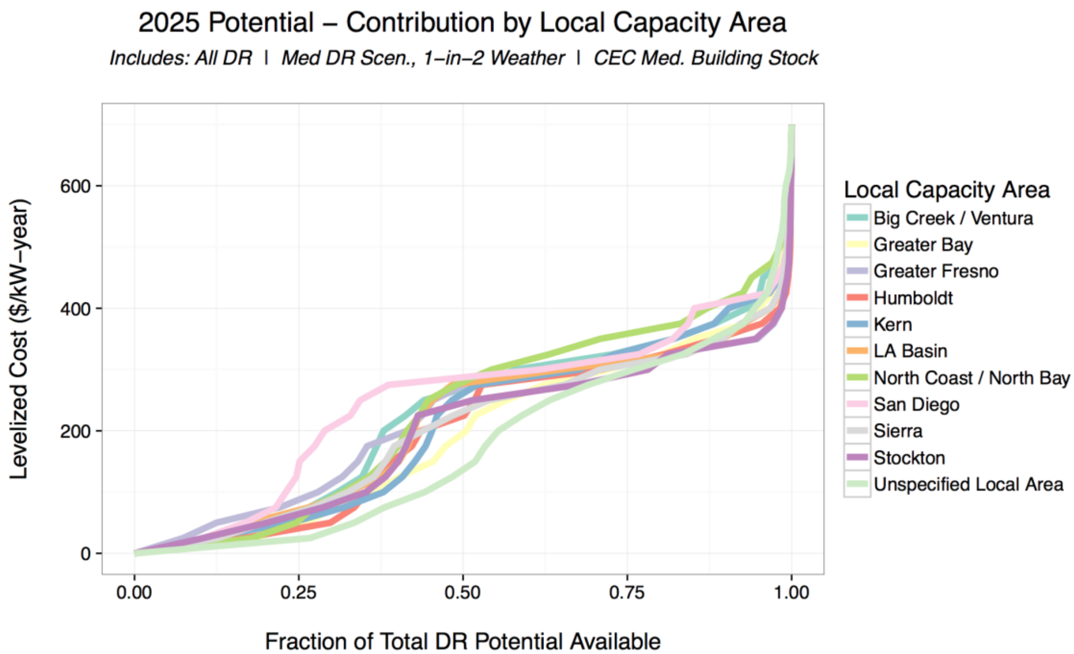


Figure 34: Fractions of total DR potential under the price referent across a range of costs, for each local capacity area.

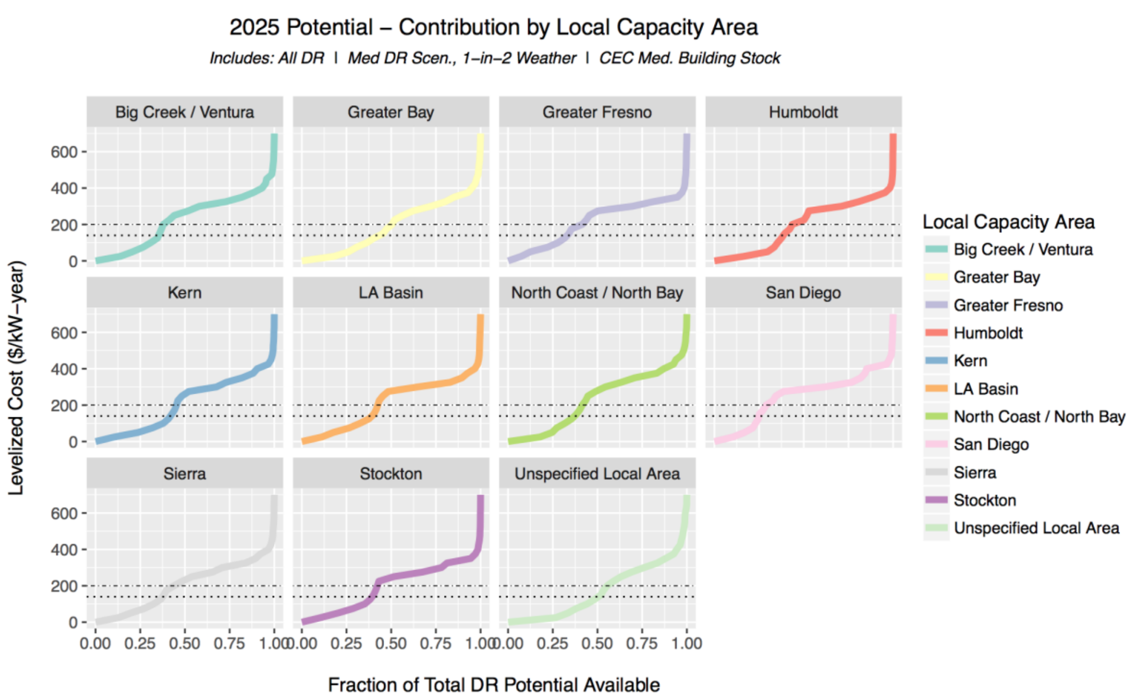


Figure 35: Fractions of total DR potential under the price referent across a range of costs, for each local capacity area, split and plotted separately for each area.

4.3. DR Potential Results by Market Product

We found that there are broadly similar availabilities of DR through the three product pathways to participation we modeled: PDR, RDRR and Local RA market products but with some important differences in resource scale at low unit cost. At the price referent, we find statewide potential near 4 GW for PDR and RDRR, and 3.5 GW for 20-minute dispatchable DR (2 GW of which is in a current-day local capacity constrained area). In Figure 36 below we show the potential for these products as supply curves, constrained to current-day local load pockets. The load pockets we included in Figure 36 are the LA Basin and Big Creek/Ventura LCAs. It is important to note that the curves are not additive. They represent the independent supply curve for each product pathway type.

While the DR available near the system-wide price referent of $200/kW-year is similar there are starker differences at low prices. If capacity is valued at $50/kW-year there is substantially more RDRR (700 MW) than 20-minute dispatch DR (200 MW). These least expensive RDRR resources that take longer to dispatch are typically manual, and include many of the large customers in current utility programs. While some facility and equipment shutdown processes can be called and deliver load reductions in less than 20 minutes, we also included resources in the technology inputs for the model that were longer-to-dispatch but represented deeper reductions for facilities able to more completely shut down.

In Phase 2, when other revenue sources for faster-dispatch DR are included, we expect that the effective cost for providing capacity will be reduced for DR that is automatically dispatched, and particularly fast DR technology. This should shift the supply curve towards higher quantities available for lower unit cost for all of the products, since revenue from ancillary services market participation can offset investment and other costs of DR technology, lowering the effective cost of capacity.

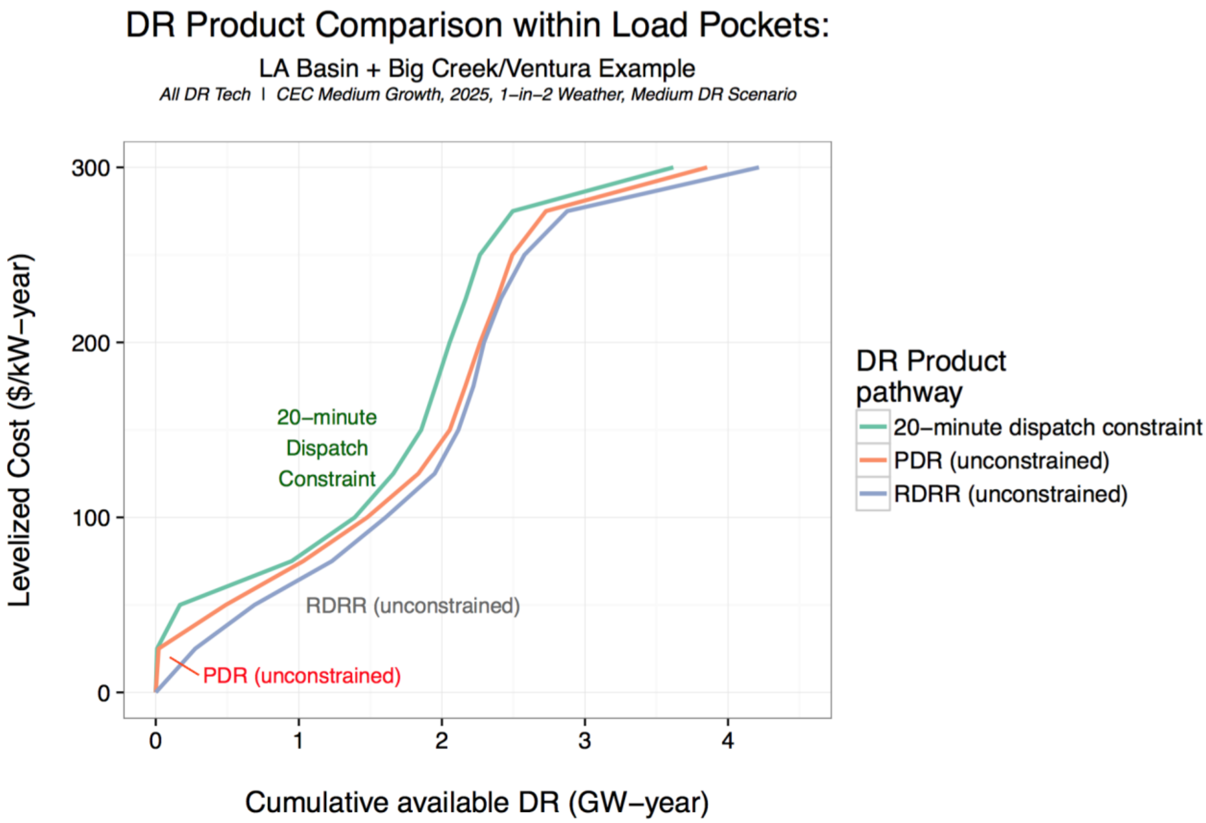


Figure 36: Independent supply curves for three DR products, only for quantity within current L.A Basin & Big Creek/Ventura load pockets: RDRR & PDR without dispatch limitation, & 20-minute dispatch. Each supply curve was calculated independently (as if the only pathway to RA credit were that product), so the results are not additive.

4.3.1. Load Modifying Demand Response Potential

Our study focuses on the impacts of time of use pricing (TOU), a form of structural load shaping demand response, as the only load-modifying DR option included in Phase 1 of the Potential Study. TOU is annually fixed differential pricing for day and/or evening hours that encourages behavioral changes to reduce peak demand or reshape hour-to-hour expected ramps. Our study evaluates a modest TOU tariff scenario for each of the utilities for the 2020 and 2025 potential results. Under the CPUC decision 15-07-001, the IOUs were required to submit advice letters with a proposed TOU rate. Our study used PG&E's Option 2 proposed tariff, below in Table 12, as the default TOU tariff in model for years 2020 and 2025. Additional rate options can be evaluated, and will be included in Phase 2 of this study. The Phase 1 load impact estimates were generated for this rate option, which includes a three-part tariff in the summer, and a two-part tariff in the non-summer months. In the analysis the rate option was compared to a flat rate of $0.217/kWh, which represents the likely flat rate that will be in effect in PG&E's service territory in 2016 based on an advice letter that was submitted to the CPUC. This rate represents the alternate rate option that customers will have available to them, and is similar in structure to the rate that most residential customers are currently on in California. The participation rates for the default tariff used in our study is 40% in 2020, to account for a staged rollout beginning in 2019, and 90% in 2025. These participation levels are based on the results from SMUD's SPO TOU pilot, where customers that were defaulted on the rate remained enrolled at approximately 94% retention[4].

Table 12: PG&E's Option 2 Residential TOU Tariffs from 2015 Advice Filing in D. 15-07-001

Season	First Off Peak Period			First Part Peak Period			Peak Period			Second Part Peak Period			Second Off Peak Period		
	Rate ($/kWh)	Start Hour	End Hour	Rate ($/kWh)	Start Hour	End Hour	Rate ($/kWh)	Start Hour	End Hour	Rate ($/kWh)	Start Hour	End Hour	Rate ($/kWh)	Start Hour	End Hour
Summer	0.295	12AM	4PM	0.402	4PM	6PM	0.459	6PM	6PM	0.402	9PM	10PM	0.295	10PM	12AM
Non-Summer	0.241	12AM	6PM	-	-	-	0.263	9PM	9PM	-	-	-	0.241	9PM	12AM

This study relied on estimates of price responsiveness from the SMUD SPO study's analysis of customers who were defaulted onto time of use (TOU) pricing. Residential response to time-based pricing is primarily driven by end-uses that are temperature dependent, most notably air conditioning. It was assumed that the price responsiveness (which is expressed in the form of elasticity) of these customers was representative of all California residents. These results were generated for low income and non-low income customers in summer, winter, and shoulder months. The demand elasticity was also conditioned over a range of temperature conditions and AC saturation levels.

The response of customers to time-varying rates is estimated using expected shed (or growth) factors in response to the price set consumers face. Commercial and industrial customers are already on mandatory TOU rates in California. For Commercial TOU we forecast a 3% load reduction for commercial and industrial customers, with the assumption that the commercial sector will continue to invest in energy efficient equipment and appliances that reduce energy consumption over the long run in response to TOU pricing. For residential customers, the model we use leads to load reductions for on peak hours exceed those of commercial, conditional on customer characteristics as described above. The key assumptions, data sources, and methodology are described in Appendix F.

4.3.2. Comparison to the JASC studies

A recent study from the joint agency (CPUC, CEC, and CAISO) staff (JASC) released a

[4] Potter, Jennifer, Stephen George, Lupe Jimenez. SMUD's SmartPricing Options Pricing Pilot Final Evaluation. United States Department of Energy, Prepared by Sacramento Municipal Utility District, 2014. https://www.smartgrid.gov/files/SMUD-CBS_Final_Evaluation_Submitted_DOE_9_9_2014.pdf

conceptual analysis for TOU Rates under aggressive rates design for residential customers. The JASC study named these rate scenarios "Scenario 5" and "Scenario 6". Under these scenarios, the rates were complex in the number of seasons, and the price ratios, (i.e. on peak, off peak, and super peak), were very aggressive, with off peak to super peak ratios of 10 to 1 price differentials. These scenarios resulted in 1.4 to 1.7 GW reductions from the residential rate group alone. The tariffs in our study offer a modest price differential of 1.7 to 1, which does not send a strong price signal to customers, unlike the rate designs modeled in the JASC study. The result is conservative load reduction forecasted in our potential analysis, as compared to the JASC study. We plan to work in Phase 2 to incorporate additional TOU price options in our analysis, including those from the JASC study.

4.3.3. Considerations for Load Modifying Demand Response

The resource size for load modifying and supply DR is thus tightly linked, the administrative approach for valuing the two resources is often separate. Load-modifying DR is typically assigned a value from the reduction in procurement of grid services through markets, (e.g. as expressed in capacity procurement needs from long-term load forecasts), while supply DR is bid into the markets as a participant. To ensure that the full size of both resource types is accurately counted it will be important to make regulatory frameworks and market settlement designs that account for the linked nature of the resource base and do not penalize technology options that contribute to both.

The reductions from LMDR are broad and shallow, but add to a large total resource. As more devices that could respond to price come online, including those meant for enabling supply DR, we expect the load impacts attributed to LMDR will increase from the amplified ability of devices and machines to respond to time-variant pricing (these technology interaction effects are not included in the Phase 1 model). This would tend to reduce the quantity of remaining load to shed in peak hours (thus also reducing the apparent resource available to bid into wholesale markets for the DR technology) but on net does not eliminate the absolute size of the DR resource when you consider the combined effect of load-modifying and supply pathways for the technology.

Figure 37 shows how nearly all of the TOU resource is highly cost effective, and illustrates why TOU was found to be the most cost-effective approach for managing peak capacity in the full analysis.

This total is comprised of both residential and commercial sector TOU impacts.

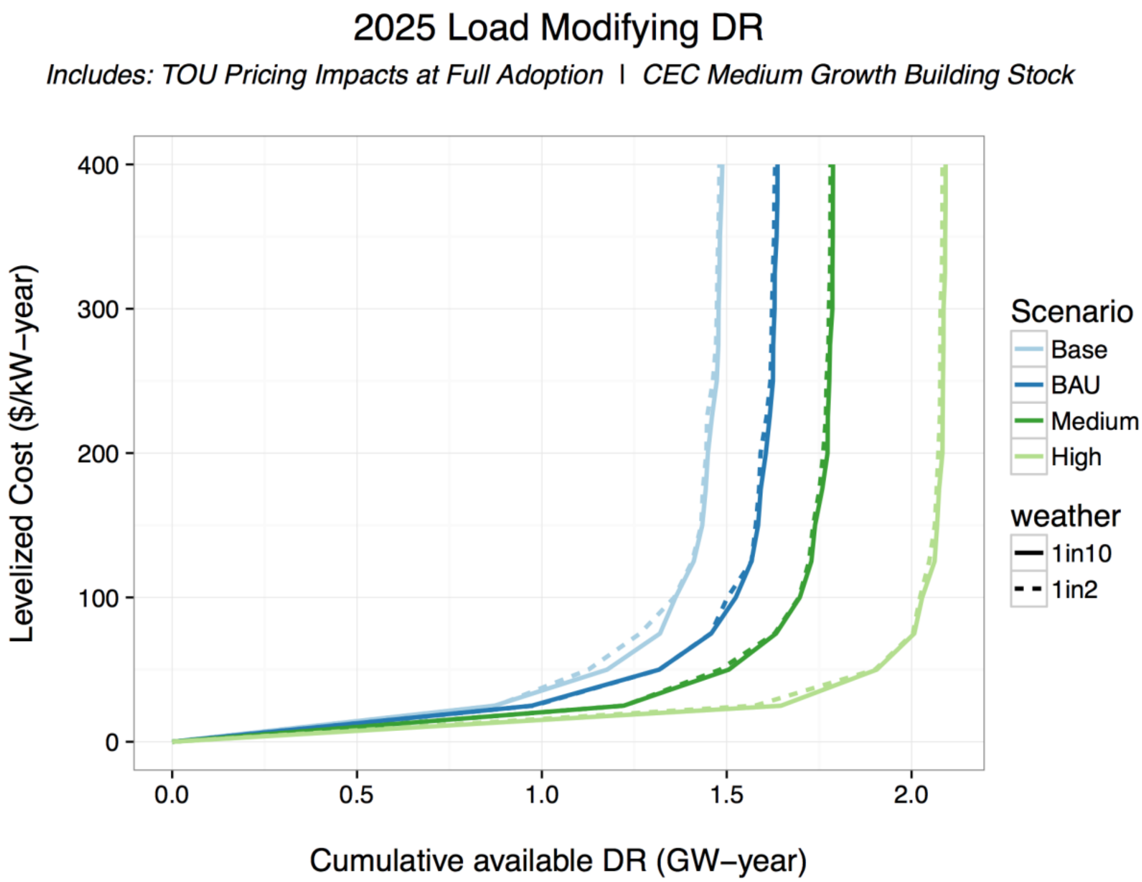


Figure 37: The cumulative DR available from TOU in 2025 for each scenario and weather year. The levelized costs are on the y-axis and the cumulative DR is on the X-axis. Adoption levels are estimated at 90% for 2025 residential TOU programs under default enrollment.

4.3.4. Behind-the meter Battery Storage

One of the key findings in our study is that the potential for behind-the-meter battery storage can significantly shift the capabilities of sites to present demand response potential to grid operators. Advances in the cost and performance of modern batteries with lithium-based chemistry could significantly contribute to the resource pool of DR technologies. Because batteries are inherently scalable, there are not the same physical limits on flexibility resource as controllable load DR. For the purposes of this study, we have defined a notional, example fleet of behind the meter batteries with reasonable capacity given trends in the battery market. If the full cost of batteries is to be covered by capacity payments and limited participation in the energy market (the Phase 1 baseline assumption), the supply curves in Figure 39 show that while the potential resource is large, there is little cost-competitive DR from batteries expected. Nearly the full potential resource is above $200/kW-year. In the discussion below we describe how there is potential for near-term breakthroughs in battery cost and market offerings that could reduce the levelized cost of capacity and dramatically shift the quantity of cost-competitive DR from batteries.

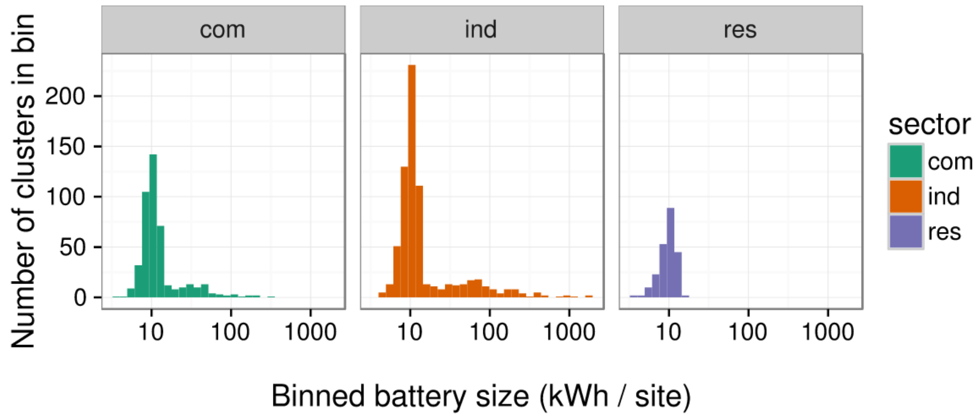


Figure 38: Histograms showing distribution in size for batteries in example fleet that totals 150 GWh if all sites adopt the technology.

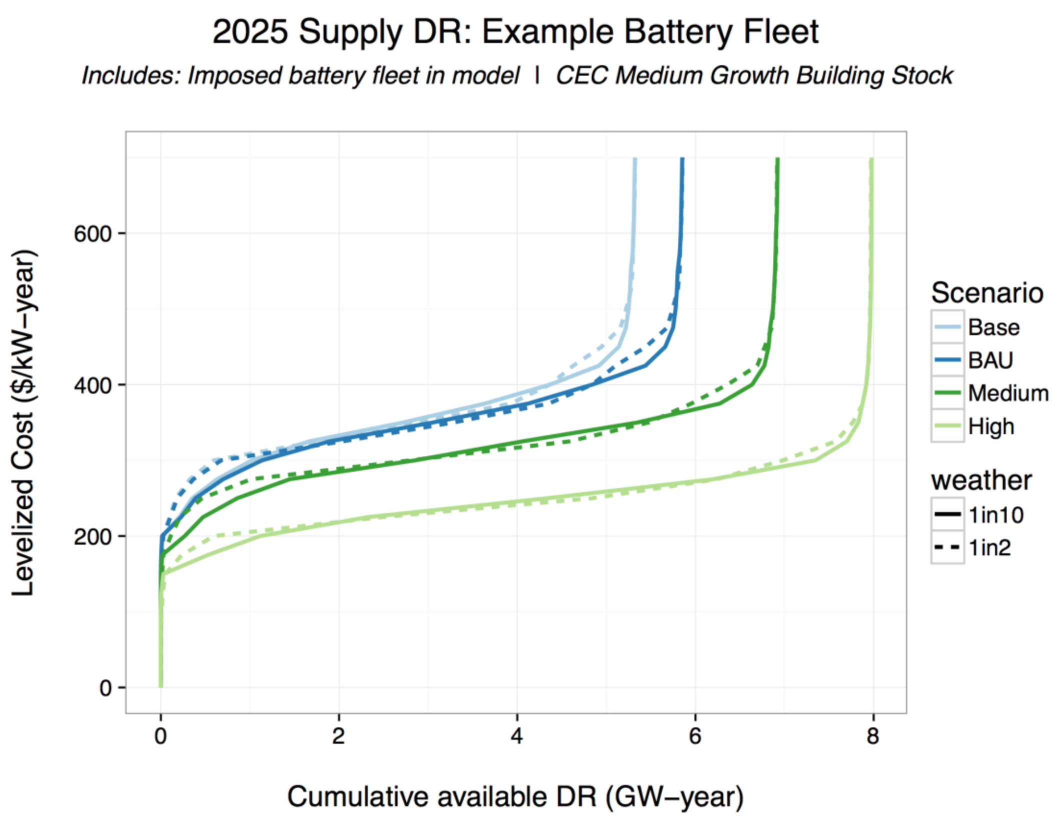


Figure 39: Supply curve for expected RA credit in California in 2025 from behind-the-meter batteries in the case where the full cost is covered by capacity payments, without accounting for other battery uses (e.g., backup power reliability value, advanced DR service, energy price arbitrage in addition to RA-related peak shaving, etc.) The four different colors represent the scenarios, as defined in Table E1.

5. Discussion

The markets and technology for DR are shaped and driven by several key **mega-trends** in energy systems-- rapid scale-up of renewable generation, advances in technology for energy storage, and fast-changing information technology capabilities and cost. It is mandated in SB350 that the California grid will experience rapid changes in technology for both generation and load by 2030, with about a **tripling of renewables by 2025** compared to 2015. This change in our energy supply systems shows up in the net load profiles that were generated to estimate the hours of capacity need, comparing loads and DR availability with the expected renewable generation for that weather case. Figure 40 below illustrates how the CA grid could be different by 2025. The conventional generation fleet was designed and planned to meet demand profiles with a distinct base load and diurnal and seasonal cycles of demand driven by weather (like the demand profile on the top panel). With substantial investment in renewables (and ignoring export capabilities) the net load is strikingly different, with some hours of over generation. The actual hours of over generation are likely to be higher than what is shown here, depending on the minimum power requirements for any generators that must be connected and operating to maintain reliability for the grid.

By 2025 the required capacity obligations to meet changing net loads will depend on the linked profiles of demand and renewables across future potential weather years. The planning process should consider how DR is intrinsically linked with weather (e.g., see supply curve figures above that compare scenarios for 1-in-2 vs. 1-in-10 weather, where the difference is hundreds of MW at the $200 price referent level).

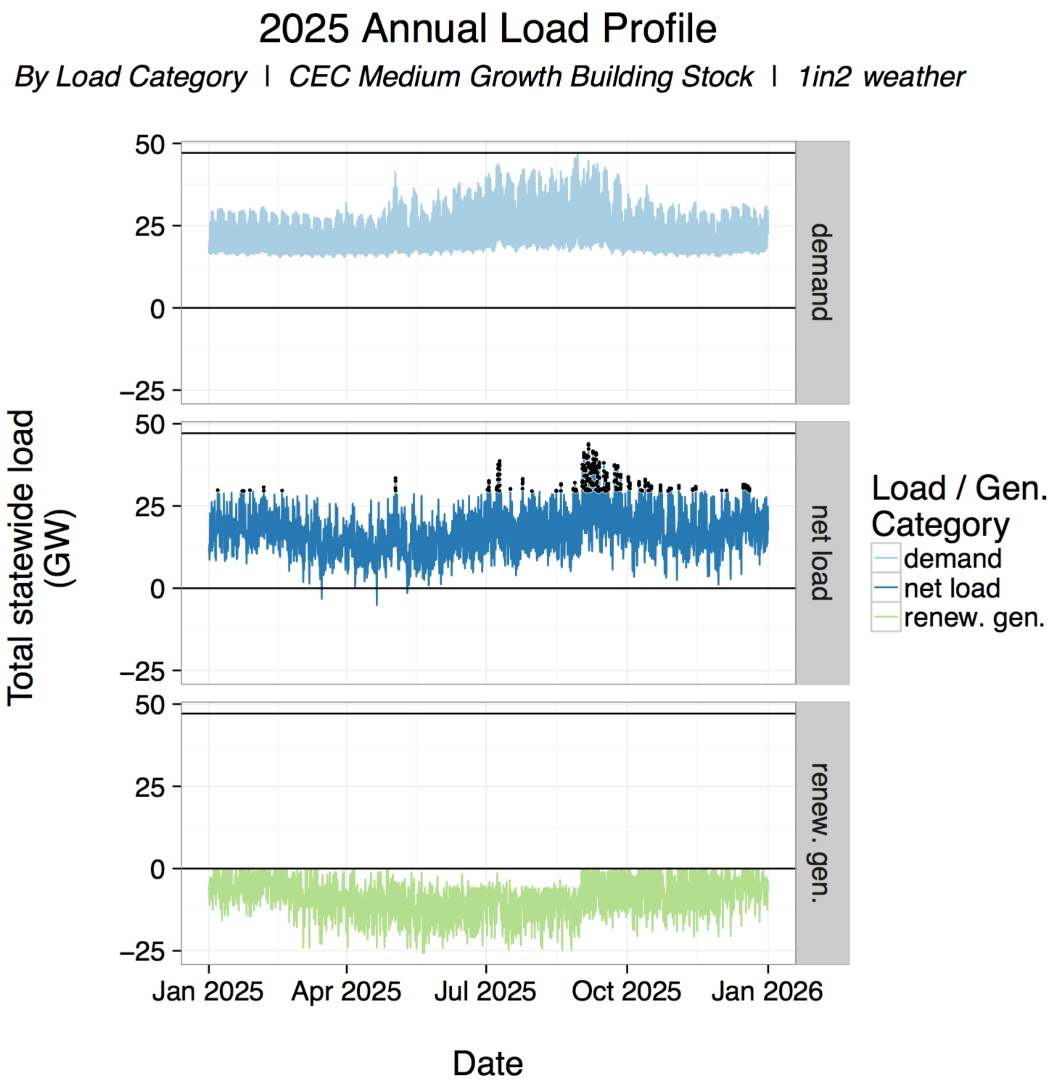


Figure 40: Forecast of Annual Net Load Profile for CASIO for 2025. Demand, net load, and renewable generation are depicted in total statewide load (GW), on individual plots. The black dots indicate the top 250 load hours, and are spread throughout the year.

Batteries for energy storage are a potentially disruptive technology system for the grid. Driven by device applications and electric vehicles, lithium ion chemistry batteries are rapidly improving in performance and falling in cost. In the model we show how behind-the-meter batteries could compete if the full cost of the system were paid for with RA capacity credit. There are, however, unique additional value streams for behind-the-meter batteries compared to load-control DR: backup power for critical loads during grid outages, generic arbitrage in response to time-varying price, and peak load management. Depending on the way retail-level storage is deployed and marketed, the net effect of these value streams could substantially reduce the cost burden for providing DR with behind-the-meter storage. Combined with the potential for cost breakthroughs that accelerate beyond the trend we use for forecasting, battery storage could be reset the price referent, replacing conventional generation or marginal T&D capacity. As a point of reference, we recalculated the available potential of DR with batteries that are half of the cost and found that if a breakthrough in technology cost or multi-value capture retail offering were to achieve that level, the potential DR at a $200/kW-year price referent is nearly double or more-- more than 15 GW in the High DR Scenario out of a peak near 40 GW. Figure 41 below illustrates how a battery breakthrough shifts the supply curve framework in this hypothetical case.

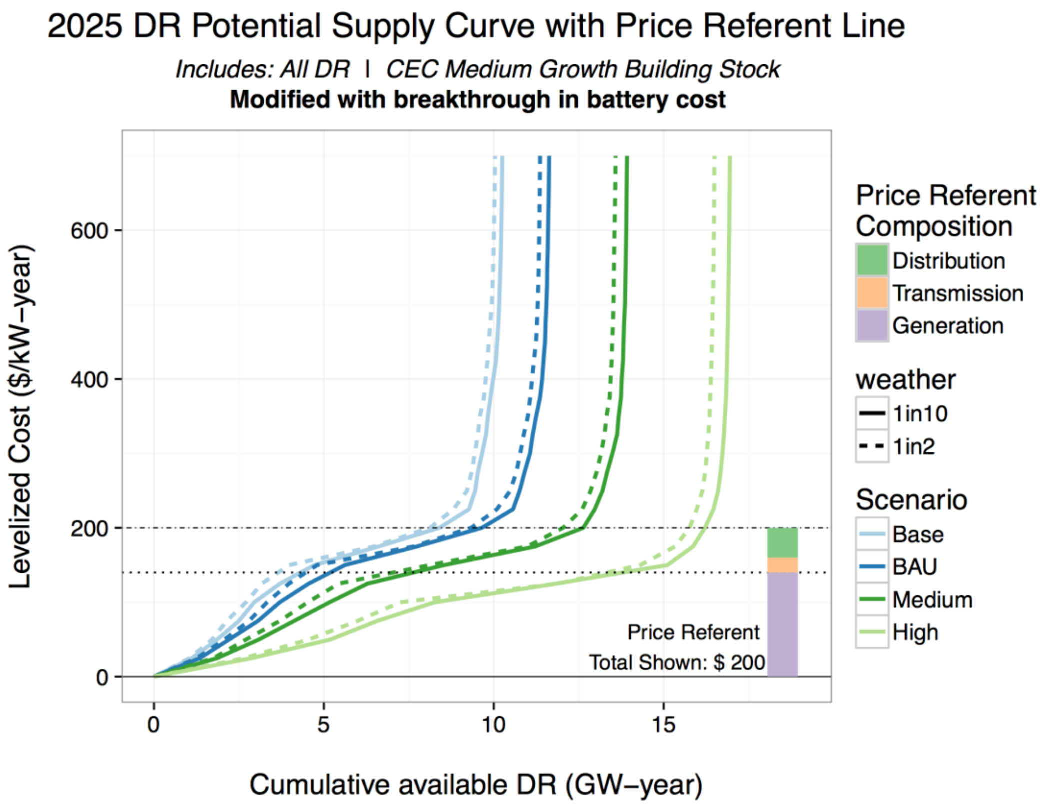


Figure 41: 2025, Supply curve for potential RA credit in CA from DR in hypothetical case where battery costs are reduced by ½, and therefore, many sites fall below the price referent.

Demand response is inherently an **information and control technology** approach to providing reliability for the grid, and is one of several linked IT layers that defines the power system—from critical peak-day marketing messages over email to real-time linked SCADA and electricity dispatch systems. All of these systems have capabilities that depend on the underlying IT, and the ubiquity of connectivity and rapidly falling cost of computing hardware make many consumer-electronics IT applications technically feasible and widely possible to adopt. (e.g., Wi-Fi-enabled thermostats, refrigerators that can tweet at you to buy milk). It is also notable that this public-interest study employing detailed bottom-up technology potential models is possible only with the use of large datasets from advanced meters. These meters already are the backbone for settlement for some DR products, and as the period of record grows the data from sites is a potentially rich information resource for long-term planning, M&V, and retail market transformation. A breakthrough in internet-of-things (IoT) approaches could also lead to shifts in the available capacity of DR, similar to battery breakthroughs. In Figure 42, we show the implications of a hypothetical IoT breakthrough, which imposes that the equipment under control in our model has built-in connectivity and control (i.e., that the up-front investment costs for technology were zero) and that the costs for marketing and administration of DR programs are reduced by 50%. We leave incentive payments in place at the normal levels. The changes to the available supply with this IoT breakthrough are less dramatic in terms of shifting the intersection of the supply curve with the price referent levels we show for discussion purposes (i.e., only modest increases in apparent cost-competitive DR are achieved, from 5.8 GW to 6.4 GW in the medium scenario with 1-in-2 weather at a $200/kW-year price referent), but there is substantially more DR available at low cost, and less sensitivity of quantity to the particular price referent in this IoT case than the standard case (i.e., the intersection angle of the supply curve and a horizontal price referent is closer to perpendicular).

Figure 43 shows how IoT and battery breakthroughs could change the market if they were both achieved. In the context of a fast-changing technology market, these developments are not out of the question, and our analysis shows they could fundamentally shift the dynamics. In the context of a roughly 40 GW peak capacity need, 10-15 GW of capacity resource from behind-the-meter sources would be a substantial contribution and would also call into question the use of a conventional price referent for determining the value and competitive quantity of DR.

In 2025, depending on the trajectory for technology and markets, grid-scale energy storage may be the appropriate price referent and much more locally-specific costs for service may set local prices for distributed resource service that are the dominant driver for DR investment (compared to the system-scale prices we use in this framework). In the context of this important and evolving resource base for supporting renewables integration, we offer a number of additional discussion points and recommendations in the sub-sections below.

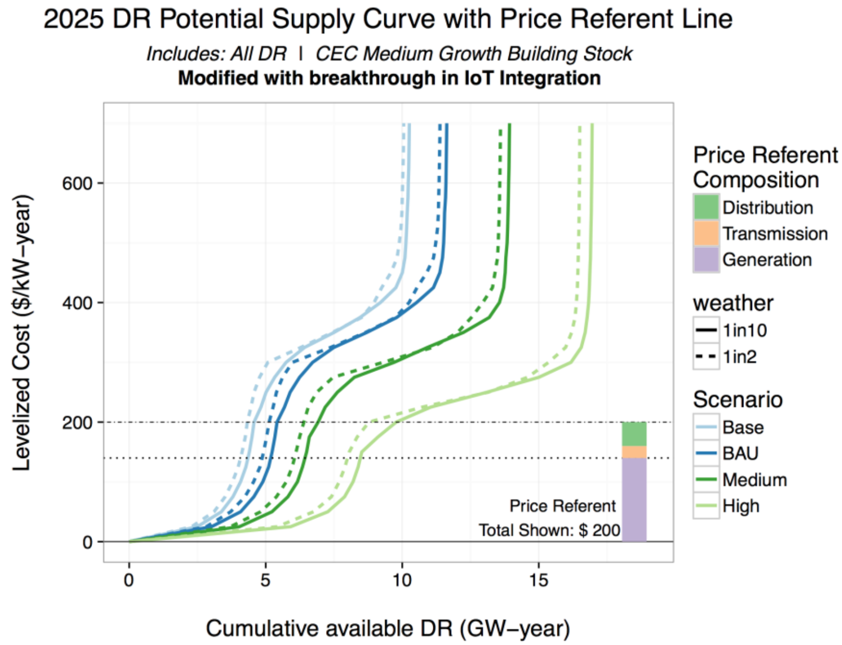


Figure 42: 2025, Supply curve for potential RA credit in CA from DR in hypothetical case where the initial technology costs are zero, and the marketing and administrative costs are reduced by ½. This is meant to simulate an "IoT" breakthrough in the market.

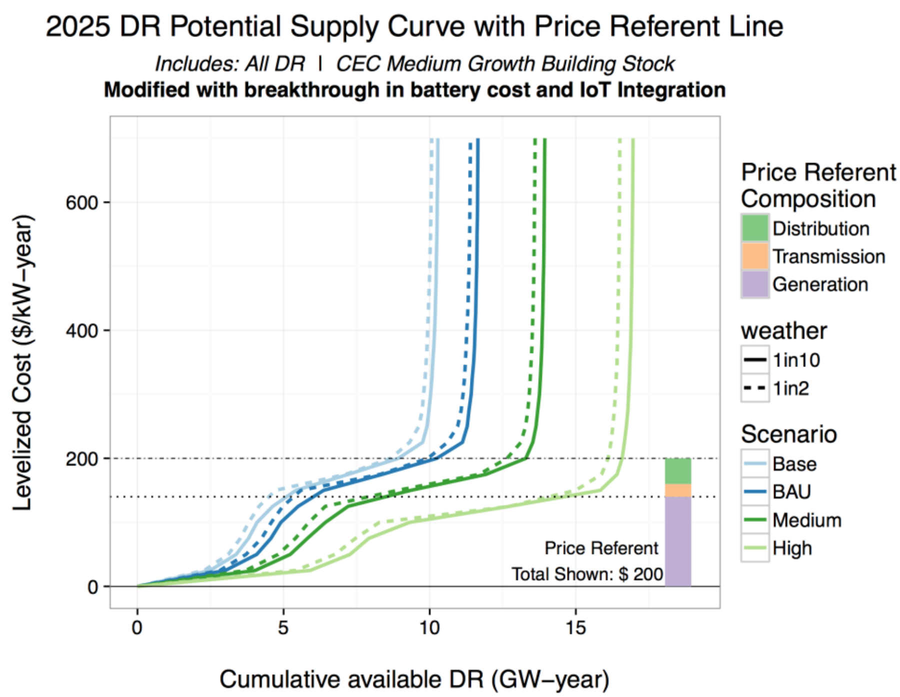


Figure 43: Supply curve for potential RA credit in California in 2025 from DR in the hypothetical case where both the battery and IoT breakthroughs described in the text occur.

5.1. Evolving Policy Context for DR

Ultimately the scale of DR potential in California will depend on how the policy environment, market design, and technology R&D progress over the coming years. Below we describe the context of the emerging next-generation grid DR landscape:

Importance of market design

The CAISO is undergoing a parallel set of reforms to the CPUC to create space in the energy and ancillary services market for distributed resources and DR. As these processes of market definition continue, there are important design decisions being made that will influence the ability of and incentives for demand response to participate.

Stakeholders we heard from in the TAG raised issues about a range of market design choices that bear directly on the potential for DR (and are core to defining it). Telemetry requirements can have significant influence on the cost of fast DR, requirements for continuously variable dispatch present challenges to some DR-ready processes that run as a continuous batch, and there are constraints in the capabilities of advanced metering infrastructure to support settlement of fast resources.

Energy efficiency, load modifying DR, and supply DR

There is an ongoing discussion around interactive effects of energy efficiency and demand response, and the bifurcation of DR into load-modifying and supply resources facilitates a new way of viewing these effects. One could broadly consider energy efficiency as a load modifying DR measure, whereby the net load is decreased by an efficiency investment (and the timing of service remains unchanged). Thus energy efficiency investments in general have “load modifying” DR effects, reducing the need for procuring peak capacity because the peak load is reduced. Depending on the load types that are upgraded or improved, it is possible as well that less flexible ramping capacity and other advanced grid products will be required due to EE.

On the other hand, improved efficiency for an end-use that also participates as supply DR reduces the availability of baseline load to actively shed. It is an important point, however, that the net sum of the DR resource is unchanged in general and could be increased through EE investment. Consider an example of an HVAC load that is 10 kW baseline and can be reduced by half of the service level – 5 kW – with dispatchable control as supply DR. If the load is efficiency upgraded with one that uses 75% of the original energy (i.e., an EE benefit of 25%), the baseline is now 7.5 kW for the same baseline level of service. If the service level is still reduced to half during a DR event, this means that there is only 3.75 kW available for supply DR (less than the original 5 kW shed) but the overall effect of the combined EE and DR on the net load is a reduction of 6.25 kW – an increase in total DR compared to the original configuration that also comes with all the benefits of energy efficiency upgrades. If one only considers the availability of supply DR in the absence of the underlying load-modifying effects however, an efficiency investment can appear to reduce the quantity of available DR.

The DR forecast potential we identify is for a frozen efficiency case. If there are significant EE investments that are linked with DR upgrades, we would expect lower availability of supply DR for upgraded end-uses but with overall net load effects that have a combined load modifying and supply DR potential that meets more of the capacity needs.

Furthermore, energy-efficiency upgrades often present opportunities for cost-effective controls upgrades (whether part of an integrated project, or if controls are built in to new equipment in an internet-of-things approach) that can reduce the cost of enabling DR. An instructive example is the case of energy-efficient lighting. LED lighting is now an established market segment and has rapidly improving efficiency, recently surpassing the incumbent fluorescent technologies prevalent for the last few decades. The efficiency benefits of LED lighting are often large, reducing the theoretical quantity of dispatchable DR available from the load, but the upgrade is an opportunity to simultaneously make the lighting stock more controllable for both occupant service and DR. The markets for distributed energy technology that provides multi-attribute service like these are still evolving and often there are challenges to ensure the services are appropriately valued. The DR market for lighting is still in its infancy and growth will be dependent on numerous market transformation activities occurring simultaneously: building product availability, lowering technology cost, increasing reliability, improving market knowledge (i.e., designers, specifiers, contractors, building owners/occupants, building officials, and facility managers all becoming conversant in the technology), and aligning capital investment support. Solutions for addressing the DR lighting in particular are the subject of a recent California Energy Commission EPIC PON 15-311 solicitation, and LBNL's awarded contract, to develop "The Value Proposition for Cost-Effective, DR-Enabling, Nonresidential Lighting System Retrofits in California Buildings". This project will explore energy and non-energy benefits in California, for DR-enabling, advanced lighting control systems leading to a more comprehensive and accurate financial analysis for the technology. The goal is to support enhancement of CA Title 24, and IDSM program offerings, to accelerate market adoption for the technology. Targeted market transformation efforts like these are critical for technology areas with significant overlap between traditionally separate value areas like EE and DR.

The overall effect of energy efficiency and DR integration could be an overall increase in combined load-modifying and supply DR availability for meeting system capacity needs, with supply DR at a lower cost compared to DR-only technology investments. Achieving this synergy will however require significant effort to align policy and market frameworks.

DR Targets and the importance of Baselines

The challenges of measuring the counterfactual baseline for DR is well documented, and the way DR is measured and accounted for in the market will strongly influence the competitiveness of DR and ability of market participants to provide resources that meet policy targets for resource adequacy and other applications. The DR we include in our modeling effort inherently has a known counterfactual expected baseline – this is the load profile that is the basis for the expected DR resource. If operational practice fails to accurately measure the load impact of DR the apparent resource could deviate from its actual value or become obscured by noise in the measurement.

There are also similar baseline issues at play for considering policy targets for DR. In many cases policy is set in terms of minimum thresholds for procurement that are a fraction of total procurement or an absolute minimum. In addition to bias or imprecision that is introduced from operational M&V, which would effect any kind of policy compliance, the magnitude of DR resources also depends on exogenous effects of weather (as shown in the comparison between weather cases for our model) and economic cycles (not shown in the model). During the recent recession there was a decrease in DR related to slowed economic activity. This slower activity can result in lower industrial electric loads and lower rates of energy use in office and retail buildings.

5.2. Opportunities for breakthrough in technology and markets

Building codes – The California Energy Commission has developed requirements to install DR automation technology as part of Title 24. These requirements' success could greatly reduce the new DR systems' first cost. Not only can the T24 requirements reduce the cost for automated DR in new buildings, but also they help to disseminate key information to control companies about the commitment to formal communication standards for DR automation. For large building control systems, the DR automation cost could be extremely low if the DR automation was available in conventional building automation system controls. The majority of large commercial and industrial DR is installed with gateway boxes. Unfortunately, there is great confusion about the current DR requirements in Title 24 and the code officials and key market players have received little to no education on the intent of these DR requirements. Similarly control companies and design engineers have expressed concerns about the lack of consistency in interpreting the code requirements. Careful attention to this issue is needed because the market confusion generated by inclusion of this DR requirement in Title 24. The CPUC and the IOUs can help address this problem by evaluating the knowledge gaps that exist around the DR code issues and develop training and information to address these gaps. Given the language that is in Title 24 on DR automation there are opportunities to ensure that retrofits and new buildings that require Title 24 compliance are provided with clear information about the DR programs the building may be eligible for. More work is needed to benchmark the costs for DR automation and compare various strategies to comply with Title 24.

Internet of Things (IoT) – California is fortunate to be the home of many established as well as emerging companies and industries taking advantage of the incredible opportunities for using the internet in new ways. One of the most promising areas for DR is the capability of new packages of technology to control, measure and automate DR. A recent study by Lanzisera, et al (2015), showed that new DR technology platforms could be capable of providing fast load shed for between \$20 and \$300 per kilowatt (kW) of available load. The study noted – *"Many new technologies will be installed for energy efficiency or non-energy benefits (e.g., improved lighting quality or controllability), and the ability to use them for fast DR is a secondary benefit. Therefore, the cost of enabling them for DR may approach zero if a software-only solution can be deployed to enable fast DR after devices are installed for other reasons."* Some of the lowest cost DR technologies are new communicating thermostats that are installed by the customer for energy management and convenience, but can also qualify for automated DR programs because they support OpenADR.

Integrated DSM (IDSM) – In recent years, the utilities' energy efficiency (EE) and DR goals are planned, managed and evaluated separately. Customers are approached separately for EE and DR programs, which produces customer confusion. The customer engagement activities will be more cost-effective if the technology costs for EE and DR technologies are integrated. For example, at SMUD, when new building HVAC automation or lighting controls are incentivized with EE DSM funds, they require the technology system to support OpenADR so that it will be less expensive for the building to join a DR program in the future. This integration creates a 'future-proofed', DR-enabling technology platform when implementing EE project investments. There is a need to explore how to better link EE and DR measures so that they are more cost-effective when bundled. To achieve this will require some creative new measurement and verification methods to value both the EE and the DR performance of an IDSM measure.

Customer Feedback and Behavior Based Programs – Recent research (Cappers and Sneer 2014, Todd et al. 2014) has found that utilities and aggregators that focus programs efforts on customer feedback, engagement and behavior have successfully encouraged DR participation and energy conservation during peak hours. Residential In-home displays and monthly "home energy reports" have been shown to help raise awareness of energy use and provide some conservation effects. Similarly, in large C&I programs, aggregators have experience providing custom feedback to C&I customers on their DR strategies' performance. This feedback occurs quickly after DR events and helps provide direct information about the customer's electric load shape and the economic incentives. This customer feedback stands in sharp contrast to the IOU program feedback.

DR Aggregators' Role – California needs to continue to explore how to optimally partner with aggregators. Key to this optimization is to ensure that CA State policy initiatives, electricity market rules, IOU interests (distribution infrastructure investments and earnings mechanisms) and CA ratepayers' (i.e., end-users'/building owners') DR value propositions align in a coherent fashion. The current market set up discourages optimization between the previously stated parties due to self-interests. There exists a significant disconnect between profit mechanisms between end-users, aggregators and IOU's.

5.3. Discussion of Phase 1 Modeling Approach

This study includes numerous simplifying assumptions that are important to note for understanding our approach and interpreting the results. In this section, we discuss several issues and indicate the likely direction of any bias that is introduced with respect to DR potential.

Frozen-Efficiency - Our model assumes that the electric end-uses we model change insignificantly over the next decade and excludes aggressive efficiency upgrades or code changes that could reshape the net load. Given the goals set in Senate Bill 350, we may expect double the savings contributions of energy efficiency by 2030[5] compared with the efficiency activities of the 2014 baseline year. The model does forecast increased load growth; there are more customers in California due to increasing population, but the energy consumption by end-use does not change significantly for the different customer sectors. We call this a "frozen efficiency" model case, whereas we have not estimated any increase in energy efficiency in end-uses such as air conditioning, pumping, refrigeration, or other loads.

Overall, we expect that the absence of energy-efficiency (EE) adjustments in our current model, leads to overestimating available supply DR, but underestimates the overall net load reduction that is possible with combined EE and DR investment. If EE facilitates lower cost opportunities for controls upgrades, the cost-effective supply DR quantity in a combined EE and DR portfolio could be higher than what we show in a frozen-efficiency case.

Co-Benefits – The Phase 1 analysis has not fully captured the co-benefit streams for products that are already installed in customer premises or installed for reasons other than DR, such as energy efficiency, or better building control. These co-benefit streams can effectively reduce the DR enabling technology costs and therefore, increase the quantity available under the price referent. A careful treatment of these co-benefit streams is part of our plan for Phase 2.

One potential way we could address the benefits of efficiency in future modeling tasks might be to consider the co-benefits of DR technology adoption. There are new technologies available to retrofit lighting systems that reduce the electricity use overall as well as provide communication and control capabilities for DR. These co-benefits frequently dwarf the value associated with implementing DR and are typically the reason for investing in the technology improvements in the first place. When we are dealing with technologies that inherently enable DR, but the main drivers may be for efficiency improvements or for non-energy benefits, we need to carefully capture, characterize and nimbly account for their effects in adoption rates and corresponding DR potential. When additional co-benefits are included, we expect the unit cost of DR to decrease and for there to be more competitive DR available.

Single Product DR: Most of the DR enabling technologies/end-uses can provide DR services to

5 http://switchboard.nrdc.org/blogs/mborgeson/CA_doubles_EE.html

more than one DR product in the supply market, but in this interim report we are only modeling participation in supply markets that directly lead to resource adequacy (RA) credit. In other words, the supply curves represent technology/end-uses, which are constrained to provide service to *a single product*. Multi-product value streams are not explored within Phase 1, and will be considered in the Phase 2 analysis that includes a full set of grid services. When additional value streams are available, it will reduce the effective cost of capacity and increase the quantity of competitive DR. If accessing additional value streams lead to negative outcomes (more customer fatigue or disenrollment) the additional uses could be avoided unless those are outweighed by the economies of diversity from access to multiple markets.

The complexity of real-world markets: We make some key assumptions about how DR is measured and qualified to participate in supply markets, but if these are not aligned with the market structure in the future the actual outcomes will diverge. For instance, we assume that there are no settlement barriers (i.e., that the existing advanced metering infrastructure is sufficient to support any settlement needs).

Interactive Effects – Another modeling challenge unaddressed are end-uses' interactive effects. The classic interactive effect example is the relationship between lighting and cooling. When lighting electricity use is decreased, cooling loads are correspondingly reduced. As mentioned, lighting loads are expected to decrease by 30 percent in the next 10 years, thereby, also decreasing cooling loads and the overall system peak. This is also a real-time effect. A building that reduces lighting during a DR event will then have a lower cooling load, and therefore, potentially a lower DR HVAC capability. The net effect from these interactive effects is uncertain, on the value DR can provide to the grid.

Excluded End-Uses –The DR potential study has focused on a set of inputs, end-uses and technologies within the model to manage the scope and breadth of the analysis. Like with any other analysis, we recognize that there are end-uses within the various customer sectors that were not included in the study. Many of these end-uses were excluded because of the limited capability that we expect them to have in the DR market within the next 10 years.

Another study limitation is that we only include DR in end-uses that have been demonstrated in current DR studies or programs in California. One end-use example that may be of interest for potential future studies is residential appliances, such as residential refrigerators or dishwashers, water heaters, or dryers. Several appliance manufacturers have offered refrigerators that have electric load reduction strategies. However these communicating appliances have extremely low market uptake. California utilities and policymakers had hoped to use the smart electric meter as a gateway for communicating with a devices that are part of a home area network (HAN), but this communication system has had numerous problems despite huge investments in the radios and communication systems. Many DR programs use water heaters as a form of electricity storage, but California water heating is dominated by gas water heating. Demand response capability storage heat pump water heaters may be a technology worth investigating in future emerging technology pilots.

Another end-use that we have excluded is plug loads or miscellaneous equipment loads (MELS) for commercial or residential buildings. MELS include printers, entertainment equipment such as TVs or cable boxes, computers, and other loads. MELS are one of the fasting growing end-uses in homes and in commercial buildings. Communicating plug load controllers may be an emerging technology that can provide both energy efficiency and automated DR capabilities. A key difficulty is the plethora of equipment types and multiple industry standards associated with MELS making this heterogeneous end-use category hard to capture within the model. Adding end-use and enabling technology options can only increase the potential DR. If the end-uses we excluded are less economic than those we included, they will not affect the result.

Hourly Independence – Since this is a 'bottom up' model by customer sector of the various end-uses' capability to provide DR, we have limited capability to model some of the important factors that influence actual DR performance. One element that we know is an issue during multi-day heat events is customer fatigue. Customer fatigue results from customers being called to participate in DR programs or markets for several days in a row. It is common, for example, to have a lower response from air conditioning on a third day or an extreme heat spell than on the first day. In Phase 1, the DR events are 4-hour events and the model estimates that the DR available from some end-uses for a 1-hour event might be larger than that of a 4-hour event. We have not modeled customer fatigue but we do model variations in hourly DR availability between a 1-hour and a 4-hour event. We do not have sufficient information on how DR events to model the DR availability of a 3-day event. Each day in the model is independent. If customer fatigue is a significant factor for future DR participation, it could degrade the capacity availability or increase the cost of DR.

Future participation: The framework for estimating the propensity to adopt and enroll in DR is based on trends and DR participation rates from past and current DR programs, with an econometric model to predict participation that is calibrated to those outcomes. The future expected participation in our scenarios is based on these current-day conditional participation rates (and expands using a scenario-specific factor). It is possible that given vastly different DR enabling technology compared to the status quo, future participation could be qualitatively different. For example, current offerings to residential customers are centered around direct load control cutoff switches for air conditioning. In the future, the opportunities will still include AC cycling, but also electric vehicle charge management, behind-the-meter battery storage, and internet-of-things enabled appliances.

6. Recommendations and Opportunities

This section provides a brief description of key recommendations for supporting appropriate and cost-effective DR technology deployment in support of renewables integration and to help meet the challenge of transforming the electricity system. These recommendations are informed by what we have learned in the course of our study so far and draw on observations regarding technology cost trends, opportunities by sector, and market issues. We also provide recommendations that are oriented toward describing opportunities for California to accelerate the potential for low-cost, automated DR that is capable of providing important reliable resources for the electric grid and achieving more aggressive DR market and technology growth.

Beyond widgets - Although there are important strides to be made in the costs of hardware for DR sensing and control, many of the DR costs we identified are "soft" costs related to administration, marketing, incentives, etc. The cost of DR can be reduced if DR is integrated with other clean energy service offerings (e.g., energy efficiency, electrification of heating and transportation, and distributed generation) in mutually supported portfolios. Beyond the specific hardware used to achieve flexibility, the full technology system employed is important for the future of DR, and in our study we identified that depending on the technology often half or more of the cost of DR is in soft-cost categories.

Open standards – California has made great strides in developing and promoting common standards for DR automation, and these are critical for enabling low-cost pathways to DR enabling the evolution of the internet-of-things approaches that use onboard, or built-in device connectivity to support DR and we show could be key to technology-oriented DR market transformation. Onboard devices can support Open Automated Demand Response (OpenADR 1.0 and 2.0), and Smart Energy Profile (SEP 1.0 and 2.0). Further work is needed to ensure that there is adequate outreach and education to ensure that the use of these standards is coordinated among IOUs, aggregators, the ISOs, vendors, controls companies, and customers. Additional outreach should be done to inform customers regarding the enhanced value to them for making sure any investment on their part adheres to most relevant standard.

Open data sets by customer segment and cluster – Given the data privacy and security concerns and legal framework in California, there is a lack of data available and a missed opportunity to promote research, technology development, public interest policy analysis, and market assessment. It would be useful to explore how to make the data sets from this project available in an anonymized form to facilitate greater understanding of the DR potential in California and support the kinds of targeting opportunities that our results identify. These anonymized data sets could empower third parties to accelerate DR-enabling technology adoption by eliminating a key market barrier related to this current lack of information; this would catalyze a range of R&D.

Expand the DR Industry and Improve Customer Outreach and Awareness – California has more than three decades of success in growing an energy-efficiency marketplace. Our experience with DR is growing, but we need to educate, enable, and evaluate customers, account managers, aggregators, policy makers and evaluators regarding DR opportunities and concepts.

Building Codes – California policy makers and IOUs need to continue to explore how to best develop and foster building codes to lower the cost of DR automation and ensure that the intention of the code results in successful compliance.

Dual Participation – This Phase 1 study has a limited set of DR products included in the evaluation. We anticipate that in Phase 2 we will explore the opportunities for dual participation. Some of the most cost effective DR is likely to be the DR that can be used in multiple programs or markets because the DR resource is called more than if it were in only one market. Thus the "value" the DR provides is greater because there will be additional value-streams to help buy down technology investment, customers could receive incentives that cover dual participation, and shared systems could otherwise achieve better economics through offering multiple products from the same portfolio of resources. This is a subject for further analysis in Phase 2 but an important policy issue for the IOUs, the CPUC and CAISO.

Long-term Market Transformation - California DSM programs have explored opportunities for MT goals such that the landscape for energy efficiency is fundamentally changed with certain DSM investments. Market transformation in energy efficiency overcomes market barriers to optimal efficiency with strategies to shift entire market sectors into a more efficient product mix. A similar perspective is needed to explore how to most aggressively promote a long-term commitment to DR in California. This may include new approaches such as upstream DR incentives for DR automation systems such as HVAC, lighting, or pumping systems. The DR automation market will be transformed when control systems have communication hardware and software capabilities that can receive and send DR signals with minimal to no additional first costs. A DR transformed controls market would enable lower cost DR with greater levels of participation. Further research on this topic is needed to explore the opportunities for California.

DR, Load Shape Comparisons and Peak Demand Benchmarking – Many large commercial building owners know the energy use intensity (EUI) of their building. EUIs are used in Energy Star benchmarking, required in disclosure laws, and are the basis of many energy-efficiency studies, In contrast, peak demand intensities and load shape data are much less available. Making energy consumption benchmarks that effectively communicate the multidimensional attributes of consumption beyond kWh could help lead to institutional and operational awareness of DR. As we move away from hot summer DR to any-time DR, peak demand benchmarking becomes even harder and new metrics and load factor data are needed for electricity customers to understand how "peaky" they are compared with similar customers, buildings, or industrial facilities. Exploratory work is needed to develop a framework for peak demand data. Such data will help customers understand their DR potential and evaluate how their peaks and hourly load shape compare with others.

7. Next Steps and Plans for Phase 2

This report summarizes the DR Potential Study Phase 1 results. In Phase 2, which is scheduled to be complete in August 2016, we plan to extend our framework and analysis to include a full set of DR for supporting the next-generation grid. This will include defining fast-DR product sets that meet broader system needs and improving our inputs and analytical framework.

Additional enabling technology options: In Phase 2, we anticipate working with stakeholders in the TAG to refine our existing set of enabling technology inputs (possibly including new end-use categories like plug loads or large appliances), fortify them with fast and advanced DR capabilities and costs, and develop new potential pathways for a broader set of technology.

Additional load-modifying approaches: We plan to improve and extend our approach to modeling load-modifying DR, aligning our approach to TOU pricing with ongoing JASC efforts across a range of rate design scenarios from that work, incorporating critical peak-day load-modifying approaches (based on both price and behavioral notifications), and incorporating the best available information about the "load-modifying" value of dispatched DR that serves distribution system capacity needs.

Additional DR Products: In Phase 1, we addressed energy and reliability DR products with specific characteristics built around today's markets. In Phase 2, we will introduce flexible products that can provide ramping services or fast DR for AS and determine the value they provide to a grid system that has increasing levels of renewables. We will explore how DR can fit into the power system as a distributed energy resource, forecast what value it can provide as a tool to integrate renewable resources, and the cost-effectiveness of various DR resources during the next 10 years.

Multi-product economic analysis: Our Phase-1 approach to modeling DR economics was based on collapsing the resource to a single effective capacity cost that is not linked to other value streams and that is compared to a market price referent. In Phase 2, we plan to work with E3 to integrate our analysis with existing models for multi-market participation of DR in advanced grid service products. We expect to develop new capabilities for using an equilibrium operations and investment model for the California grid (RESOLVE) to estimate the value of ramping and fast DR, and to validate and improve our Phase 1 capacity credit allocation approach in collaboration with E3 and based on their experience in developing the RECAP model. The Phase 2 approach will provide a way to estimate DR's potential value for both capacity and other grid needs in combination and in dynamic competition with a mix of conventional generation and grid-scale storage.

8. References

California Independent System Operator (CAISO), "What the duck curve tells us about managing a green grid," October 2013.

California Independent System Operator (CAISO), 2010. Reliability Demand Response Product, Revised Draft Final Proposal, Version 2.0. Prepared for The Reliability Demand Response Product Stakeholder Initiative. October 14, 2010. Available at https://www.caiso.com/Documents/RevisedDraftFinalProposalVersion2-ReliabilityDemandResponseProduct.pdf

Peter Cappers, Richard Sneer. 2014. Experiences from the Consumer Behavior Studies on Engaging Customers, Lawrence Berkeley National Laboratory, LBNL-182975. https://eaei.lbl.gov/sites/all/files/lbnl-182975.pdf

Cappers, Peter, Andrew D. Mills, Charles A. Goldman, Ryan H. Wiser, and Joseph H. Eto. Mass Market Demand Response and Variable Generation Integration Issues: A Scoping Study. Berkeley: LBNL, 2011. Available at:

http://emp.lbl.gov/publications/mass-market-demand-response-and-variable-generation-integration-issues-scoping-study.

Cappers, P., J. MacDonald, and C. A. Goldman. Market and Policy Barriers for Demand Response Providing Ancillary Services in U.S. Markets., 2013. Available at:

http://emp.lbl.gov/publications/market-and-policy-barriers-demand-response-providing-ancillary-services-us-markets.

California Energy Commission (CEC), "California Energy Demand 2014-2024 Forecast," January 2014.

California Energy Commission (CEC). 2010. 2009 Residential Appliance Saturation Study Volume 2: Results. CEC- 200-2010-004. Available at: http://www.energy.ca.gov/appliances/rass/. Accessed Feb 10, 2016.

California Energy Commission (CEC), "The State of DR in California, 2007, " CEC-200-2007-003-F.

2011 California Building Energy Efficiency Standards, Measure Information Template – Demand Responsive Lighting Controls, California Utilities Statewide Codes and Standards Team, February 2011

Edmonds, T., Al Lamont, V. Bulaevskaya, C. Meyers, J. Mirocha, A. Schmidt, M. Simpson, S. Smith, P. Sotorrio, P. Top, Y. Yao. The Value of Energy Storage and Demand Response for Renewable Integration in California. June 2013.

ftp://ftp2.cpuc.ca.gov/PG&E20150130ResponseToA1312012Ruling/2013/10/SB_GT&S_08904

38.pdf.

ESMAP, "Good Practices in City Energy Efficiency: Los Angeles, USA- Light Emitting Diode (LED) Street Lighting Retrofit," October 2011.

Faruqui A., and R. Hledik, "The State of Demand Response in California," September 2007. CEC-200-2007-003-F.

Federal Energy Regulatory Commission, "A National Assessment of Demand Response Potential," June 2009.

Ghatikar, G. D. Riess and M.A. Piette. Analysis of Open Automated Demand Response Deployments in California and Guidelines to Transition to Industry Standards. Lawrence Berkeley National Laboratory. LBNL-6560E. 2014.

Hawaiian Electric, Maui Electric, and Hawai'I Electric Light, "Integrated Demand Response Portfolio Plan," July 2014.

Kiliccote, S., M.A. Piette, J. Mathieu, and K. Parrish. Findings from Seven Years of Field Performance Data for Automated Demand Response in Commercial Buildings. Proceedings of the 2010 ACEEE Summer Study on Energy Efficiency in Buildings. Pacific Grove, CA, 2010. LBNL-3643E. 2010.

Kiliccote, S. G. K. Homan, R. W. Anderson, and J. Herdandez. Intermittent Renewable Management Pilot Two. LBNL-179019. 2015.

Lanzisera, S., A. Weber, A. Liao, O. Schetrit, S. Kiliccote and M.A. Piette. Field Testing of Telemetry for Demand Response Control of Small Loads. LBNL Number Forthcoming. 2015.

Long, Jane, Miriam John, Jeffery Greenblatt, Max Wei, Christopher Yang, Burton Richter, Bryan Hannegan, and Heather Youngs. "California's Energy Future-The View to 2050." 2011.

National Oceanic and Atmospheric Administration. 2015. Integrated Surface Database. Available at: https://www.ncdc.noaa.gov/isd. Accessed Feb 10, 2016.

Navigant. "2013 California Energy Efficiency Potential and Goals Study." November 26, 2013.

Olsen, D., M. D. Sohn, N. Matson, J. Dudley, S. Goli, and S. Kiliccote, M. Hummon, P. Denholm, J. Jorgenson, D. Palchak, O. Ma "Grid Integration of Aggregated Demand Response, Part I: Load Availability Profiles and Constraints for the Western Interconnection," LBNL-6417E, 2013.

Olsen, D., M. Sohn, M.A Piette and S. Kiliccote. "Demand Response Availability Profiles for California in the Year 2020." LBNL-1004414. 2014.

Pacific Gas and Electric Company, 2015. Tarriff Book. Accessed March 17, 2015 at: http://www.pge.com/tariffs/ERS.SHTML#ERS.

San Diego Gas and Electric, 2015. Current and Effective Tarriffs. Accessed March 17, 2015 at: http://www.sdge.com/rates-regulations/current-and-effective-tariffs/current-and-effective-tariffs.

Santos, Adella, et al. *Summary of travel trends: 2009 national household travel survey.* No. FHWA-PL-ll-022. 2011.

Southern California Edison (SCE). 2008. Pool Pump Demand Response Potential: Demand and run-time monitored data. Available at: http://www.etcc-ca.com/sites/default/files/reports/dr07_01_pool_pump_demand_response_potential_report.pdf. Accessed Feb 10, 2016.

Southern California Edison, 2015. Regulatory Information – Rates Pricing. Accessed March 17, 2015 at https://www.sce.com/wps/portal/home/regulatory/tariff-books/rates-pricing-choices.

Todd, A., M. Perry, B. Smith, M. Sullivan, P. Cappers, and C. Goldman. 2014. Insights from Smart Meters: The Potential for Peak Hour Savings from Behavior-Based Programs. Lawrence Berkeley National Laboratory, LBNL-6598E. http://emp.lbl.gov/publications/insights-smart-meterspotential-peak-hour-savings-behavior-based-programs

U.S. Census Bureau. 2015. 2015 U.S. Gazetteer Files. Available at: https://www.census.gov/geo/maps-data/data/gazetteer2015.html. Accessed Feb 10, 2016.

Appendices A - J

2015 California Demand Response Potential Study

Charting California's Demand Response Future

Peter Alstone, Jennifer Potter, Mary Ann Piette, Peter Schwartz,
Michael A. Berger, Laurel N. Dunn, Sarah J. Smith, Michael D. Sohn,
Arian Aghajanzadeh, Sofia Stensson, Julia Szinai

April 1, 2016

Table of Contents

Word did not find any entries for your table of contents.

In your document, select the words to include in the table of contents, and then on the Home tab, under Styles, click a heading style. Repeat for each heading that you want to include, and then insert the table of contents in your document. To manually create a table of contents, on the Document Elements tab, under Table of Contents, point to a style and then click the down arrow button. Click one of the styles under Manual Table of Contents, and then type the entries manually.

Tables and Figures

Tables

Figures

Appendix A: DR Potential Study Secondary Output Figures

Appendix A: DR Potential Study Secondary Output Figures

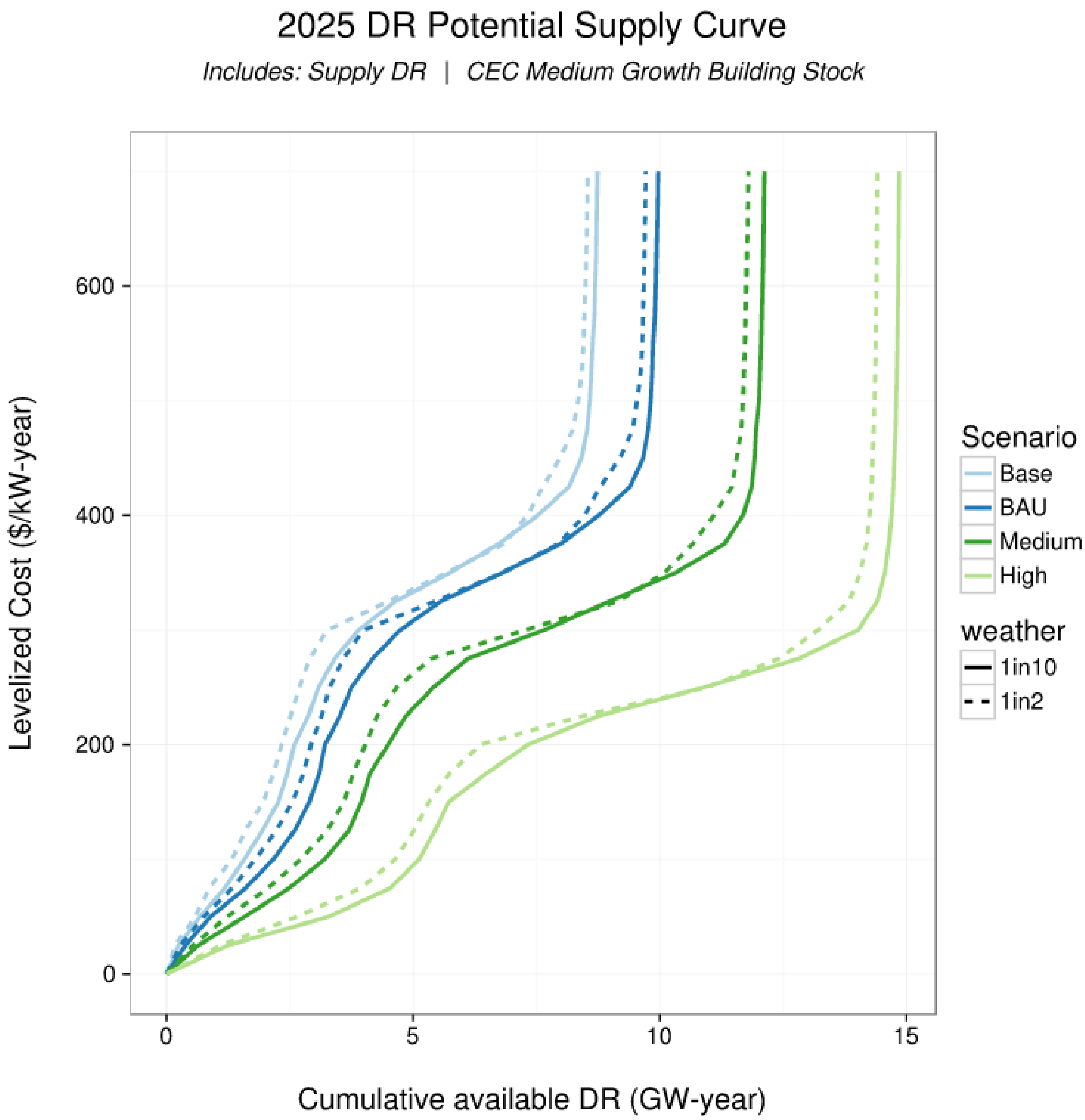


Figure A-1: Potential demand response results for the year 2025. Levelized cost (y-axis) refers to the annualized cost per unit of energy, with consideration for technology purchase, maintenance and repair, and amortization.

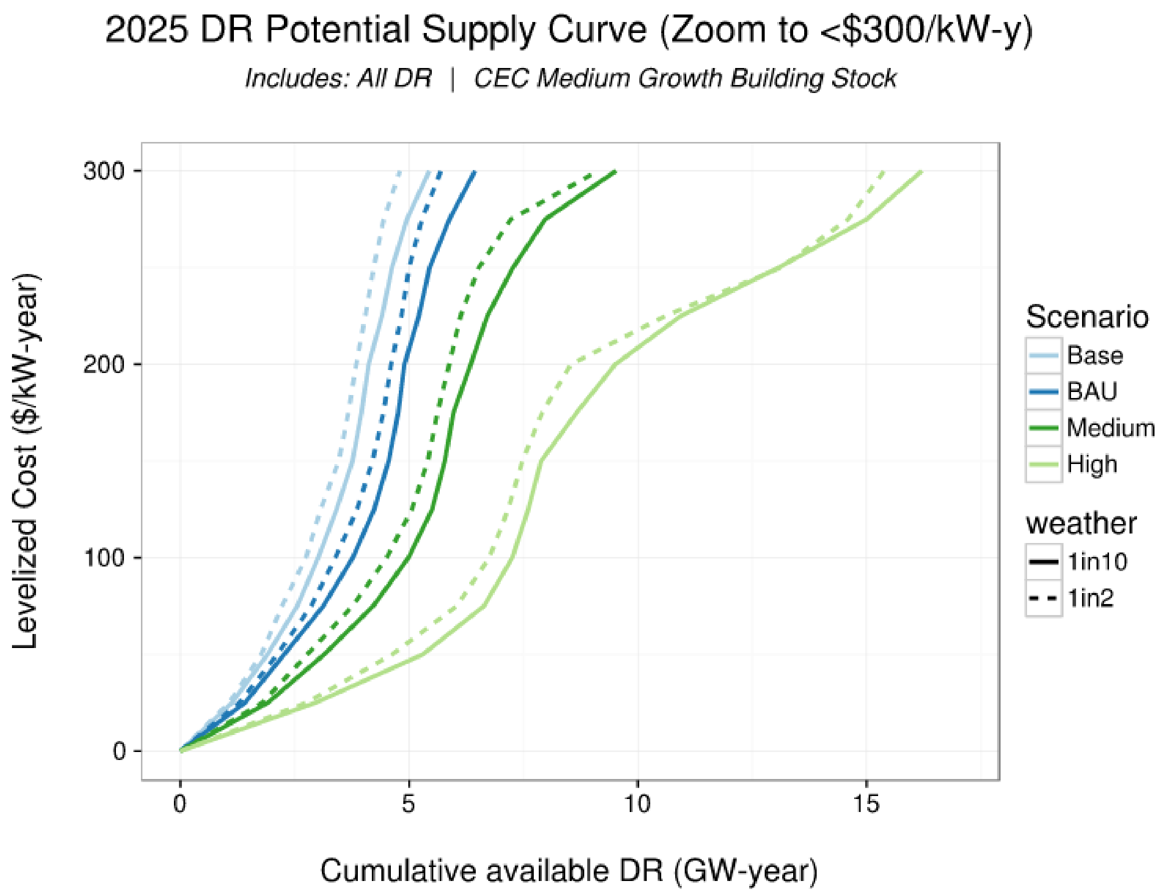


Figure A-2: Area around price referent intersection is zoomed to show detail on scenarios. Levelized cost (y-axis) refers to the annualized cost per unit of energy, with consideration for technology purchase, maintenance and repair, and amortization.

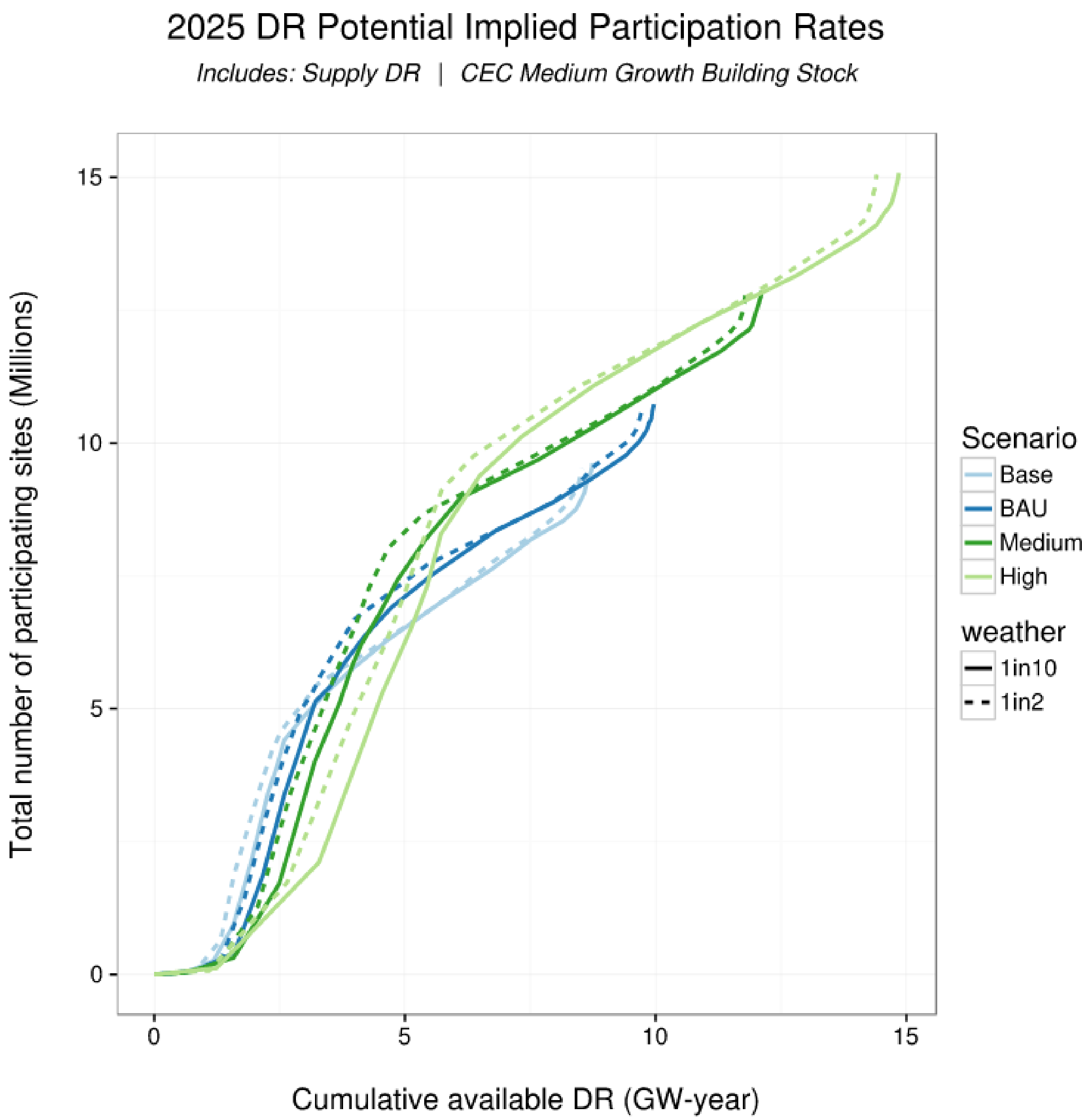


Figure A-3: Participation required to meet demand response potential results for the year 2025 supply curves shown above.

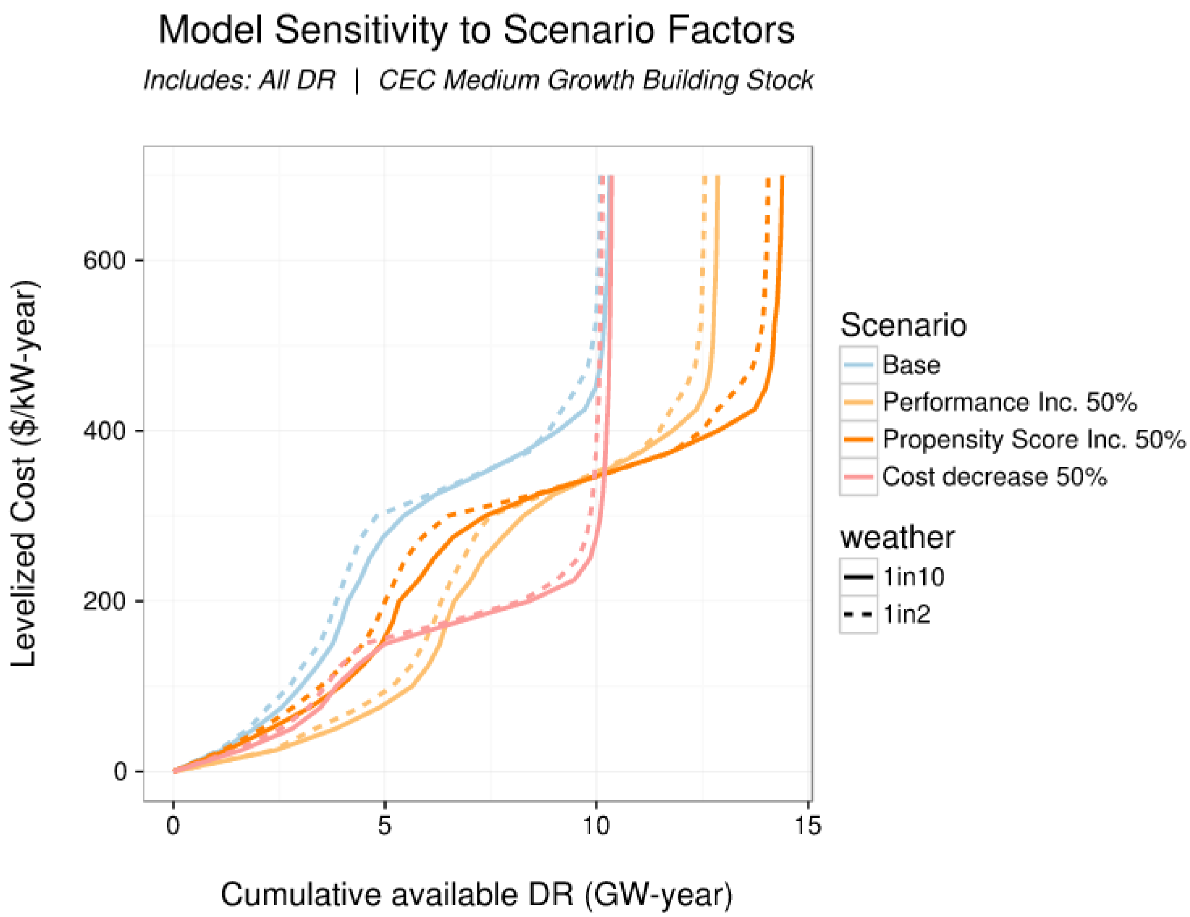


Figure A-4: Model sensitivity, relative to base case, to factors that define the scenarios: system cost, technology performance, and propensity to adopt and participate.

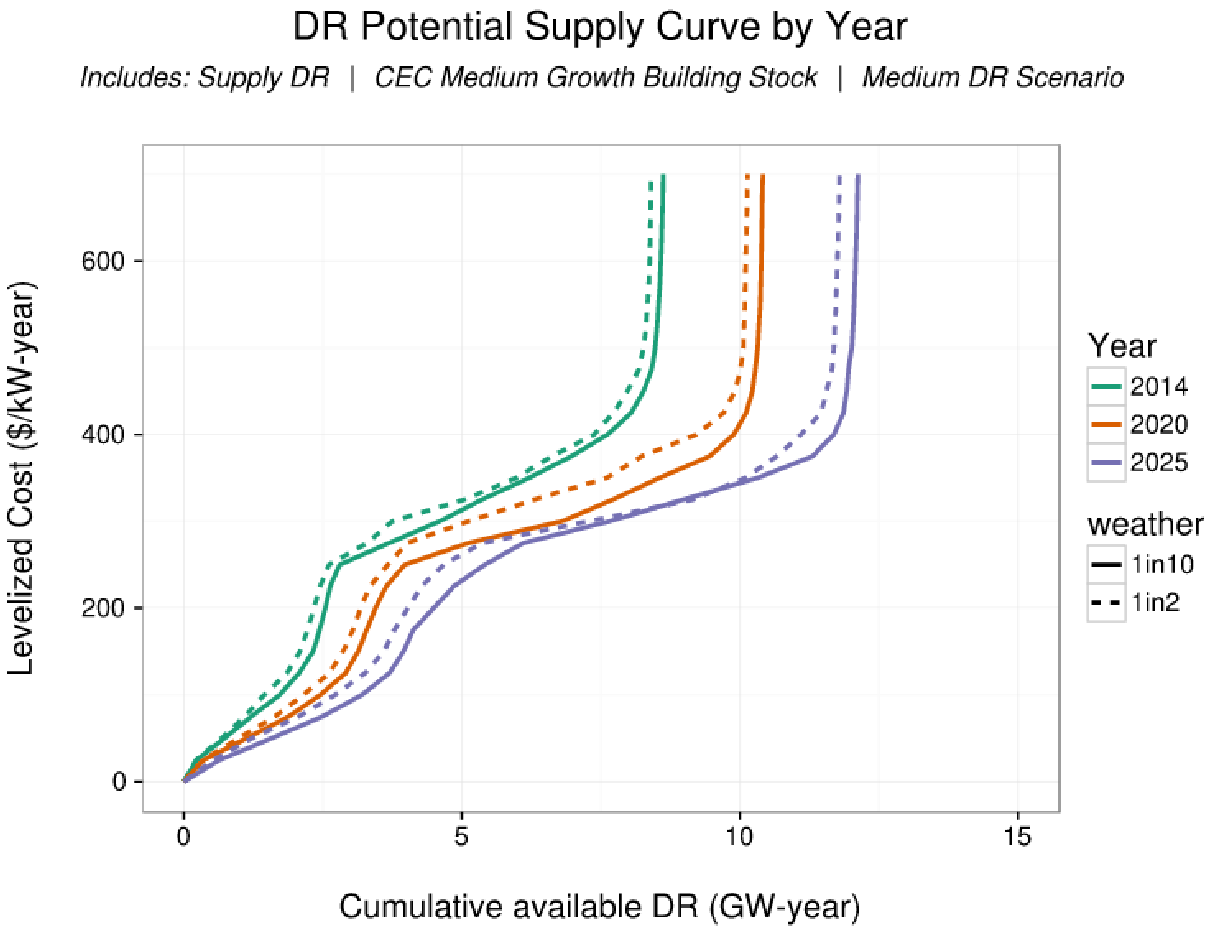


Figure A-5: Potential demand response for the high-DR-potential scenario for years 2014, 2020 and 2025. Supply curves are developed for a "1-in-2" weather year. Only includes supply DR.

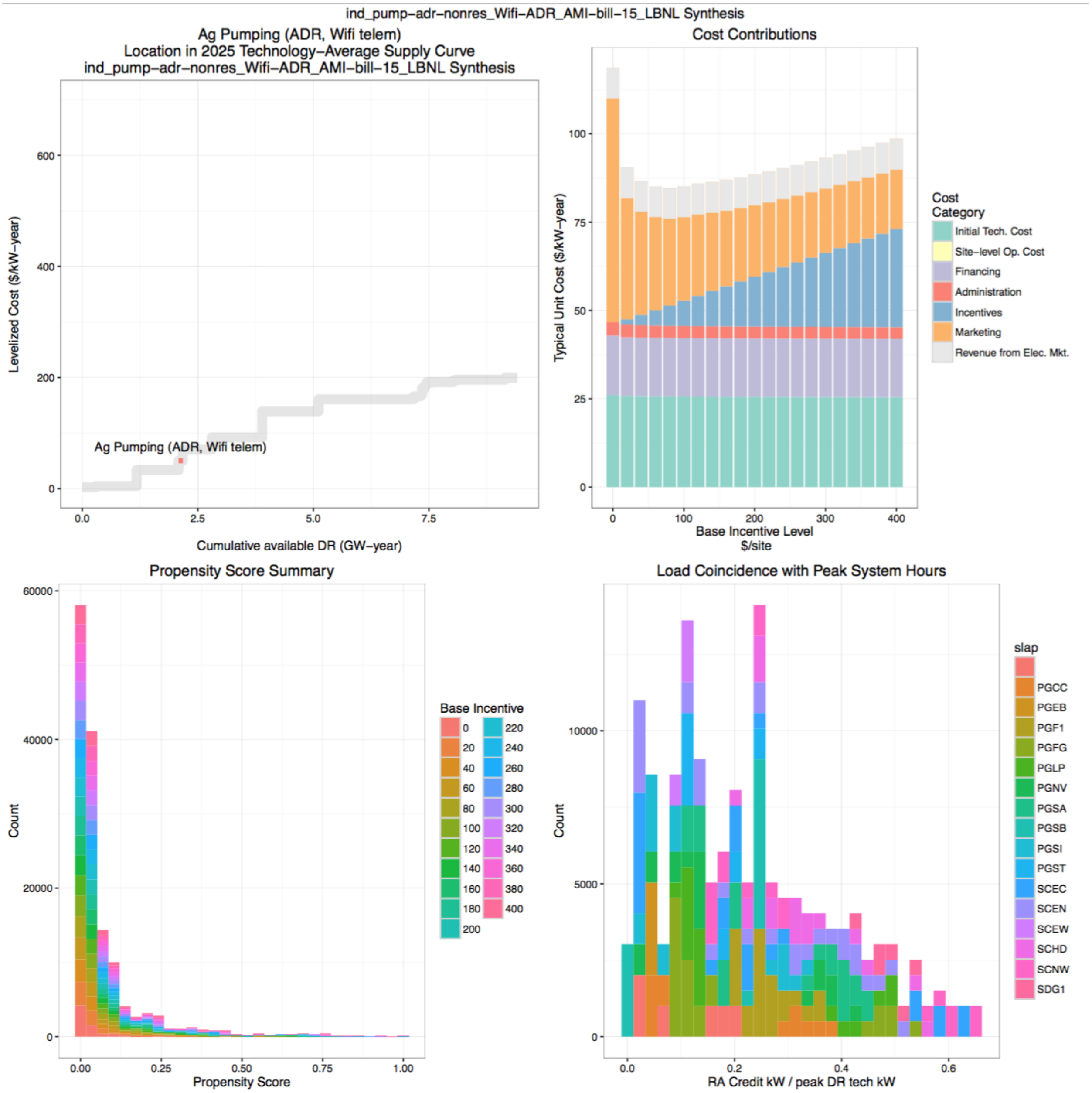


Figure A-6: This is an example of a set of figures for each enabling technology. The first panel (top left) shows the position of the technology option in an aggregated supply curve. The second (top right) shows the proportion of the various cost components of a typical unit, with varying base incentive levels. The third (bottom left) shows the distribution in enrollment probability (propensity scores) for the customers eligible for using the technology and the final plot (bottom right) shows the coincidence fraction between the peak DR load under control and effective RA value.

Appendix B: Forecasting End-Use Loads

Appendix B: Forecasting End-Use Load

This appendix describes LBNL's approach for forecasting end use load. Figure B-1 illustrates the overall analysis approach. In Section B-1, we list primary data sources. Section B-2 describes the aggregation of IOU customers into like-groups, or "clusters." Section B-3 describes end-use disaggregation. Finally, Section B-4 describes forecasting load for future years and Section B-4.3.2. provides a summary of load forecasting results.

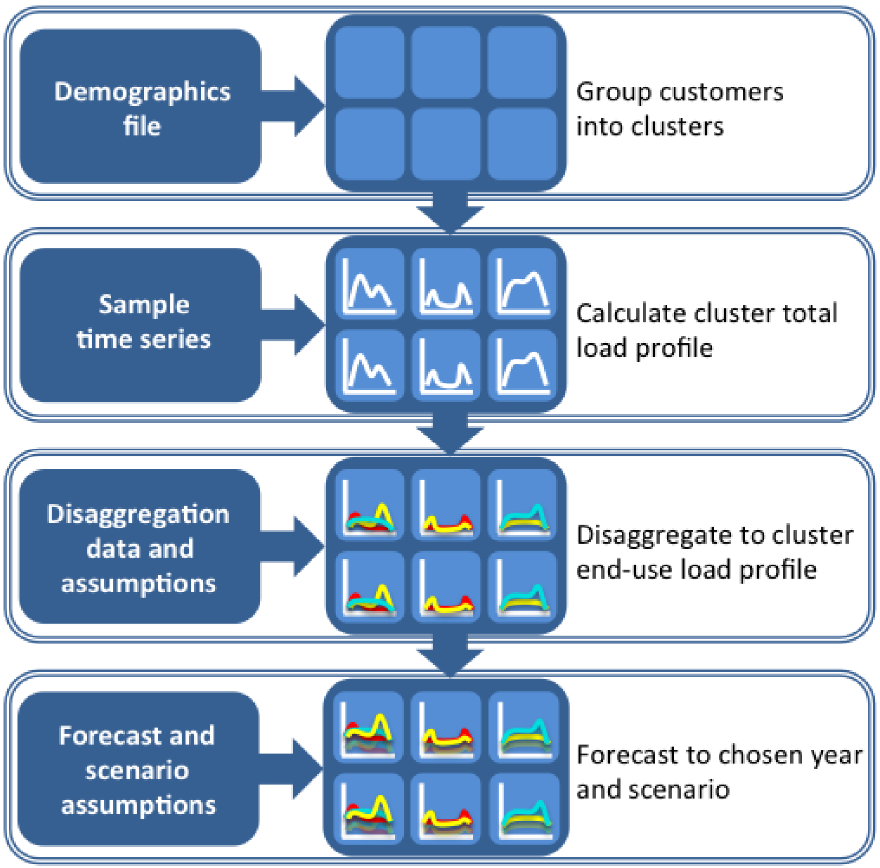


Figure B-1: End-use forecasting methodology.

B-1. Input Datasets

This section describes the source datasets used throughout the technical baseline methodology.

B-1.1. California Commercial End-Use Survey (CEUS)

The California Commercial End-Use Survey (CEUS) is a comprehensive study of commercial sector energy use (CEC, 2006). The latest survey was completed in 2006. It consists of energy use data and building characteristics from 2,790 commercial facilities in California. The survey is comprised of buildings from most regions, climates, and building types in California. Though the survey is a fraction of the number of facilities in California, it is believed to provide broad view of energy use in commercial buildings in California. Based on survey results, the CEUS data includes simulated hourly load profiles indicating the percent of commercial building loads attributable to individual end uses. We use these profiles to disaggregate commercial end uses from commercial building loads.

B-1.2. Manufacturing Energy Consumption Survey (MECS)

The Manufacturing Energy Consumption Survey (MECS) is a nationwide survey of energy use in the U.S. manufacturing industry (USDOE, 2010). The most recent survey was conducted in 2010. The survey provides a broad view energy use for most US industries, as classified by the North American Industry Classification System (NAICS). We use MECS to disaggregate industrial demand into process and non-process loads.

B-1.3. Residential Appliance Saturation Survey (RASS)

The Residential Appliance Saturation Survey (RASS) provides a broad view of appliance use and energy use in California residences (CEC, 2010). The last survey was conducted in 2009. It estimates the saturation of residential end uses statewide and for each of the IOUs. We use RASS to estimate the penetration levels of pool pumps installed in each of the IOUs.

B-1.4. Farm and Ranch Irrigation Survey (FRIS)

The Farm and Ranch Irrigation Survey (FRIS) is part of the U.S. Department of Agriculture's Census of Agricultural methods, costs, and energy use in most regions of the US (USDA, 2014). We use FRIS to estimate energy use from on-farm irrigation.

B-1.5. County Growth Forecasts

The California Department of Transportation Office of State Planning commissions an annual California County-Level Economic Forecast (California Economic Forecast, 2015). The 2015 forecast provides information on local population, income, and employment for each of California’s 58 counties for the years 2000-2040. Household and total employment data are used to predict county-level growth rates for 2014-2020 and 2014-2025.

B-1.6. 2014 California Energy Almanac

The CEC provides historical electricity sales by sector through the California Energy Almanac (CEC, 2016). These sales are grouped into, “Ag & Water Pump”, “Commercial Building”, "Commercial Other", "Industry", "Mining & Construction", "Residential", and "Streetlight" sectors. We use this information to calibrate 2014 model outputs to actual electricity sales.

B-1.7. CEC California Energy Demand (CED) Forecast

The California Energy Demand Forecast (CEC, 2014) provides predictions of energy load for California. We use the CEC load forecasts to estimate industrial sector load growth and to predict the future number of electric vehicles in operation. For industrial growth factors, we calculate average annual growth rate from 2014 to 2025 from the CED's 2014-2024 forecast using Forecast Category levels (primary metals, water, etc.). For predicting the number of electric vehicles on the road in California, we use the CED's 2014-2024 forecast estimates for 2012, 2015, 2018, 2020, and 2024.

B-1.8. NOAA Integrated Surface Database (ISD)

The Integrated Surface Database (ISD) provides historical hourly weather data for weather stations globally (NOAA, 2016). We use temperature data for 45 weather stations in California, selected to achieve geographic coverage across the state. The hourly weather data is combined with customer load data to estimate temperature-sensitive loads for residential customers.

B-1.9. Vehicle-to-Grid Simulator (V2G-Sim)

The Vehicle-to-Grid Simulator (V2G-Sim) (LBNL, 2016) is an LBNL tool for predicting vehicle-grid integration. We apply this model to predict total statewide electric vehicle (EV) demand in each hour of a typical week and weekend day for both commercially- and residentially-owned battery electric vehicles (BEV) and plug-in hybrid electric vehicles (PHEV). We also use V2G-Sim to predict 4-hour DR events at each hour of the day, in order to estimate the percent of load that could be shed without conflicting with mobility needs. Details of the tool are available at: v2gsim.lbl.gov.

B-1.10. Utility Demographics Files

For analysis specific to this study, the three California IOUs provided demographic information from nearly every customer in their service territories. The information provided includes annual energy use, peak power consumption (if available), and customer characteristics including ZIP code, rate class, and sector. This information was used to group (or "cluster") customers, as detailed in Section B-2.

B-1.11. IOU Customer Time Series

For analysis specific to this study, the three California IOUs provided hourly or 15-minute energy use data for approximately 50,000 residential, 35,000 commercial, and all industrial customers in their service territories. We use this data to predict customer end-use loads and temperature-sensitive customer loads in each utility service territory.

B-1.12. SCE Pool Pump Demand Response Potential Study

Reports on a survey of pool pump demand and pumping schedules in the SCE service territory (SCE, 2008). Includes average rated kW of pool pumps, and hourly pumping profiles indicating the percent of pumps on at a particular time of day. These results were used to estimate the energy demand for pool pumps, and the hourly shape of aggregate pool pump loads for residential clusters.

B-1.13. 2015 U.S. Gazetteer Files

The U.S. Gazetteer Files are data files released annually by the U.S. Census Bureau reporting geographic and census data at various geographic scales (US Census Bureau, 2016). Included in the dataset are latitude and longitude coordinates for U.S. ZIP Code Tabulation Areas. We use these as a proxy for ZIP codes, and used the centroid coordinates to locate the nearest NOAA weather station for each utility customer. We then used the weather data for the nearest weather station to estimate the temperature-sensitivity of residential and commercial loads.

B-2. Customer Grouping

This section describes LBNL's approach to aggregate customers into like groups. The resulting groups, or clusters, represent the primary unit of analysis in this study. For this analysis, customers were grouped into clusters according to a set of characteristics that were selected to preserve the balance of geographic specificity and customer diversity while maintaining computational practicality. Section B-2.1 discusses characteristics were used for the clustering analysis, while Section B-2.2 describes the approach to generating the load profiles of the resulting clusters.

B-2.1. Grouping Characteristics

B-2.1.1. Sector

Customers were first grouped into residential, commercial, industrial, and "other" sectors based on the customer's rate class and NAICS code, if applicable. We identify residential customers by their rate class, commercial customers by NAICS code, and industrial customers by a combination of rate class and NAICS code, with the "other" sector including customers who did not meet the criteria for three primary sectors. We categorize Agricultural customers, as identified by their rate class, as a subset of the industrial sector.

B-2.1.2. Sub-Load Aggregation Points

California's Independent System Operator (CAISO) has defined 23 Sub-Load Aggregation Points (Sub-LAPs), which are geographic areas that divide the electric grid. Figure B-2 shows a map of the Sub-LAPs in California. PG&E's service territory is divided into 16 Sub-LAPs; SCE's service territory is divided into 6 Sub-LAPs; and SDG&E's service territory consists of one Sub-LAP. Sub-LAPs are the common unit at which day ahead load forecasting is done, and affect how loads can be aggregated into market bids.

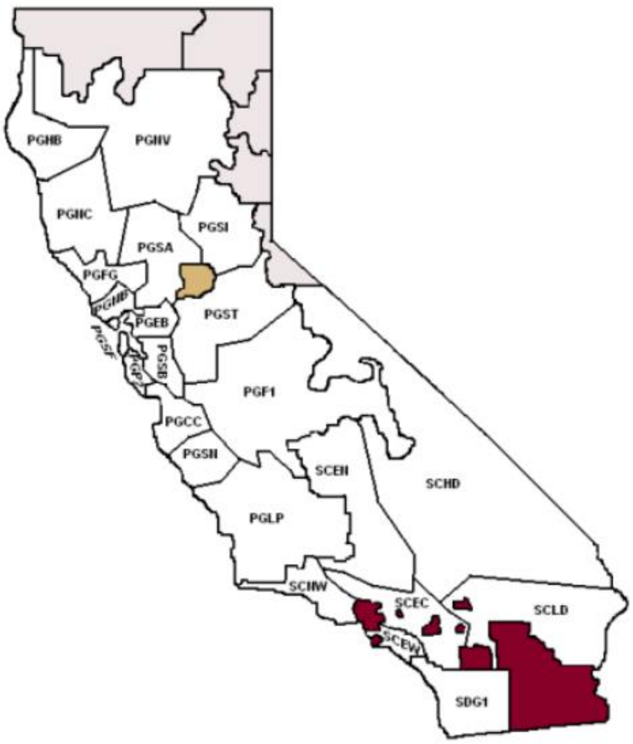


Figure B-2: Map of sub-load aggregation point (sub-LAPs) in the CAISO. Brown areas are outside the CAISO (CAISO, 2010).

B-2.1.3. Building Type

Commercial customers are further clustered into the primary building types of interest for load disaggregation and DR: offices, retail, refrigerated warehouses, and "other". Offices and retail buildings are some of those most commonly targeted for DR programs, due to the flexible nature of the large HVAC and lighting loads. Refrigerated warehouses were included as a building type despite their low energy use as a fraction of the commercial sector, past work identifies refrigeration loads as highly flexible because they are coupled with thermal storage. Finally, "other" includes any buildings identified as commercial with NAICS classifications other than office, retail, or refrigerated warehouse.

B-2.1.4. Rate Class

While commercial customers are grouped by building type, residential customers are grouped by rate class. Customers on CARE rates are separated from those on standard rates. This is primarily to isolate the effects of pricing within clusters, as CARE customers react differently to price than non-CARE customers, and a lower price signal may affect their load profiles, annual energy consumption, and propensity to participate in DR programs.

B-2.1.5. Annual Consumption

Finally, within groupings of sector, Sub-LAP, and building type or rate class, the customers are evenly divided into clusters based on their annual electricity use. The number of clusters into which customers in a grouping are divided is dynamic, and based on the number of customers that match the sector, Sub-LAP, and building type or rate class criteria, as well as the number of timeseries available to represent that cluster. The maximum number of annual consumption clusters is 5, and the minimum is 1. For example, if grouping residential, non-CARE customers in the PGEB Sub-LAP results in 15,000 customers represented by 1000 hourly load profiles, they will likely be divided into 5 annual consumption clusters. Meanwhile, a Primary Metals industrial cluster in the PGNB Sub-LAP that has only 5 customers represented by 3 hourly load profiles will only be grouped into one annual kWh cluster, containing all 5 customers. This allows us to maintain a reasonable number of load profiles per cluster.

B-2.2. Cluster Load Profile Aggregation

Once clusters have been defined and all customers in the IOU demographics files have been assigned a cluster, we use hourly time series data available to approximate the cluster's load shape. To do so, we collect all time series data available for customers in the cluster and scale the aggregate load profile so that the total annual load of the cluster time series agrees with the aggregate load for all customers in the cluster, as calculated using the IOU-provided customer demographics data.

However, the demographics files provided by the IOUs do not include all customers in the state, as they only contain customers for whom at least 6 months of energy consumption data is available[6]. Therefore, the total electricity consumption represented by the clusters must be calibrated to the historical reported sales (CEC, 2016). Calibration factors are developed using Equation 1, and are developed concurrently with and independent of the cluster load profile

[6] After investigation of the data provided by the three IOUs, there was also found to be a dearth of small and medium commercial customers in one of the IOUs. This issue was addressed prior to clustering by resampling from the small and medium customers to match the sector-level counts provided by the IOUs.

aggregation step.

$$F(sector, IOU) = Reported\ Sales\ (sector, IOU)\ all\ clusters\ in\ sector, IOUCluster\ kWh \quad (1)$$

B-3. End Use Disaggregation

B-3.1. Residential

We consider three end-uses for residential customers: cooling, pool pumps, and plug loads. Although other end uses are viable candidates for DR, we chose to focus on these end uses for this study.

B-3.1.1. Cooling

Cooling load is estimated using a three-parameter change point model, which is fitted to customer load data to identify and represent the relationship between outdoor air temperature and customer load (Walter, 2014). The form of the model is illustrated in **Error! Reference source not found.**, and is defined as follows:

$$\hat{y}(T) = \begin{cases} mT + b, & for\ T > T_{sp} \\ b, & for\ T \leq T_{sp} \end{cases} \quad (2)$$

Where $\hat{y}(T)$ is the estimated customer load at temperature T, and the parameters of the model include:

1. Set point temperature (T_{sp}): the temperature at which customers begin cooling; in other words, the temperature set on a customer's thermostat.
2. Temperature sensitivity (m): the incremental increase in load (kW) associated with an increase in temperature.
3. Base load (b): approximate magnitude of customer load when cooling load is zero.

We use a grid search to fit a model for set point temperatures T_{sp} ranging between 60 and 90 F (in increments of 5 F). For each set point temperature, we estimate base load by taking the mean load across hours where outdoor air temperature is below the set point temperature, and use least squares regression to estimate the temperature sensitivity of load during hours where outdoor air temperature exceeds the set point temperature. We evaluate the parameters m and b for all set point temperatures, and select the model with the smallest sum squared error ϵ, defined as follows:

$$\epsilon = \sum_{all\ hours} (\hat{y}(T) - y)^2 \quad (3)$$

Where y is the customer's reported time series data.

Once a model is developed, we evaluate whether or not the model indicates significant temperature sensitivity. For customers with low temperature sensitivity ($m \leq 0.01\ kWh/F$), we assume no cooling load. For customers with high temperature sensitivity $m > 0.01\ kWh/F$, we estimate cooling load as follows:

$$Cooling\ Load(T) = \begin{cases} mT, & T > T_{sp} \\ 0, & T \le T_{sp} \end{cases} \tag{4}$$

Linking Equation 3 with hourly temperature data, we predict hourly cooling load for each customer. We compute cooling non-cooling load by taking the difference between total load and estimated cooling load, subject to the following constraint:

$$Cooling\ load_i \le 0.9\ \times\ Total\ load_i \text{ for all hours } i \tag{5}$$

In hours where this constraint is not met, we fix $Cooling\ load_i$ in that hour at 90% of total load in that hour. Using the resulting model, we can generate an hourly cooling load profile for each customer using any hourly temperature profile.

To estimate cooling load for a cluster, we sum cooling loads for all customers in the cluster. We then scale the resulting values using the same adjustment factors as are applied to the total cluster loads.

For the 1-in-2 and 1-in-10 weather scenarios, we assume non-temperature sensitive load to be the same as we compute for 2014. To estimate cooling load, we predict $Cooling\ Load(T)$ using Equation 4, with different input temperature profiles (T) for each scenario.

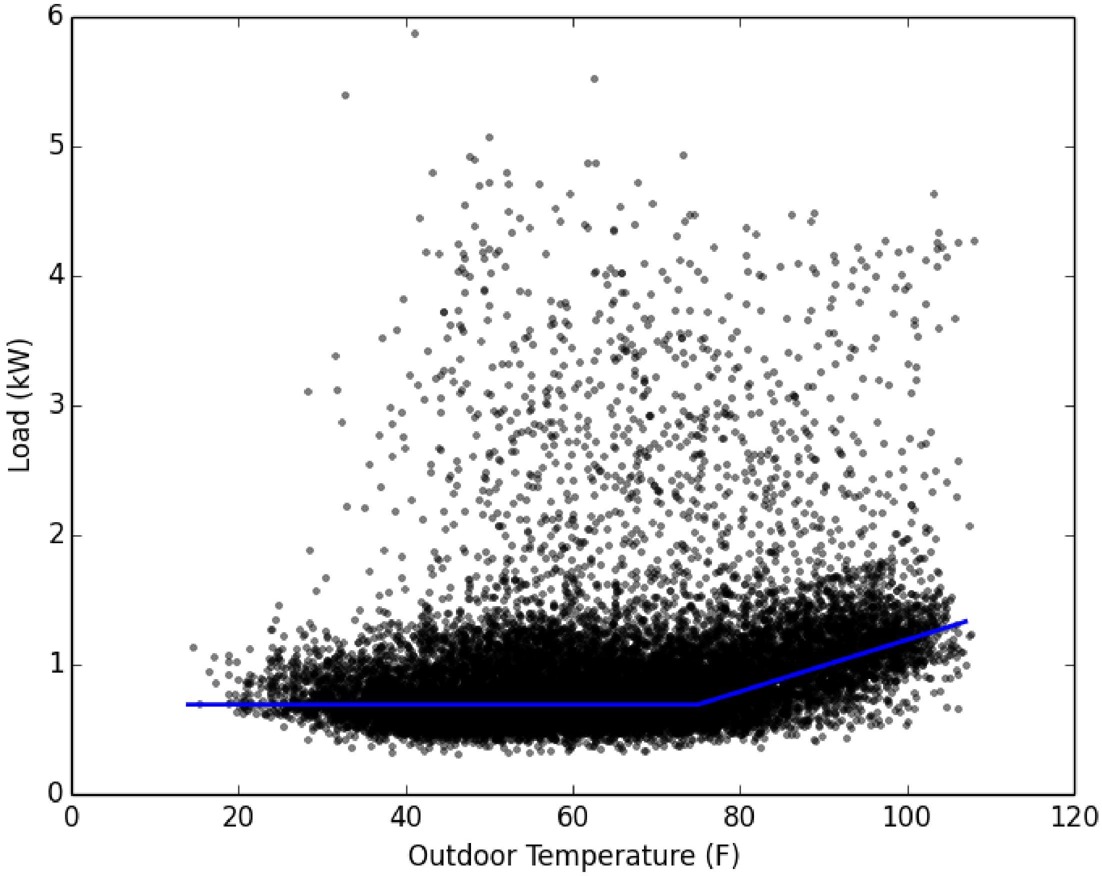


Figure B-3: Illustrative example of change point model for estimating temperature-sensitivity of customer load.

B-3.1.2. Pool Pumps

Pool pump loads are estimated at the cluster level. We estimate the penetration of pool pumps in residential clusters for each IOU using RASS saturation estimates for the IOU Table B-1). We use these values to estimate the number of pool pumps in a cluster, and estimate the coincident pool pump load using an average pump capacity of 1.4 kW (SCE, 2008). We then apply results from SCE 2008, shown in Figure B-4, to determine the fraction of pumps operating during each hour in the day.

Table B-1: Swimming pool saturation across IOU service territories. (RASS, 2009)

Utility	PG&E	SDG&E	SCE
Fraction of customers with a swimming pool	0.09	0.11	0.12

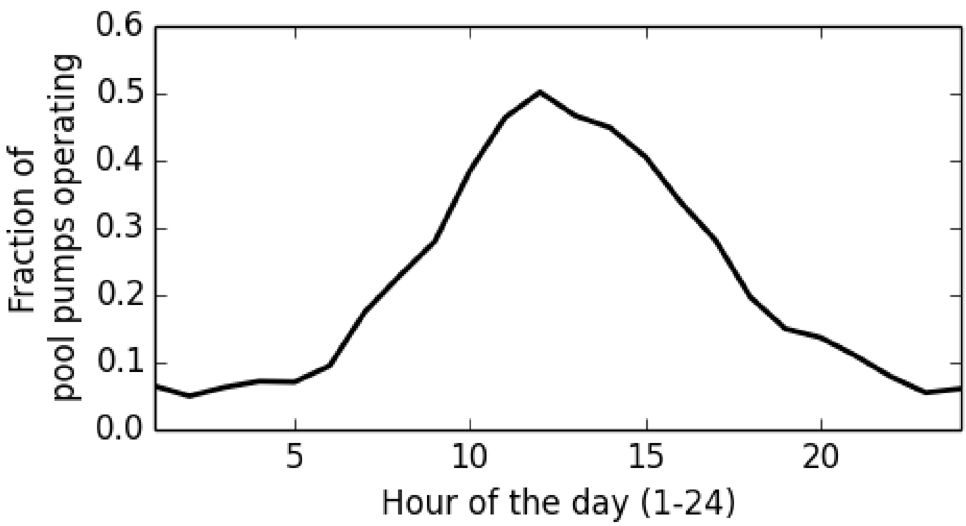


Figure B-4: Diurnal hourly shape of pool pumping load. (SCE, 2008)

B-3.1.3. Plug Loads

Plug loads are not readily observable, because sources of the load are not linked with specific environmental factors (e.g., temperature), and they do not follow fixed usage schedules (as do pool pumps). To estimate plug loads, we first compute unassigned load, defined as follows:

$$Unassigned\ load = Total\ load - cooling\ load - pool\ pump\ load \tag{6}$$

We then assume that plug loads constitute 30% of unassigned load (RASS, 2009). Currently, we consider plug loads to be devices enabled for DR using smart strip technology. As such, small and large appliances are not included in the plug load estimate.

B-3.2. Commercial

We classify commercial buildings into building types based on their NAICS code: retail, office, refrigerated warehouse, and “other”. The present study focuses on DR potential in retail and office buildings because they constitute the largest portion of commercial loads and are already readily targeted for DR. We also examine refrigerated warehouses because refrigerators provide large thermal storage reservoirs, making refrigeration loads very flexible. The following sections describe our methodology for estimating the breakdown of customer loads by end use. For retail and office buildings, we consider HVAC and lighting loads, where HVAC includes electric heating, cooling and ventilation. For refrigerated warehouses, we consider refrigeration and lighting loads.

B-3.2.1. Temperature-sensitive loads: heating and cooling

Similar to residential cooling, we fit a change point model to identify temperature-sensitive loads in commercial buildings. We expand the model presented in Section B-3.1.1. to include both heating and cooling. The form of the model is given by Equation 7:

$$\hat{y}(T) = \begin{cases} m_1 T + b, \ for\ T > T_{sp,cool} \\ m_2 T + b, \ for\ T < T_{sp,heat} \\ \qquad\quad b, \ for\ T_{sp,heat} \leq T \leq T_{sp,cool} \end{cases} \tag{7}$$

where $\hat{y}(T)$ is the estimated load at temperature T. Heating and cooling set point temperatures, $T_{sp,cool}$ and $T_{sp,heat}$ respectively, are determined using a grid search for all combinations of temperatures between 50 and 70°F for heating, and between 60 and 90°F for cooling. We choose the set point temperatures that minimize overall prediction error ($\hat{y} - y$), where $\hat{y}$ is computed based on temperature data coincident with the available interval data. We assign a minimum temperature-sensitivity threshold of 0.1% increase in load ($\hat{y}(T)$) per °F. Customers whose heating and/or cooling coefficients (m_1 and/or m_2) are below that threshold are assumed to have no heating and/or cooling loads.

Once the model coefficients and set point temperatures are selected, we compute the temperature-dependent load by predicting load for a given annual weather profile, and subtracting the base-load b.

These methods are applied to identify retail and office buildings with heating and/or cooling loads. We assume refrigerated warehouse loads to be largely independent of temperature; thus their temperature-dependent loads are assumed to be zero.

For the 1-in-2 and 1-in-10 weather scenarios, we assume non-temperature sensitive load to be the same as we compute for 2014. To estimate temperature-sensitive loads, we make predictions for $\hat{y}(T) - b$ using Equation 7 with different input temperature profiles (T) for each scenario.

B-3.2.2. Non-temperature-sensitive loads: ventilation, lighting, and refrigeration

Non-temperature-sensitive loads are estimated using daily breakdowns of commercial loads available as part of the CEUS dataset (CEC, 2003). Daily breakdowns are available by climate zone, building type, and for weekends and weekdays. Using these daily profiles, we piece together an annual percent breakdown of customer loads into ventilation and lighting (for retail and office buildings), and refrigeration and lighting (for refrigerated warehouses).

To estimate the contributions of each end use, we filter to the customer's non-temperature-sensitive load using the annual end use breakdown specific to each customer's climate zone and building type. For customers with no temperature-sensitive load, the non-temperature sensitive load is equal to total load. For retail and office buildings identified as having no heating or cooling loads, we assume ventilation load is also zero. Finally, for office and retail buildings, we report an aggregate HVAC load, comprised of heating, cooling, and ventilation loads.

Once the relevant loads are computed (HVAC and lighting for office/retail buildings, and refrigeration and lighting for refrigerated warehouses), we assign the remaining uncategorized loads as “other”. These loads are carried through our analysis to aid in identifying hourly and peak system load, but are not taken to be viable candidates for DR. As DR-enabling technologies evolve, end uses and building types currently classified as “other” can be integrated into our model.

B-3.3. Industrial

B-3.3.1. Manufacturing

The manufacturing subsectors included in our analysis are:

- Petroleum Refining and Related Industries
- Food Manufacturing, Beverage and Tobacco
- Chemicals
- Computer and Electronic Product Manufacturing
- Plastics and Rubber Products Manufacturing
- Primary Metals

The annual load profiles generated for the clusters of these subsectors are disaggregated at a coarse level by leveraging the national MECS dataset (MECS, 2010). MECS provides a breakdown of the energy inputs, and their associated end uses, for various manufacturing industries. MECS categorizes end uses as process and non-process, and has further breakdowns within these two groupings. For our analysis of the industrial sector, the process vs. non-process distinction provides sufficient resolution.

These energy breakdowns are at the annual consumption level, giving no information about the seasonal or daily distribution of energy use for the different end uses. As such, the annual consumption values for process and non-process loads are calculated as a fraction of the total load from the MECS dataset for each industry. These disaggregation fractions are then multiplied by every hour of the year in the industry’s load profile.

B-3.3.2. Agriculture - Crops

The primary end use of focus in the agricultural sector is the electrical pumping load required for irrigating crops. Since very little work has been done to quantify and represent the pumping load patterns of on-farm irrigation loads, a coarse estimate was made that 80% of an agricultural customer’s load is due to pumping at all hours of the year.

B-3.3.3. Water & Wastewater

The water and wastewater subsectors are comprised of a number of end uses, including water pumping, aeration, and centrifuges. An estimate that 75% of total facility load is due to DR-capable process loads was made based on past research (Olsen, 2012). This fraction was applied for every hour of the year.

B-3.3.4. Data Centers

The Information Technology (IT) and IT-related cooling loads in large data centers are estimated to consume 75% of the facilities total load (Ghatikar, 2012). As very little research has been done studying the temporal pattern of end use loads in large data centers, this fraction is applied for every hour of the year to estimate the IT-related loads available for DR events. The other 25% of load includes support end uses such as lighting and uninterruptible power supplies.

B-4. Load Forecasting

Once 2014 cluster load profiles are generated for the actual 2014 weather, we generate simulated load profiles for the 1-in-2 and 1-in-10 weather years, as described above. Then we forecast load growth for 2020 and 2025. Load growth includes both increasing population and demand, and introduction of new end uses. The following sections describe methods for forecasting load growth by cluster.

B-4.1. Growth Factors

B-4.1.1. Residential

The California County-Level Economic Forecast forecasts the number of households that are in each of California's 58 counties annually out to 2040 (California Economic Forecast, 2015). Using this data, we calculate the county-level household growth rate for 2014-2020 and 2020-2025. We then calculate the average growth rate for each cluster by determining the number of customers in each cluster that reside in each county (using customer ZIP codes) and taking the weighted average of county growth rates. This growth rate is then applied the cluster's aggregate load profile as well as the count of customers that exist in the cluster. By applying the growth rate to both, the average customer-level energy use in the cluster remains constant.

B-4.1.2. Commercial

Growth in employment is used as a proxy for growth in energy consumption in the commercial sector. The California County-Level Economic Forecast forecasts annual employment in each of California's 58 counties out to 2040 (California Economic Forecast, 2015). Using this data, we calculate the county-level employment growth rate for 2014-2020 and 2020-2025. We then calculate the average growth rate for each cluster by determining the number of customers that reside in each cluster in each county (using customer ZIP codes) and taking the weighted average of county growth rates. This growth rate is then applied the cluster's aggregate load profile as well as the count of customers that exist in the cluster. By applying the growth rate to both, the average customer-level energy use in the cluster remains constant.

B-4.1.3. Industrial

Growth factors for industrial sectors in our model are calculated from the California Energy Commission's 2014-2024 California Energy Demand forecast (CEC, 2014). The medium growth forecast is used for the Forecast Categories that most closely match the subsectors included for DR analysis in our model. A summary of these growth rates is shown in Table B-2.

Table B-2: Industrial kWh consumption growth rates, in percent change from 2014.

Utility	Industrial Subsector	2020	2025
SCE	Crops	+0.34	+0.68
	Petroleum Refining and Related Industries	-3.75	-7.49
	Food Manufacturing, Beverage and Tobacco	-1.34	-2.68
	Chemicals	+1.03	+2.06
	Computer and Electronic Product Manufacturing	-3.10	-0.062
	Plastics and Rubber Products Manufacturing	+18.85	+37.7
	Primary Metals	+5.98	+11.95
	Water	+0.34	+0.68
	Wastewater	+5.21	+10.41
	Data Centers	+4.07	+8.14
	Other	0.00	0.00
PG&E	Crops	+11.52	+23.03
	Petroleum Refining and Related Industries	-3.55	-7.10
	Food Manufacturing, Beverage and Tobacco	-0.45	-0.90
	Chemicals	+1.74	+3.47
	Computer and Electronic Product Manufacturing	-3.09	-6.17
	Plastics and Rubber Products Manufacturing	+25.22	+50.43
	Primary Metals	+5.94	+11.88
	Water	+11.80	+23.59
	Wastewater	+5.07	+10.14
	Data Centers	+5.07	+10.13
	Other	0.00	0.00
SDG&E	Crops	+3.72	+7.43
	Petroleum Refining and Related Industries	-3.28	-6.56
	Food Manufacturing, Beverage and Tobacco	-1.60	-3.19
	Chemicals	+2.90	+5.80
	Computer and Electronic Product Manufacturing	-2.73	-5.45
	Plastics and Rubber Products Manufacturing	+22.63	+45.25
	Primary Metals	+5.12	+10.24
	Water	+4.31	+8.62
	Wastewater	+4.09	+8.17
	Data Centers	+6.76	+13.52

	Other	0.00	0.00

B-4.2. Emerging Resources

B-4.2.1. Electric Vehicles

We estimate aggregate EV demand for all of California using vehicle adoption forecasts, California Clean Vehicle Rebate Project (CVRP) rebate data and EV owner surveys, and LBNL's Vehicle-to-Grid Simulator (V2G-Sim). We then distribute this demand amongst the clusters first geographically, according to state rebate data, then proportional to total annual consumption (kWh).

Estimating statewide demand

Lawrence Berkeley National Lab's Vehicle-to-Grid Simulator[7] (V2G-Sim) is used to estimate the hourly demand curve associated with future EV adoption. Inputs to V2G-Sim specific to this study are summarized in **Error! Reference source not found.**. We utilize CEC forecasts to estimate statewide adoption of battery electric vehicles (BEV) and plug-in hybrid electric vehicles (PHEV) for high, mid, and low cases in 2020 and 2025 (CEC, 2014). EV adoption totals for the mid-case are shown in Table B-4. Vehicles were disaggregated as being either individually- or commercially-owned using EV rebate data[8] collected from the California Clean Vehicle Rebate Project (CVRP) (CCSE, 2015). This disaggregation is important to allow V2G-Sim to predict the location of vehicle charging, so that we can then assign demand to residential and commercial clusters accordingly.

In addition to rebate data, the CVRP conducts periodic surveys of EV owners (CCSE, 2013). Data from these surveys were used to develop assumptions about the portion of EV owners with Level 2 charging stations and the number of EV owners who charge at their place of work on a given day. Charging level impacts the power demand and required duration of charging sessions, and was reported by the 2013 survey as Level 2 for 46% of PHEV owners, and 88% of BEV owners. For commercially-owned electric vehicles and individual vehicles being charged

---

[7] V2G-Sim models the driving and charging behavior of individual PEVs to generate temporally- and spatially-resolved predictions of grid impacts and opportunities from increased plug-in electric vehicle (PEV) deployment. V2G-Sim provides bottom up modeling from individual vehicle dynamics all the way up to aggregate grid impacts and opportunities. (http://v2gsim.lbl.gov/)

[8] CVRP data contains information on all alternative fuel vehicle rebates claimed in California since March 2010, including: owner type, used to map to residential or commercial sectors; vehicle category, which we aggregate into battery electric vehicle (BEV), plug-in hybrid electric vehicle (PHEV), and "other"; ZIP code, used to map to sub-lap and climate zone; and other information such as vehicle make and rebate amount, which are not used in our analysis.

at their place of work, we assume all charging takes place on Level 2 charging stations. The distinction of individually-owned vehicles charging at work allows us to allocate the appropriate demand to commercial clusters. CVRP surveys report (1) the number of owners who have access to workplace charging (2) the portion of those with access for whom charging is free and (3) the frequency with which owners with free or paid charging charge at work. Using this information from the March 2012, October 2012, and May 2013 surveys, we estimate that in 2020-2025, approximately 25% of EV owners will charge at work on a given day.

Accordingly, the V2G-Sim model predicts aggregate hourly demand profiles for an average weekday and average weekend for six vehicle types: residentially-owned BEV and PHEV charging at "home" and "work" locations, and commercially-owned BEV and PHEV charging at their "home" location. We then use these to create six 8760-hour single-vehicle demand profiles. Weekday demand results for the 2025 mid-case are shown in aggregate in **Error! Reference source not found.**, and for a single average vehicle in **Error! Reference source not found.**.

B-4.3. Cluster-level EV demand

For each EV rebate claimed in the state, CVRP data provides the owner's utility provider and zip code. This information allows us to disaggregate statewide EV estimates into each Sub-LAP in the three IOUs. This allocation is computed for each owner type (individual vs. commercial) and vehicle type (BEV vs. PHEV). To account for geographical variation in rebate participation, and therefore bias in CVRP data, each rebate in the CVRP database is weighted by its county's estimated participation rate (Williams et al., 2015). Results for the allocation of PHEV and BEV across state utilities and owner types are shown in Table B-5.

In a given Sub-LAP, the total number of individually-owned EVs are allocated to the residential sector, and the number of commercially-owned EVs are allocated to the commercial sector. Additionally, 25% of the individually-owned EV count in a given Sub-LAP is allocated to the commercial sector in that Sub-LAP to represent individually-owned EVs charging at the owner's work location. The number of EVs in each sector and sub-lap is then allocated to individual clusters proportional to the cluster's total annual load. We assume no variation in propensity to adopt EVs between customers in various building types or rate categories. This results in a count of BEV and PHEV for each residential cluster, and a count of site-owned BEV and PHEV as well as "employee"-owned BEV and PHEV for each commercial cluster. These counts are multiplied by the appropriate single-vehicle load profiles to determine the cluster's total EV load.

Table B-3: Statewide EV demand forecast assumptions.

Input	2025 Assumption	Source
Total number of BEV and PHEV in state	See Table B-4	CEC 2014-2024 Demand Forecast
Distribution of EV that are individually vs. commercially owned	98% of PHEV and 96% of BEV owned by individuals	CVRP state rebate data
Owners with Level 2 charging	Commercial: All Individuals: 46% of PHEV, 88% of BEV	CVRP survey
Individuals who charge at work on an average day	25%	Estimated from CVRP surveys

Table B-4: California EV adoption forecast. (CEC, 2014)

	BEV	PHEV	Total
2015	30,478	195,466	225,943
2020	119,936	1,198,909	1,318,845
2024	340,013	2,009,710	2,349,722
2025*	395,032	2,212,410	2,607,441
**extrapolated*			

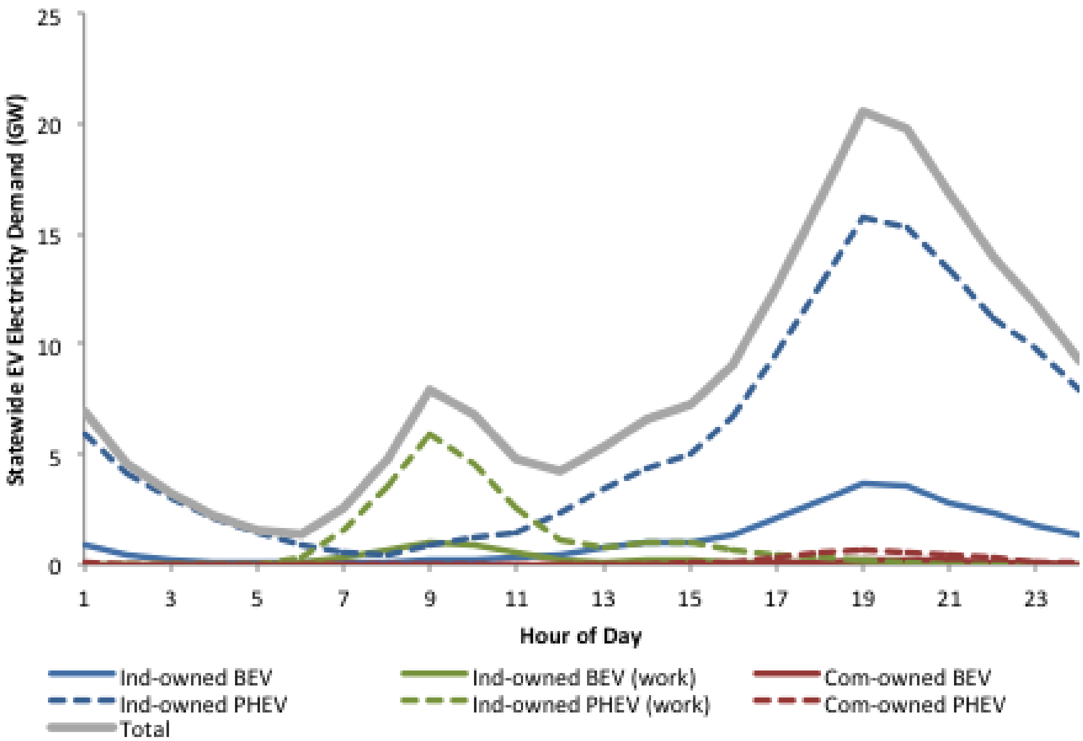


Figure B-5: California EV Electricity Demand for 2025 mid-case for six vehicle charging categories.

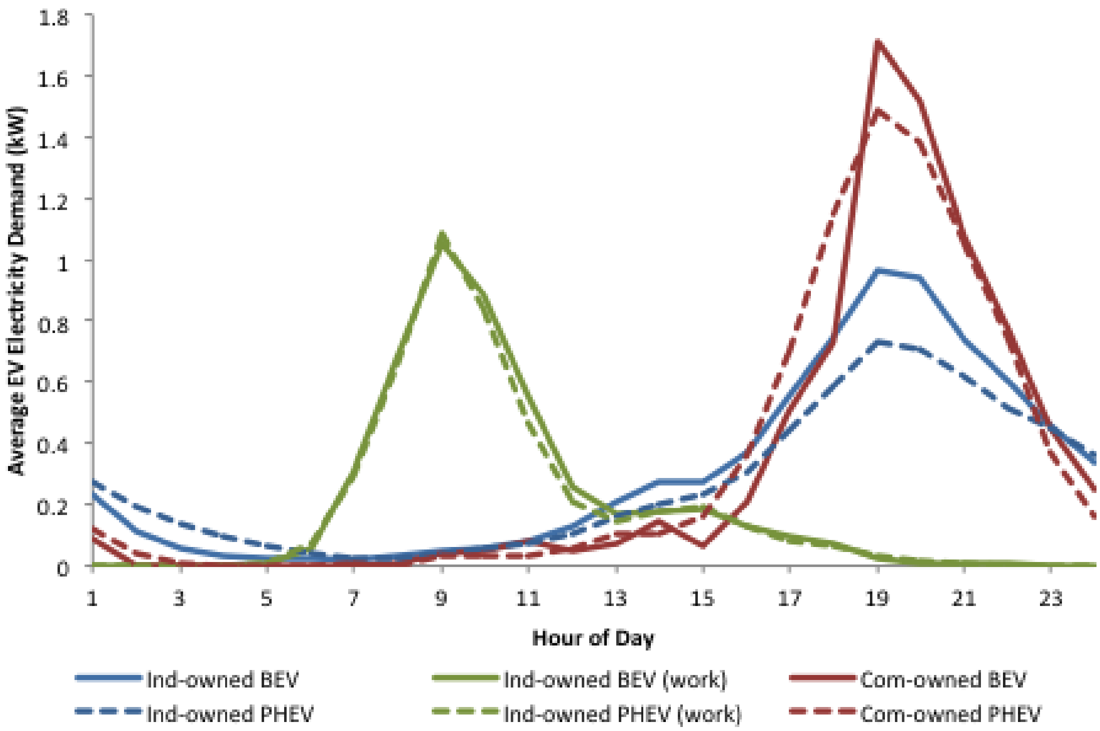


***Figure B-6:** Average electricity demand for a single vehicle for six vehicle charging categories.*

Table B-5: Portion of statewide EV totals in each utility by owner type.

(a) PHEV

Utility	Ind.	Com.	Total*
PGE&E	36%	1%	36%
SCE	34%	1%	35%
SDG&E	9%	0%	9%
Other	19%	1%	20%
Total*	98%	2%	100%

(b) BEV

Utility	Ind.	Com.	Total*
PGE&E	46%	1%	47%
SCE	23%	1%	24%
SDG&E	10%	1%	11%
Other	17%	1%	18%
Total*	96%	4%	100%

** Numbers may not sum to totals due to rounding.*

B-4.3.1. Batteries

Behind-the-meter (BTM) batteries offer a potentially flexible resource capable of providing multiple DR products and other economic benefits (e.g. TOU price arbitrage, demand charge reduction). For this study, we assume that a customer installs batteries for the sole purpose of providing DR benefits. We are thus implying that (1) BTM batteries are available to provide DR at all hours of the day and (2) the full cost of the battery is borne by the DR program. Technically, any capacity of batteries could be purchased and operated solely for DR purposes in this way. Despite this, we chose to estimate a hypothetical installed battery capacity to aid in cost calculations, and to demonstrate a reasonable level of potential capacity. We do so by first assigning a "maximum practical" installed battery capacity (kWh) to each customer cluster, as described in the following section, and assuming the state of the battery's power (kW) availability.

Sizing methodology

We estimate a hypothetical battery capacity for California by first assuming that every customer installs a battery that is similar in size to batteries currently used for common non-DR applications. For residential customers, it is common for batteries to be paired with the installation of solar photovoltaic panels. Currently, batteries marketed towards residential consumers come in a somewhat narrow range of capacities: 6.4 kWh for Tesla's Powerwall (Tesla, 2016) and 4 kWh-16kWh for sonnenBatterie's Eco (sonnenBatterie, 2016). For this study, we assumed a maximum practical battery capacity of 7 kWh for every residential customer.

For commercial and industrial customers, a common non-DR battery application is management of peak demand electricity charges. We estimate the potential capacity of these batteries using a methodology proposed by NREL in a 2015 Technical Report (Neubauer and Simpson, 2015). This methodology requires time series data for the site's energy consumption, which we do not have for the vast majority of customers in our analysis. Therefore, we first apply the NREL analysis to a sample of 2,400 commercial and industrial customers for whom we have time series data, and then examine how the resulting battery metrics relate to other site characteristics (peak kW and annual kWh) that are known for all customers. The results indicate that maximum practical battery size is linearly related to the customer's annual peak consumption with an R-squared value of 0.86, as shown in Figure B-7. This linear regression estimates that battery capacity in kWh is approximately 7.2% of peak consumption in kW. Using this relationship, along with the assumed system duration of 120 minutes (e.g. power to energy ratio of 1:2), we assign a maximum practical battery capacity and power rating for all commercial and industrial customer clusters.

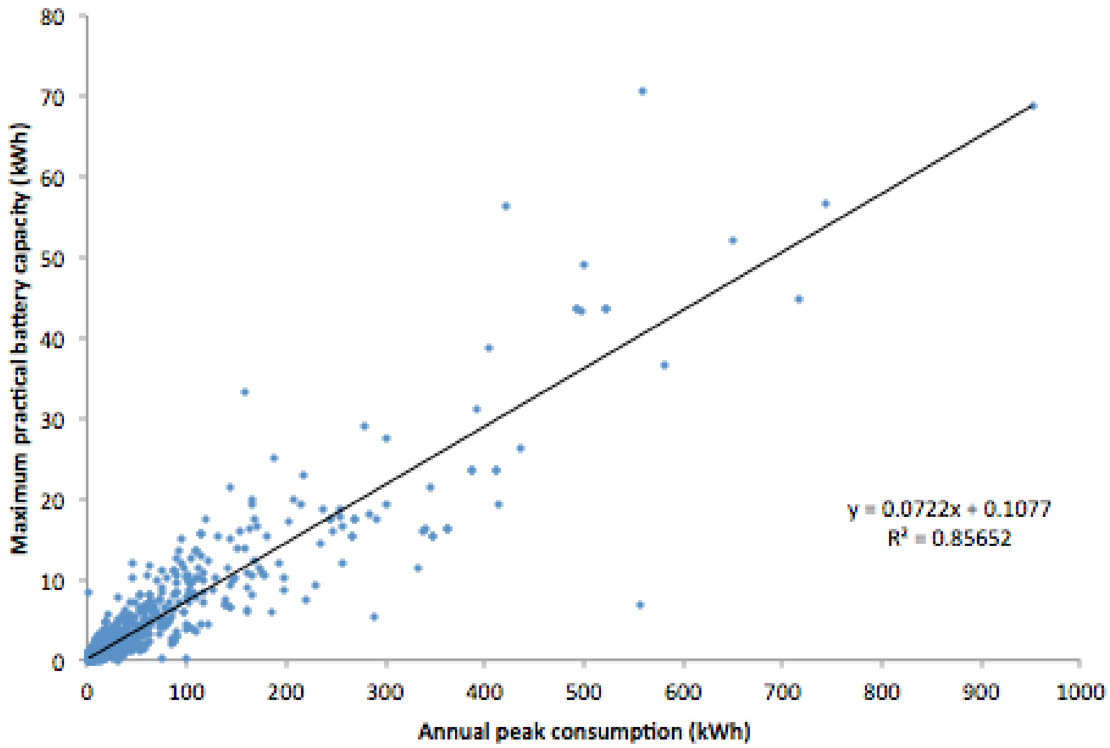


Figure B-7: Battery sized for demand charge using NREL (Neubauer and Simpson, 2015) methodology in relation to site peak consumption for 2,400 commercial and industrial utility customers.

This analysis greatly simplifies the battery market by only considering batteries that exist solely for DR purposes. Future work should additionally include batteries that have non-DR primary uses. This could involve analyzing battery market projections to forecast total installed capacity, and determining hourly DR availability based on the state-of-charge curves associated with the battery's primary use. Additionally, allocation of costs between the primary and DR uses would need to be determined. This analysis could result in additional battery DR potential that is at minimal (program-only) cost. Without this analysis, we are estimating the maximum cost of using batteries to provide DR, and showing a DR potential that is purely demonstrative.

B-4.3.2. Results

Results of the LBNL-LOAD model are detailed below. Table B-6 describes total annual energy consumption and customer forecasts by utility and sector in the 1-in-2 and 1-in-10 weather scenarios for each forecasting year (2020 and 2025). Figure B-8describes the total hourly energy consumption across all three IOUs for each sector on the peak day in each forecasting scenario. Figure B-9 through Figure B-23 further disaggregate these peak day profiles by end use. Finally, Figure B-24through Figure B-31 present heat maps of forecasted energy consumption (in MW) for each day in the year (x-axis) and each hour in the day (y-axis) in 2020 system-wide and by sector for the two weather scenarios. Figure B-32 through Figure B-35 present similar heat maps for residential end uses using the 1-in-2 weather scenario as an example.

Table B-6: Summary of energy forecasts for 1-in-2 and 1-in-10 weather scenarios by year, utility, and sector. Forecasts include the number of customers and annual energy consumption in GWh for 2020 and 2025.

Forecast Year	Weather Years	Utility	Sector	Number of Customers	Annual GWh
2020	1 in 2	PG&E	Commercial	636,100	40,500
	1 in 2	PG&E	Industrial	159,700	21,500
	1 in 2	PG&E	Residential	4,644,200	32,600
	1 in 2	SCE	Commercial	704,000	41,600
	1 in 2	SCE	Industrial	92,600	18,500
	1 in 2	SCE	Residential	4,541,900	32,100
	1 in 2	SDG&E	Commercial	158,400	11,900
	1 in 2	SDG&E	Industrial	18,000	1,800
	1 in 2	SDG&E	Residential	1,310,900	7,900
	1 in 10	PG&E	Commercial	701,400	41,000
	1 in 10	PG&E	Industrial	171,600	21,400
	1 in 10	PG&E	Residential	4,873,600	33,300
	1 in 10	SCE	Commercial	773,600	42,700
	1 in 10	SCE	Industrial	93,500	18,500
	1 in 10	SCE	Residential	4,764,000	33,300
	1 in 10	SDG&E	Commercial	174,400	12,000
	1 in 10	SDG&E	Industrial	18,200	1,800
	1 in 10	SDG&E	Residential	1,383,100	8,000
2025	1 in 2	PG&E	Commercial	802,500	42,200
	1 in 2	PG&E	Industrial	198,500	22,000
	1 in 2	PG&E	Residential	5,303,900	35,000
	1 in 2	SCE	Commercial	884,500	43,400
	1 in 2	SCE	Industrial	95,400	18,900
	1 in 2	SCE	Residential	5,187,400	34,300

	1 in 2	SDG&E	Commercial	200,300	12,400
	1 in 2	SDG&E	Industrial	18,700	1,800
	1 in 2	SDG&E	Residential	1,524,500	8,500
	1 in 10	PG&E	Commercial	918,300	42,800
	1 in 10	PG&E	Industrial	231,600	21,900
	1 in 10	PG&E	Residential	5,776,000	35,700
	1 in 10	SCE	Commercial	1,011,300	44,600
	1 in 10	SCE	Industrial	97,800	18,900
	1 in 10	SCE	Residential	5,650,100	35,600
	1 in 10	SDG&E	Commercial	230,000	12,500
	1 in 10	SDG&E	Industrial	19,300	1,800
	1 in 10	SDG&E	Residential	1,680,400	8,700

B-4.4. Area Plots Summarizing Peak Day Energy Consumption

B-4.4.1. System-Wide by Sector

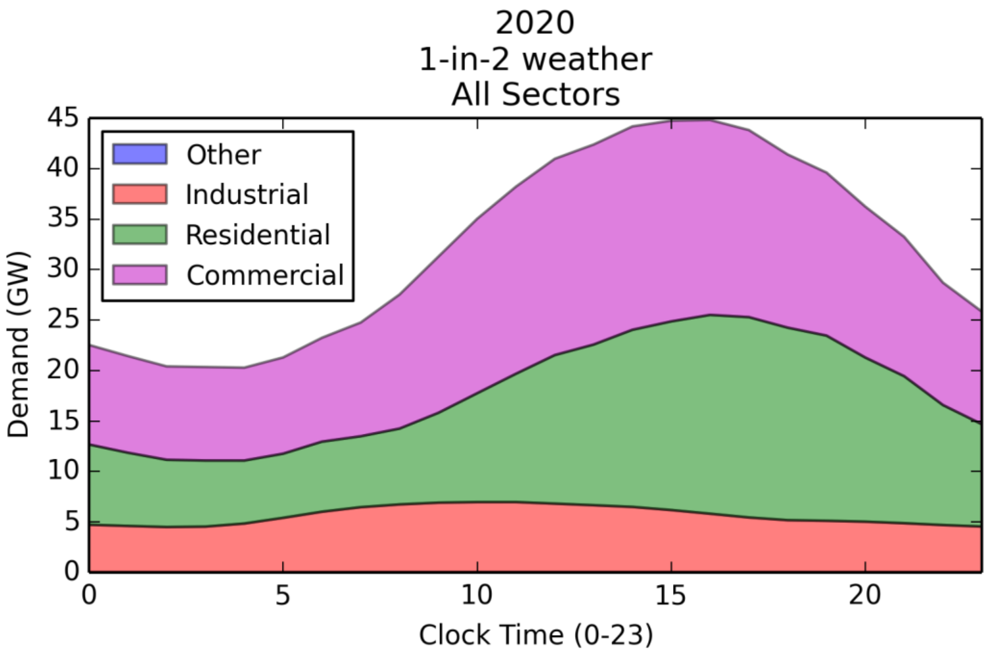


Figure B-8: Forecasted peak day hourly demand (in GW) across all three IOUs by customer type in 2020 for the 1-in-2 weather scenario.

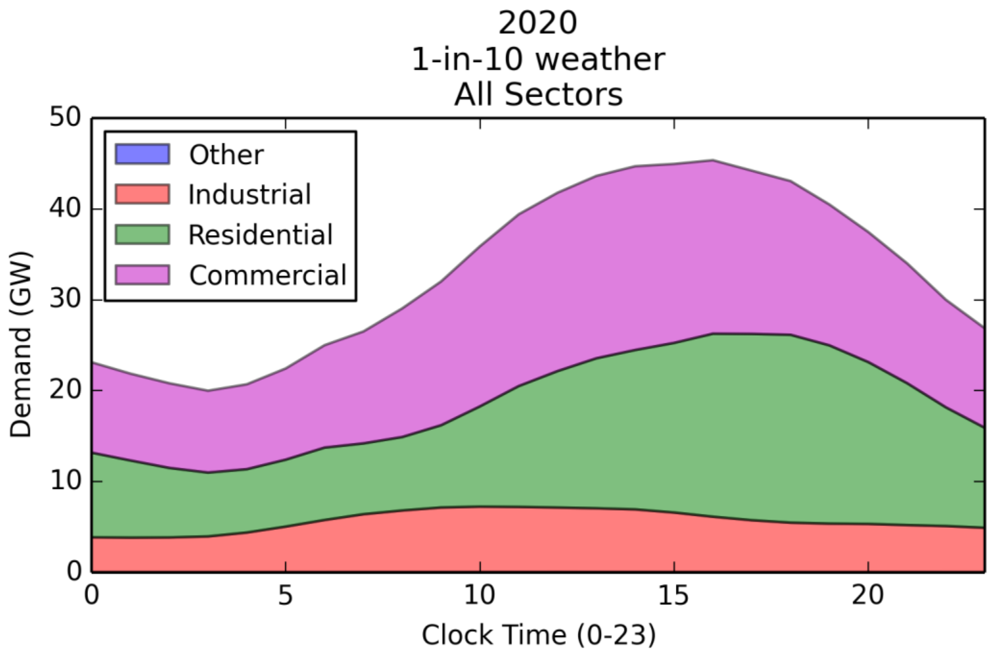


Figure B-9: Forecasted peak day hourly demand (in GW) across all three IOUs by customer type in 2020 for the 1-in-10 weather scenario.

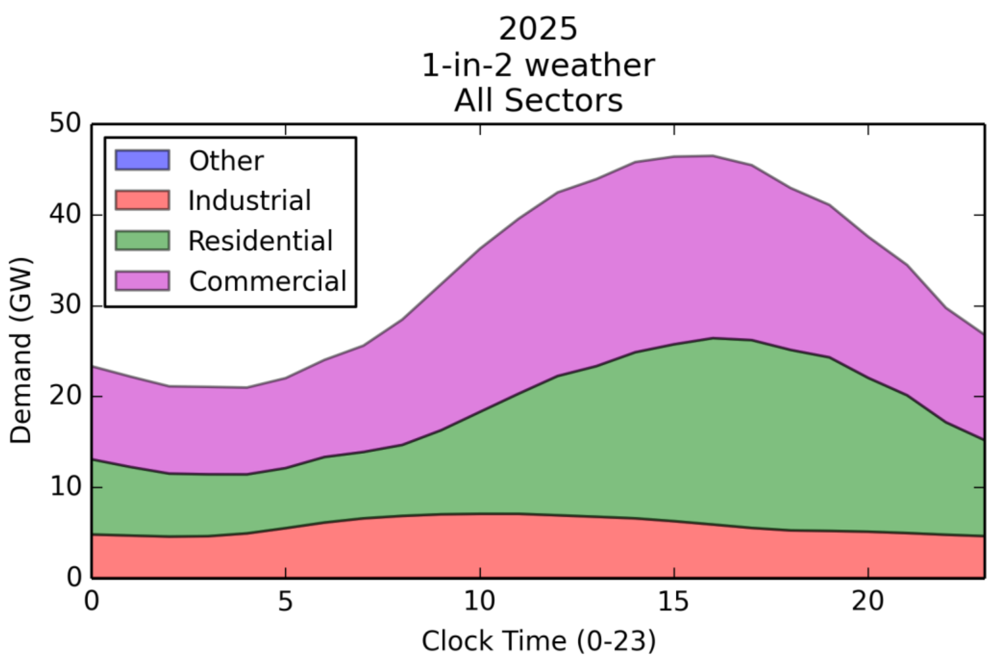


Figure B-10: Forecasted peak day hourly demand (in GW) across all three IOUs by customer type in 2025 for the 1-in-2 weather scenario.

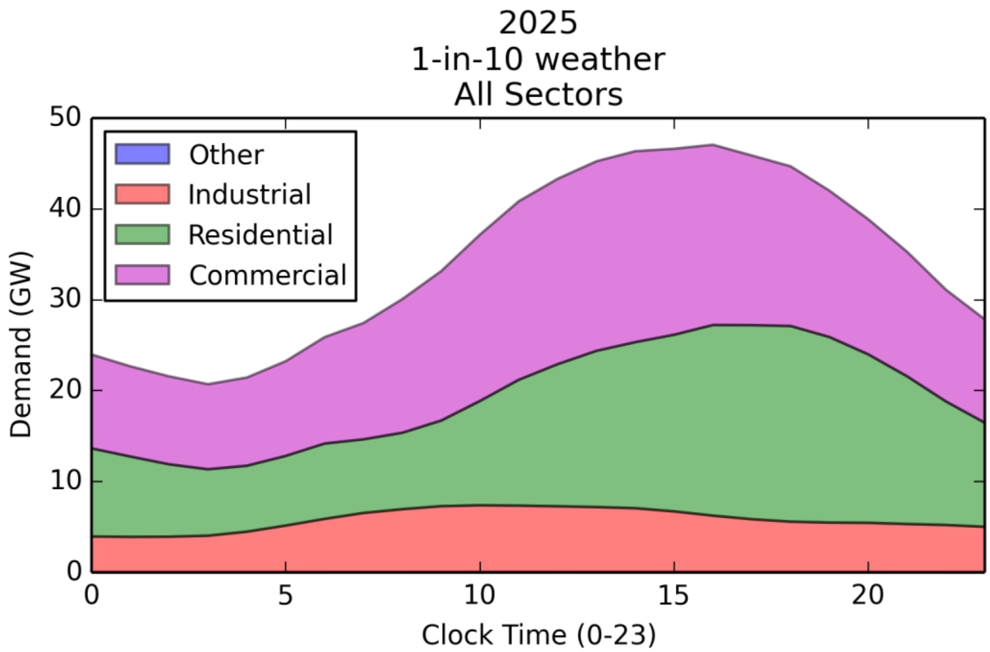


Figure B-11: Forecasted peak day hourly demand (in GW) across all three IOUs by customer type in 2025 for the 1-in-10 weather scenario.

B-4.4.2. System-Wide by Sector and End Use

Results for 2020 in 1-in-2 weather scenario:

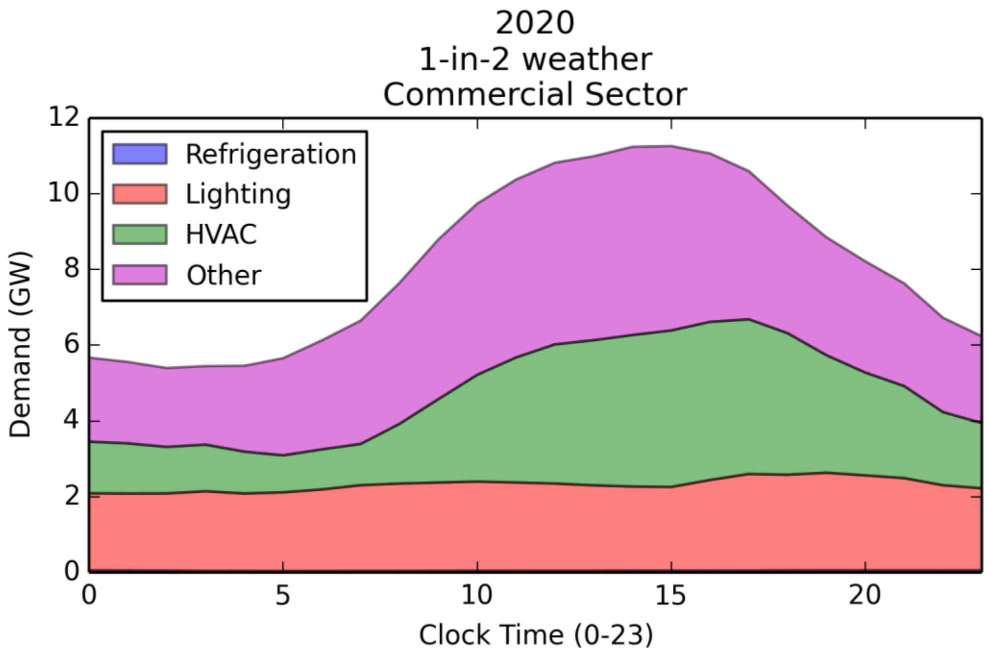


Figure B-12: Forecasted peak day hourly demand (in GW) for Commercial sector end uses in 2020 for the 1-in-2 weather scenario.

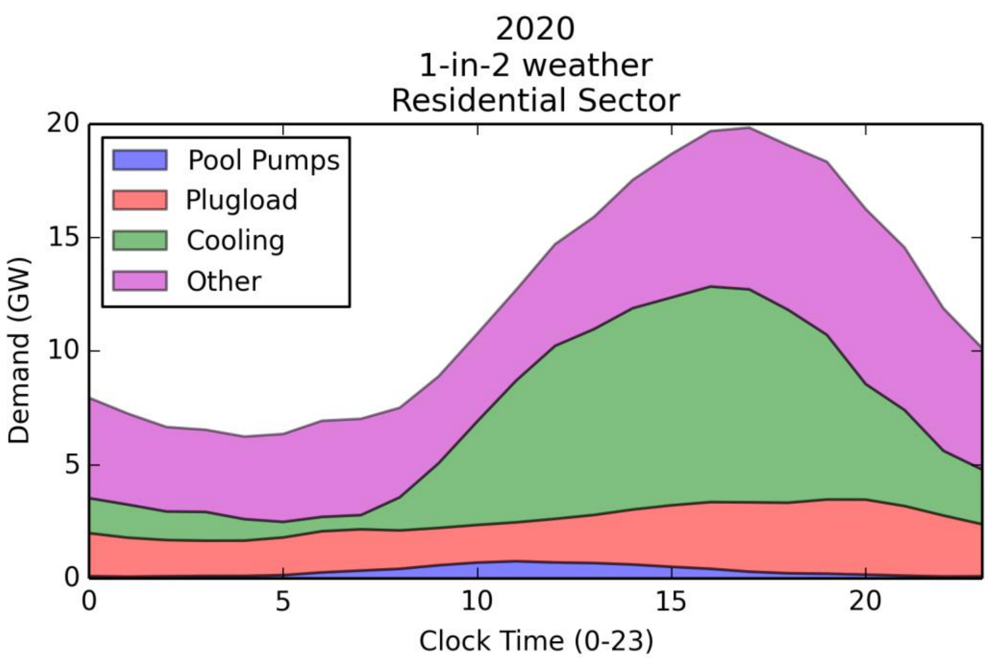


Figure B-13: Forecasted peak day hourly demand (in GW) for Residential sector end uses in 2020 for the 1-in-2 weather scenario.

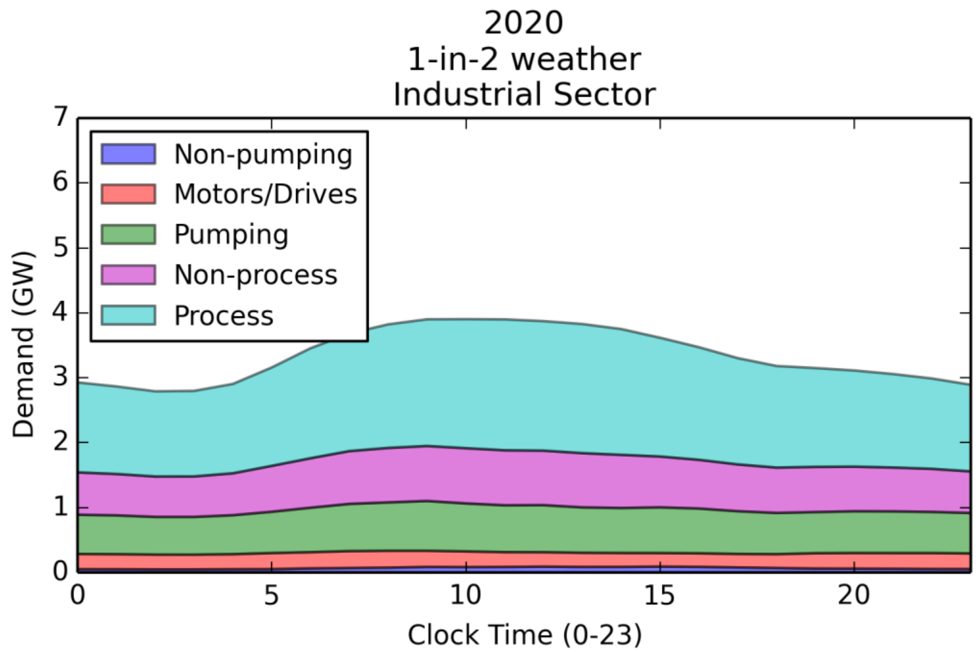


Figure B-14: Forecasted peak day hourly demand (in GW) for Industrial sector end uses in 2020 for the 1-in-2 weather scenario.

Results for 2020 in 1-in-10 weather scenario:

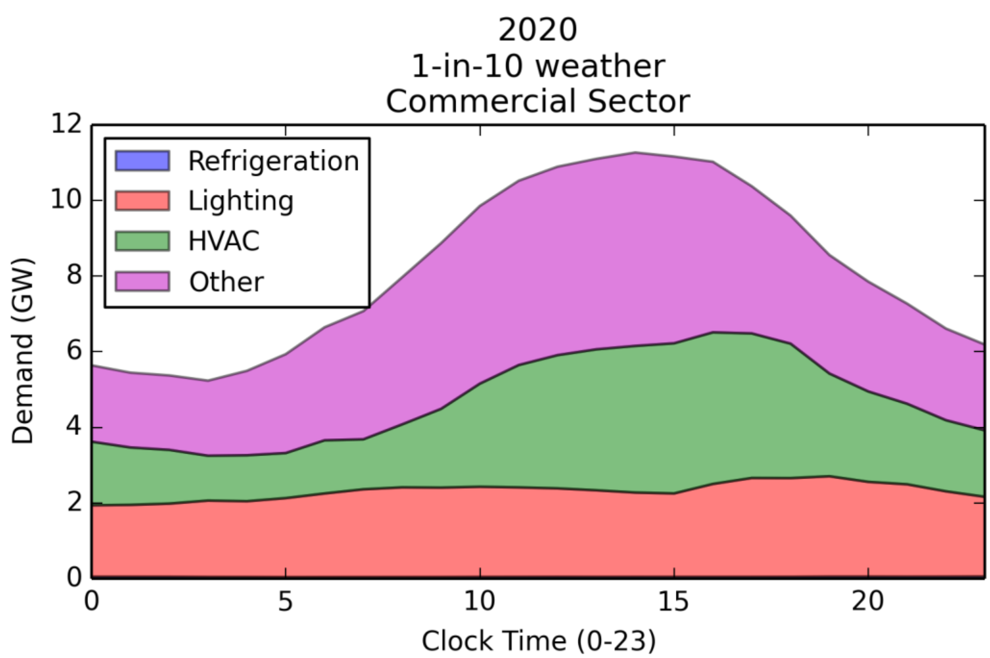


Figure B-15: Forecasted peak day hourly demand (in GW) for Commercial sector end uses in 2020 for the 1-in-10 weather scenario.

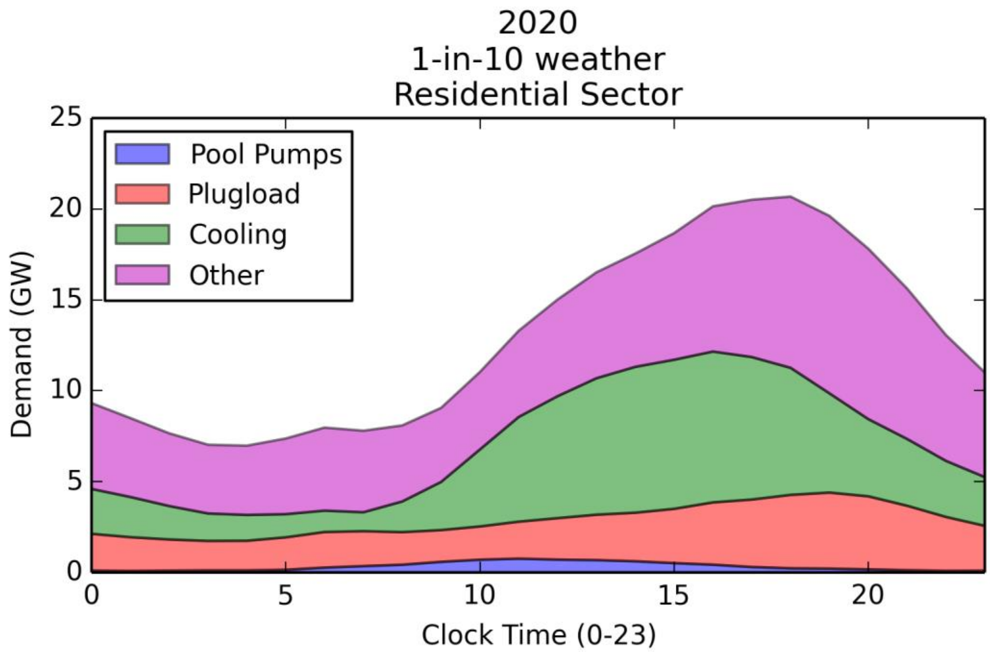


Figure B-16: Forecasted peak day hourly demand (in GW) for Residential sector end uses in 2020 for the 1-in-10 weather scenario.

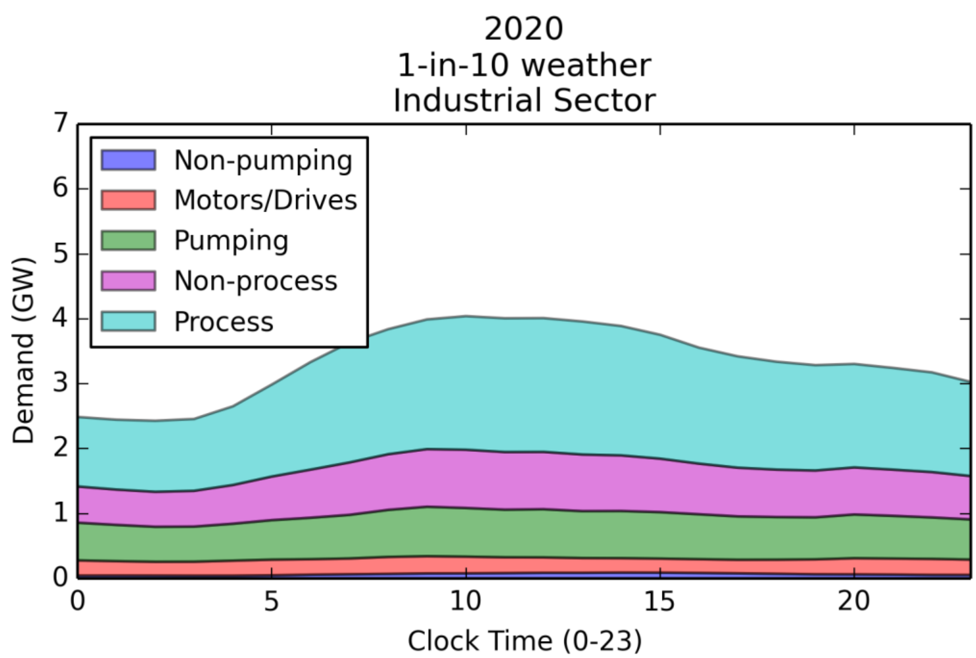


Figure B-17: Forecasted peak day hourly demand (in GW) for Industrial sector end uses in 2020 for the 1-in-10 weather scenario.

Results for 2025 in 1-in-2 weather scenario:

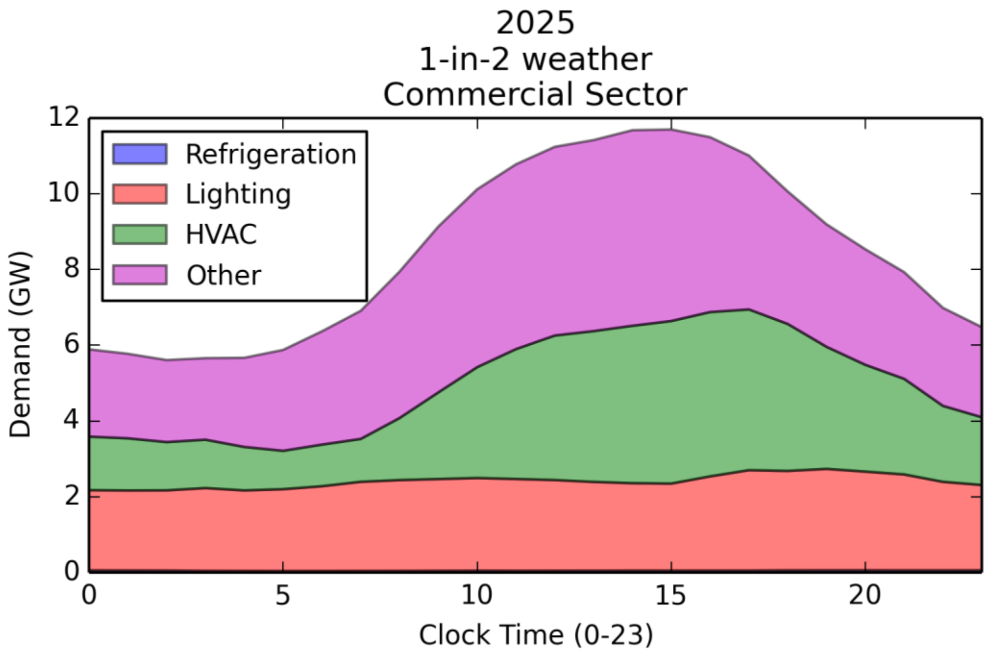


Figure B-18: Forecasted peak day hourly demand (in GW) for Commercial sector end uses in 2025 for the 1-in-2 weather scenario.

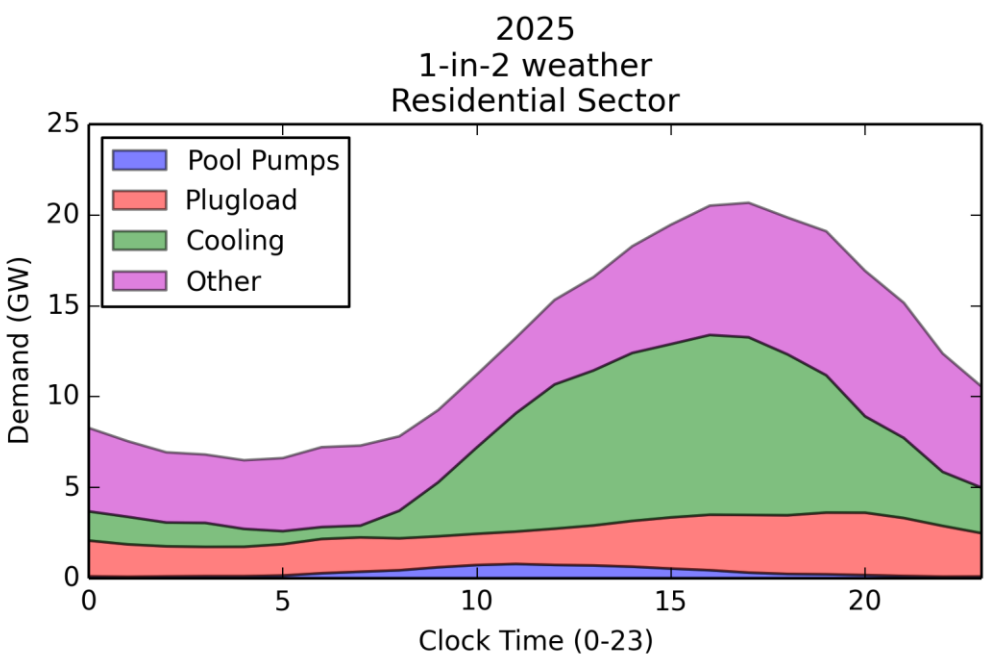


Figure B-19: Forecasted peak day hourly demand (in GW) for Residential sector end uses in 2025 for the 1-in-2 weather scenario.

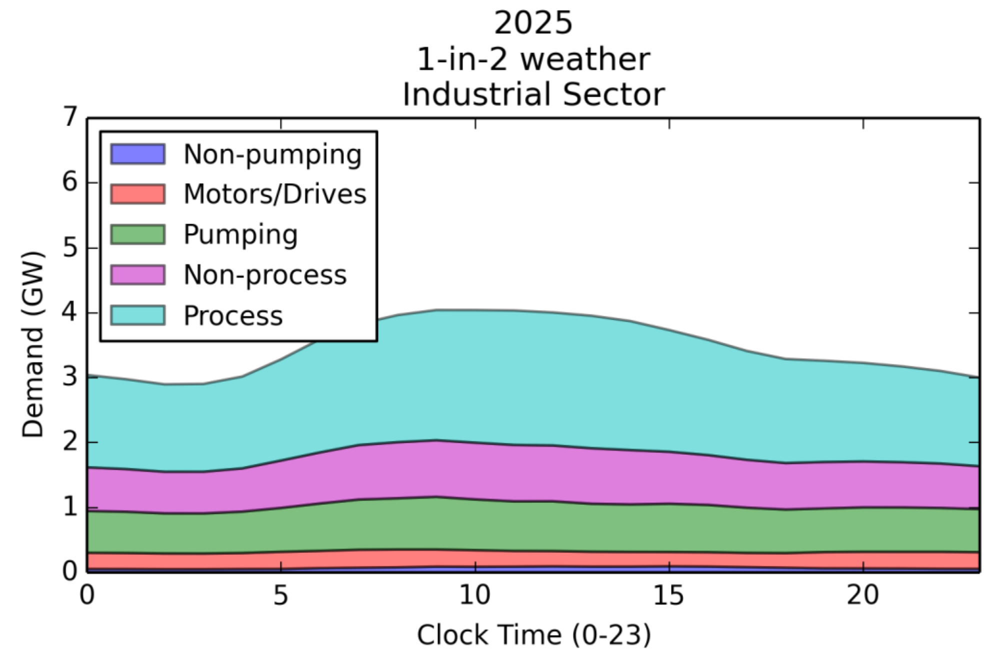


Figure B-20: Forecasted peak day hourly demand (in GW) for Industrial sector end uses in 2025 for the 1-in-2 weather scenario.

Results for 2025 in 1-in-10 weather scenario:

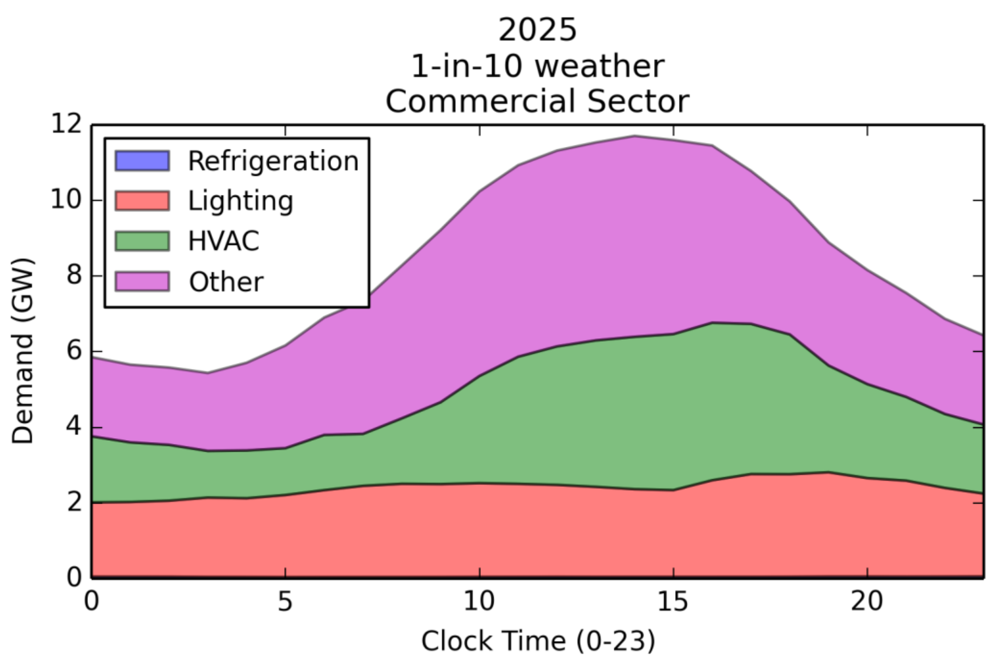


Figure B-21: Forecasted peak day hourly demand (in GW) for Commercial sector end uses in 2025 for the 1-in-10 weather scenario.

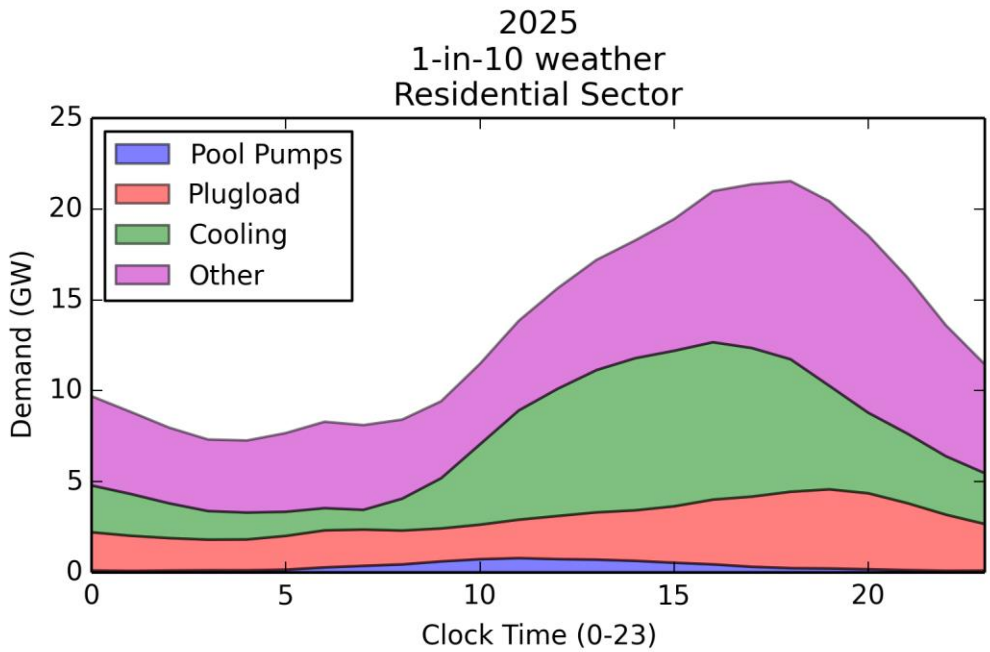


Figure B-22: Forecasted peak day hourly demand (in GW) for Residential sector end uses in 2025 for the 1-in-10 weather scenario.

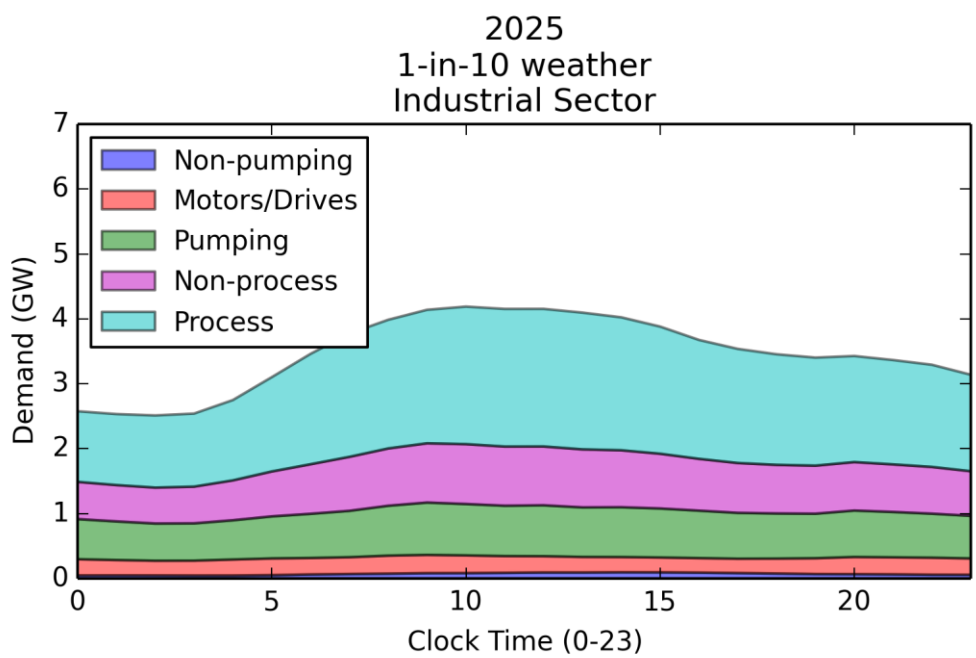


Figure B-23: Forecasted peak day hourly demand (in GW) for Industrial sector end uses in 2025 for the 1-in-10 weather scenario.

B-4.4.3. Energy Consumption Heat Maps by Sector

2020 forecast results for 1-in-2 weather scenario:

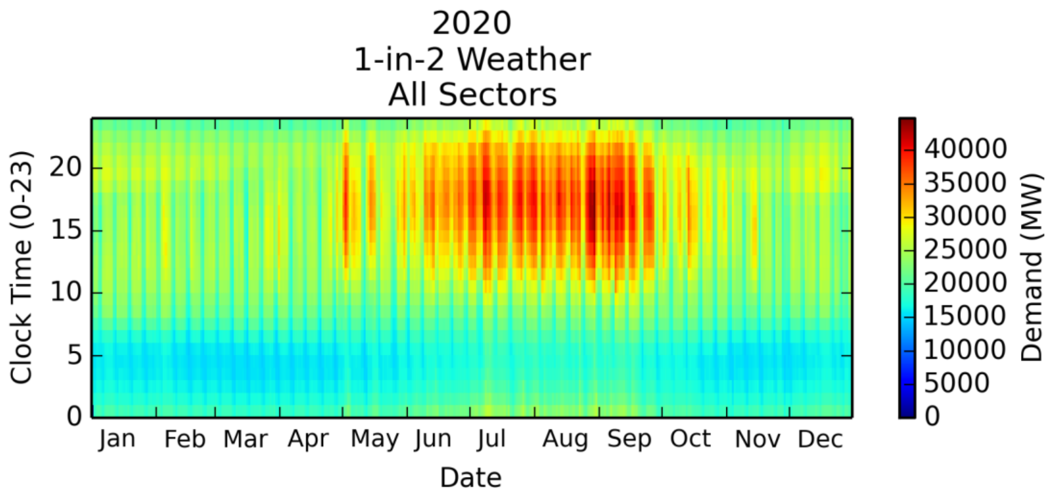


Figure B-24: Heat map of forecasted total energy consumption for all sectors in 2020 in the 1-in-2 weather scenario by date (x-axis) and hour (y-axis).

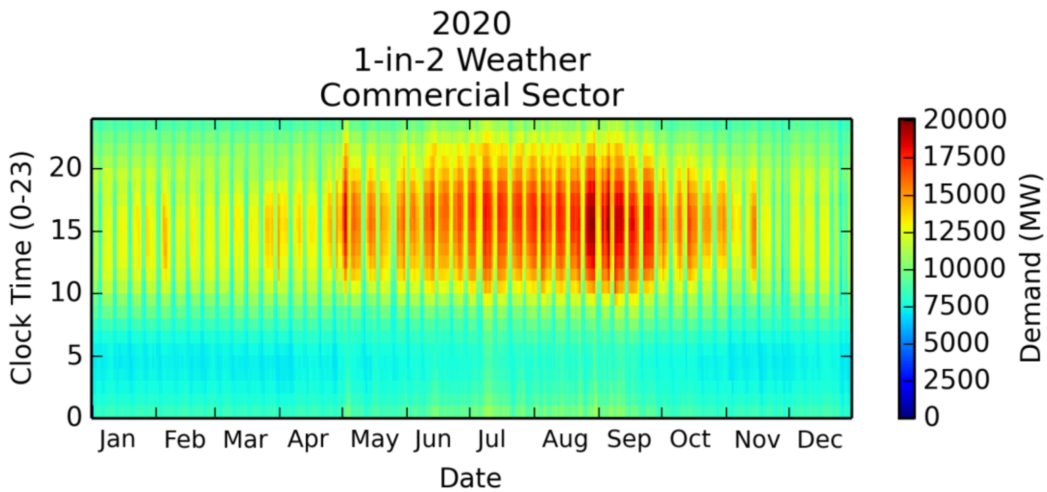


Figure B-25: Heat map of forecasted Commercial sector energy consumption in 2020 in the 1-in-2 weather scenario by date (x-axis) and hour (y-axis).

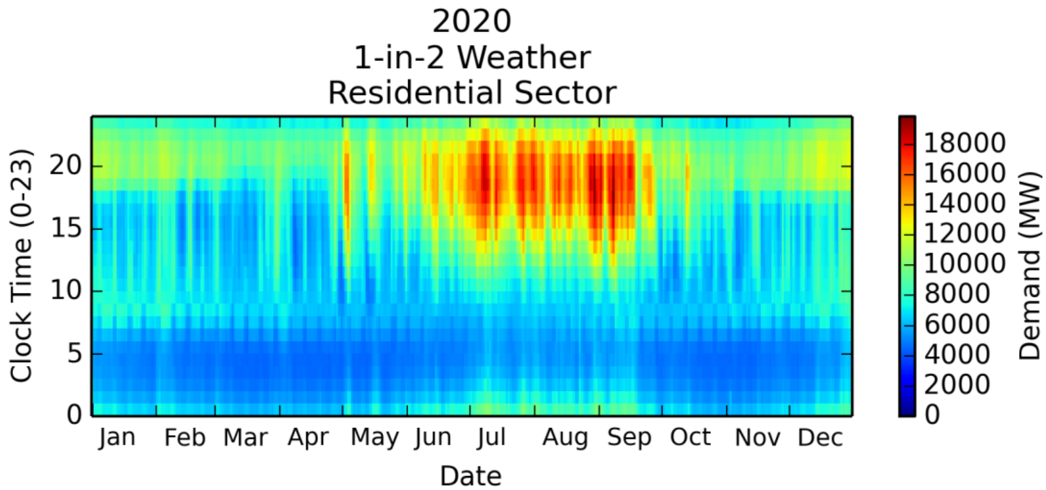


Figure B-26: Heat map of forecasted Residential sector energy consumption in 2020 in the 1-in-2 weather scenario by date (x-axis) and hour (y-axis).

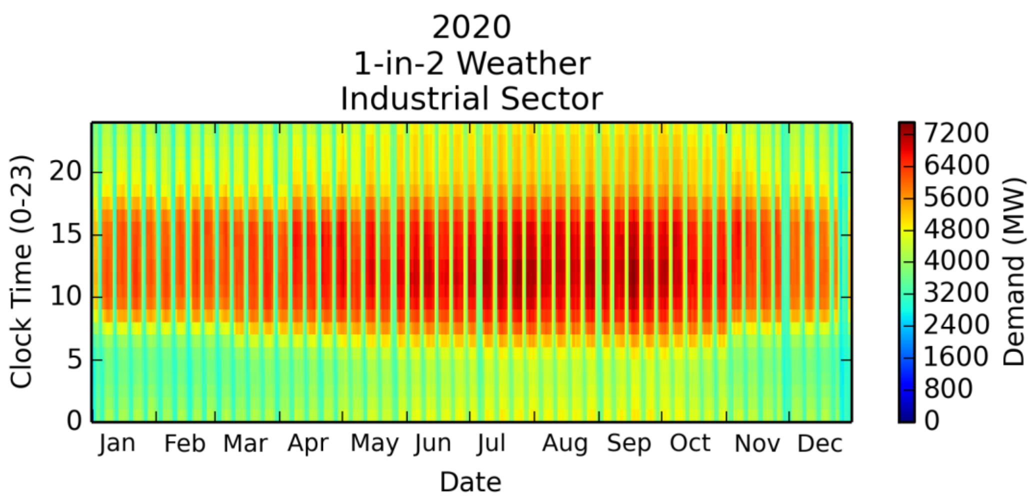


Figure B-27: Heat map of forecasted Industrial sector energy consumption in 2020 in the 1-in-2 weather scenario by date (x-axis) and hour (y-axis).

2020 forecast results for 1-in-10 weather scenario:

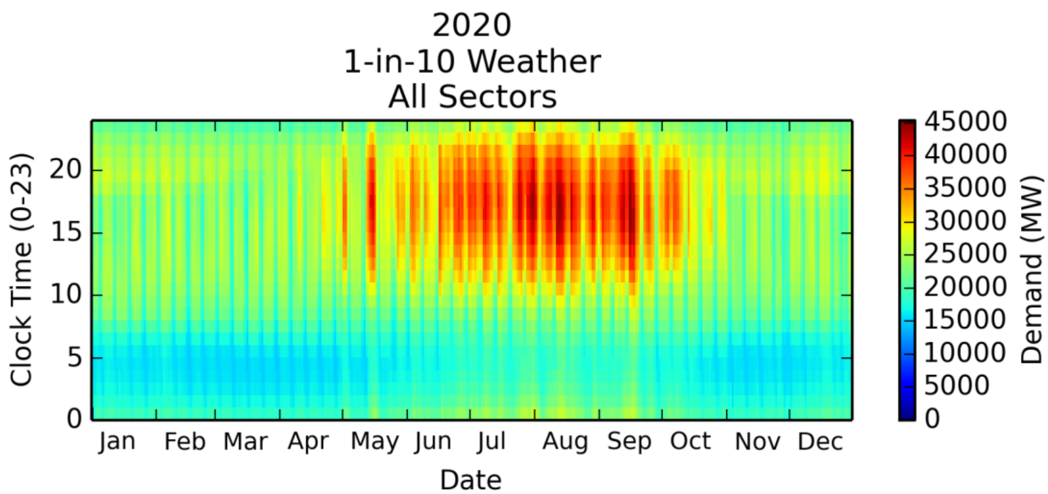


Figure B-28: Heat map of forecasted energy consumption for all sectors in 2020 in the 1-in-10 weather scenario by date (x-axis) and hour (y-axis).

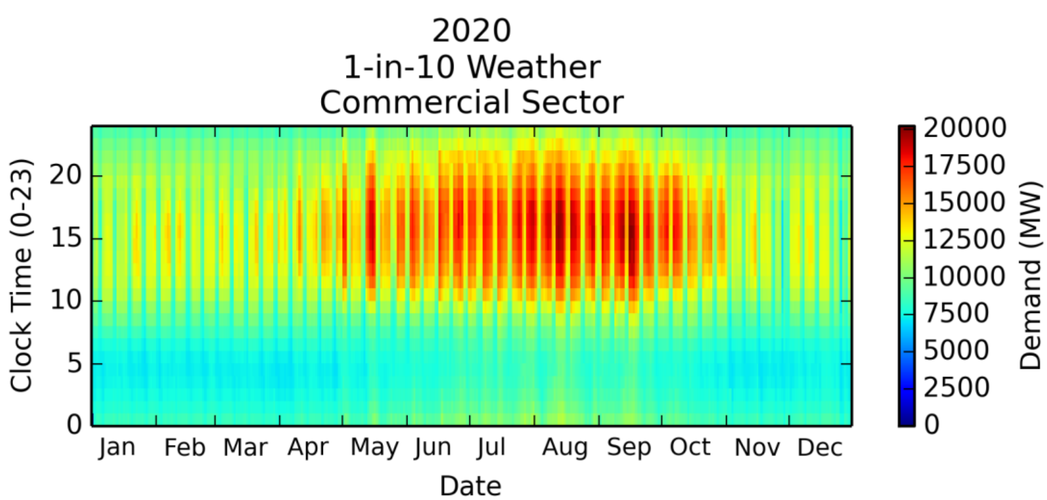


Figure B-29: Heat map of forecasted Commercial sector energy consumption in 2020 in the 1-in-10 weather scenario by date (x-axis) and hour (y-axis).

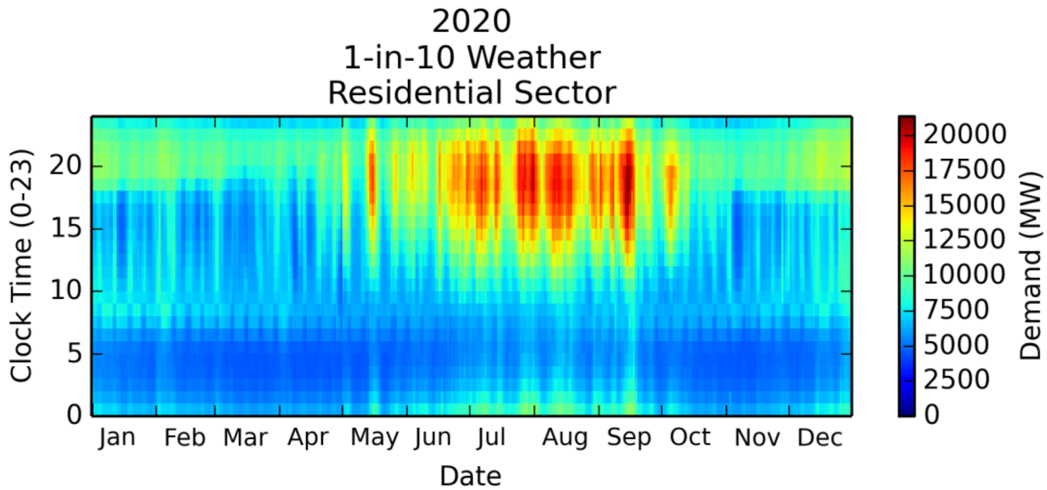


Figure B-30: Heat map of forecasted Residential sector energy consumption in 2020 in the 1-in-10 weather scenario by date (x-axis) and hour (y-axis).

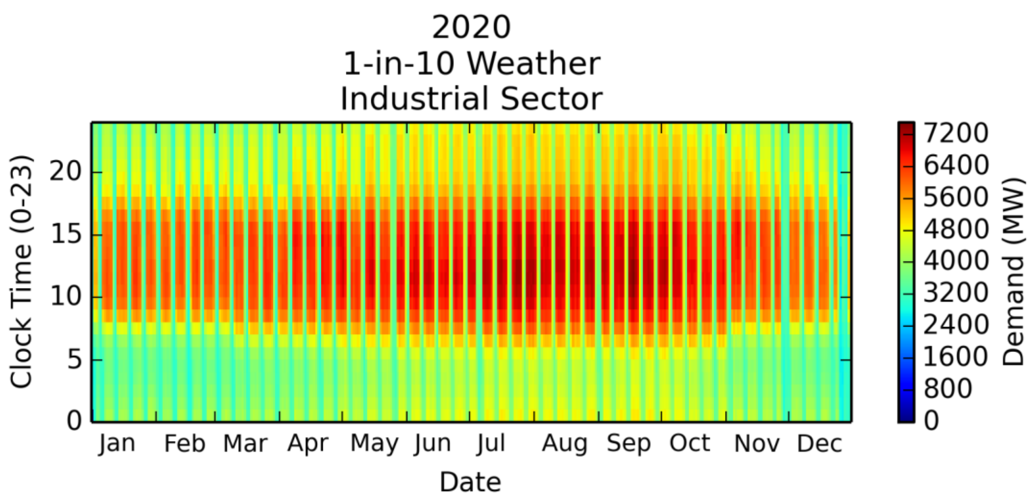


Figure B-31: Heat map of forecasted Industrial sector energy consumption in 2020 in the 1-in-10 weather scenario by date (x-axis) and hour (y-axis).

2020 forecast results for residential end uses in the 1-in-2 weather scenario:

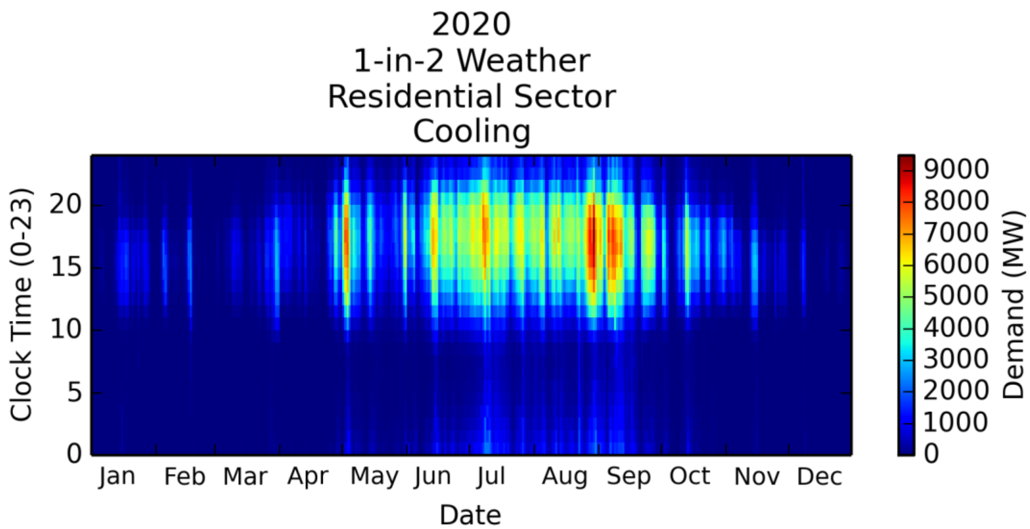


Figure B-32: Heat map of forecasted energy consumption for residential cooling in 2020 in the 1-in-2 weather scenario by date (x-axis) and hour (y-axis).

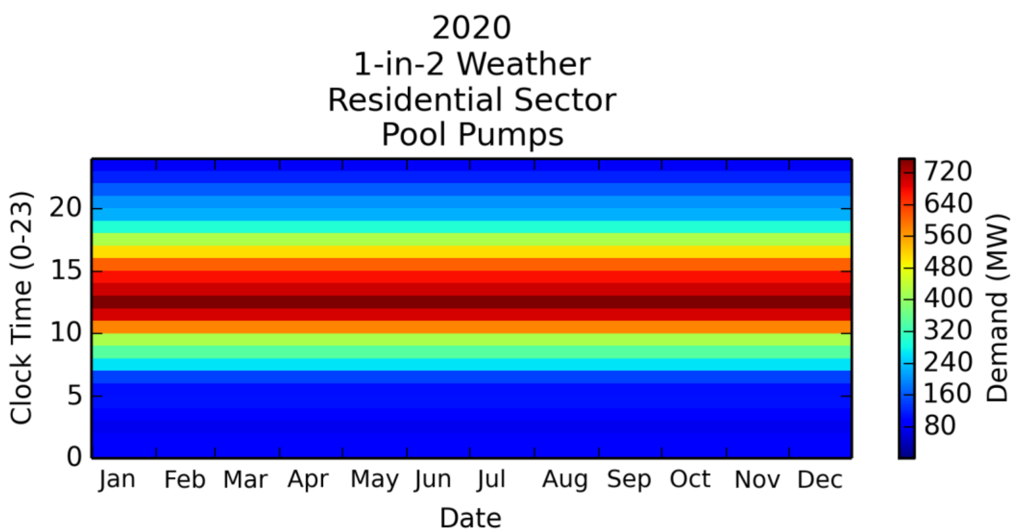


Figure B-33: Heat map of forecasted energy consumption for residential pool pumping in 2020 in the 1-in-2 weather scenario by date (x-axis) and hour (y-axis).

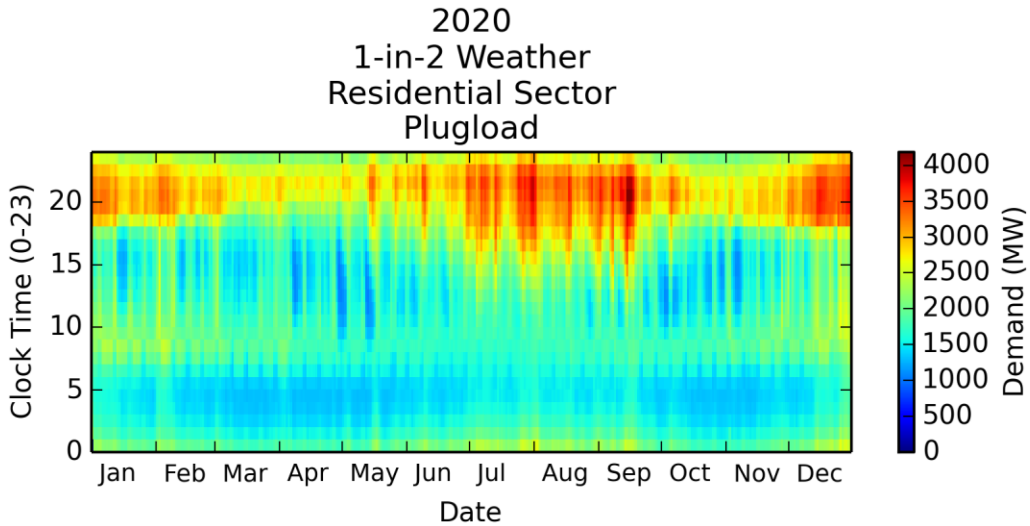


Figure B-34: Heat map of forecasted energy consumption residential plug loads in 2020 in the 1-in-2 weather scenario by date (x-axis) and hour (y-axis).

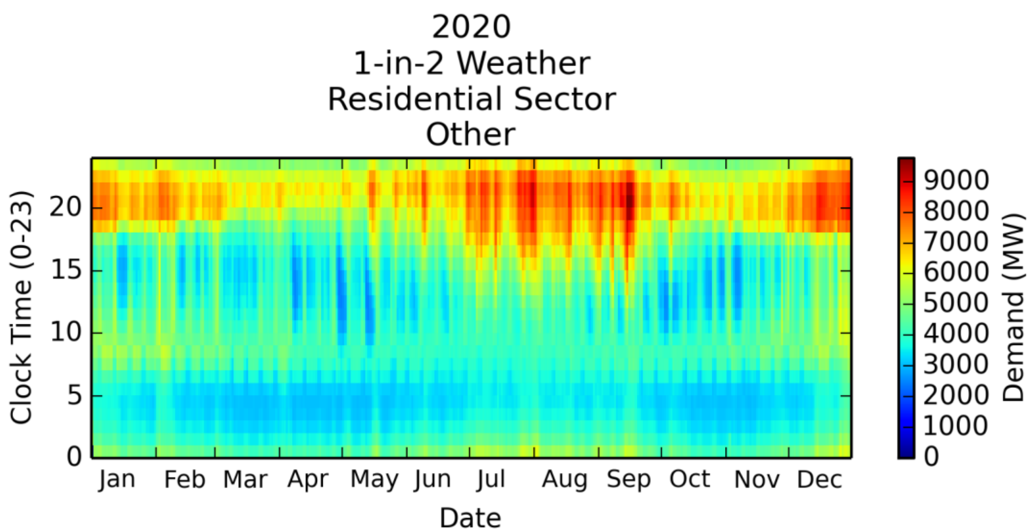


Figure B-35: Heat map of forecasted energy consumption for other residential loads in 2020 in the 1-in-2 weather scenario by date (x-axis) and hour (y-axis).

References

2009 California Residential Appliance Saturation Study (RASS) Volume 2: Results. Prepared for California Energy Commission by KEMA, Inc., 2010. Web.

"California Commercial End-Use Survey (CEUS) on the Web." N.p., n.d. Web. 30 Mar. 2016.

"California Electricity Data, Facts, & Statistics." *California Energy Commission Energy Almanac*. N.p., n.d. Web. 30 Mar. 2016.

California Energy Demand 2014–2024 Final Forecast Volume 1: Statewide Electricity Demand, End-User Natural Gas Demand, and Energy Efficiency. California Energy Commission, 2014. Web.

"CVRP Rebate Statistics." *Clean Vehicle Rebate Project*. N.p., 16 May 2013. Web. 30 Mar. 2016.

Farm and Ranch Irrigation Survey: 2013. U.S. Department of Agriculture, 2014. Web.

Francfort, Jim et al. *Plug-in Electric Vehicle and Infrastructure Analysis*. Idaho National Laboratory, 2015. Web.

Geography, US Census Bureau. "2015 U.S. Gazetteer Files Record Layouts." N.p., n.d. Web. 30 Mar. 2016.

Ghatikar, Girish et al. *Demand Response Opportunities and Enabling Technologies for Data Centers: Findings From Field Studies*. PG&E/SDG&E/CEC/LBNL, 2012. Print.

"Integrated Surface Database (ISD) | National Centers for Environmental Information (NCEI) Formerly Known as National Climatic Data Center (NCDC)." *Integrated Surface Database (ISD), National Oceanic and Atmospheric Administration (NOAA)*. N.p., n.d. Web. 30 Mar. 2016.

"Manufacturing Energy Consumption Survey (MECS) - U.S. Energy Information Administration (EIA)." N.p., n.d. Web. 30 Mar. 2016.

Neubauer, J., and M. Simpson. *Deployment of Behind-The-Meter Energy Storage for Demand Charge Reduction*. National Renewable Energy Laboratory, 2015. Web.

Olsen, Daniel et al. *Opportunities for Automated Demand Response in Wastewater Treatment Facilities in California - Southeast Water Pollution Control Plant Case Study*. Lawrence Berkeley National Laboratory, 2012. Print.

Pool Pump Demand Response Potential: Demand and Run-Time Monitored Data. Prepared for Southern California Edison by Design & Engineering Services, 2008. Web.

Reliability Demand Response Product: Revised Draft Final Proposal Version 2.0. California Independent System Operator (CAISO), 2010. Print.

Schniepp, Mark. *California County-Level Economic Forecast 2014 - 2040*. The California Economic Forecast prepared for Economic Analysis Branch, Office of State Planning, California Department of Transportation, 2014. Web.

"sonnenBatterie." *Tech specs sonnenBatterie Eco*. N.p., 22 Jan. 2016. Web. 30 Mar. 2016.

"Tesla Powerwall." N.p., n.d. Web. 30 Mar. 2016.

Williams, B. et al. *Clean Vehicle Rebate Project Participation Rates: The First Five Years (March 2010 – March 2015)*. San Diego CA: Center for Sustainable Energy, 2015. Print.

Appendix C: Enabling Technology Methodology-Framework, Inputs, and Assumptions

Appendix C: Enabling technology methodology - Framework, inputs and assumptions

This appendix describes the framework of the DR-PATH Model, and explains the inputs to the model. The inputs and underlying assumptions to the DR-PATH model are contained in a spreadsheet, referred to as the Enabling-Tech-DB.

C-1. Technology inputs to DR-PATH Model

The DR-PATH model estimates the potential to provide grid service with demand response (DR) across a range of technology and market pathways (hence, "DR-PATH").

This document describes the framework for defining DR enabling technology performance and cost and how these inputs are combined in a calculation methodology to estimate the quantity and unit cost of grid service. Regarding model inputs, this document covers only the cost of the DR enabling technology and its performance, and does not cover any DR program or other costs.

The inputs to the model are organized in a specially-formatted Microsoft Excel workbook, the enabling-tech-DB, with a set of tabs that define various elements to the input file of the DR-PATH Model.

Tabs in the enabling-tech-DB used to specify a set of input assumptions:

1. **`product_req`** - the set of grid products and requirements for participation
2. **`tech_list`** - a specified set of technology defining a potential pathway, including one of each below:
    a. **`local_control`** - building-level load controllability
    b. **`dispatch`** - communication for receiving DR signals
    c. **`telemetry`** - data acquisition and communication for operations and settlement
3. **`scenarios`** - a set of assumptions defining the trajectory of DR technology and markets.
4. **`metadata-options`** - a set of options used in the other tabs of the database

C-2. Defining Enabling Technology

Demand response enabling technology is the mix of load control and communications hardware and software that makes loads flexible. The enabling technologies used in this potential study are defined in terms that are conducive to estimating the expected costs and performance in future scenarios. We draw on a mix of past experience, current trends, and future projections for the types and characteristics of DR enabling technology.

In the context of this study, we define each enabling technology in terms of three key attributes: Local Control, Dispatch, and Telemetry. A single instance of enabling technology will consist of one "option" from each of these areas. The combined capabilities of the *DR technology system* in the context of the building systems under control are compared to the needs and requirements of grid service DR products (e.g., participation as a proxy demand resource in the energy market) to qualify for providing service. The technology systems are also the basis for our estimates of cost and market factors.

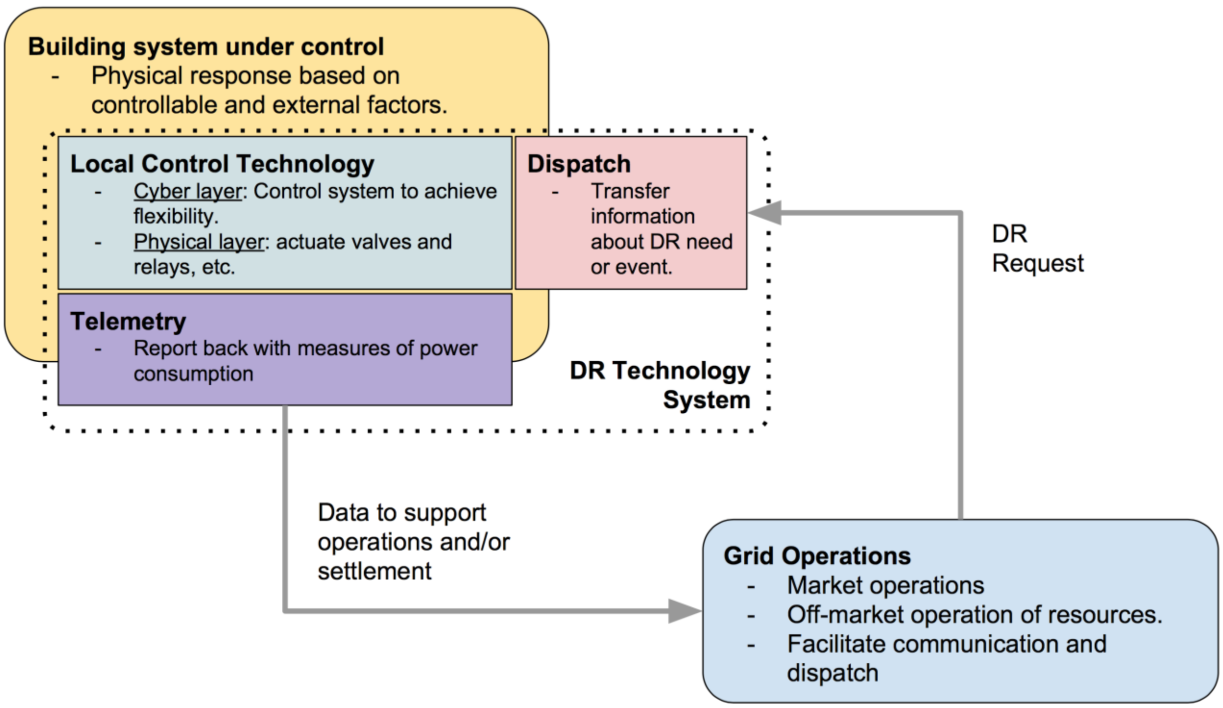


Figure C-1: Interactions between the DR technology system, grid operations, and the building systems under control. The dotted area represents the behaviors considered in DR-PATH.

C-2.1. Local Control Technology

Local Control: The local control technology describes the capabilities to manage and/or change the demand characteristics of a particular end-use load or group of end use loads together. The following are key characteristics for the local control technology (defined in the input file on the local_control tab).

Table C-1: Local control technology (defined in the input file on the local_control tab).

Input file field	Description	Notes
`lc_id`	Local control ID	Used to uniquely identify local control technology.
`sector`	Applicable sector (res/com/ind)	These are specified for each local control technology since there are often significant differences in technology that may operate on similar principles in difference sectors.
`sub_sector`	Applicable building type within sector (or all of above)	
`dr_type`	Supply or Load-Modifying DR	Both types can be specified in the framework, with some difference in the way the calculations are applied as appropriate.
`end_use`	The type or set of end-uses that are controlled by the particular instance of local control.	Each technology must apply to a specific end_use type.
`t_delay_local`	The delay between receiving of a control signal and the start of a control action at the site.	Timing features are added to the round trip communications latency to estimate the total system latency when combined with dispatch and telemetry signals as appropriate.
`t_ramp`	The time from the start of the control action to the full response from the end-use.	
`t_resolution_ … local_control`	The shortest time-step between two different control signals.	
`shed_peak`	The peak level of load shed possible with the technology for short (~10 minute) amounts of time. If Load Modifying DR, this field can indicate the expected reduction in use during peak times for "direct input" option of specifying lmdr.	Sheds beyond peak shed for supply resources typically have diminishing availability fractions to account for needs to cycle load and manage rebound.
`shed_1_hour`	1-hour Shed: The shed level over a	

Input file field	Description	Notes
	continuous one-hour period	
shed_2_hour	...over 2 hours	
shed_4_hour	..over 4 hours	
lmdr_input_…option	“direct” or “file”	For LMDR, if “direct” input option only the shed_peak will be used, taken to define the expected shed fraction during system peak times. If “file” input option the fraction of shed during the full year is specified based on a file at the filename in lmdr_file.
lmdr_file	A filename for load impact from LMDR	in 'flex_market_econ/… input/lmdr_shapes'
To be added in Phase 2: Take capabilities, regulation capabilities, shift capabilities.		

C-2.2. Dispatch Technology

Dispatch: The dispatch technology defines the performance of communications for DR dispatch methods used to send and receive control or other signals from a central or decentralized authority.

Table C-2: Dispatch technology (defined in the input file on the dispatch tab).

Input File field	Description	Notes
`sig_id`	Dispatch signal type ID	Used to uniquely identify dispatch technology
`t_delay_ … dispatch`	The delay from identification of dispatch need to signal receipt at premises.	The timing is added to the round trip communications latency to estimate the total system latency for comparing to DR product requirements.
`t_resolution_ … dispatch`	The shortest time-step between two different DR signals.	The resolution is compared to requirements for DR products.
`reliability`	The fraction of times dispatch is successfully communicated to the site.	Used to derate available capacity.
To be added in Phase 2: Spatial resolution of dispatch (e.g., IOU territory, SubLAP, Feeder, Device), regulation capabilities		

C-2.3. Telemetry

`Telemetry:` The telemetry defines the visibility provided to system operators for feedback during operations and settling markets ex-post.

Table C-3: Telemetry (defined in the input file on the telemetry tab).

Input File field	Description	Notes
`telem_id`	Telemetry type ID	Used to uniquely identify telemetry technology
`t_delay_telem`	The delay from measured control actions to receipt of verification at DR settlement entity (normally CAISO).	The timing and resolution characteristics are compared to requirements for particular DR products.
`t_resolution_… telem`	The shortest time-step between two DR measurements returned by telemetry.	
To be added in Phase 2: regulation capabilities.		

C-2.4. Integrated DR Technology List

`Technology list:` Each DR enabling technology set includes an element of **`local_control`**, **`dispatch`**, and **`telemetry`**, described in the tables above, and inherits all of the attributes from each of those. Each row in the Technology List is defined by an enabling technology combination applied to specific end uses in particular sectors and/or building types. For each unique technology possibility, the following factors are defined:

Table C-4: Integrated DR Technology List.

Input File field	Description	Notes
`tech_name`	DR technology name	A string describing the technology name in "plain English".
`tech_ID`	DR technology ID (automatically generated as the combination of lc_id, sig_id, and telem_id that are specified)	Used to uniquely identify DR technology. The technology inherits all attributes that are defined for each of the constituent elements.
`source`	The data source of the inputs.	Usually "LBNL Synthesis" if based on synthesis of LBNL institutional knowledge as well as best available external data.
`scenario`	A label to define if the technology is included in the base scenario or only in development (not used in model runs unless explicitly called).	The timing and resolution characteristics are compared to requirements for particular DR products.
`adopt_drtech_2015`	The fraction of eligible sites in 2015 that adopt the local control technology (i.e., have a controllable site / end-use) for non-DR reasons.	Used to define the threshold in a random draw to determine if certain cost components are zeroed out in the analysis. This value is related to the Integrated Demand Side Management (IDSM) and qualitative benefits of controllability.

Input File field	Description	Notes
`adopt_drtech_2025`	Same as above, for 2025.	This allows for an expansion in expected non-DR adoption over time if appropriate.
`adopt_stock_2015`	The fraction of eligible sites that have DR enabling technology installed in 2015.	Used to trace implied trajectory in technology adoption rate. Values that are "NA" are replaced by the benchmark propensity score.
`ratio_ps_2015`	The expected ratio of the propensity to adopt for this particular DR technology in 2015 to the benchmark propensity score.	Propensity is higher for technology with qualitative improvements in site-level service or marketing effectiveness compared to the technology and marketing combinations that were available during periods when data were captured to train benchmark propensity score model.
`ratio_ps_2025`	Same as above, for 2025	Propensity ratio can improve over time if qualitative technology or marketing attributes are expected to shift.
`ratio_cost_2025`	The expected ratio of 2025:2015 technology cost	Typically <= 1 for improvement.
`ratio_perf_2025`	The expected ratio of 2025:2015 technology performance	Typically <= 1 for improvement.
`cost_unit_var`	This defines the units for calculating variable cost components.	Typically either not used, or based on $/kW under control.
`Site-level comm and control cost`	This defines the known separate fixed $ 2015 cost for site-level DR comms (e.g., for building gateway necessary for DR)	Typically 0. This applies to site-level DR-specific communications equipment cost.

Input File field	Description	Notes
`cost_fix_init`	The **fixed initial costs** for achieving controllability "per site" for the given end-use.	To pay for hardware and soft costs of installation per site. *If there is non-DR adoption at a site these costs are zeroed out.*
`cost_var_init`	The **variable initial costs** for achieving controllability "per unit" of the variable portion.	To pay for hardware and soft costs of installation. *If there is non-DR adoption at a site these costs are zeroed out.*
`cost_fix_opco`	The **fixed annual operating costs** for maintaining controllability and/or paying communication fees "per unit" of the fixed portion.	To cover technology-related (not administrative etc.) annual operating costs.
`cost_var_opco`	The **variable annual operating costs** for maintaining controllability and/or paying communication fees "per unit" of the variable portion.	To cover technology-related (not administrative etc.) annual operating costs.
`cost_fix_ …` `co_benefit`	The **expected fixed level of co-benefit buy-in** per end use for enabling costs (i.e., expected monetary contributions to initial costs by site operators where there has been non-DR related adoption of the technology, represented as a levelized benefit over the lifetime).	Often set to zero. Only set to non-zero number when there is strong evidence or expectation that site owners will buy-in to share initial costs of DR based on qualitative improvements in building performance or other benefits related to fixed portion.
`cost_var_ …` `co_benefit`	The **expected variable level of co-benefit buy-in** per end use for enabling costs (i.e., expected monetary contributions to initial costs per variable unit).	Used primarily to account to demand charge reduction for commercial and industrial customers.
`cost_margin_ …` `dispatch_day`	The marginal additional cost per day of dispatch.	Used to account for scheduling coordinator fees, additional administrative costs, etc. related to actual dispatch of DR events.

Input File field	Description	Notes
tech_lifetime	The lifetime of the DR technology	Used to amortize initial costs over the lifetime to get a levelized annual average.
To be added in Phase 2: Cost data for advanced / fast DR		

C-3. Eligibility for Grid Product Services

Within the framework of the DR-PATH model, each end-use/technology combination has a set of characteristics (i.e. telemetry, signal, local control) that define the ability for the end-use to respond to a DR dispatch signal, as defined in previous sections. In order to determine if those end-use and technology characteristics match the requirements for a specific DR product and service, we have created a set of filters for the requirements for each of the DR products in the model. Below is a list of the descriptions and requirements of the filters used for PDR and RDRR products in the DR-PATH model. Each of the filter requirements is compared to the combined DR system response characteristics to determine if there is a match between the DR product and DR technology system (i.e., if the technology is qualified to participate in the market).

Technologies are filtered for their grid product eligibility in terms of:

- Regulation-quality telemetry and dispatch required (True or False)
  - Does the product categorically require dispatch and telemetry technology performance?
- Expected dispatches per year (number of days)
  - This can disqualify technology that are extremely dispatch-limited (only a small number have this constraint)
- Maximum dispatch delay allowed (seconds)
  - The maximum time between when a dispatch request is made (black diamond in figure below) and the start of local response (the delay to start of local response).
- Maximum ramp allowed (seconds)
  - The maximum additional time allowed for ramping. The total response delay including the ramp should be less than the sum of the maximum dispatch delay and ramp allowed.
- Maximum resolution for control signal
  - The maximum time between control signal steps (the “local control resolution”). For example, a load that can change its operation every 10 minutes has a “10 minute” local control resolution.

- Minimum bid duration
  - The minimum continuous time that a load must be able to participate when dispatched.
- Maximum telemetry delay
  - The maximum delay between DR response and telemetry signals back to the system operator (or if there is no active telemetry, the settlement signal).
- Maximum telemetry resolution
  - The maximum time step resolution on telemetry.

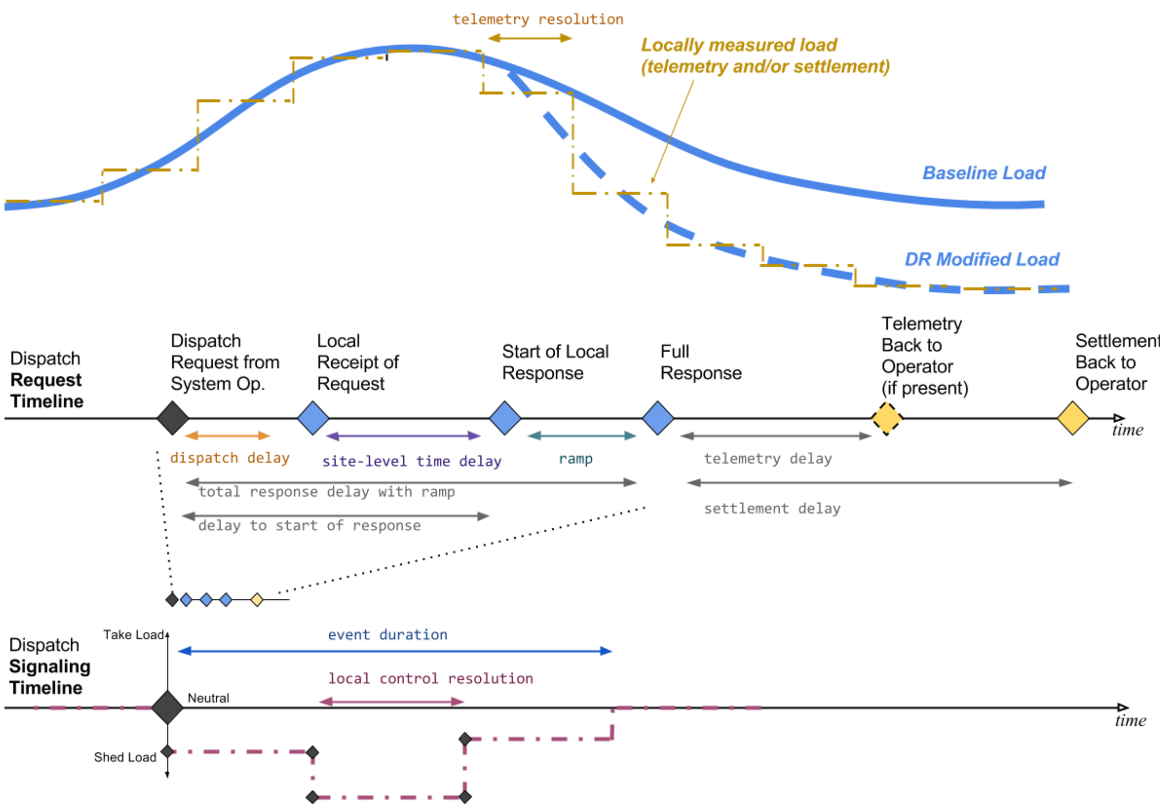


Figure C-2: Illustration of DR Technology system dispatch, local control, and telemetry timing characteristics that determine qualification for product service provision.

Table C-5: Service comparisons.

Product Name	[string] plain English	local capacity DR	Energy market via RDRR	Energy market via PDR
Product category		energy	energy	energy
Demand Response type allowed		supply	supply	supply
Scenario Name	[scenario ID]	base	base	base
Expected number of dispatches / year	[days/year]	50	2	50
ID	Unique ID for DR enabling technology	energy_pdr_local	energy_rdrr	energy_pdr
Requires reg quality dispatch and telem?	[T/F] if regulation must be T	F	F	F
max delay for dispatch	[SECONDS] max expected dispatch delay time	1200	64801	64801
max ramp allowed	[SECONDS] additional time allowed for ramp	0	500	500
max resolution for control signal	[SECONDS] maximum tenable resolution of control signal	3601	86401	3601
min bid duration	[HOURS] minimum for continuous bid from a resource	4	4	4
max telem delay	[SECONDS]	2592000	2592000	2592000
max telem resolution	[SECONDS]	3600	3600	3600

C-3.1. DR Product Service Qualification: Step 1

The dispatch, telemetry and control characteristics for each end-use/technology is compared to the requirements of the DR Product to determine if the combination can provide the DR service. The model tags each one of the requirements as a True or False for each end-use, and only those end-uses that pass the qualification test are passed to step 2 of the qualification process.

C-3.2. DR Product Service Qualification: Step 2

For those end-uses that pass the product screening, the model then determines how much DR is available from that end-use. The available DR is defined as the baseline end-use in each hour times a fraction of sheddability available over a continuous a DR event window that lasts as long as the minimum bid duration, which is indicated in the Table C-1Table C-1 above. This shed filter duration matches the required bid duration requirement of four hours for both PDR and RDRR (i.e., in Phase 1 only 4-hour duration bids are considered).

Our data inputs include options for sheds of different durations besides a 4-hour shed, but these inputs are not utilized in the Phase 1 model. We have captured and documented (in preceding sections) peak shed, 1-hour, 2-hour and 4-hour shed capabilities for each of the end-use/enabling technology combinations. We expect to utilize these additional shed filters in Phase 2 efforts, and to potentially model impacts to DR Potential estimates if requirements were to change and allow for load participation with a 1-hour or 2-hour shed. In these modeling exercises with shorter duration shed filters, we could expect to have more DR available to serve the grid.

C-3.3. Capabilities Model for DR Technology - Quantity of RA credit

The capacity credit for each DR enabling technology is based on the weighted sum of the available shed capabilities, which were calculated in Step 2 above. For load modifying DR, the magnitude of RA credit ($m_{RA,LMDR}$) is defined as the sum of the difference between the baseline and modified baseline load times a capacity weighting vector for each hour. For supply DR ($m_{RA,supply}$), a fraction of the modified baseline is defined for each hour and aggregated in a similar way, multiplied by a weighting vector and summed across all 8760 hours in the year.

$$m_{RA,LMDR} = \sum_{hour=1}^{8760} \{ (\underline{b_{tot}} - \underline{b_{tot,mod}}) \odot \underline{c_{RA}} \}$$

$$m_{RA,supply} = d_{rel} * \sum_{hour\,=\,1}^{8760} \{ (S_X \circ \underline{b_{eu,mod}}) \odot \underline{c_{RA}} \}$$

Note on notation in equations above:

- *In both equations the circle with dot is an element-wise product of the remaining two vectors after the first operation is complete.*
- *Subtraction of vectors is element-wise in the load modifying equation.*
- *In the equation describing supply-side DR, the empty circle denotes an element-wise product of the scalar S_X (the available load reduction fraction) and $\underline{b_{eu,mod}}$ (the modified baseline load shape).*

For the PDR and RDRR DR Products, (i.e. Phase 1 supply DR), the quantity of RA credit (in kW/yr), is calculated by multiplying the 4-hour filter sheddable load fraction for each end-use 8760 hourly load profile. This vector of sheddable load values is multiplied by the vector of relative capacity weights, in this case the weighted top 250 hours (conventional RA calculation), which is based on net system load. These hourly values are summed and (as described below) adjusted for dispatch reliability, operating reserves, T&D, improvements in performance within the scenarios (BAU, medium, and high), and for changes in the year to year trajectory, (i.e. 2020 - 2025). As the source of DR capacity is at the end-user, the RA credit is adjusted for T&D and operating reserves to be consistent with capacity from conventional generation.

Adjustments to performance

- CE Protocols: The protocols include performance adjustments for Operating Reserves and T&D to capture the benefits of DR in the supply market. For example, this adjustment captures the fact that a MW of DR is not equal to a MW from a generator, because the MW from a generator will lose energy/capacity over transmission and distribution lines.
- Adjusted for scenarios: The performance ratios within the BAU, Medium and High scenarios include technology performance improvements for forecasting DR Potential in 2020 and 2025. The performance improvements are captured as increases in the shed factors for each technology.
- Adjustments for year-to-year trajectory: From 2015-2025, the performance of technology for some technologies is expected to improve beyond 2015 levels, which require additional adjustments outside of those performance adjustments made within the scenarios.

Table C-6: DR performance variables from input and calculated as intermediate values in the model and their mathematical symbols for use in equations below.

Input File Field or Model Variable	**Symbol in equations below**	**Example / Notes**
baseline (calculated)	$\underline{b_{tot}}$	The total baseline load, a vector of 1:8760 values, one for each hour of the year, in kW/site. (e.g., {4, 4.5, 5.5 … 2.4, 2.3, … N})
baseline (calculated)	$\underline{b_{eu}}$	The end use baseline load, a vector of 1:8760 values, one for each hour of the year, in kW/site. (e.g., {4, 4.5, 5.5 … 2.4, 2.3, … N})
baseline_mod (calculated)	$\underline{b_{tot,mod}}$	The modified total baseline load (after load modifying DR), a vector of 1:8760 values, one for each hour of the year, in kW/site. (e.g., {4, 4.2, 5.1 … 2.1, 2.0, … N})
baseline_mod (calculated)	$\underline{b_{eu,mod}}$	The modified end use baseline load (after load modifying DR), a vector of 1:8760 values, one for each hour of the year, in kW/site. (e.g., {4, 4.2, 5.1 … 2.1, 2.0, … N})
shed_***X***_hour	S_X	The fraction of load that can be shed over ***X*** hours of continuous time, where the continuous period is defined in the product requirements., (e.g., 0.4)
cap_ra_weight (calculated)	$\bar{c}_{RA}$	The relative value of capacity value in each hour of the year, a vector of 1:8760 values that sum to one, one for each hour of the year, unitless. This is calculated dynamically based on the top 250 hours of system net load. (e.g., {0, 0, 0, 0.1, 0, … , N}}
reliability	d_{rel}	Dispatch reliability fraction derates capacity.

C-4. Cost Model for DR Sites

The narrative above describes the methodology for deriving the quantity (kW) of DR eligible for each grid product. This section describes how the model estimates the average annual costs for each DR enabling technology for the site of installation at the customer clusters level, as defined in the LBNL LOAD Forecasting model. These average annual costs are analogous to the "levelized" cost of DR service -- the equivalent annual cost of having a resource installed, enrolled, and working. Levelized costs have a long history of use for considering alternative investments in generation assets and we use them here to facilitate comparisons between generator and non-generator technology for meeting peak capacity needs on the grid.

For residential and small/medium commercial customers, costs are estimated by end use. Our approach uses the perspective of estimating the total costs to enable a site with a specific end-use/enabling tech combination. For large and industrial customers, a premise-wide, rather than end-use, approach is taken to evaluate DR technologies and enablement (e.g. $200/kW installed). We define the average annual costs as the sum of all the costs over the lifetime of the technology divided by the useful life of the measure.

For each of the end uses, we estimate the initial fixed, variable and operating costs for a customer site, based on customer sector and size[9]. A description of each are as follows:

- Initial Costs:
    - The fixed initial costs for achieving controllability "per site" for the given end-use, e.g., paying for communication and control gateways.
    - The variable initial costs for achieving controllability "per kW", e.g., scaling costs appropriately for large facilities.
    - The initial costs are increased using a factor to account for the expected cost of financing
    - The initial costs are levelized over the lifetime of the technology
- Operating Costs:
    - The fixed annual operating costs for maintaining controllability, e.g., paying communication or license fees
    - The variable annual operating costs for maintaining controllability, e.g., control system maintenance.
- Administrative and marketing costs are assigned "per site" on an annual basis
- Note: "per kWh" used as variable cost unit for batteries.

The DR-PATH model also utilizes a propensity to adopt DR (Pscore) which is based on customer characteristics and historical precedence for customer participation and adoption of DR programs and technologies[10].

The equations outlined in the steps below define the way cost is estimated at the cluster-end_use

---

[9] The details and assumptions are provided in later chapters of this Appendix C, categorized by customer end use and sector.

[10] The propensity score (Pscore) is discussed in detail in Appendix E.

level.

C-4.1. Cost Model Step 1: Estimate unit cost by category

Each of these is estimated in terms of "$/kW-year" based on the expected RA credit, which was calculated in the *Capabilities Model for DR Technology - Quantity of RA credit* section above. Some of the factors are adjusted by a scenario-year specific cost adjustment factor ($A_{C,scen-y}$).

Initial cost:

$$c_{init} = A_{C,scen-y} * (C_{site,enab} + C_{fix,init} + M_{var}c_{var,init}) \;/\; t_{lifetime} \;/\; RA_{site}$$

Financing cost:

$$c_{finance} = (1 - F_{t,r}) * C_{init}$$

Operating cost:

$$c_{opco} = A_{C,scen-y} * (C_{fix,opco} + M_{var}c_{var,opco}) \;/\; RA_{site}$$

Administrative cost:

$$c_{admin} = A_{C,scen-y} * C_{admin} \;/\; RA_{site}$$

Marketing cost (note adjustment for expected propensity to adopt DR):

$$c_{market} = A_{C,scen-y} * C_{market} \;/\; RA_{site} \;/\; P_{cluster}$$

Incentive cost:

$$c_{incentive} = C_{incentive} \;/\; RA_{site}$$

Buy-down value (results in a negative number):

$$c_{buydown} = -((C_{fix,coben} + M_{var}c_{var,coben}) \;/\; t_{lifetime} + C_{coben,other}) \;/\; RA_{site}$$

C-4.2. Cost Model Step 2: Aggregate to expected unit cost total

This is an estimate of the effective levelized unit cost of DR at the site, in $/kW-year.

$$c_{cluster} = (1 - A_{ndr,Y}) * (c_{init} + c_{finance}) + c_{opco} + c_{admin} + c_{market} + c_{incentive} + c_{buydown}$$

The total cost of DR for the cluster can be estimated by multiplying the unit cost by the expected quantity of RA, etc.

Table C-7: Cost variables from input and calculated as intermediate values in the model and their mathematical symbols for use in equations above and below.

Input File Field or Model Variable	**Symbol in equations below**	**Example / Notes**
`cost_unit_fix`	--	This defines the units for M_{fix}
`unit_fix_prem`	M_{fix}	Magnitude of fixed portion (e.g., 1 premise)
`cost_unit_var`	--	This defines the units for M_{var} (e.g. kW-peak or kWh-battery)
`mag_var_prem` *(calculated)*	M_{var}	Magnitude of variable cost portion, not defined in input file but dynamically calculated for each cluster at the site level. (e.g., 100 kW under control)
`cost_site_enab`	C_{enab}	Site-level commissioning and control costs, e.g., $1,000 / site
`cost_fix_init`	$C_{fix,init}$	Hardware, installation and software cost per premise e.g., $10,000 / site If there is non-DR adoption at the site these costs are zeroed out.
`cost_var_init`	$C_{var,init}$	Hardware, installation and software cost per variable unit, e.g., $200 / kW under control If there is non-DR adoption at the site these costs are zeroed out.
`cost_fix_opco`	$C_{fix,opco}$	Annual operating costs per site including software licensing, testing/certification, e.g., $100 / premise-year
`cost_var_opco`	$C_{var,opco}$	Annual operating costs per variable unit including software licensing, testing/certification per variable unit, e.g., $2 / kW under control / year

Input File Field or Model Variable	Symbol in equations below	Example / Notes
cost_fix_co_benefit	$C_{fix,coben}$	e.g., $100 / year from expectation in improved system performance.
cost_var_co_benefit	$C_{var,coben}$	e.g., $3 / kW under control / year in expected demand charge reduction from day-to-day controllability.
other co-benefits (calculated)	$C_{coben,other}$	Other co-benefit value streams (e.g., expected energy market gains).
`tech_lifetime`	$t_{lifetime}$	e.g. 15 years
`cluster_p_score` (calculated)	$P_{cluster}$	Benchmark propensity to adopt DR, adjusted based on the year and scenario.
`cost_marketing` (calculated based on cluster characteristics)	C_{market}	Cost of marketing to the cluster for the particular end-use type.
`cost_admin` (calculated based on cluster characteristics)	C_{admin}	Administrative costs are assigned per site on an annual basis
Incentive	$C_{incentive}$	Incentive level per site
`adopt_nondr_`***YYYY***	$A_{ndr,Y}$	non-DR adoption rate in year **YYYY,** estimated with straight line assumption from 2015 to 2025.
financing premium adjustment factor (calculated)	$F_{t,r}$	Financing premium for a project of lifetime t with discount rate (i.e. weighted average cost of capital) r. Equal to: $F_{t,r} = \frac{t_{lifetime}}{A_{t,r}}$ where $A_{t,r}$ is an equivalent annuity lifetime factor defined by: $A_{t,r} = \frac{1-\frac{1}{(1+r)^t}}{r}$
Resource adequacy credit	RA_{site}	Capacity credit per site that adopts (kW-year)

C-4.3. Identifying Unit Costs of Demand Response and Expected Quantity

The expected quantity of DR involves derating the magnitude of RA from enabled sites by the propensity to adopt:

$$m_{RA,expected} = P_{cluster} * m_{RA}$$

Where the propensity to adopt depends on the benchmark propensity score adjustment factor for supply DR, and is assigned based on the year and approach for each type of load modifying or supply DR.

C-5. Incentives and Propensity Scores

The cost of customer incentives for DR is not included in the Enabling Technology database framework, but are captured elsewhere in the model, under the propensity to adopt model framework. The propensity score model outputs provide lookup tables with values for adoption that vary depending on marketing and incentive levels, and influence the expected likelihood of customer adoption of each technology. The propensity score value is used in the DR-PATH cost model to predict cluster level DR technology costs, while the incentive levels are used to help determine the quantity of DR available at various levels of incentive payments.

C-6. Marketing and Administrative Costs

The marketing and administrative costs are included in the model as fixed values for each customer site.

The annual marketing costs are estimated as follows:

- $5 / site /year for residential
- $10 / site / year commercial
- $20 /site / year industrial

The initial administrative costs are defined as:

- Residential and small commercial: $50/ customer
- Large Commercial/ Industrial: $350/customer (range of $200- $400)

Recurring administrative costs are set to $10/ customer for all customers.

C-7. Co-benefits

Some DR enabling technologies may have other co-benefits for the building occupant or owner in addition to providing DR. For example, DR-enabled lighting can also be more efficient and advanced than standard lighting, and batteries can provide backup power and other revenue streams besides from DR services. For the technologies with known co-benefits that are readily quantifiable, we subtract out the co-benefits and therefore do not attribute the full DR enabling technology cost to the site. However, this is not fully captured in our model for Phase 1, and only a limited number of sites capture co-benefit streams. We assume DLC switches and manual DR do not have any co-benefits.

C-8. Dispatch costs

In addition to the cost of enabling a DR technology, for some technologies there may be a nominal cost associated with each dispatch or DR event. In the event that there are additional costs for dispatching a device or interrupting a load, those estimated costs were incorporated into the level cost calculations.

C-9. Site-level commissioning and control cost

For Phase I of the reports, the site-level commissioning and control costs **are** captured within the initial cost categories for each DR enabling technology and the field within the DR enabling technology database for this variable is zeroed out. For more advanced DR technologies with more sophisticated controls that we will study in Phase II, we will utilize this variable to account for the associated additional site-level commission and control costs.

C-10. Model "Tree" Structure

The structure of the DR-PATH model is based on estimating a wide range of possible pathways that each end-use can take for providing DR—a "tree of possible outcomes". This is illustrated below. For each scenario / year / weather case we estimate the available DR along each possible pathway.

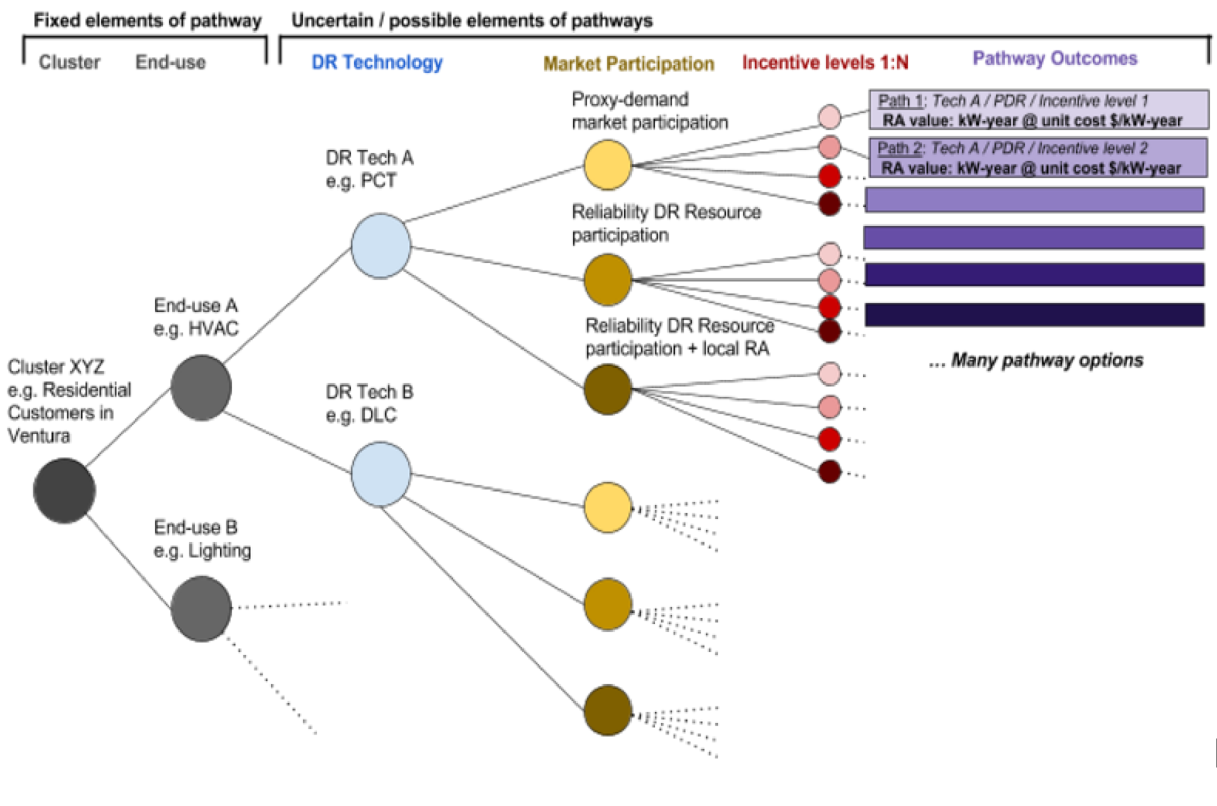


Figure C-3: DR-PATH schematic of the tree of possible pathway outcomes

C-11. Scenarios

The base case costs and performance for each technology LBNL collected for the study reflect 2016 levels. To capture expected performance improvements over time between now and the study years, we multiply the shed factors by 110% for the Business as Usual (BAU) scenario. To test for possible decreases in costs and further performance improvements, we have Medium and High scenarios with 90% and 70% of base case costs, respectively, and 120% and 140% of base case shed factors (performance), respectively. The BAU, Medium and High scenarios also adjust for non-DR related adoption of DR technologies, and the propensity scores. In the summary tables by sector in the sections below, we only show the cost and performance adjustments as those impact the DR enabling technology cost and shed factors directly.

Table C-8: Summary of parameter adjustments of each scenario in DR-PATH model.

	Scenarios			
Parameters	**Base**	**Business as Usual**	**Medium**	**High**
Cost	100%	100%	90%	70%
Performance	100%	110%	120%	140%
Non-DR adoption	100%	110%	140%	150%
Propensity Score	100%	110%	130%	150%

C-12. DR enabling technology costs and performance data

Cost and performance data on the DR enabling technologies modeled in DR-PATH for each pathway option illustrated above from come from a variety of sources, including other DR potential study reports, LBNL studies and institutional experience, academic literature, industry and stakeholder feedback, and available market data. We document the sources and specific data inputs by end-use sector below. Across data sources naming conventions differ, but we assume data quoted per customer, site and premise are comparable.

C-12.1. Data Sources:

C-12.1.1. LBNL data:

LBNL has many years of experience researching demand response technologies. For this potential study we referred to several LBNL reports focused on DR technologies in certain sectors (industrial, commercial, agricultural) for cost data as well as typical load shed capabilities. When cost or performance data was limited we also consulted with internal subject matter experts on the most appropriate values to use based on their institutional experience in the DR sector.

C-12.1.2. Industry and Market Data:

For this study, LBNL issued data requests and asked the IOUs for current and planned DR technology investments and costs for those investments, by end use and technology. The costs reported by the utilities responding to the data requests are considered in our estimates where applicable. Additionally, IOU load impact evaluations that include program and technology costs are also used to calibrate our estimates for technologies and soft costs. For certain sectors which have little publicly available cost data, such as commercial and industrial, we consulted with industry experts, including DR providers, for estimates on DR technology costs and performance. For the residential sector, we also referenced price information available for DR technologies that were available online, through retailers such as Amazon.

C-12.1.3. Navigant data:

We derive a portion of the cost data for the DR enabling technologies from a report prepared by Navigant Consulting for the Northwest Power and Conservation Council's Seventh Power Plan (Navigant Consulting, 2015). The Navigant study estimates costs for some residential, commercial, agricultural and industrial DR technologies, and provides costs for basic and AutoDR enabling devices. The study estimates "Enablement Cost" and includes technology costs, installation costs, and customer incentives as part of this measure. In our DR Potential study, we draw from Navigant's estimates of technology and installation costs, but do not include any of their incentive costs. These technology and installation costs are either provided as an aggregate $/customer value or calculated from a unit ($/kW) value times a (kW) load impact value. Whenever possible we isolate the $/kW costs as initial variable costs to avoid relying on Navigant's assumptions of load impact. The Navigant also includes an "Implementation cost" in their study to account for program administration, DR program management systems, and evaluation studies. In the LBNL DR Potential study, these costs are not considered to be part of the actual enabling technology cost, and therefore we do not include them. The tables below contain Navigant's cost estimates for DR technologies they categorize as either "Capacity DR - Base" or "Capacity DR - Smart."

Definition of Smart DR (ie PCT and AutoDR): Technologies that fall into the Smart DR category are PCTs for heating and cooling applications and automated demand response (AutoDR) measures linked with energy management control systems. PCTs are mostly used in small commercial and AutoDR in medium to large commercial buildings.

Table C-9: Navigant cost assumptions for capacity DR - Base

DR Type	**DR Component**	**DR Technology**	**Technology Cost** ($/customer)	**Installation Cost** ($/kW)
Residential DR	Space Heating - DLC	Switch	$60	$80
	Water Heating - DLC	Switch	$60	$80
	Space Cooling - CAC DLC	Switch	$60	$80
	Space Cooling - RAC DLC	Switch	$40	$80
Commercial DR	Space Cooling, Small - CAC DLC	Switch	$100	$60
	Space Cooling, Medium - CAC DLC	Switch	$100	$60
	Lighting Controls	N/A	N/A	N/A
Agricultural / Industrial DR	Irrigation Pumping - DLC	Switch	$100	$40
	Curtailable/Interruptible Tariffs	-	$ -	$ -
	Load Aggregator	N/A	N/A	N/A
	Refrigerated Warehouses	N/A	N/A	N/A

Table C-10: Navigant cost assumptions for capacity DR - Smart

DR Type	DR Component	DR Technology	Technology Cost (Note: inconsistent units)	Installation Cost (Note: inconsistent units)
Residential DR	Space Heating - DLC	PCT	$400/kW	$114.90/kW
	Water Heating - DLC	Water Heater Controls	$400/kW	$114.90/kW
	Space Cooling - CAC DLC	PCT	$400/kW	$114.90/kW
	Space Cooling - RAC DLC	PCT	$400/kW	$114.90/kW
Commercial DR	Space Cooling, Small - CAC DLC	PCT	$285.17/kW	$82.07/kW
	Space Cooling, Medium - CAC DLC	AutoDR	$138.50/kW	$96.00/kW
	Lighting Controls	AutoDR	$138.50/kW	$96.00/kW
Agricultural / Industrial DR	Irrigation Pumping - DLC	AutoDR	$138.50/kW	$96.00/kW
	Curtailable/Interruptible Tariffs	AutoDR	$2,500/customer	$1,250/customer
	Load Aggregator	AutoDR	$2,500/customer	$1,250.00/customer
	Refrigerated Warehouses	Refrigerated Warehouse Controls	$5000/customer	$2,500/customer

C-12.2. Commercial sector

Commercial customers are categorized based on size. Commercial facilities with a peak demand less than 50 kW are categorized as small. Medium commercial ranges from 50 kW to 200 kW, and peak demands greater than 200 kW are categorized as large. The categorization is consistent with the Navigant study.

Table C-11: Typical peak demand for small, medium and large commercial.

	Small Commercial	Medium Commercial	Large Commercial
Typical peak demand [kW]	<50	50 - 200	>200

We have modeled 4 local control technologies for commercial HVAC:

- Tech 1. Direct load control switches
- Tech 2. Programmable communicating thermostats
- Tech 3. Automated demand response
- Tech 4. Manual demand response

C-12.2.1. Commercial HVAC

The tables below give an overview of the key cost and performance assumptions for HVAC DR enabling technologies, for the base case, Business as Usual, Medium and High scenarios. The LBNL synthesis for the base case values are presented in greater detail in later tables.

Table C-12: Summary Table: Commercial HVAC Enabling Technology Costs - Base Case.

			Initial costs		Operating costs	
End Use	**Commercial Class/Sector**	**Enabling Technology Component**	**Equipment & Installation Costs ($/Site)**	**Variable Initial costs ($/kW)**	**Fixed Operating Costs ($/yr)**	**Variable Operating Costs ($/kW/yr)**
HVAC	Small	Direct load control switches (DLC)	$100	$60	$0	$0
		Programmable communicating thermostats (PCT)	$0	$368	$0	$0
	Medium	Direct load control switches (DLC)	$100	$60	$0	$0
		Manual demand response	$800	$20	$0	$0
		Automated demand response (ADR)	$0	$235	$0	$0
	Large	Manual demand response	$0	$0	$0	$0
		Automated demand response (ADR)	$0	$235	$0	$0

Table C-13: Summary Table: Commercial HVAC End-Use Shed Filters - Base Case.

End Use	Commercial Class/Sector	Enabling Technology Component	Peak Shed	Average 1-Hour Shed [Fraction]	Average 2-Hour Shed [Fraction]	Average 4-Hour Shed [Fraction]
HVAC	Small	Direct load control switches (DLC)	0.5	0.4	0.4	0.35
		Programmable communicating thermostats (PCT)	0.8	0.7	0.7	0.6
	Medium	Direct load control switches (DLC)	0.5	0.4	0.4	0.35
		Manual demand response	0.6	0.5	0.45	0.35
		Automated demand response (ADR)	0.8	0.7	0.7	0.6
	Large	Manual demand response	0.6	0.5	0.45	0.35
		Automated demand response (ADR)	0.8	0.7	0.7	0.6

Table C-14: Summary Table: Commercial HVAC Enabling Technology Costs - BAU Case.

End Use	Commercial Class/Sector	Enabling Technology Component	Initial costs: Equipment & Installation Costs ($/Site)	Initial costs: Variable Initial costs ($/kW)	Operating costs: Fixed Operating Costs ($/yr)	Operating costs: Variable Operating Costs ($/kW/yr)
HVAC	Small	Direct load control switches (DLC)	$100	$60	$0	$0
		Programmable communicating thermostats (PCT)	$0	$368	$0	$0
	Medium	Direct load control switches (DLC)	$100	$60	$0	$0
		Manual demand response	$800	$20	$0	$0
		Automated demand response (ADR)	$0	$235	$0	$0
	Large	Manual demand response	$0	$0	$0	$0
		Automated demand response (ADR)	$0	$235	$0	$0

Table C-15: Summary Table: Commercial HVAC End-Use Shed Filters - BAU Case.

End Use	Commercial Class/Sector	Enabling Technology Component	Peak Shed	Average 1-Hour Shed [Fraction]	Average 2-Hour Shed [Fraction]	Average 4-Hour Shed [Fraction]
HVAC	Small	Direct load control switches (DLC)	0.55	0.44	0.44	0.39
		Programmable communicating thermostats (PCT)	0.88	0.77	0.77	0.66
	Medium	Direct load control switches (DLC)	0.55	0.44	0.44	0.39
		Manual demand response	0.66	0.55	0.50	0.39
		Automated demand response (ADR)	0.88	0.77	0.77	0.66
	Large	Manual demand response	0.66	0.55	0.50	0.39
		Automated demand response (ADR)	0.88	0.77	0.77	0.66

Table C-16: Summary Table: Commercial HVAC Enabling Technology Costs - Medium Case.

			Initial costs		Operating costs	
End Use	**Commercial Class/Sector**	**Enabling Technology Component**	**Equipment & Installation Costs ($/Site)**	**Variable Initial costs ($/kW)**	**Fixed Operating Costs ($/yr)**	**Variable Operating Costs ($/kW/yr)**
HVAC	Small	Direct load control switches (DLC)	$90	$54	$0	$0
		Programmable communicating thermostats (PCT)	$0	$331	$0	$0
	Medium	Direct load control switches (DLC)	$90	$54	$0	$0
		Manual demand response	$720	$18	$0	$0
		Automated demand response (ADR)	$0	$211	$0	$0
	Large	Manual demand response	$0	$0	$0	$0
		Automated demand response (ADR)	$0	$211	$0	$0

Table C-17: Summary Table: Commercial HVAC End-Use Shed Filters - Medium Case.

End Use	Commercial Class/Sector	Enabling Technology Component	Peak Shed	Average 1-Hour Shed [Fraction]	Average 2-Hour Shed [Fraction]	Average 4-Hour Shed [Fraction]
HVAC	Small	Direct load control switches (DLC)	0.60	0.48	0.48	0.42
		Programmable communicating thermostats (PCT)	0.96	0.84	0.84	0.72
	Medium	Direct load control switches (DLC)	0.60	0.48	0.48	0.42
		Manual demand response	0.72	0.60	0.54	0.42
		Automated demand response (ADR)	0.96	0.84	0.84	0.72
	Large	Manual demand response	0.72	0.60	0.54	0.42
		Automated demand response (ADR)	0.96	0.84	0.84	0.72

Table C-18: Summary Table: Commercial HVAC Enabling Technology Costs – High Case.

			Initial costs		Operating costs	
End Use	Commercial Class/Sector	Enabling Technology Component	Equipment & Installation Costs ($/Site)	Variable Initial costs ($/kW)	Fixed Operating Costs ($/yr)	Variable Operating Costs ($/kW/yr)
HVAC	Small	Direct load control switches (DLC)	$70	$42	$0	$0
		Programmable communicating thermostats (PCT)	$0	$257	$0	$0
	Medium	Direct load control switches (DLC)	$70	$42	$0	$0
		Manual demand response	$560	$14	$0	$0
		Automated demand response (ADR)	$0	$164	$0	$0
	Large	Manual demand response	$0	$0	$0	$0
		Automated demand response (ADR)	$0	$164	$0	$0

Table C-19: Summary Table: Commercial HVAC End-Use Shed Filters - High Case.

End Use	Commercial Class/Sector	Enabling Technology Component	Peak Shed	Average 1-Hour Shed [Fraction]	Average 2-Hour Shed [Fraction]	Average 4-Hour Shed [Fraction]
HVAC	Small	Direct load control switches (DLC)	0.70	0.56	0.56	0.49
		Programmable communicating thermostats (PCT)	1.12	0.98	0.98	0.84
	Medium	Direct load control switches (DLC)	0.70	0.56	0.56	0.49
		Manual demand response	0.84	0.70	0.63	0.49
		Automated demand response (ADR)	1.12	0.98	0.98	0.84
	Large	Manual demand response	0.84	0.70	0.63	0.49
		Automated demand response (ADR)	1.12	0.98	0.98	0.84

C-12.2.2. HVAC: Direct load control switches (DLC)

In the commercial sector, traditional switch-based Direct Load Control (DLC) technology is the most common. With this technology, customers respond to peak-shaving DR events using basic methods to reduce their loads (e.g., simple switches and manual approaches such as turning off lights and raising/lowering thermostats)

DLC switches are typically installed on the central air conditioner (or heat pump), which cycles the units on and off during a DR event. This technology is most commonly applied in small to medium commercial buildings, and less so in large commercial buildings.

According to Navigant, a commercial DLC switch costs $100, based on an analysis conducted for Tucson Electric Power's mass market DLC program (Navigant Consulting, 2015). The cost does not include costs associated with installation and integration. The variable cost for Commercial DLC switches is $60/kW. In estimating this cost, Navigant assumes a downward trend in installation costs from the residential sector, based on a larger load offset (Navigant Consulting, 2015).

Table C-20: HVAC cost and performance assumptions: Direct load control switches (DLC), small and medium commercial, 50% control

Input field	LBNL Synthesis Value Small commercial		Other Estimates/ Bounds on Assumption		Notes
Building size	Small	Medium	Small	Medium	
Cost Assumptions					
`cost_unit_var`	kW-peak	kW-peak			
`cost_site_enab`	$0	$0			Default assumption
`cost_fix_init`	$100	$100	Navigant Technology cost: $100/customer	Navigant Technology cost: $100/customer	Navigant assumptions (from Excel spreadsheet and the Key Assumptions tab)
`cost_var_init`	$60/kW	$60/kW	Navigant Installation cost: $60/kW Navigant assumes a 2.8 kW/customer for small commercial, which would come to $168/customer	Navigant Installation cost: $60/kW Navigant assumes a 15kW/customer for small commercial, which would come to $900/customer	
`cost_fix_opco`	0	0			Default Assumption
`cost_var_opco`	0	0	Navigant Implementation cost:$10/kW/yr	Navigant Implementation cost:$10/kW/yr	The Navigant implementation cost is not used in our study since it is not considered an enablement cost

cost_fix_ … co_benefit	0	0			Default Assumption
cost_var_ … co_benefit	0	0			Default Assumption
cost_margin_ … dispatch_day	$0.5/day	$0.5/day			LBNL estimate
tech_lifetime	15 years	15 years			LBNL estimate
Performance Assumptions					
T_delay_local (seconds)	1	1			LBNL estimate
T_ramp (seconds)	10	10			LBNL estimate
t_resolution_ … local_control (seconds)	3600	3600			LBNL estimate
Shed_peak (Fraction of end use sheddability)	0.5	0.5			LBNL estimate
Shed_1_hour (Fraction of end use sheddability)	0.4	0.4			LBNL estimate
Shed_2_hour (Fraction of end use sheddability)	0.4	0.4			LBNL estimate
Shed_4_hour (Fraction of end use	0.35	0.35			LBNL estimate

sheddability)					

C-12.2.3. HVAC: Programmable communicating thermostats

PCT for cooling (50%): According to Navigant a Commercial PCT costs $285.71/kW, based on their analysis conducted for a BPA smart grid investment case in 2014. The Installation Cost for Commercial PCT is $82.07/kW (Navigant Consulting, 2015). We use the sum of these two $/kW costs as the variable initial cost of the technology.

Table C-21: HVAC cost and performance assumptions: Programmable communicating thermostats (PCT), small commercial, 50% control

Input field	LBNL Synthesis Value	Other Estimates/ Bounds on Assumption	Notes
Cost Assumptions			
cost_unit_var	kW-peak		
cost_site_enab	0		Default assumption
cost_fix_init	0		Default assumption
cost_var_init	$367.78/kW	From Navigant: $285.71/kW (Technology cost) + $82.07/kW (Installation cost)= $367.78/kW On a $/customer value from Navigant: Technology cost: $798.48/customer Installation cost: $229.8/customer	We use the $/kW value from Navigant instead of $/customer
cost_fix_opco	0		Default assumption
cost_var_opco	0	Navigant Implementation cost: $20/kW/yr	The Navigant implementation cost is not used in our study since it is not considered an enablement cost
cost_fix_ …	0		Default assumption

co_benefit			
cost_var_ … co_benefit	0		Default assumption
cost_margin_ … dispatch_day	0		LBNL estimate
tech_lifetime	12 years		LBNL estimate
Performance Assumptions			
T_delay_local (seconds)	1		LBNL estimate
T_ramp (seconds)	10		LBNL estimate
t_resolution_ … local_control (seconds)	15		LBNL estimate
Shed_peak (Fraction of end use sheddability)	0.8		LBNL estimate
Shed_1_hour (Fraction of end use sheddability)	0.7		LBNL estimate
Shed_2_hour (Fraction of end use sheddability)	0.7		LBNL estimate
Shed_4_hour (Fraction of end use sheddability)	0.6		LBNL estimate

C-12.2.4. HVAC: Automated demand response

According to Piette et al., the median cost for 56 installed automated DR systems is about $200/kW. The difference between minimum and maximum cost is more that a factor of ten, based on the wide range of "system age, size of load reduction, sophistication, and type of equipment included in cost analysis." However, "the cost to automate DR in new buildings that comply with the 2013 building code are expected to be less than the costs of retrofitting an existing building's DR system to automate it" (Piette et al.,2015).

According to Navigant Auto DR + Energy Management System costs $138.50/kW * the load impact, based on its analysis conducted for a BPA smart grid investment case in 2014 (Navigant Consulting, 2015).

Table C-22: HVAC cost and performance assumptions: Automated demand response, medium and large commercial

Input field	LBNL Synthesis Value	Other Estimates/ Bounds on Assumption	Notes
Cost Assumptions			
`cost_unit_var`	kW-peak		
`cost_site_enab`	0		Default assumption
`cost_fix_init`	0		Default assumption
`cost_var_init`	$234.5/kW	Navigant: $138.5/kW (Technology cost) + $96/kW (Installation cost) 138.5 = $234.5/kW On a $/customer value from Navigant: Technology cost: $2077.5/kW Installation cost: $1440.00/customer	The initial variable cost is now based on Navigant's assumptions. An alternative is to use $200/kW, based on typical commercial DR from Piette et al. (2015)
`cost_fix_opco`	0		Default assumption
`cost_var_opco`	0	$20/kW/yr	The Navigant implementation cost is not used in our study since it is not considered a enablement cost
`cost_fix_ …`	0		Default assumption

co_benefit			
cost_var_ … co_benefit	0		Default assumption
cost_margin_ … dispatch_day	$2/day		LBNL estimate
tech_lifetime	12 years		LBNL estimate
Performance Assumptions			
T_delay_local (seconds)	1		LBNL estimate
T_ramp (seconds)	120		LBNL estimate
t_resolution_ … local_control (seconds)	15		LBNL estimate
Shed_peak (Fraction of end use sheddability)	0.8		LBNL estimate
Shed_1_hour (Fraction of end use sheddability)	0.7		LBNL estimate
Shed_2_hour (Fraction of end use sheddability)	0.7		LBNL estimate
Shed_4_hour (Fraction of end use sheddability)	0.6		LBNL estimate

C-12.2.5. HVAC: Manual demand response

The cost assumption for manual DR is based on a Google search. Below is an example of a thermostat from Ecobee, at a cost of $383. The Ecobee and similar products can be used for manual DR. The LBNL synthesis estimates a technology cost of $400 and an additional installation cost of $400 for manual DR.

Table C-23: HVAC cost and performance assumptions: Manual DR with EMS, medium and large commercial

Input field	LBNL Synthesis Value		Other Estimates/ Bounds on Assumption	Notes
Building size	Large	Medium	Medium and large	
Cost Assumptions				
cost_unit_var	kW-peak	kW-peak		
cost_site_enab	$0	$0		Default assumption
cost_fix_init	$0	$800	Ecobee: $800	Ecobee, hardware $400 and installation $400
cost_var_init	0	$20/kW		LBNL estimate
cost_fix_opco	0	0		Default assumption

cost_var_opco	0	0		Default assumption
cost_fix_ … co_benefit	0	0		Default assumption
cost_var_ … co_benefit	0	0		Default assumption
cost_margin_ … dispatch_day	0	$2/day		LBNL estimate
tech_lifetime	5 years	15 years		LBNL estimate
Performance Assumptions				
T_delay_local (seconds)	86400	3600		LBNL estimate
T_ramp (seconds)	300	300		LBNL estimate
t_resolution_ … local_control (seconds)	3600	1800		LBNL estimate
Shed_peak (Fraction of end use sheddability)	0.5	0.6		LBNL estimate
Shed_1_hour (Fraction of end use sheddability)	0.4	0.5		LBNL estimate
Shed_2_hour (Fraction of end use	0.4	0.45		LBNL estimate

sheddability)				
Shed_4_hour (Fraction of end use sheddability)	0.3	0.35		LBNL estimate

C-12.2.6. Commercial lighting

Information regarding DR-enabling technologies represented by advanced lighting control systems for commercial (office and retail) buildings, is drawn from multiple sources to extract appropriate data for system functionality, DR savings potential (maximum, expected and value based on costs), and system costs. A key challenge with DR-enabling advanced lighting control systems is that they are seldom installed solely for the DR benefit. In fact, the key market instigator is frequently for non-energy benefits, or at a minimum, for their energy-efficiency (EE) benefits. Therefore, the enabling cost and generated benefits is not solely born by the system cost and DR value. If this were the case, the assigned enabling costs would quickly rise to over $20,000/kW. At that value, we would never see the technology deployed, but in fact, we see the acceleration of advanced lighting control system installations.

Ultimately, to approach this issue rationally, we need to strip off or 'temper' the DR-enabling costs and DR values from the EE system costs and values. Our model does that as represented in the table below, which lists for small, medium and large, commercial office and retail electrical loads, three DR-enabling technology cases; 1) highly granular control including digitally addressable, individual luminaires (fixtures); 2) zonally controlled luminaires; and 3) existing standard practice lighting system consistent with meeting CA Title 24 Energy Code baseline.

The summary tables below show the cost and shed factors for the lighting technologies for the base, BAU, Medium and High scenarios.

Table C-24 Summary Table: Commercial lighting Enabling Technology Costs - Base Case.

			Initial costs		Operating costs	
End Use	**Commercial Class/Sector**	**Enabling Technology Component**	**Equipment & Installation Costs ($/Site)**	**Variable Initial costs ($/kW)**	**Fixed Operating Costs ($/yr)**	**Variable Operating Costs ($/kW/yr)**
Lighting	Small	Office Luminaire	$0	$337	$0	$0
		Office Zonal	$0	$250	$0	$0
		Office Std.	$0	$438	$0	$0
		Retail Luminaire	$0	$316	$0	$0
		Retail Zonal	$0	$235	$0	$0
		Retail Std.	$0	$410	$0	$0
	Medium	Office Luminaire	$0	$953	$0	$0
		Office Zonal	$0	$708	$0	$0
		Office Std.	$0	$1,239	$0	$0
		Retail Luminaire	$0	$311	$0	$0
		Retail Zonal	$0	$232	$0	$0
		Retail Std.	$0	$405	$0	$0
	Large	Office Luminaire	$0	$531	$0	$0
		Office Zonal	$0	$394	$0	$0
		Office Std.	$0	$690	$0	$0
		Retail Luminaire	$0	$416	$0	$0
		Retail Zonal	$0	$309	$0	$0
		Retail Std.	$0	$541	$0	$0

Table C-25 Summary Table: Commercial lighting End-Use Shed Filters - Base Case.

End Use	Commercial Class/Sector	Enabling Technology Component	Peak Shed	Average 1-Hour Shed [Fraction]	Average 2-Hour Shed [Fraction]	Average 4-Hour Shed [Fraction]
Lighting	Small	Office Luminaire	0.35	0.35	0.35	0.35
		Office Zonal	0.3	0.3	0.3	0.3
		Office Std.	0.2	0.2	0.2	0.2
		Retail Luminaire	0.35	0.35	0.35	0.35
		Retail Zonal	0.3	0.3	0.3	0.3
		Retail Std.	0.2	0.2	0.2	0.2
	Medium	Office Luminaire	0.65	0.65	0.65	0.65
		Office Zonal	0.35	0.35	0.35	0.35
		Office Std.	0.25	0.25	0.25	0.25
		Retail Luminaire	0.5	0.5	0.5	0.5
		Retail Zonal	0.3	0.3	0.3	0.3
		Retail Std.	0.2	0.2	0.2	0.2
	Large	Office Luminaire	0.65	0.65	0.65	0.65
		Office Zonal	0.35	0.35	0.35	0.35
		Office Std.	0.65	0.65	0.65	0.65
		Retail Luminaire	0.5	0.5	0.5	0.5
		Retail Zonal	0.3	0.3	0.3	0.3
		Retail Std.	0.2	0.2	0.2	0.2

Table C-26: Summary Table: Commercial lighting Enabling Technology Costs –BAU.

End Use	Commercial Class/Sector	Enabling Technology Component	Initial costs: Equipment & Installation Costs ($/Site)	Initial costs: Variable Initial costs ($/kW)	Operating costs: Fixed Operating Costs ($/yr)	Operating costs: Variable Operating Costs ($/kW/yr)
Lighting	Small	Office Luminaire	$0	$337	$0	$0
		Office Zonal	$0	$250	$0	$0
		Office Std.	$0	$438	$0	$0
		Retail Luminaire	$0	$316	$0	$0
		Retail Zonal	$0	$235	$0	$0
		Retail Std.	$0	$410	$0	$0
	Medium	Office Luminaire	$0	$953	$0	$0
		Office Zonal	$0	$708	$0	$0
		Office Std.	$0	$1,239	$0	$0
		Retail Luminaire	$0	$311	$0	$0
		Retail Zonal	$0	$232	$0	$0
		Retail Std.	$0	$405	$0	$0
	Large	Office Luminaire	$0	$531	$0	$0
		Office Zonal	$0	$394	$0	$0
		Office Std.	$0	$690	$0	$0
		Retail Luminaire	$0	$416	$0	$0
		Retail Zonal	$0	$309	$0	$0
		Retail Std.	$0	$541	$0	$0

Table C-27: Summary Table: Commercial lighting End-Use Shed Filters - BAU Case.

End Use	Commercial Class/Sector	Enabling Technology Component	Peak Shed	Average 1-Hour Shed [Fraction]	Average 2-Hour Shed [Fraction]	Average 4-Hour Shed [Fraction]
Lighting	Small	Office Luminaire	0.39	0.39	0.39	0.39
		Office Zonal	0.33	0.33	0.33	0.33
		Office Std.	0.22	0.22	0.22	0.22
		Retail Luminaire	0.39	0.39	0.39	0.39
		Retail Zonal	0.33	0.33	0.33	0.33
		Retail Std.	0.22	0.22	0.22	0.22
	Medium	Office Luminaire	0.72	0.72	0.72	0.72
		Office Zonal	0.39	0.39	0.39	0.39
		Office Std.	0.28	0.28	0.28	0.28
		Retail Luminaire	0.55	0.55	0.55	0.55
		Retail Zonal	0.33	0.33	0.33	0.33
		Retail Std.	0.22	0.22	0.22	0.22
	Large	Office Luminaire	0.72	0.72	0.72	0.72
		Office Zonal	0.39	0.39	0.39	0.39
		Office Std.	0.72	0.72	0.72	0.72
		Retail Luminaire	0.55	0.55	0.55	0.55
		Retail Zonal	0.33	0.33	0.33	0.33
		Retail Std.	0.22	0.22	0.22	0.22

Table C-28: Summary Table: Commercial lighting Enabling Technology Costs - Medium Case.

			Initial costs		Operating costs	
End Use	Commercial Class/Sector	Enabling Technology Component	Equipment & Installation Costs ($/Site)	Variable Initial costs ($/kW)	Fixed Operating Costs ($/yr)	Variable Operating Costs ($/kW/yr)
Lighting	Small	Office Luminaire	$0	$303	$0	$0
		Office Zonal	$0	$225	$0	$0
		Office Std.	$0	$394	$0	$0
		Retail Luminaire	$0	$284	$0	$0
		Retail Zonal	$0	$212	$0	$0
		Retail Std.	$0	$369	$0	$0
	Medium	Office Luminaire	$0	$858	$0	$0
		Office Zonal	$0	$637	$0	$0
		Office Std.	$0	$1,115	$0	$0
		Retail Luminaire	$0	$280	$0	$0
		Retail Zonal	$0	$209	$0	$0
		Retail Std.	$0	$365	$0	$0
	Large	Office Luminaire	$0	$478	$0	$0
		Office Zonal	$0	$355	$0	$0
		Office Std.	$0	$621	$0	$0
		Retail Luminaire	$0	$374	$0	$0
		Retail Zonal	$0	$278	$0	$0
		Retail Std.	$0	$487	$0	$0

Table C-29 Summary Table: Commercial lighting End-Use Shed Filters - Medium Case.

End Use	Commercial Class/Sector	Enabling Technology Component	Peak Shed	Average 1-Hour Shed [Fraction]	Average 2-Hour Shed [Fraction]	Average 4-Hour Shed [Fraction]
Lighting	Small	Office Luminaire	0.42	0.42	0.42	0.42
		Office Zonal	0.36	0.36	0.36	0.36
		Office Std.	0.24	0.24	0.24	0.24
		Retail Luminaire	0.42	0.42	0.42	0.42
		Retail Zonal	0.36	0.36	0.36	0.36
		Retail Std.	0.24	0.24	0.24	0.24
	Medium	Office Luminaire	0.78	0.78	0.78	0.78
		Office Zonal	0.42	0.42	0.42	0.42
		Office Std.	0.30	0.30	0.30	0.30
		Retail Luminaire	0.60	0.60	0.60	0.60
		Retail Zonal	0.36	0.36	0.36	0.36
		Retail Std.	0.24	0.24	0.24	0.24
	Large	Office Luminaire	0.78	0.78	0.78	0.78
		Office Zonal	0.42	0.42	0.42	0.42
		Office Std.	0.78	0.78	0.78	0.78
		Retail Luminaire	0.60	0.60	0.60	0.60
		Retail Zonal	0.36	0.36	0.36	0.36
		Retail Std.	0.24	0.24	0.24	0.24

Table C-30 Summary Table: Commercial lighting Enabling Technology Costs - High Case.

End Use	Commercial Class/Sector	Enabling Technology Component	Initial costs: Equipment & Installation Costs ($/Site)	Initial costs: Variable Initial costs ($/kW)	Operating costs: Fixed Operating Costs ($/yr)	Operating costs: Variable Operating Costs ($/kW/yr)
Lighting	Small	Office Luminaire	$0	$236	$0	$0
		Office Zonal	$0	$175	$0	$0
		Office Std.	$0	$307	$0	$0
		Retail Luminaire	$0	$221	$0	$0
		Retail Zonal	$0	$165	$0	$0
		Retail Std.	$0	$287	$0	$0
	Medium	Office Luminaire	$0	$667	$0	$0
		Office Zonal	$0	$496	$0	$0
		Office Std.	$0	$867	$0	$0
		Retail Luminaire	$0	$218	$0	$0
		Retail Zonal	$0	$162	$0	$0
		Retail Std.	$0	$284	$0	$0
	Large	Office Luminaire	$0	$372	$0	$0
		Office Zonal	$0	$276	$0	$0
		Office Std.	$0	$483	$0	$0
		Retail Luminaire	$0	$291	$0	$0
		Retail Zonal	$0	$216	$0	$0
		Retail Std.	$0	$379	$0	$0

Table C-31 Summary Table: Commercial lighting End-Use Shed Filters - High Case.

End Use	Commercial Class/Sector	Enabling Technology Component	Peak Shed	Average 1-Hour Shed [Fraction]	Average 2-Hour Shed [Fraction]	Average 4-Hour Shed [Fraction]
Lighting	Small	Office Luminaire	0.49	0.49	0.49	0.49
		Office Zonal	0.42	0.42	0.42	0.42
		Office Std.	0.28	0.28	0.28	0.28
		Retail Luminaire	0.49	0.49	0.49	0.49
		Retail Zonal	0.42	0.42	0.42	0.42
		Retail Std.	0.28	0.28	0.28	0.28
	Medium	Office Luminaire	0.91	0.91	0.91	0.91
		Office Zonal	0.49	0.49	0.49	0.49
		Office Std.	0.35	0.35	0.35	0.35
		Retail Luminaire	0.70	0.70	0.70	0.70
		Retail Zonal	0.42	0.42	0.42	0.42
		Retail Std.	0.28	0.28	0.28	0.28
	Large	Office Luminaire	0.91	0.91	0.91	0.91
		Office Zonal	0.49	0.49	0.49	0.49
		Office Std.	0.91	0.91	0.91	0.91
		Retail Luminaire	0.70	0.70	0.70	0.70
		Retail Zonal	0.42	0.42	0.42	0.42
		Retail Std.	0.28	0.28	0.28	0.28

We base our cost assumptions for ‘activating’ advanced lighting controls in commercial buildings to enable DR on a ‘frozen efficiency’ regime to be consistent with the other technology analyses.

By way of reference, Navigant Consulting also estimated DR enabling costs for lighting applications. Based on their analyses conducted on a BPA smart grid investment case, the costs of Auto DR + Lighting Control System = $138.50/kW * load impact (Navigant Consulting, 2015).

Commercial lighting is undergoing broad shifts in technology as LED light sources have improved in performance and had radical reductions in cost.

The approach for modeling DR includes some key steps:

- Estimate for each cluster what the baseline lighting system efficiency is (CEUS + sector characteristics). Above a particular efficacy (high efficiency) the lighting is controllable.
- For each pathway, estimate the new lighting system efficacy for a controllable lighting system, and find an adjusted baseline.
- For each pathway, estimate the DR potential working from the base.

The cost of installations of controls range between \$0.10/sq.ft. - \$0.38/sq.ft. A cost value of \$0.24/sq.ft. is chosen. The cost for sensors, switches etc is assumed to be \$0,52/sq.ft. The resulting total variable initial cost is therefore \$0,76/sq.ft. The fixed initial cost is assumed to be \$0,0/sq.ft. since lighting is highly dependent on sq.ft. and because available cost data is expressed in terms of sq.ft.

Cost justification:

The cost analysis is based on the 2011 California Building Energy Efficiency Standards, Measure Information Template (*2011 California Building Energy Efficiency Standards, Measure Information Template – Demand Responsive Lighting Controls*).

These include a digitally addressable lighting system, and a zone-based digital lighting system. The addressable lighting system is similar in design to that of a centralized control panel, but with additional control granularity with each fixture can be addressed individually, whereas, in the zonal control, a centralized control panel is limited to an entire channel, or circuit, being controlled in unison. The enabling DR on a system with a centralized control panel is more of a fixed cost than the zone based system. Existing requirements in Title 24, including Section 131(d) automatic shutoff control, are assumed to require a centralized network connection to a timeclock or a control panel with built in time-clock functionality. There are some exceptions to this assumption, for example in scenarios when each space is connected to occupancy sensors, which meets the requirements for automatic shutoff control without the need for a time-clock. In those scenarios, the assumptions for the zone based lighting system will apply, utilizing network adapters to enable each room to be monitored and controlled for demand response.

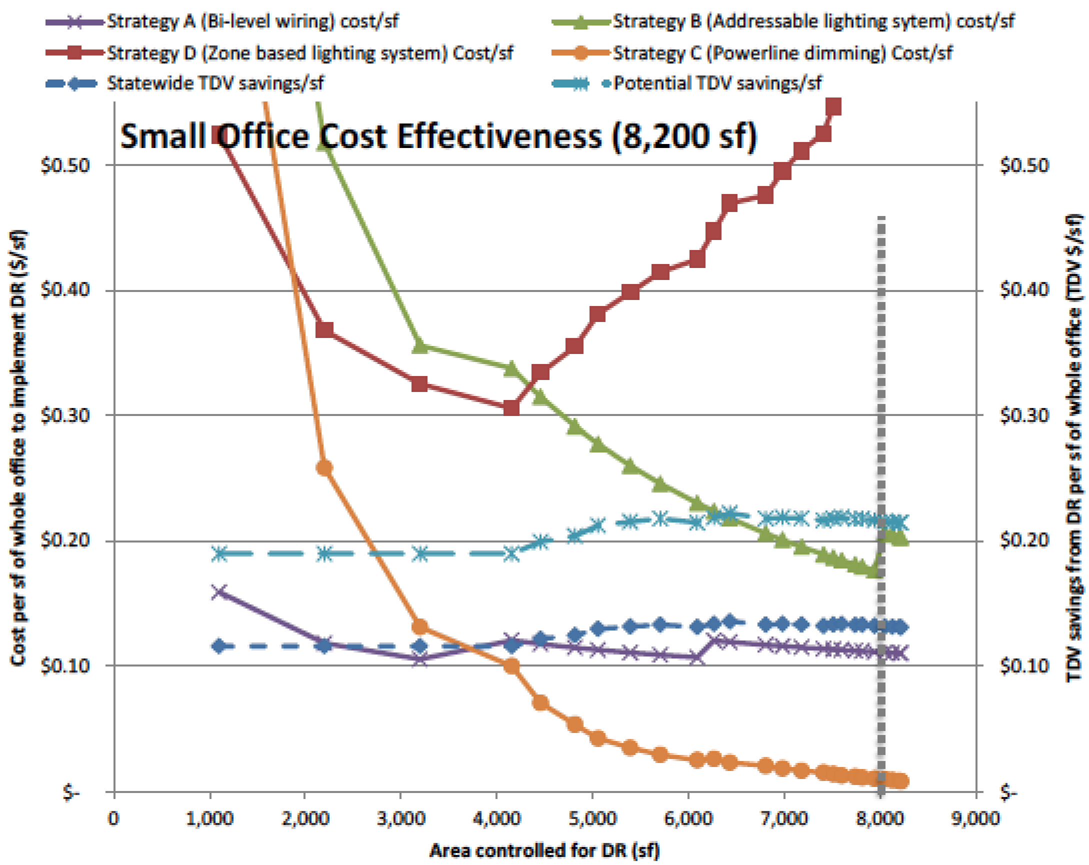


Figure C-4: Cost effectiveness of DR in small office prototype.

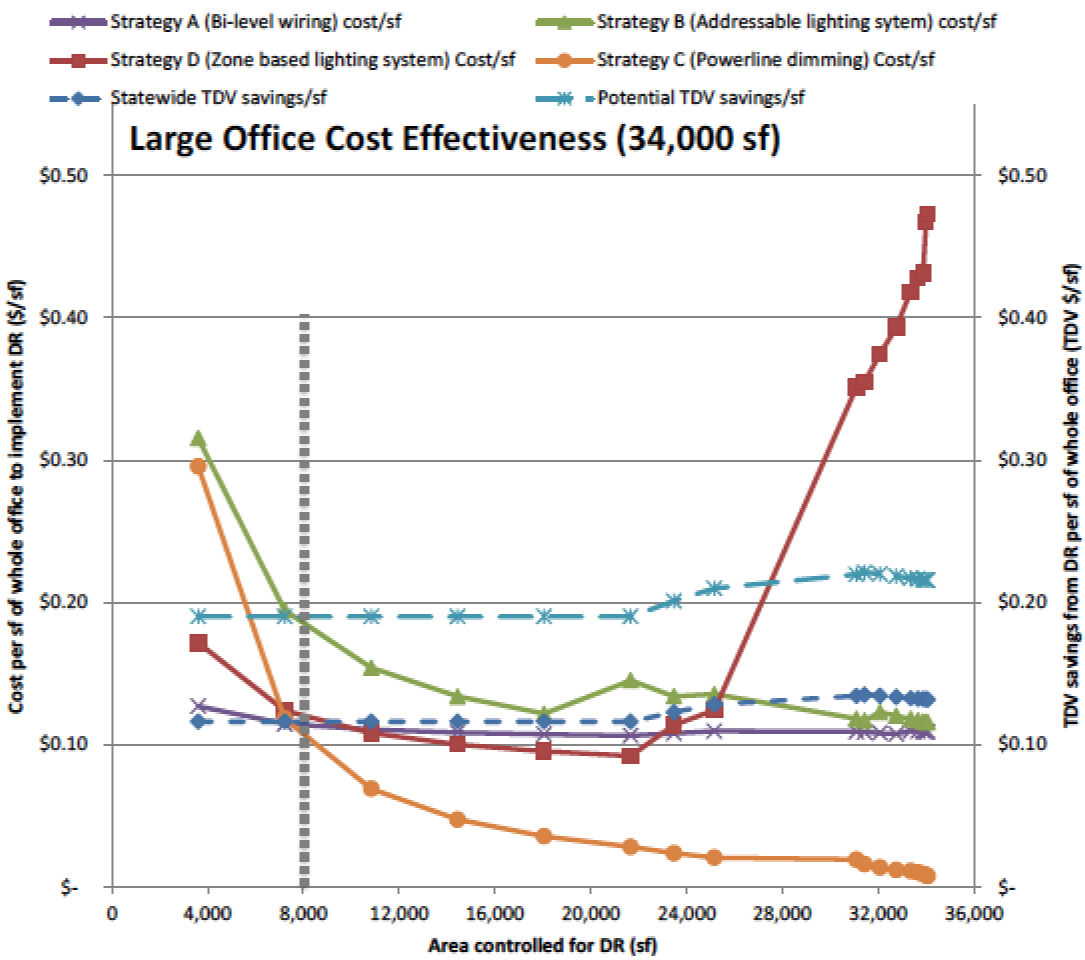


Figure C-5: Cost effectiveness of DR in large office prototype.

Figure C-4 and Figure C-5 depict enabling-DR technology cost-effectiveness for small and large office prototypes respectively. The blue dashed lines indicate the DR responsive lighting controls' savings per SF of DR-controlled area within a building. The light blue dashed lines displays the energy savings ($ dollar value) assuming a 20% load shed (Watts) for the controlled area shed 87 hours per year over a 15-year life cycle. This value is the weighted average TDV value for the top 1% hours, approximately $16/kWh. The lower, darker blue line reflects the adjusted load shed potential based upon a 70% enrollment rate; 97% signal reception; and 90% participation rate.

Average building sizes were chosen to represent the cost and value for small and large offices as exhibited in the spreadsheet excerpts below. The goal in the exercise below is to derive the average cost per kW ($/kW) in Columns 25, 26 and 27 for DR lighting load shed. You'll notice that in Columns 18, 19 and 20, the 'bare' costs per kW ($/kW) for enabling DR lighting is exorbitant and reflects the full technology cost burden independent of the EE value generated by installing the varying lighting controls systems. This why we used the 2013 CASE report (*2011 California Building Energy Efficiency Standards, Measure Information Template – Demand Responsive Lighting Controls*) because it delineates the lighting controls systems' installed cost relative to the DR enablement only.

Calculation:

- Average Premise Size (ft^2) x Scenario Average Cost per square foot($\$/ft^2$) = Average Cost per Premise ($)
- Then this value is normalized for the Average Load Shed per Site (kW/Site) =
- The Average Load Shed per Site was derived from CEUS: Interior Lighting Non-coincident Peak Load (Watts/ft^2) data (highlighted in YELLOW below) for each occupancy type and size, Average Premise Size (ft^2) x the Percent (%) Load Shed for the three DR-enabling technology cases:
    1. Highly granular control including digitally addressable, individual luminaires (fixtures) - 20%
    2. Zonally controlled luminaires - 35%
    3. Existing standard practice lighting system consistent with meeting CA Title 24 Energy Code baseline - 65%
- The DR-enabling technology Cost per Square Foot ($\$/ft^2$) is divided by the Average Load Shed per Square Foot (kW/ft^2) to determine the DR-enabling technology Cost per kW of load shed per technology case ($/kW)

Table C-32: CEUS Data and Lighting Calculation and Analysis Table A

Occupancy Type	Premises	Est. Average Annual Electricity Consumption (kWh/yr)	Ave. Premise Size (ft^2)	Total Electric Energy Intensity (kWh/ft^2-yr)	Low (BAU) Scenario-Ave. Cost/SF ($\$/ft^2$)	Medium Scenario-Ave. Cost/SF ($\$/ft^2$)	High Scenario-Ave. Cost/SF ($\$/ft^2$)	BAU Ave. Cost/Premises ($)	Medium Scenario Ave. Cost/Premises ($)	High Scenario Ave. Cost/Premises ($)
1	2	3	4	5	6	7	8	9	10	11
		Est.	=3/5	CEUS Database	Est.	Est.	Est.	=4x6	=4x7	=4x8
Large Office	Large	10,000,000	564,972	17.70	$ 1.00	$ 3.50	$ 6.00	$ 564,972	$ 1,977,401	$3,389,831
	Medium	3,500,000	217,662	16.08	$ 1.00	$ 3.50	$ 6.00	$ 217,662	$ 761,816	$1,305,970
	Small	1,500,000	114,504	13.10	$ 1.00	$ 3.50	$ 6.00	$ 114,504	$ 400,763	$ 687,023
Small Office	Large	1,000,000	56,497	17.70	$ 1.50	$ 4.50	$ 6.00	$ 84,746	$ 254,237	$ 338,983
	Medium	75,000	4,664	16.08	$ 1.50	$ 4.50	$ 7.50	$ 6,996	$ 20,989	$ 34,981
	Small	15,000	1,145	13.10	$ 2.00	$ 5.00	$ 10.00	$ 2,290	$ 5,725	$ 11,450
Retail	Large	1,500,000	106,686	14.06	$ 1.00	$ 3.50	$ 6.00	$ 106,686	$ 373,400	$ 640,114
	Medium	650,000	46,230	14.06	$ 1.00	$ 3.50	$ 6.00	$ 46,230	$ 161,807	$ 277,383
	Small	75,000	5,334	14.06	$ 2.00	$ 4.50	$ 7.50	$ 10,669	$ 24,004	$ 40,007

Table C-33: CEUS Data and Lighting Calculation and Analysis Table B

Occupancy Type	Premises	Lighting Electric Demand Intensity (W/ft^2)	Code Standard Ave. Load Shed (kW/Site)	Zone Level Ave. Load Shed (kW/Site)	Luminaire Level Ave.Load Shed (kW/Site)	Lighting Electric Demand/ Site (kW/Site)	Luminaire Level (New LED Lighting System Baseline) Lighting Electric Demand Intensity (W/ft^2)	Std. Ave. Cost/kW ($/kW)	Zone Level Ave. Cost/kW ($/kW)	Luminaire Level Ave. Cost/kW ($/kW)
Percent Load Shed			20%	35%	65%					
1	2	12	13	14	15	16	17	18	19	20
		CEUS: Interior Lighting Non-coincident Peak Load (Watts/ft^2)	=12x4x20% /1000	=12x4x35% /1000	=12x4x65% /1000	=4x12/1000	=12x0.40	=9/13	=10/14	=11/15
Large Office	Large	0.87	98.2	171.9	127.7	491.1	0.35	$ 5,752	$ 11,505	$ 26,550
	Medium	0.87	37.9	66.3	49.2	189.4	0.35	$ 5,747	$ 11,494	$ 26,525
	Small	0.87	19.9	34.9	25.9	99.6	0.35	$ 5,747	$ 11,494	$ 26,525
Small Office	Large	1.09	12.3	21.6	16.0	61.6	0.44	$ 6,881	$ 11,796	$ 21,171
	Medium	1.09	1.0	1.8	1.3	5.1	0.44	$ 6,881	$ 11,796	$ 26,464
	Small	1.37	0.3	0.5	0.4	1.6	0.55	$ 7,299	$ 10,428	$ 28,074
Retail	Large	1.11	23.7	41.4	30.8	118.4	0.44	$ 4,505	$ 9,009	$ 20,790
	Medium	1.11	10.3	18.0	13.3	51.3	0.44	$ 4,505	$ 9,009	$ 20,790
	Small	1.34	1.4	2.5	1.9	7.1	0.54	$ 7,463	$ 9,595	$ 21,527

Table C-34: CEUS Data and Lighting Calculation and Analysis Table C

Occupancy Type	Premises	Cost ($/SF)	Code Standard Ave. Load Shed per SF (kW/ft^2)	Zone Level Ave. Load Shed per SF (kW/ft^2)	Luminaire Level Ave. Load Shed per SF (kW/ft^2)	Std. Ave. Cost/kW ($/kW)	Zone Level Ave. Cost/kW ($/kW)	Luminair e Level Ave. Cost/kW ($/kW)
1	2	21	22	23	24	25	26	27
			=13/4	=14/4	=15/4	=21/22	=21/23	=21/24
Large Office	Large	0.12	0.000174	0.000304	0.000226	$ 690	$ 394	$ 531
	Medium	0.09	0.000174	0.000305	0.000226	$ 517	$ 296	$ 398
	Small	0.11	0.000174	0.000305	0.000226	$ 632	$ 361	$ 486
Small Office	Large	0.27	0.000218	0.000382	0.000283	$ 1,239	$ 708	$ 953
	Medium	0.35	0.000218	0.000382	0.000283	$ 1,606	$ 917	$ 1,235
	Small	0.12	0.000274	0.000480	0.000356	$ 438	$ 250	$ 337
Retail	Large	0.12	0.000222	0.000389	0.000289	$ 541	$ 309	$ 416
	Medium	0.09	0.000222	0.000389	0.000289	$ 405	$ 232	$ 312
	Small	0.11	0.000268	0.000469	0.000348	$ 410	$ 235	$ 316

Table C-35: CEUS data: Annual Electric Summary Statistics

Annual Electric Summary Statistics
CA_LOFF - Large Office (>=50k ft2)

End Use	EUFS End-use Floor Stock (kSqFt)	EUI Energy-use Indices (kWh/EUFS/Year) (a)	End-use Floor Stock Distribution (%) (b)	EI Energy Intensity (kWh/Segment FS/Year) (a*b)	End-use Energy Distribution (%)	Non-coincident Peak Load (watts/SF)	Connected Load (watts/SF)	Annual Energy Usage (GWh)
Heating	509,049	0.63	77.1%	0.49	2.8%	0.18	618.46 SF/kB	322
Cooling	608,796	3.87	92.2%	3.57	20.2%	1.67	360.25 SF/ton	2,358
Ventilation	623,559	3.24	94.4%	3.06	17.3%	0.59	1.10	2,019
Water Heating	339,024	0.24	51.3%	0.12	0.7%	0.02	0.17	80
Cooking	647,306	0.12	98.0%	0.12	0.7%	0.04	0.37	77
Refrigeration	648,945	0.41	98.3%	0.41	2.3%	0.05	0.24	268
Exterior Lighting	634,106	0.51	96.0%	0.49	2.8%	0.11	0.11	324
Interior Lighting	660,429	4.46	100.0%	4.46	25.2%	0.87	0.99	2,945
Office Equipment	660,429	3.58	100.0%	3.58	20.2%	0.60	1.73	2,365
Miscellaneous	593,264	0.65	89.8%	0.58	3.3%	0.10	0.47	383
Process	11,292	1.60	1.7%	0.03	0.2%	0.00	0.01	18
Motors	591,579	0.80	89.6%	0.72	4.1%	0.18	0.80	474
Air Compressors	402,211	0.15	60.9%	0.09	0.5%	0.02	0.05	60
Segment Total	660,429	--	--	17.70	100.0%	4.09	--	11,691

Annual Electric Summary Statistics
CA_SOFF - Small Office (<50k ft2)

End Use	EUFS End-use Floor Stock (kSqFt)	EUI Energy-use Indices (kWh/EUFS/Year) (a)	End-use Floor Stock Distribution (%) (b)	EI Energy Intensity (kWh/Segment FS/Year) (a*b)	End-use Energy Distribution (%)	Non-coincident Peak Load (watts/SF)	Connected Load (watts/SF)	Annual Energy Usage (GWh)
Heating	164,537	0.44	45.5%	0.20	1.5%	0.42	159.44 SF/kB	72
Cooling	325,672	2.90	90.1%	2.61	19.9%	2.26	342.69 SF/ton	943
Ventilation	330,459	1.41	91.4%	1.29	9.8%	0.37	0.57	467
Water Heating	218,530	0.41	60.4%	0.25	1.9%	0.05	0.49	90
Cooking	336,712	0.11	93.1%	0.10	0.8%	0.04	0.69	38
Refrigeration	339,105	0.61	93.8%	0.58	4.4%	0.07	0.40	208
Exterior Lighting	266,643	1.28	73.7%	0.95	7.2%	0.23	0.26	343
Interior Lighting	361,584	3.83	100.0%	3.83	29.3%	1.09	1.39	1,386
Office Equipment	359,449	2.21	99.4%	2.19	16.7%	0.52	2.21	793
Miscellaneous	285,767	0.99	79.0%	0.78	6.0%	0.20	1.55	283
Process	1,497	0.76	0.4%	0.00	0.0%	0.00	0.00	1
Motors	79,443	0.99	22.0%	0.22	1.7%	0.05	0.23	79
Air Compressors	61,734	0.58	17.1%	0.10	0.8%	0.03	0.13	36
Segment Total	361,584	--	--	13.10	100.0%	4.51	--	4,738

Annual Electric Summary Statistics
CA_RETL - Retail

End Use	EUFS End-use Floor Stock (kSqFt)	EUI Energy-use Indices (kWh/EUFS/Year) (a)	End-use Floor Stock Distribution (%) (b)	EI Energy Intensity (kWh/Segment FS/Year) (a*b)	End-use Energy Distribution (%)	Non-coincident Peak Load (watts/SF)	Connected Load (watts/SF)	Annual Energy Usage (GWh)
Heating	154,345	0.36	22.0%	0.08	0.6%	0.11	495 SF/kB	55
Cooling	511,774	3.03	72.9%	2.21	15.7%	1.40	504.59 SF/ton	1,553
Ventilation	539,874	2.35	76.9%	1.81	12.8%	0.34	0.51	1,267
Water Heating	389,564	0.25	55.5%	0.14	1.0%	0.03	0.19	96
Cooking	613,138	0.26	87.3%	0.22	1.6%	0.05	0.32	157
Refrigeration	631,176	1.15	89.9%	1.03	7.4%	0.14	1.26	726
Exterior Lighting	579,626	1.11	82.6%	0.92	6.5%	0.25	0.28	644
Interior Lighting	702,053	6.05	100.0%	6.05	43.0%	1.11	1.34	4,246
Office Equipment	701,522	0.49	99.9%	0.49	3.5%	0.10	0.49	343
Miscellaneous	603,181	0.80	85.9%	0.69	4.9%	0.13	0.82	483
Process	11,105	3.30	1.6%	0.05	0.4%	0.01	0.03	37
Motors	282,040	0.71	40.2%	0.29	2.0%	0.06	0.28	200
Air Compressors	162,774	0.39	23.2%	0.09	0.6%	0.02	0.10	64
Segment Total	702,053	--	--	14.06	100.0%	3.37	--	9,871

Annual Electric Summary Statistics CA_GROC - Food Store								
End Use	EUFS End-use Floor Stock (kSqFt)	EUI Energy-use Indices (kWh/EUFS/Year)	End-use Floor Stock Distribution (%)	EI Energy Intensity (kWh/Segment FS/Year)	End-use Energy Distribution (%)	Non-coincident Peak Load (watts/SF)	Connected Load (watts/SF)	Annual Energy Usage (GWh)
		(a)	(b)	(a*b)				
Heating	21,419	0.55	14.9%	0.08	0.2%	0.08	512.69 SF/kB	12
Cooling	91,496	4.54	63.4%	2.88	7.0%	1.40	548.31 SF/ton	415
Ventilation	97,434	3.82	67.6%	2.58	6.3%	0.36	0.51	372
Water Heating	38,298	0.51	26.6%	0.14	0.3%	0.02	0.23	20
Cooking	122,674	2.17	85.1%	1.85	4.5%	0.33	1.13	266
Refrigeration	144,209	22.42	100.0%	22.42	54.7%	3.24	33.32	3,233
Exterior Lighting	130,007	1.05	90.2%	0.95	2.3%	0.22	0.23	137
Interior Lighting	144,209	8.55	100.0%	8.55	20.9%	1.23	1.34	1,233
Office Equipment	142,288	0.38	98.7%	0.37	0.9%	0.06	0.30	54
Miscellaneous	135,042	1.02	93.6%	0.95	2.3%	0.15	0.87	138
Process	955	1.14	0.7%	0.01	0.0%	0.00	0.00	1
Motors	49,960	0.51	34.6%	0.18	0.4%	0.03	0.12	26
Air Compressors	12,525	0.47	8.7%	0.04	0.1%	0.01	0.02	6
Segment Total	144,209	--	--	40.99	100.0%	6.75	--	5,911

C-12.2.7. Refrigerated Warehouses

Table C-36: Summary Table: Commercial Refrigerated Warehouses Enabling Technology Costs - Base Case

			Initial costs		Operating costs	
End Use	Commercial Class/ Sector	Enabling Technology Component	Equipment & Installation Costs ($/Site)	Variable Initial costs ($/kW)	Fixed Operating Costs ($/yr)	Variable Operating Costs ($/kW/yr)
Refrigerated warehouses	All Commercial	Automated demand response (ADR)	$0	$280	$20	$0

Table C-37: Summary Table: Commercial Refrigerated Warehouses Shed Filters - Base Case.

End Use	Commercial Class/Sector	Enabling Technology Component	Peak Shed	Average 1-Hour Shed [Fraction]	Average 2-Hour Shed [Fraction]	Average 4-Hour Shed [Fraction]
Refrigerated warehouses	All Commercial	Automated demand response (ADR)	0.65	0.65	0.65	0.5

Table C-38: Summary Table: Commercial Refrigerated Warehouses Enabling Technology Costs - BAU Case.

			Initial costs		Operating costs	
End Use	**Commercial Class/ Sector**	**Enabling Technology Component**	**Equipment & Installation Costs ($/Site)**	**Variable Initial costs ($/kW)**	**Fixed Operating Costs ($/yr)**	**Variable Operating Costs ($/kW/yr)**
Refrigerated warehouses	All Commercial	Automated demand response (ADR)	$0	$280	$20	$0

Table C-39: Summary Table: Commercial Refrigerated Warehouses Shed Filters - BAU Case.

End Use	Commercial Class/Sector	Enabling Technology Component	Peak Shed	Average 1-Hour Shed [Fraction]	Average 2-Hour Shed [Fraction]	Average 4-Hour Shed [Fraction]
Refrigerated warehouses	All Commercial	Automated demand response (ADR)	0.72	0.72	0.72	0.55

Table C-40: Summary Table: Commercial Refrigerated Warehouses Enabling Technology Costs - Medium Case.

			Initial costs		Operating costs	
End Use	**Commercial Class/ Sector**	**Enabling Technology Component**	**Equipment & Installation Costs ($/Site)**	**Variable Initial costs ($/kW)**	**Fixed Operating Costs ($/yr)**	**Variable Operating Costs ($/kW/yr)**
Refrigerated warehouses	All Commercial	Automated demand response (ADR)	$0	$252	$18	$0

Table C-41: Summary Table: Commercial Refrigerated Warehouses Shed Filters - Medium Case.

End Use	Commercial Class/Sector	Enabling Technology Component	Peak Shed	Average 1-Hour Shed [Fraction]	Average 2-Hour Shed [Fraction]	Average 4-Hour Shed [Fraction]
Refrigerated warehouses	All Commercial	Automated demand response (ADR)	0.78	0.78	0.78	0.60

Table C-42: Summary Table: Commercial Refrigerated Warehouses Enabling Technology Costs - High Case.

			Initial costs		Operating costs	
End Use	Commercial Class/ Sector	Enabling Technology Component	Equipment & Installation Costs ($/Site)	Variable Initial costs ($/kW)	Fixed Operating Costs ($/yr)	Variable Operating Costs ($/kW/yr)
Refrigerated warehouses	All Commercial	Automated demand response (ADR)	$0	$196	$14	$0

Table C-43: Summary Table: Commercial Refrigerated Warehouses Shed Filters - High Case.

End Use	Commercial Class/Sector	Enabling Technology Component	Peak Shed	Average 1-Hour Shed [Fraction]	Average 2-Hour Shed [Fraction]	Average 4-Hour Shed [Fraction]
Refrigerated warehouses	All Commercial	Automated demand response (ADR)	0.91	0.91	0.91	0.70

Navigant estimates the technology cost of refrigerated warehouse controls to be $5000, based on their assumption that the controls comprised half the cost of BPA's pilot hardware cost of $10000. The estimated installation costs are $7500 (Navigant Consulting, 2015).

Several sources that compiled data, including IEEE and the DOE (Lekov et al.,2009), estimated the cost to average $280/kW, and is the value used by the LBNL model. Several of the utilities, including PG&E, offer incentives up to $400/kW for ADR in various sectors, including refrigerated warehouses.

Table C-44: Refrigerated Warehouses, ADR.

Input field	LBNL Synthesis	Other Estimates/ Bounds on Assumption	Notes

	Value		
Cost Assumptions			
cost_unit_var	kW-peak		Navigant report listed all variable cost as per kW-year. We assume this is same as kW-peak
cost_site_enab	0		Default Assumption
cost_fix_init	0	$7500 estimated by Navigant report as sum of the technology cost and installation costs per customer.	Navigant report. (Sum of technology and installation costs per customer)
cost_var_init	$280/kW		DOE and IEEE report
cost_fix_opco	$20/site/year	Costs for communication ADR	IOU data request data
cost_var_opco	0		Default Assumption
cost_fix_ … co_benefit	0		Default Assumption
cost_var_ … co_benefit	0		Default Assumption
cost_margin_ … dispatch_day	$0.5/day		Estimate based on marginal dispatch cost of other ADR enabling technology
tech_lifetime	15 years		Estimate based on lifetime of other ADR enabling technology
Performance Assumptions			
T_delay_local (seconds)	0.1		LBNL Estimate

T_ramp (seconds)	120		LBNL Estimate
t_resolution_ … local_control (seconds)	15		LBNL Estimate
Shed_peak (Fraction of end use sheddability)	0.65		LBNL Estimate
Shed_1_hour (Fraction of end use sheddability)	0.65		LBNL Estimate
Shed_2_hour (Fraction of end use sheddability)	0.65		LBNL Estimate
Shed_4_hour (Fraction of end use sheddability)	0.5		LBNL Estimate

C-12.3. Residential sector

Residential sector demand response programs have historically focused on controlling residential central air conditioning units with a DLC switch and have recently begun including programmable communicating technologies such as thermostats. Over the next decade, we expect to see the number of residential end-uses available for DR enablement increase as a result of emerging technology in the residential sector. These include battery storage and battery/plug-in electric vehicles, which are entering the marketplace now, but should have a strong presence in the residential sector over the next decade.

This study focuses on five residential end uses, as outlined in the table below. For central AC, we have identified three technology pathways, including DLC, programmable communicating thermostats (PCTs), and Manual DR. For the remaining end uses, we have focused on a single technology pathway, given the current and future market conditions for technology that can impact load for DR purposes. In the following sections, we provide references on the costs and shed capabilities for residential end uses and enabling technology options used in the DR-PATH model.

Below, the tables provide an overview of the costs and shed filters that serve as inputs in the DR-PATH model. Following the tables, we take a deeper dive into the specifics with references for each end-use subsection.

Table C-45: Summary Table: Residential Enabling Technology Costs by End-Use - Base Case.

		Initial costs		Operating costs	
End Use	**Enabling Technology Component**	**Equipment and Installation Costs**	**Variable Initial costs ($/kW)**	**Fixed Operating Costs ($/yr)**	**Variable Operating Costs ($/kW/yr)**
HVAC	Direct load control switches (DLC) (100% cycle)	$160	$0	$6	$0
	Programmable communicating thermostats (PCT) (100% cycle)	$309	$0	$20	$0
	Direct load control switches (DLC) (50% cycle)	$160	$0	$6	$0
	Programmable communicating thermostats (PCT) (50% cycle)	$309	$0	$20	$0
Pool Pumps	Direct load control switches (DLC, FM telem)	$141	$0	$4	$0
	Direct load control switches (DLC, Wifi telem)	$141	$0	$4	$0
Battery Storage	Automated demand response (ADR) * Note that the fixed and variable initial cost for battery storage are expressed in a different unit, $/kWh	$550/kWh*	$324/kWh*	$34	$0
Battery Electric Vehicles	Automated demand response (Level 2 Chargers)	$3,400	$0	$20	$0
	Level 1 Chargers IoT Automated	$0	$0	$20	$0
	Level 1 Chargers, Manual	$0	$0	$20	$0
Plug in Hybrid EV	Automated demand response (Level 2 Chargers)	$3,400	$0	$20	$0
	Level 1 Chargers, IoT Automated	$0	$0	$20	$0
	Level 1 Chargers, Manual	$0	$0	$20	$0

Table C-46: Summary Table: Residential End-Use Shed Filters - Base Case.

End Use	Enabling Technology Component	Peak shed	Average 1-hour shed [Fraction]	Average 2-hour shed [Fraction]	Average 4-hour shed [Fraction]
HVAC	Direct load control switches (DLC)	0.85	0.7	0.7	0.65
	Programmable communicating thermostats (PCT)	0.85	0.85	0.75	0.65
	Direct load control switches (DLC) (50% cycle)	0.6	0.4	0.4	0.35
	Programmable communicating thermostats (PCT) (50% cycle)	0.42	0.42	0.42	0.37
Pool Pumps	Direct load control switches (DLC, FM telem)	0.79	0.7	0.7	0.7
	Direct load control switches (DLC, Wifi telem)	0.79	0.7	0.7	0.7
Battery Storage	Automated demand response (ADR)	1	1	0.5	0.25
Battery Electric Vehicles	Automated demand response (Level 2 Chargers)	0.9	0.9	0.9	0.9
	Level 1 Chargers IoT Automated	0.8	0.8	0.8	0.8
	Level 1 Chargers, Manual	0.8	0.8	0.8	0.8
Plug in Hybrid EV	Automated demand response (Level 2 Chargers)	0.86	0.86	0.86	0.86
	Level 1 Chargers, IoT Automated	0.8	0.8	0.8	0.8
	Level 1 Chargers, Manual	0.8	0.8	0.8	0.8

Table C-47: Summary Table: Residential Enabling Technology Costs by End-Use - BAU Case.

		Initial costs		Operating costs	
End Use	**Enabling Technology Component**	**Equipment and Installation Costs**	**Variable Initial costs ($/kW)**	**Fixed Operating Costs ($/yr)**	**Variable Operating Costs ($/kW/yr)**
HVAC	Direct load control switches (DLC) (100% cycle)	$160	$0	$6	$0
	Programmable communicating thermostats (PCT) (100% cycle)	$309	$0	$15	$0
	Direct load control switches (DLC) (50% cycle)	$160	$0	$6	$0
	Programmable communicating thermostats (PCT) (50% cycle)	$309	$0	$15	$0
Pool Pumps	Direct load control switches (DLC, FM telem)	$141	$0	$4	$0
	Direct load control switches (DLC, Wifi telem)	$141	$0	$4	$0
Battery Storage	Automated demand response (ADR) * Note that the fixed and variable initial cost for battery storage are expressed in a different unit, $/kWh	$550*	$324*	$34	$0
Battery Electric Vehicles	Automated demand response (Level 2 Chargers)	$3,400	$0	$20	$0
	Level 1 Chargers IoT Automated	$0	$0	$20	$0
	Level 1 Chargers, Manual	$0	$0	$20	$0
Plug in Hybrid EV	Automated demand response (Level 2 Chargers)	$3,400	$0	$20	$0
	Level 1 Chargers, IoT Automated	$0	$0	$20	$0
	Level 1 Chargers, Manual	$0	$0	$20	$0

* Note that the fixed and variable initial cost for battery storage are expressed in a different unit, $/kWh

Table C-48: Summary Table: Residential End-Use Shed Filters - BAU Case.

End Use	Enabling Technology Component	Peak shed	Average 1-hour shed [Fraction]	Average 2-hour shed [Fraction]	Average 4-hour shed [Fraction]
HVAC	Direct load control switches (DLC)	0.94	0.77	0.77	0.72
	Programmable communicating thermostats (PCT)	0.94	0.94	0.83	0.72
	Direct load control switches (DLC) (50% cycle)	0.66	0.44	0.44	0.39
	Programmable communicating thermostats (PCT) (50% cycle)	0.46	0.46	0.46	0.41
Pool Pumps	Direct load control switches (DLC, FM telem)	0.87	0.77	0.77	0.77
	Direct load control switches (DLC, Wifi telem)	0.87	0.77	0.77	0.77
Battery Storage	Automated demand response (ADR)	1.10	1.10	0.55	0.28
Battery Electric Vehicles	Automated demand response (Level 2 Chargers)	0.99	0.99	0.99	0.99
	Level 1 Chargers IoT Automated	0.88	0.88	0.88	0.88
	Level 1 Chargers, Manual	0.88	0.88	0.88	0.88
Plug in Hybrid EV	Automated demand response (Level 2 Chargers)	0.95	0.95	0.95	0.95
	Level 1 Chargers, IoT Automated	0.88	0.88	0.88	0.88
	Level 1 Chargers, Manual	0.88	0.88	0.88	0.88

Table C-49: Summary Table: Residential Enabling Technology Costs by End-Use - Medium Case.

		Initial costs		Operating costs	
End Use	**Enabling Technology Component**	**Equipment and Installation Costs**	**Variable Initial costs ($/kW)**	**Fixed Operating Costs ($/yr)**	**Variable Operating Costs ($/kW/yr)**
HVAC	Direct load control switches (DLC) (100% cycle)	$144	$0	$5	$0
	Programmable communicating thermostats (PCT) (100% cycle)	$278	$0	$14	$0
	Direct load control switches (DLC) (50% cycle)	$144	$0	$5	$0
	Programmable communicating thermostats (PCT) (50% cycle)	$278	$0	$14	$0
Pool Pumps	Direct load control switches (DLC, FM telem)	$127	$0	$4	$0
	Direct load control switches (DLC, Wifi telem)	$127	$0	$4	$0
Battery Storage	Automated demand response (ADR) * Note that the fixed and variable initial cost for battery storage are expressed in a different unit, $/kWh	$495*	$292*	$31	$0
Battery Electric Vehicles	Automated demand response (Level 2 Chargers)	$3,060	$0	$18	$0
	Level 1 Chargers IoT Automated	$0	$0	$18	$0
	Level 1 Chargers, Manual	$0	$0	$18	$0
Plug in Hybrid EV	Automated demand response (Level 2 Chargers)	$3,060	$0	$18	$0
	Level 1 Chargers, IoT Automated	$0	$0	$18	$0
	Automated demand response (Level 2 Chargers)	$0	$0	$18	$0

Table C-50. Summary Table: Residential End-Use Shed Filters - Medium Case.

End Use	Enabling Technology Component	Peak shed	Average 1-hour shed [Fraction]	Average 2-hour shed [Fraction]	Average 4-hour shed [Fraction]
HVAC	Direct load control switches (DLC)	1.02	0.84	0.84	0.78
	Programmable communicating thermostats (PCT)	1.02	1.02	0.90	0.78
	Direct load control switches (DLC) (50% cycle)	0.72	0.48	0.48	0.42
	Programmable communicating thermostats (PCT) (50% cycle)	0.50	0.50	0.50	0.44
Pool Pumps	Direct load control switches (DLC, FM telem)	0.95	0.84	0.84	0.84
	Direct load control switches (DLC, Wifi telem)	0.95	0.84	0.84	0.84
Battery Storage	Automated demand response (ADR)	1.20	1.20	0.60	0.30
Battery Electric Vehicles	Automated demand response (Level 2 Chargers)	1.08	1.08	1.08	1.08
	Level 1 Chargers IoT Automated	0.96	0.96	0.96	0.96
	Level 1 Chargers, Manual	0.96	0.96	0.96	0.96
Plug in Hybrid EV	Automated demand response (Level 2 Chargers)	1.03	1.03	1.03	1.03
	Level 1 Chargers, IoT Automated	0.96	0.96	0.96	0.96
	Automated demand response (Level 2 Chargers)	0.96	0.96	0.96	0.96

Table C-51: Summary Table: Residential Enabling Technology Costs by End-Use - High Case.

		Initial costs		Operating costs	
End Use	**Enabling Technology Component**	**Equipment and Installation Costs**	**Variable Initial costs ($/kW)**	**Fixed Operating Costs ($/yr)**	**Variable Operating Costs ($/kW/yr)**
HVAC	Direct load control switches (DLC) (100% cycle)	$112	$0	$4	$0
	Programmable communicating thermostats (PCT) (100% cycle)	$216	$0	$11	$0
	Direct load control switches (DLC) (50% cycle)	$112	$0	$4	$0
	Programmable communicating thermostats (PCT) (50% cycle)	$216	$0	$11	$0
Pool Pumps	Direct load control switches (DLC, FM telem)	$99	$0	$3	$0
	Direct load control switches (DLC, Wifi telem)	$99	$0	$3	$0
Battery Storage	Automated demand response (ADR) * Note that the fixed and variable initial cost for battery storage are expressed in a different unit, $/kWh	$550*	$324*	$24	$0
Battery Electric Vehicles	Automated demand response (Level 2 Chargers)	$2,380	$0	$14	$0
	Level 1 Chargers IoT Automated	$0	$0	$14	$0
	Level 1 Chargers, Manual	$0	$0	$14	$0
Plug in Hybrid EV	Automated demand response (Level 2 Chargers)	1.26	1.26	1.26	1.26
	Level 1 Chargers, IoT Automated	1.12	1.12	1.12	1.12
	Automated demand response (Level 2 Chargers)	1.112	1.12	1.12	1.12

Table C-52: Summary Table: Residential End-Use Shed Filters - High Case.

End Use	Enabling Technology Component	Peak shed	Average 1-hour shed [Fraction]	Average 2-hour shed [Fraction]	Average 4-hour shed [Fraction]
HVAC	Direct load control switches (DLC)	1.19	0.98	0.98	0.91
	Programmable communicating thermostats (PCT)	1.19	1.19	1.05	0.91
	Direct load control switches (DLC) (50% cycle)	0.84	0.56	0.56	0.49
	Programmable communicating thermostats (PCT) (50% cycle)	0.588	0.588	0.588	0.518
Pool Pumps	Direct load control switches (DLC, FM telem)	1.106	0.98	0.98	0.98
	Direct load control switches (DLC, Wifi telem)	1.106	0.98	0.98	0.98
Battery Storage	Automated demand response (ADR)	1.4	1.4	0.7	0.35
Battery Electric Vehicles	Automated demand response (Level 2 Chargers)	1.26	1.26	1.26	1.26
	Level 1 Chargers IoT Automated	1.12	1.12	1.12	1.12
	Level 1 Chargers, Manual	1.12	1.12	1.12	1.12
Plug in Hybrid EV	Automated demand response (Level 2 Chargers)	1.20	1.20	1.20	1.20
	Level 1 Chargers, IoT Automated	1.12	1.12	1.12	1.12
	Automated demand response (Level 2 Chargers)	1.12	1.12	1.12	1.12

C-12.3.1. Residential Air Conditioning

Residential central air conditioning (AC) generally consists of a supply fan and a compressor conditioner. While there are other technologies for space cooling (e.g., evaporative swamp coolers) we are not modeling those in this study. For DR applications, a residential central air conditioning unit can be controlled either via DLC, which turns off the compressor for a selected period of time, or via adjustment to the setpoint temperature of a PCT, which controls the compressor and the fan of the entire central AC unit.

C-12.3.2. Load Control Tech 1: Direct Load Control Switches

Direct load control switches typically interrupt the operation of loads using a relay. In applications with residential air conditioning, the relay is installed on the condensing fan unit (typically outdoors). The switch can interrupt operation (or prevent operation once the next cooling cycle is started by the thermostat). DLC switches on AC units are appropriate for fast operation, and we can assume their participation in regulation and fast, energy-neutral ancillary services, although is it is not currently utilized for this purpose (Sullivan et al.,2013). DLC on AC units is primarily used for peak shaving and multi-hour net load reshaping.

Legacy programs and emerging technology: DLC have a long history in utility program offerings, with FM radio communication serving as the primary channel for signaling curtailment. More recently, two way FM communication technologies have come to market, allowing the administrator to monitor the success and failure rates of DLC switches in the the field. This functionality can permit LSEs and aggregators transparency in the monitoring progress of these devices and directly attribute load reductions to the devices when coupled with AMI data. While these technologies have not yet been implemented in large scale, several of the IOUs are planning on implementing these two way communicating DLC switches in the coming years. This could be due to the aging fleet of existing DLC switches and communication platforms, which is estimated to be upwards of 10-15 years old.

Shed assumptions justification: During normal operation the condensing unit represents approximately 70% of the load. The condensing unit is the controllable portion of load with a DLC switch. This DR technology allows for the fan to continuing operating while the condensing unit is controlled, and 30% of the AC load continues to draw power. The shed rates used in the model reflect the 70% shed reduction from the condensing unit but also reflects some operational limitations to shed rates. Most DR administrators elect to offer program participant varying degrees of AC cycling within their programs, such as 50% cycling which equates to 30 minutes of cycling each hour. Our model accounts for 50% cycling and 100% cycling of the condensing unit, which is reflected in the shed rates below.

Cost justification: Several data sources were used to estimate costs for the DLC switches and installation. Data was gathered from the IOUs regarding the costs of existing and planned programs and corresponding technologies. The data provided by the IOUs varied in price ranges, dependent on the technology vendors, and also by IOU. The values used in the model represent the average of all reported prices by the utilities. The initial costs include device and installation costs and are ~$160. The Navigant study reported a costs of $108 dollars for the device and installation, which is lower than reported by the California utilities, and that value is not used within our model (Navigant Consulting, 2015).

Table C-53: Residential AC, DLC (50% and 100% cycling respectively)

Input field	LBNL Synthesis Value	Other Estimates/ Bounds on Assumption	Notes
Cost Assumptions			
cost_fix_init	$160	Average Device Cost - $70 Average Install Cost - $90	IOU data request #3 report on enabling technology. Navigant report is $108. (Sum of technology and installation costs per customer)
cost_var_init	0		Default Assumption
cost_fix_opco	$6		IOU data request #3 report on enabling technology.
cost_var_opco	0		Default Assumption
cost_fix_ … co_benefit	0		Default Assumption
cost_var_ … co_benefit	0		Default Assumption
cost_margin_ … dispatch_day	$0.5/day		Estimated from NegaWatt study on DLC switches in pool pumps
tech_lifetime	15 years		IOU data request #3 with assumptions on lifetime
Performance Assumptions - 50% Cycling			
T_delay_local (seconds)	1		LBNL Estimate
T_ramp (seconds)	10		LBNL Estimate

t_resolution_ … local_control (seconds)	3600		LBNL Estimate
Shed_peak (Fraction of end use sheddability)	0.6		LBNL Estimate
Shed_1_hour (Fraction of end use sheddability)	0.4		LBNL Estimate
Shed_2_hour (Fraction of end use sheddability)	0.4		LBNL Estimate
Shed_4_hour (Fraction of end use sheddability)	0.35		LBNL Estimate
Performance Assumptions - 100% Cycling			
T_delay_local (seconds)	1		LBNL Estimate
T_ramp (seconds)	10		LBNL Estimate
t_resolution_ … local_control (seconds)	3600		LBNL Estimate
Shed_peak (Fraction of end use sheddability)	0.85		LBNL Estimate
Shed_1_hour (Fraction of end use sheddability)	0.70		LBNL Estimate
Shed_2_hour (Fraction of end use sheddability)	0.70		LBNL Estimate

Shed_4_hour (Fraction of end use sheddability)	0.65		LBNL Estimate

C-12.3.3. Load Control Tech 2: Programmable Communicating Thermostat + Wifi (100% shed and 50% shed, respectively)

The 2010 Statewide RASS survey conducted by Gilmore Research group reports that 46% of customers in the collective IOU territories have a programmable thermostat, while an estimate 26% have a programmable communicating thermostat (PCT) (*2010 Statewide Residential Appliance Saturation Study (RASS)*). It is expected that PCTs will continue to grow in popularity among consumers and adoption of this technology, for non-DR purposes, and for DR specifically, will promote greater participation in DR programs and opportunities. PCTs are equipped with capabilities to communicate with a smart meter. They are a two-way communication device that can receive signals from the utility, the internet, or a mobile phone. PCTs allow for the consumer to control, or let a DR program administrator control, the device using signals to curtail the use of an AC unit, either by changing a setpoint, or by turning the AC off. PCT devices do not require constant programming input by the consumer.

Shed assumptions justification: Unlike DLC switches, PCTs can turn off the entire AC unit, by adjusting the setpoint or signaling the device to turn off. Thus, both the fan and compression unit are controlled in a DR event, which allows for greater shed. Most DR administrators elect to offer program participant varying degrees of AC cycling within their programs, such as 50% cycling which equates to 30 minutes of cycling each hour. For the purpose of PCTs, we can think of this as a 2, 4, or 6 degree setpoint change, where the PCT allows the temperature to rise the premise until the new setpoint is reached. For example, if a consumer had set their PCT to 75 degrees and the DR event signaled the thermostat to adjust by 4 degrees, the new setpoint is 79 degrees. The AC unit would not resume operation until the new setpoint is reached, meaning the temperature in the premise is now 79 degrees. For simplicity, we reflect these setpoint adjustments in terms of cycling levels, and our model accounts for 50% cycling and 100% cycling of the AC unit, which is reflected in the shed rates below.

Cost justification: Several data sources were used to estimate costs for the Programmable Communicating Thermostats and installation of the devices. Data was gathered from the IOUs regarding the costs of existing and planned programs and corresponding technologies. The data provided by the IOUs varied in price ranges, dependent on the technology vendors, and also by IOU. The values used in the model represent the average of all reported prices by the utilities. The initial costs include device and installation costs and are ~$309. The Navigant study reported a costs of $309 dollars for the device and installation, which is average of what was reported by the California utilities, and that value is used within our model (Navigant Consulting, 2015).

Table C-54: Residential AC, PCT (50% and 100% cycling respectively)

Input field	LBNL Synthesis Value	Other Estimates/ Bounds on Assumption	Notes
Cost Assumptions			
`cost_unit_var`	0		Default Assumption
`cost_site_enab`	0		Default Assumption
`cost_fix_init`	$309	$120- $130 for installation, and average tech costs of $160- $200	Navigant report. (Sum of technology and installation costs per customer). Utility data request #3- average cost for installation and technology
`cost_var_init`	0		Default Assumption
`cost_fix_opco`	$20	range from $6/pct/yr to $38/pct/yr	Utility data request #3- average annual cost for communications for each device
`cost_var_opco`	0		Default Assumption
`cost_fix_ … co_benefit`	0		Default Assumption
`cost_var_ … co_benefit`	0		Default Assumption
`cost_margin_ … dispatch_day`	$0.5/day		Estimated from NegaWatt study on DLC switches in pool pumps (*Demand Response Enabled Pool Pump Analysis, 2013*), (*Information & Energy Services, Inc. Multi-Family Residential Variable Speed Swimming Pool/Spa Pump Retrofit., 2012*)
`tech_lifetime`	12 years		LBNL Estimate

Performance Assumptions - 100% Cycling			
T_delay_local (seconds)	1		LBNL Estimate
T_ramp (seconds)	10		LBNL Estimate
t_resolution_ … local_control (seconds)	15		LBNL Estimate
Shed_peak (Fraction of end use sheddability)	0.85		LBNL Estimate
Shed_1_hour (Fraction of end use sheddability)	0.85		LBNL Estimate
Shed_2_hour (Fraction of end use sheddability)	0.75		LBNL Estimate
Shed_4_hour (Fraction of end use sheddability)	0.65		LBNL Estimate
Performance Assumptions - 50% Cycling			
T_delay_local (seconds)	1		LBNL Estimate
T_ramp (seconds)	10		LBNL Estimate
t_resolution_ … local_control (seconds)	15		LBNL Estimate

Shed_peak (Fraction of end use sheddability)	0.42		LBNL Estimate
Shed_1_hour (Fraction of end use sheddability)	0.42		LBNL Estimate
Shed_2_hour (Fraction of end use sheddability)	0.42		LBNL Estimate
Shed_4_hour (Fraction of end use sheddability)	0.37		LBNL Estimate

C-12.3.4. Pool Pumps

DLC switches on pool pumps have a limited role in current utility program offerings, with FM radio communication serving as the primary channel for signaling curtailment. More recently, WiFi connected pool pump DLC switches have entered the market, and may take a limited market share in the future, but for the purpose of our analysis, we address only the radio DLC switches for pool pumps, albeit with two-way communication. Below we provide details from a recent NegaWatt study commissioned by SDG&E (*Demand Response Enabled Pool Pump Analysis, 2013*).

Cost justification: In a pilot conducted by SDG&E for a ETCC effort on emerging technologies, costs for DR enabled pool pump switches were reported to be $141 for a retrofit installation DLC switch on residential pool pumps (*Demand Response Enabled Pool Pump Analysis, 2013*).]

Shed justification: LBNL estimates that a pool pump could reduce power consumption by 70%, which has been adjusted for the expected availability of the device and the amount of load available from the pumping duty.

Table C-55 Residential Pool pump, DCL, FM and Wifi Telemetry

Input field	LBNL Synthesis	Other Estimates/ Bounds on	Notes

	Value	Assumption	
Cost Assumptions			
cost_unit_var	End-use		Default Assumption
cost_site_enab	0		Default Assumption
cost_fix_init	$141		Average cost for installed retrofit DLC switch from NegaWatt study.
cost_var_init	0		Default Assumption
cost_fix_opco	$4		NegaWatt study average annual operating costs.
cost_var_opco	0		Default Assumption
cost_fix_ … co_benefit	0		Default Assumption
cost_var_ … co_benefit	0		Default Assumption
cost_margin_ … dispatch_day	$0.5/day	$1/day for FM Telemetry, and $0.50/day for Wifi	NegaWatt study and LBNL Synthesis
tech_lifetime	10 years		NegaWatt study
Performance Assumptions			
T_delay_local (seconds)	0.1		LBNL Estimate
T_ramp (seconds)	0.1		LBNL Estimate
t_resolution_ … local_control (seconds)	600		LBNL Estimate

Shed_peak (Fraction of end use sheddability)	0.79		LBNL Estimate
Shed_1_hour (Fraction of end use sheddability)	0.7		LBNL Estimate
Shed_2_hour (Fraction of end use sheddability)	0.7		LBNL Estimate
Shed_4_hour (Fraction of end use sheddability)	0.7		LBNL Estimate

C-12.3.5. Electric Vehicles

Electric Vehicles have the ability to provide a range of DR opportunities which include shedding and taking load from the grid. Although many of these innovative DR load modifications are still in experimental and pilot stages, we can expect to see much progress over the next decade that can bring Electric Vehicles (EVs) to market as a DR end use. However, many factors will influence the willingness of consumers to participate in DR programs with their EVs, including IoT development, pricing incentives and tariffs, program incentives, improvements in two way communicating technologies within EVs and charging stations, and decreases in costs for Level 2 charging stations. Commercial customers and fleets, and residential customers will all need to see some level of market transformation before full scale adoption levels could be achieved.

Cost justifications:

For our analysis, we derived costs estimates from several recent pilots conducted by California Utilities: SMUD and SDG&E (*Final Evaluation for San Diego Gas & Electric's Plug-in Electric Vehicle TOU Pricing and Technology Study, 2014*). In these pilots, both utilities reported similar costs from their 2012 and 2013 pilots, which totaled around $3,400 for installation and technology components that allowed for two-way communication to the EV. The costs included dedicated circuit and meter socket box, a smart charging station with Level 2 power at 240 Volts, and a DC fast charge port on the vehicle. SMUD also included a AMI TOU sub-meter with the installations. The breakdown of costs is provided in the table below.

Shed Filter assumptions:

We derived the shed filters for both Battery Electric Vehicles (BEV) and Plug-in Hybrid Electric Vehicles (PHEV) from modeling done with V2G Sim model developed at LBNL. The estimates for shed range are estimated at 94% for PHEV and 95% for BEV.

Table C-56 Battery Electric Vehicle, ADR Level 2 Chargers, Commercial (public and fleet) and Residential Cost and Performance

Input field	LBNL Synthesis Value	Other Estimates/ Bounds on Assumption	Notes
Cost Assumptions			
cost_unit_var			Default Assumption
cost_site_enab			Default Assumption
cost_fix_init	$3,400	Installation of Dedicated Circuit, Meter Socket Box, and smart charging station ~$1500, $1,300 for installation, and ~$600 for charging socket on EV	Average costs reported from SDG&E PHEV tech study and the DOE SGIG EV charging study
cost_var_init	0		Default Assumption
cost_fix_opco	0	$20/yr for residential, $0/yr for commercial	LBNL Estimate
cost_var_opco	0		Default Assumption
cost_fix_ … co_benefit	0		Default Assumption
cost_var_ … co_benefit	0		Default Assumption
cost_margin_ … dispatch_day	$0.50		LBNL Estimate
tech_lifetime	10 years		SDG&E PHEV tech study assumption
Performance Assumptions - Commercial Sector (public and fleet)			

T_delay_local (seconds)	1		LBNL Estimate
T_ramp (seconds)	10		LBNL Estimate
t_resolution_ … local_control (seconds)	15		LBNL Estimate
Shed_peak (Fraction of end use sheddability)	0.95		LBNL Estimate
Shed_1_hour (Fraction of end use sheddability)	0.95		LBNL Estimate
Shed_2_hour (Fraction of end use sheddability)	0.95		LBNL Estimate
Shed_4_hour (Fraction of end use sheddability)	0.95		LBNL Estimate
Performance Assumptions - Residential Sector			
T_delay_local (seconds)	1		LBNL Estimate
T_ramp (seconds)	10		LBNL Estimate
t_resolution_ … local_control (seconds)	15		LBNL Estimate
Shed_peak (Fraction of end use sheddability)	0.90		LBNL Estimate
Shed_1_hour (Fraction of end	0.90		LBNL Estimate

use sheddability)			
Shed_2_hour (Fraction of end use sheddability)	0.90		LBNL Estimate
Shed_4_hour (Fraction of end use sheddability)	0.90		LBNL Estimate

Table C-57: Residential Battery Electric Vehicle, Level 1 Internet of Things (IoT) Auto Charging

Input field	LBNL Synthesis Value	Other Estimates/ Bounds on Assumption	Notes
Cost Assumptions			
cost_unit_var			Default Assumption
cost_site_enab			Default Assumption
cost_fix_init	0		LBNL Estimate
cost_var_init	0		LBNL Estimate
cost_fix_opco	$20/year		LBNL Estimate
cost_var_opco	0		Default Assumption
cost_fix_ … co_benefit	0		Default Assumption
cost_var_ … co_benefit	0		Default Assumption
cost_margin_ … dispatch_day	0		Default Assumption

tech_lifetime	15 years		LBNL Estimate
Performance Assumptions			
T_delay_local (seconds)	3600		LBNL Estimate
T_ramp (seconds)	300		LBNL Estimate
t_resolution_ … local_control (seconds)	600		LBNL Estimate
Shed_peak (Fraction of end use sheddability)	0.8		LBNL Estimate
Shed_1_hour (Fraction of end use sheddability)	0.8		LBNL Estimate
Shed_2_hour (Fraction of end use sheddability)	0.8		LBNL Estimate
Shed_4_hour (Fraction of end use sheddability)	0.8		LBNL Estimate

Table C-58: Residential Battery Electric Vehicle, Residential Level 1 Manual Charging

Input field	LBNL Synthesis Value	Other Estimates/ Bounds on Assumption	Notes
Cost Assumptions			
cost_unit_var			Default Assumption
cost_site_enab			Default Assumption

cost_fix_init	0		LBNL Estimate
cost_var_init	0		LBNL Estimate
cost_fix_opco	$20/year		LBNL Estimate
cost_var_opco	0		Default Assumption
cost_fix_ … co_benefit	0		Default Assumption
cost_var_ … co_benefit	0		Default Assumption
cost_margin_ … dispatch_day	$2/day		LBNL Estimate
tech_lifetime	10 years		LBNL Estimate
Performance Assumptions			
T_delay_local (seconds)	3600		LBNL Estimate
T_ramp (seconds)	300		LBNL Estimate
t_resolution_ … local_control (seconds)	7200		LBNL Estimate
Shed_peak (Fraction of end use sheddability)	0.8		LBNL Estimate
Shed_1_hour (Fraction of end use sheddability)	0.8		LBNL Estimate
Shed_2_hour (Fraction of end use sheddability)	0.8		LBNL Estimate

Shed_4_hour (Fraction of end use sheddability)	0.8		LBNL Estimate

C-12.3.6. Plug-in Hybrid Electric Vehicles

In the table below cost justifications for plug-in hybrid electric vehicles are presented.

Table C-59 Plug-in Electric Vehicle, ADR Level 2 Chargers, Commercial (public and fleet) and Residential Cost and Performance

Input field	LBNL Synthesis Value	Other Estimates/ Bounds on Assumption	Notes
Cost Assumptions			
cost_unit_var			Default Assumption
cost_site_enab			Default Assumption
cost_fix_init	$3,400	Installation of Dedicated Circuit, Meter Socket Box, and smart charging station ~$1500, $1,300 for installation, and ~$600 for charging socket on EV	Average costs reported from SDG&E PHEV tech study and the DOE SGIG EV charging study
cost_var_init	0		Default Assumption
cost_fix_opco	$20/yr	$20/yr for residential and for commercial	LBNL Estimate
cost_var_opco	0		Default Assumption
cost_fix_ … co_benefit	0		Default Assumption
cost_var_ … co_benefit	0		Default Assumption
cost_margin_ … dispatch_day	$0.5		Default Assumption
tech_lifetime	10 years		SDG&E PHEV tech

			study assumption
Performance Assumptions - Commercial Sector (public and fleet)			
T_delay_local (seconds)	1		LBNL Estimate
T_ramp (seconds)	10		LBNL Estimate
t_resolution_ … local_control (seconds)	15		LBNL Estimate
Shed_peak (Fraction of end use sheddability)	0.94		LBNL Estimate
Shed_1_hour (Fraction of end use sheddability)	0.94		LBNL Estimate
Shed_2_hour (Fraction of end use sheddability)	0.94		LBNL Estimate
Shed_4_hour (Fraction of end use sheddability)	0.94		LBNL Estimate

Performance Assumptions - Residential Sector			
T_delay_local (seconds)	1		LBNL Estimate
T_ramp (seconds)	10		LBNL Estimate
t_resolution_ … local_control (seconds)	15		LBNL Estimate
Shed_peak (Fraction of end use sheddability)	0.86		LBNL Estimate
Shed_1_hour (Fraction of end use sheddability)	0.86		LBNL Estimate
Shed_2_hour (Fraction of end use sheddability)	0.86		LBNL Estimate
Shed_4_hour (Fraction of end use sheddability)	0.86		LBNL Estimate

Table C-60: Residential Plug-In Electric Vehicle, Level 1 Internet of Things (IoT) Auto Charging

Input field	LBNL Synthesis Value	Other Estimates/ Bounds on Assumption	Notes
Cost Assumptions			
cost_unit_var			Default Assumption
cost_site_enab			Default Assumption
cost_fix_init	0		LBNL Estimate
cost_var_init	0		LBNL Estimate
cost_fix_opco	$20/year		LBNL Estimate
cost_var_opco	0		Default Assumption

cost_fix_ … co_benefit	0		Default Assumption
cost_var_ … co_benefit	0		Default Assumption
cost_margin_ … dispatch_day	0		Default Assumption
tech_lifetime	15 years		LBNL Estimate
Performance Assumptions			
T_delay_local (seconds)	3600		LBNL Estimate
T_ramp (seconds)	300		LBNL Estimate
t_resolution_ … local_control (seconds)	600		LBNL Estimate
Shed_peak (Fraction of end use sheddability)	0.8		LBNL Estimate
Shed_1_hour (Fraction of end use sheddability)	0.8		LBNL Estimate
Shed_2_hour (Fraction of end use sheddability)	0.8		LBNL Estimate
Shed_4_hour (Fraction of end use sheddability)	0.8		LBNL Estimate

Table C-61: Residential Plug-In Electric Vehicle, Level 1 Manual Charging

Input field	LBNL Synthesis Value	Other Estimates/ Bounds on Assumption	Notes

Cost Assumptions			
cost_unit_var			Default Assumption
cost_site_enab			Default Assumption
cost_fix_init	0		LBNL Estimate
cost_var_init	0		LBNL Estimate
cost_fix_opco	$20/year		LBNL Estimate
cost_var_opco	0		Default Assumption
cost_fix_ … co_benefit	0		Default Assumption
cost_var_ … co_benefit	0		Default Assumption
cost_margin_ … dispatch_day	$2/day		Default Assumption
tech_lifetime	10 years		LBNL Estimate
Performance Assumptions			
T_delay_local (seconds)	3600		LBNL Estimate
T_ramp (seconds)	300		LBNL Estimate
t_resolution_ … local_control (seconds)	7200		LBNL Estimate
Shed_peak (Fraction of end use sheddability)	0.8		LBNL Estimate

Shed_1_hour (Fraction of end use sheddability)	0.8		LBNL Estimate
Shed_2_hour (Fraction of end use sheddability)	0.8		LBNL Estimate
Shed_4_hour (Fraction of end use sheddability)	0.8		LBNL Estimate

C-13. Industrial Sector

Within the industrial sector we focused on DR enabling technologies at large production facilities and for agricultural pumping of water.

C-13.1.1. Industrial Processes

Table C-62: Summary Table: Industrial Enabling Technology Costs by End-Use - Base Case.

			Initial costs		Operating costs	
End Use	**Building Class**	**Enabling Technology Component**	**Equipment and Installation Costs**	**Variable Initial costs ($/kW)**	**Fixed Operating Costs ($/yr)**	**Variable Operating Costs ($/kW/yr)**
Process	**Industrial**	Manual Process Interrupt	$3,000	$0	$0	$0
		Semi-Automated Process Interrupt	$0	$200	$0	$0
		Automated demand response (ADR)	$0	$250	$0	$0

Table C-63: Summary Table: Industrial End-Use Shed Filters - Base Case.

End Use	Building Class	Enabling Technology Component	Peak shed	Average 1-hour shed [Fraction]	Average 2-hour shed [Fraction]	Average 4-hour shed [Fraction]
Process	Industrial	Manual Process Interrupt	0.5	0.5	0.5	0.5
		Semi-Automated Process Interrupt	0.55	0.55	0.55	0.55
		Automated demand response (ADR)	0.6	0.6	0.6	0.6

Table C-64: Summary Table: Industrial Enabling Technology Costs by End-Use - BAU Case.

			Initial costs		Operating costs	
End Use	Building Class	Enabling Technology Component	Equipment and Installation Costs	Variable Initial costs ($/kW)	Fixed Operating Costs ($/yr)	Variable Operating Costs ($/kW/yr)
Process	Industrial	Manual Process Interrupt	$3,000	$0	$0	$0
		Semi-Automated Process Interrupt	$0	$200	$0	$0
		Automated demand response (ADR)	$0	$250	$0	$0

Table C-65: Summary Table: Industrial End-Use Shed Filters - BAU Case

End Use	Building Class	Enabling Technology Component	Peak shed	Average 1-hour shed [Fraction]	Average 2-hour shed [Fraction]	Average 4-hour shed [Fraction]
Process	Industrial	Manual Process Interrupt	0.55	0.55	0.55	0.55
		Semi-Automated Process Interrupt	0.605	0.605	0.605	0.605
		Automated demand response (ADR)	0.66	0.66	0.66	0.66

Table C-66: Summary Table: Industrial Enabling Technology Costs by End-Use - Medium Case.

			Initial costs		Operating costs	
End Use	Building Class	Enabling Technology Component	Equipment and Installation Costs	Variable Initial costs ($/kW)	Fixed Operating Costs ($/yr)	Variable Operating Costs ($/kW/yr)
Process	Industrial	Manual Process Interrupt	$2,700	$0	$0	$0
		Semi-Automated Process Interrupt	$0	$180	$0	$0
		Automated demand response (ADR)	$0	$225	$0	$0

Table C-67: Summary Table: Industrial End-Use Shed Filters - Medium Case.

End Use	Building Class	Enabling Technology Component	Peak shed	Average 1-hour shed [Fraction]	Average 2-hour shed [Fraction]	Average 4-hour shed [Fraction]
Process	Industrial	Manual Process Interrupt	0.6	0.6	0.6	0.6
		Semi-Automated Process Interrupt	0.66	0.66	0.66	0.66
		Automated demand response (ADR)	0.72	0.72	0.72	0.72

Table C-68: Summary Table: Industrial Enabling Technology Costs by End-Use - High Case.

			Initial costs		Operating costs	
End Use	Building Class	Enabling Technology Component	Equipment and Installation Costs	Variable Initial costs ($/kW)	Fixed Operating Costs ($/yr)	Variable Operating Costs ($/kW/yr)
Process	Industrial	Manual Process Interrupt	$2,100	$0	$0	$0
		Semi-Automated Process Interrupt	$0	$140	$0	$0
		Automated demand response (ADR)	$0	$175	$0	$0

Table C-69: Summary Table: Industrial End-Use Shed Filters - High Case.

End Use	Building Class	Enabling Technology Component	Peak shed	Average 1-hour shed [Fraction]	Average 2-hour shed [Fraction]	Average 4-hour shed [Fraction]
Process	**Industrial**	Manual Process Interrupt	0.7	0.7	0.7	0.7
		Semi-Automated Process Interrupt	0.77	0.77	0.77	0.77
		Automated demand response (ADR)	0.84	0.84	0.84	0.84

For customers at large production facilities—such as factories, food processing plants or metal product manufacturing sites—utilities pay an incentive to interrupt a process and either partially or completely shut down load during a contingency event. The notification by utilities to these industrial customers is either a phone call, typically providing 30 minutes advanced notice, or through an AutoDR system. Once notified, customers either manually shut down their facility processes or automatically shed load through an AutoDR signal. There are also facilities with semi-automated controls, where some elements of the industrial process still need to be switched off manually during a DR event (Ghatikar et. al, 2012).

Navigant studied the curtailable industrial programs at Idaho Power, PG&E, and SMUD, among those of other utilities. If the notification to customers is by phone and the load shed is fully manual, we assume no DR enabling device need be installed but that there are still upfront enabling costs. If the customer participates in the Curtailable/Interruptible program with an AutoDR system, Navigant estimates the upfront installation ($1250) and technology ($2500) cost together to be approximately $3750 per customer, which is about $7.5/kW using their 500 kW load shed assumption (Navigant Consulting, 2015). LBNL finds this estimate too low, compared to a study (Piette et. al, 2015) of 56 installed AutoDR systems which approximated the median technology enabling cost to be $200/kW. Cost data from this study of 23 industrial sites in PG&E's 2007 industrial DR program ranged from $9/kW to $236/kW (Piette et. al, 2015). These cost estimates from the LBNL study included technical coordination and installation. We use the median $200/kW cost for both AutoDR and semi-automated DR as we think of this as a more realistic value than the Navigant estimate.

Table C-70: AutoDR Industrial Process Interrupt

Input field	LBNL Synthesis Value	Other Estimates/ Bounds on Assumption	Notes
Cost Assumptions			
cost_unit_var	kW-peak		LBNL report listed cost as per kW value. We assume this is same as kW-peak
cost_site_enab	0		Default Assumption
cost_fix_init	0	Navigant assumes this cost (sum of technology and installation cost) as $3750 per customer with a 500 kW load shed.	LBNL report estimates all upfront costs as $/kW
cost_var_init	$250/kW		LBNL report median AutoDR cost
cost_fix_opco	0		Default Assumption
cost_var_opco	0		Default Assumption
cost_fix_ … co_benefit	0		Default Assumption
cost_var_ … co_benefit	0		Default Assumption
cost_margin_ … dispatch_day	$1/day		Estimate to account for communication fees
tech_lifetime	10 years		Estimate based on the lifetimes of other ADR enabling technologies
Performance Assumptions			
T_delay_local (seconds)	0.1		LBNL estimate

T_ramp (seconds)	120		LBNL estimate
t_resolution_ … local_control (seconds)	600		LBNL estimate
Shed_peak (Fraction of end use sheddability)	0.6		LBNL estimate
Shed_1_hour (Fraction of end use sheddability)	0.6		LBNL estimate
Shed_2_hour (Fraction of end use sheddability)	0.6		LBNL estimate
Shed_4_hour (Fraction of end use sheddability)	0.6		LBNL estimate

Table C-71: Industrial Manual Process Interrupt, normal and deep cuts.

Input field	LBNL Synthesis Value	Other Estimates/ Bounds on Assumption	Notes
Cost Assumptions			
cost_unit_var	kW-peak		Navigant report listed all variable cost as per kW-year. We assume this is same as kW-peak
cost_site_enab	0		Default Assumption
cost_fix_init	$3000		Navigant report estimates AutoDR fixed initial costs to be $3750, and we assume the Manual fixed initial costs are lower than for AutoDR. Assumed that no equipment needs to be installed for manual load shed

			and telephone notification but there are other upfront costs.
cost_var_init	0		Default Assumption
cost_fix_opco	0		Default Assumption
cost_var_opco	0		Default Assumption
cost_fix_ … co_benefit	0		Default Assumption
cost_var_ … co_benefit	0		Default Assumption
cost_margin_ … dispatch_day	$1/day		Estimate to account for marginal dispatch costs
tech_lifetime	10 years		Based on estimate of average contract term and possible renewal terms
Performance Assumptions (normal cut)			
T_delay_local (seconds)	1800		LBNL estimate
T_ramp (seconds)	300		LBNL estimate
t_resolution_ … local_control (seconds)	3600		LBNL estimate
Shed_peak (Fraction of end use sheddability)	0.5		LBNL estimate
Shed_1_hour (Fraction of end use sheddability)	0.5		LBNL estimate
Shed_2_hour	0.5		LBNL estimate

(Fraction of end use sheddability)			
Shed_4_hour (Fraction of end use sheddability)	0.5		LBNL estimate
Performance Assumptions (deep cuts)			
T_delay_local (seconds)	7200		LBNL estimate
T_ramp (seconds)	3600		LBNL estimate
t_resolution_ … local_control (seconds)	28800		LBNL estimate
Shed_peak (Fraction of end use sheddability)	0.95		LBNL estimate
Shed_1_hour (Fraction of end use sheddability)	0.95		LBNL estimate
Shed_2_hour (Fraction of end use sheddability)	0.95		LBNL estimate
Shed_4_hour (Fraction of end use sheddability)	0.95		LBNL estimate

Table C-72: Semi-Automatic Industrial Process Interrupt

Input field	LBNL Synthesis Value	Other Estimates/ Bounds on Assumption	Notes
Cost Assumptions			
cost_unit_var	kW-peak		LBNL report listed cost as per kW value. We assume this is same as kW-peak
cost_site_enab	0		Default Assumption
cost_fix_init	0		LBNL report estimates all upfront costs as $/kW
cost_var_init	$200/kW		LBNL report median AutoDR cost. Semi-automated DR assumed to be similar cost.
cost_fix_opco	0		Default Assumption
cost_var_opco	0		Default Assumption
cost_fix_ … co_benefit	0		Default Assumption
cost_var_ … co_benefit	0		Default Assumption
cost_margin_ … dispatch_day	$1/day		Estimate to account for communication fees
tech_lifetime	10 years		Estimate based on the lifetimes of other ADR enabling technologies
Performance Assumptions			
T_delay_local (seconds)	1800		Estimated to be same as manual
T_ramp (seconds)	180		Estimated to be between

			automated and manual
t_resolution_ … local_control (seconds)	600		LBNL estimate
Shed_peak (Fraction of end use sheddability)	0.55		LBNL estimate
Shed_1_hour (Fraction of end use sheddability)	0.55		LBNL estimate
Shed_2_hour (Fraction of end use sheddability)	0.55		LBNL estimate
Shed_4_hour (Fraction of end use sheddability)	0.55		LBNL estimate

C-13.1.2. Agricultural Pumping

Table C-73: Summary Table: Agricultural Pumping Enabling Technology Costs by End-Use - Base Case.

			Initial costs		Operating costs	
End Use	**Building Class**	**Enabling Technology Component**	**Equipment and Installation Costs**	**Variable Initial costs ($/kW)**	**Fixed Operating Costs ($/yr)**	**Variable Operating Costs ($/kW/yr)**
Irrigation Pumping	**Agricultural**	Direct load control switch (DLC)	$100	$60	$0	$0
		Automated demand response (ADR)	$0	$235	$0	$0

Table C-74: Summary Table: Agricultural Pumping End-Use Shed Filters - Base Case.

End Use	Building	Enabling	Peak	Average 1-	Average 2-	Average 4-

	Class	Technology Component	shed	hour shed [Fraction]	hour shed [Fraction]	hour shed [Fraction]
Irrigation Pumping	Agricultural	Direct load control switch (DLC)	0.7	0.7	0.7	0.7
		Automated demand response (ADR)	0.8	0.8	0.8	0.8

Table C-75: Summary Table: Agricultural Pumping Enabling Technology Costs by End-Use - BAU Case.

			Initial costs		Operating costs	
End Use	**Building Class**	**Enabling Technology Component**	**Equipment and Installation Costs**	**Variable Initial costs ($/kW)**	**Fixed Operating Costs ($/yr)**	**Variable Operating Costs ($/kW/yr)**
Irrigation Pumping	**Agricultural**	Direct load control switch (DLC)	$100	$40	$0	$0
		Automated demand response (ADR)	$0	$235	$0	$0

Table C-76: Summary Table: Agricultural Pumping End-Use Shed Filters - BAU Case.

End Use	Building Class	Enabling Technology Component	Peak shed	Average 1-hour shed [Fraction]	Average 2-hour shed [Fraction]	Average 4-hour shed [Fraction]
Irrigation Pumping	**Agricultural**	Direct load control switch (DLC)	0.77	0.77	0.77	0.77
		Automated demand response (ADR)	0.88	0.88	0.88	0.88

Table C-77: Summary Table: Agricultural Pumping Enabling Technology Costs by End-Use - Medium Case.

			Initial costs		Operating costs	
End Use	Building Class	Enabling Technology Component	Equipment and Installation Costs	Variable Initial costs ($/kW)	Fixed Operating Costs ($/yr)	Variable Operating Costs ($/kW/yr)
Irrigation Pumping	Agricultural	Direct load control switch (DLC)	$90	$36	$0	$0
		Automated demand response (ADR)	$0	$211	$0	$0

Table C-78: Summary Table: Agricultural Pumping End-Use Shed Filters - Medium Case.

End Use	Building Class	Enabling Technology Component	Peak shed	Average 1-hour shed [Fraction]	Average 2-hour shed [Fraction]	Average 4-hour shed [Fraction]
Irrigation Pumping	Agricultural	Direct load control switch (DLC)	0.84	0.84	0.84	0.84
		Automated demand response (ADR)	0.96	0.96	0.96	0.96

Table C-79: Summary Table: Agricultural Pumping Enabling Technology Costs by End-Use - High Case.

			Initial costs		Operating costs	
End Use	**Building Class**	**Enabling Technology Component**	**Equipment and Installation Costs**	**Variable Initial costs ($/kW)**	**Fixed Operating Costs ($/yr)**	**Variable Operating Costs ($/kW/yr)**
Irrigation Pumping	**Agricultural**	Direct load control switch (DLC)	$70	$28	$0	$0
		Automated demand response (ADR)	$0	$164	$0	$0

Table C-80: Summary Table: Agricultural Pumping End-Use Shed Filters - High Case.

End Use	**Building Class**	**Enabling Technology Component**	**Peak shed**	**Average 1-hour shed [Fraction]**	**Average 2-hour shed [Fraction]**	**Average 4-hour shed [Fraction]**
Irrigation Pumping	**Agricultural**	Direct load control switch (DLC)	0.98	0.98	0.98	0.98
		Automated demand response (ADR)	1.12	1.12	1.12	1.12

DR can be enabled for agricultural loads for the irrigation season by either a basic DLC switch or with an AutoDR system on the water pumps and other irrigation devices. Based on sampling Idaho Power and PacifiCorp and Bonneville Power's irrigation pumping DR programs, Navigant estimated the fixed initial installation cost to be $100 and technology cost to be $60/kW for a basic DLC system. We use installation cost as a fixed upfront cost and the technology cost as a variable upfront cost. For an AutoDR system Navigant estimated the variable installation and technology costs to be approximately $235/kW (when accounting for their kW of load shed assumed), and we use these costs as the variable upfront cost for the study (Navigant Consulting, 2015). An LBNL report on AutoDR potential in California's irrigation sector (Olsen et. al, 2015) noted that shed rates around 80 percent were common.

Table C-81: Agricultural pumping, basic DLC switch.

Input field	LBNL Synthesis Value	Other Estimates/ Bounds on Assumption	Notes
Cost Assumptions			
cost_unit_var	kW-peak		Navigant report listed all variable cost as per kW-year. We assume this is same as kW-peak
cost_site_enab	0		Default Assumption
cost_fix_init	$100		Navigant report. (Technology cost)
cost_var_init	$40		Navigant report (installation cost divided by kW of load shed to get $/kW value)
cost_fix_opco	0		Default Assumption
cost_var_opco	0		Default Assumption
cost_fix_ … co_benefit	0		Default Assumption
cost_var_ … co_benefit	0		Default Assumption
cost_margin_ … dispatch_day	0		Default Assumption
tech_lifetime	15 years		Estimate based on lifetime of other DLC enabling technology
Performance Assumptions			
T_delay_local (seconds)	0.1		LBNL Estimate
T_ramp (seconds)	0.1		LBNL Estimate

t_resolution_ … local_control (seconds)	600		LBNL Estimate
Shed_peak (Fraction of end use sheddability)	0.7		Based on LBNL report (Olsen 2015) and average shed factors
Shed_1_hour (Fraction of end use sheddability)	0.7		Based on LBNL report (Olsen 2015) and average shed factors
Shed_2_hour (Fraction of end use sheddability)	0.7		Based on LBNL report (Olsen 2015) and average shed factors
Shed_4_hour (Fraction of end use sheddability)	0.7		Based on LBNL report (Olsen 2015) and average shed factors

Table C-82: Agricultural pumping, ADR.

Input field	LBNL Synthesis Value	Other Estimates/ Bounds on Assumption	Notes
Cost Assumptions			
cost_unit_var	kW-peak		Navigant report listed all variable cost as per kW-year. We assume this is same as kW-peak
cost_site_enab	0		Default Assumption
cost_fix_init	0		Navigant report has costs in $/kW
cost_var_init	$235		Navigant report (sum of technology and installation cost divided by kW of load shed to get $/kW value)

cost_fix_opco	0		Default Assumption
cost_var_opco	0		Default Assumption
cost_fix_ … co_benefit	0		Default Assumption
cost_var_ … co_benefit	0		Default Assumption
cost_margin_ … dispatch_day	$0.5/day		Estimate based on marginal dispatch cost of other ADR enabling technology
tech_lifetime	15 years		Estimate based on lifetime of other ADR enabling technology
Performance Assumptions			
T_delay_local (seconds)	0.1		LBNL estimate
T_ramp (seconds)	0.1		LBNL estimate
t_resolution_ … local_control (seconds)	600		LBNL estimate
Shed_peak (Fraction of end use sheddability)	0.8		Based on LBNL report (Olsen 2015) and average shed factors
Shed_1_hour (Fraction of end use sheddability)	0.8		Based on LBNL report (Olsen 2015) and average shed factors
Shed_2_hour (Fraction of end use sheddability)	0.8		Based on LBNL report (Olsen 2015) and average shed factors
Shed_4_hour (Fraction of end	0.8		Based on LBNL report (Olsen 2015) and average shed factors

use sheddability)			

C-13.1.3. Wastewater Treatment and Pumping

Our assumptions for DR opportunities with wastewater treatment and pumping facilities are based on previous research conducted by LBNL on Wastewater treatment plant DR opportunities (Thompson et al.) (Olsen et al.). Our study includes two types of enabling technologies, manual DR and ADR. Manual DR is much more commonplace today, however, ADR installations in Wastewater treatment facilities are expected to gain traction in the market over the coming decade.

For manual process interruption, we assume the costs would be an upfront initial cost of $3000 for an audit of the site by the LSE or aggregator. We base this assumption on information provided by one of the IOUs in the study. For ADR installations, we used data collected by LBNL from a variety of pilot efforts that implemented ADR in commercial buildings, and took the average of the installations, approximately $258/kW. The kW reductions came from LBNL research that determined facility load reduction of 26% could be achieved through automation or manual process interrupt (Thompson et al., 2009) (Olsen et al., 2012).

Table C-83: Summary Table: Wastewater Enabling Technology - Base Case.

		Initial costs		Operating costs	
Building Class	**Enabling Tech Component**	**Equipment and Installation Costs**	**Variable Initial costs ($/kW)**	**Fixed Operating Costs ($/yr)**	**Variable Operating Costs ($/kW/yr)**
WW Pumping	Manual Process Interrupt	$3,000	$0	$0	$0
	Automated demand response (ADR)	$0	$262	$50	$0
WW Treatment	Manual Process Interrupt	$3,000	$0	$0	$0
	Automated demand response (ADR)	$0	$258	$50	$0

Table C-84: Summary Table: Wastewater Shed Filters - Base Case.

Building Class	Enabling Tech Component	Peak shed	Average 1-hour shed [Fraction]	Average 2-hour shed [Fraction]	Average 4-hour shed [Fraction]
WW	Manual Process	0.76	0.7	0.6	0.6

Pumping	Interrupt				
	Automated demand response (ADR)	0.76	0.7	0.6	0.6
WW Treatment	Manual Process Interrupt	0.26	0.26	0.2	0.15
	Automated demand response (ADR)	0.26	0.26	0.2	0.15

Table C-85: Summary Table: Wastewater Enabling Technology - BAU Case.

		Initial costs		Operating costs	
Building Class	**Enabling Tech Component**	**Equipment and Installation Costs**	**Variable Initial costs ($/kW)**	**Fixed Operating Costs ($/yr)**	**Variable Operating Costs ($/kW/yr)**
WW. Pumping	Manual Process Interrupt	$3,000	$0	$0	$0
	Automated demand response (ADR)	$0	$262	$50	$0
WW Treatment	Manual Process Interrupt	$3,000	$0	$0	$0
	Automated demand response (ADR)	$0	$258	$50	$0

Table C-86: Wastewater Enabling Shed Filters - BAU Case.

Building Class	Enabling Tech Component	Peak shed	Average 1-hour shed [Fraction]	Average 2-hour shed [Fraction]	Average 4-hour shed [Fraction]
WW. Pumping	Manual Process Interrupt	0.84	0.77	0.66	0.66
	Automated demand response (ADR)	0.84	0.77	0.66	0.66
WW Treatment	Manual Process Interrupt	0.29	0.29	0.22	0.17
	Automated demand response (ADR)	0.29	0.29	0.22	0.17

Table C-87: Summary Table: Wastewater Enabling Technology Costs - Medium Case.

		Initial costs		Operating costs	
Building Class	**Enabling Tech Component**	**Equipment and Installation Costs**	**Variable Initial costs ($/kW)**	**Fixed Operating Costs ($/yr)**	**Variable Operating Costs ($/kW/yr)**
WW. Pumping	Manual Process Interrupt	$2,700	$0	$0	$0
	Automated demand response (ADR)	$0	$236	$45	$0
WW Treatment	Manual Process Interrupt	$2,700	$0	$0	$0
	Automated demand response (ADR)	$0	$232	$45	$0

Table C-88: Summary Table: Wastewater Shed Filters - Medium Case.

Building Class	Enabling Tech Component	Peak shed	Average 1-hour shed [Fraction]	Average 2-hour shed [Fraction]	Average 4-hour shed [Fraction]
WW. Pumping	Manual Process Interrupt	0.91	0.84	0.72	0.72
	Automated demand response (ADR)	0.91	0.84	0.72	0.72
WW Treatment	Manual Process Interrupt	0.31	0.31	0.24	0.18
	Automated demand response (ADR)	0.31	0.31	0.24	0.18

Table C-89: Summary Table: Wastewater Enabling Technology Costs - High Case.

		Initial costs		Operating costs	
Building Class	**Enabling Tech Component**	**Equipment and Installation Costs**	**Variable Initial costs ($/kW)**	**Fixed Operating Costs ($/yr)**	**Variable Operating Costs ($/kW/yr)**
WW. Pumping	Manual Process Interrupt	$2,100	$0	$0	$0
	Automated demand response (ADR)	$0	$183	$35	$0
WW Treatment	Manual Process Interrupt	$2,100	$0	$0	$0
	Automated demand response (ADR)	$0	$181	$35	$0

Table C-90: Summary Table: Wastewater Shed Filters - High Case.

Building Class	Enabling Tech Component	Peak shed	Average 1-hour shed [Fraction]	Average 2-hour shed [Fraction]	Average 4-hour shed [Fraction]
WW. Pumping	Manual Process Interrupt	1.06	0.98	0.84	0.84
	Automated demand response (ADR)	1.06	0.98	0.84	0.84
WW Treatment	Manual Process Interrupt	0.36	0.36	0.28	0.21
	Automated demand response (ADR)	0.36	0.36	0.28	0.21

C-13.1.4. Data Centers

Data centers have two main energy consuming loads, IT servers and HVAC. The Demand response strategies in data centers have opportunities to reduce demand by employing the following strategies:

- Load migration (moving the IT load to another data center)
- Job delay (queuing the IT jobs to be done at a later time)
- Shutting off the HVAC system and letting the temperature drift

Since the complexity and dynamism of managing data centers does not lend itself easily to automation, there are only a few data center DR participants in the market today, and those that are, participate on manual response platforms. It is difficult to target a specific end-use or enabling technology, in particular, for data centers within our model, given the lack of information on the topic. Therefore, our model examines DR load reduction at the site level, without focusing on specific end-uses, and assumes that manual intervention will be used to respond to a DR event. Based on previous research conducted by LBNL on DR in Data Centers, we assumed a whole facility load reduction of 17%, with an facility audit of $3000 to confirm that load could be reduced at the site (Ghatikar, Ganti, et al., 2012).

Table C-91: Summary Table: Data Center Technology Costs and Shed Filters - Base Case.

		Initial costs		Operating costs					
Building Class	Enabling Tech Component	Equipment and Install Costs	Variable Initial costs ($/kW)	Fixed Op. Costs ($/yr)	Var. Op. Costs ($/kW/yr)	Peak shed	Average 1-hour shed	Average 2-hour shed	Average 4-hour shed
Data Centers	Manual DR	$3,000	$0	$0	$0	0.15	0.15	0.15	0.15

Table C-92: Summary Table: Data Center Technology Costs and Shed Filters - BAU Case.

		Initial costs		Operating costs					
Building Class	Enabling Tech Component	Equipment and Install Costs	Variable Initial costs ($/kW)	Fixed Op. Costs ($/yr)	Var. Op. Costs ($/kW/yr)	Peak shed	Average 1-hour shed	Average 2-hour shed	Average 4-hour shed
Data Centers	Manual DR	$3,000	$0	$0	$0	0.17	0.17	0.17	0.17

Table C-93: Summary Table: Data Center Technology Costs and Shed Filters - Medium Case.

		Initial costs		Operating costs					
Building Class	Enabling Tech Component	Equipment and Install Costs	Variable Initial costs ($/kW)	Fixed Op. Costs ($/yr)	Var. Op. Costs ($/kW/yr)	Peak shed	Average 1-hour shed	Average 2-hour shed	Average 4-hour shed
Data Centers	Manual DR	$2,700	$0	$0	$0	0.18	0.18	0.18	0.18

Table C-94: Summary Table: Data Center Technology Costs and Shed Filters - High Case.

		Initial costs		Operating costs					
Building Class	**Enabling Tech Component**	**Equipment and Install Costs**	**Variable Initial costs ($/kW)**	**Fixed Op. Costs ($/yr)**	**Var. Op. Costs ($/kW/yr)**	**Peak shed**	**Average 1-hour shed**	**Average 2-hour shed**	**Average 4-hour shed**
Data Centers	Manual DR	$2,100	$0	$0	$0	0.21	0.21	0.21	0.21

C-14. Energy Storage- Batteries

Table C-95: Summary Table: Commercial and Industrial Storage Technology Costs and Shed Filters - Base Case.

		Initial costs		Operating costs					
Building Class	**Enabling Tech Component**	**Equipment and Install Costs**	**Variable Initial costs ($/kW)**	**Fixed Op. Costs ($/yr)**	**Var. Op. Costs ($/kW/yr)**	**Peak shed**	**Average 1-hour shed**	**Average 2-hour shed**	**Average 4-hour shed**
Com. Storage	ADR	$550/kWh	$324/kWh	$34	$0	1	1	0.5	0.25
Industrial Storage	ADR	$550	$324/kWh	$34	$0	1	1	0.5	0.25

Table C-96: Summary Table: Commercial Storage Technology Costs and Shed Filters - BAU Case.

		Initial costs		Operating costs					
Building Class	**Enabling Tech Component**	**Equipment and Install Costs**	**Variable Initial costs ($/kW)**	**Fixed Op. Costs ($/yr)**	**Var. Op. Costs ($/kW/yr)**	**Peak shed**	**Average 1-hour shed**	**Average 2-hour shed**	**Average 4-hour shed**
Com. Storage	ADR	$550/kWh	$324/kWh	$34	$0	1.10	1.10	0.55	0.28
Industrial Storage	ADR	$550/kWh	$324/kWh	$34	$0	1.10	1.10	0.55	0.28

Table C-97: Summary Table: Commercial Storage Technology Costs and Shed Filters - Medium Case.

		Initial costs		Operating costs					
Building Class	**Enabling Tech Component**	**Equipment and Install Costs**	**Variable Initial costs ($/kW)**	**Fixed Op. Costs ($/yr)**	**Var. Op. Costs ($/kW/yr)**	**Peak shed**	**Average 1-hour shed**	**Average 2-hour shed**	**Average 4-hour shed**
Com. Storage	ADR	$495/kWh	$292/ kWh	$31	$0	1.2	1.2	0.6	0.3
Industrial Storage	ADR	$495/kWh	$292/ kWh	$31	$0	1.2	1.2	0.6	0.3

Table C-98: Summary Table: Commercial Storage Technology Costs and Shed Filters - High Case.

		Initial costs		Operating costs					
Building Class	**Enabling Tech Component**	**Equipment and Install Costs**	**Variable Initial costs ($/kW)**	**Fixed Op. Costs ($/yr)**	**Var. Op. Costs ($/kW/yr)**	**Peak shed**	**Average 1-hour shed**	**Average 2-hour shed**	**Average 4-hour shed**
Com. Storage	ADR	$385/kWh	$227/ kWh	$24	$0	1.4	1.4	0.7	0.35
Industrial Storage	ADR	$385/kWh	$227/ kWh	$24	$0	1.4	1.4	0.7	0.35

Locally-sited, “behind the meter” energy storage can make any load appear flexible to grid operators. Batteries that are equipped with the right telemetry, control, and intelligence can provide a wide range of services to both local load (increased reliability, power quality correction, reduction in demand charges, etc.) and the grid (through demand response and other grid services).

The cost of energy storage is changing rapidly from economies of scale in manufacturing for batteries (lithium in particular) and innovation on soft costs of installation and operation.

C-14.1. Battery storage benefits streams from non-DR sources

Many consumers adopt and install various end uses and technologies for cost saving reasons other than DR. For battery storage, we expect that adoption among consumers will be largely driven by non-DR benefit streams, most of which involve managing energy costs and improving service at the premise. However, some storage benefit streams come from engaging in the supply market to provide grid services such as regulation and spinning/non-spinning reserves, but these benefits typically apply only to customers with large battery stacks, such as large C&I or utilities.

Below, we have summarized data from a study conducted by the Rocky Mountain Institute in 2015 titled "The Economics of Battery Energy Storage" (Fitzgerald et al.,2015). The study aimed at capturing various value streams from BTM battery storage and compared those benefits to the total costs of installation for residential, commercial and utility scale battery systems. Our study includes total costs, including Balance of System (BOS) and battery storage cells/racks, along with benefit streams from DR and non-DR economic transactions, as detailed below.

Table C-99: Battery Energy Storage Value Streams

SERVICE	Value [$/kW/yr]	CAISO ranges
ARBITRAGE & LOAD FOLLOWING	$3-$97	34-47
REGUL.	$28- $204	$7.8- $10.36
SPIN/ NONSPIN	$1-$65	
RA (Includes Forward Capacity)	$65-$155	
VOLTAGE SUPPORT	$56	
TRANS & DISTR. UPGRADE DEFERRAL	$51-$900	$67-$128
TRANS CONGEST RELIEF	$10-$12	
TOU	$23- $230	
kW CHARGE	$58- $269	
BLACK START	$6	
SELF CONSUMP. OPTIMIZATION (with PV)	$10-$51	

*Values from Rocky Mountain Institute Report *The Economics of Battery Storage, Appendix A, 2015*

Customers with larger battery storage systems can participate in the energy markets and benefit financially from these interactions. For example, battery storage systems can be used for regulation capacity or spinning and non-spinning reserves just as a conventional generator participates. or residential or small commercial applications of battery storage, the systems can be utilized for self-consumption optimization, (with a PV system to generate energy where excess can be stored for later use, rather than sending over generation back to the grid), or for demand charge minimization.

C-14.2. Battery Storage Costs

Battery storage is a rapidly evolving technology that promises to become dramatically more cost competitive over the next decade. For our analysis, we sought the expertise of E3, another subcontractor on this research study, and they assisted with providing references and a recommended approach for appropriately costing a solution, independent of the duration of the system. The DR-PATH analysis incorporates cost data from E3's research efforts, which rely heavily on "Electrical energy storage systems: A comparative life cycle cost analysis" (Zakeri and Syri, 2015), along with the DOE 2013 Energy Storage Handbook (Akhil et al.).

C-14.3. Balance of System (BOS)

Energy storage systems require equipment such as permitting and interconnection, inverter/converter costs, and specific power electronics and are commonly referred to as 'balance of system'" (BOS). These costs are often not reported by manufacturers or it is unclear what costs are included. For our analysis, we consider the kW costs as fixed initial costs, and the variable costs of a battery system to include the kWh costs for the battery stack.

Storage systems present a unique challenge when categorizing costs because unlike power plants, which are valued at their max capacity value, battery storage has both a maximum power output and a maximum energy output, typically characterized as the capacity (kW), and the energy (kWh) or duration (hours). The energy output (kWh) from a battery can vary considerably because of the duration of discharge, even for units with similar capacity. Because of this, E3 recommended a unique approach for overcoming some of the challenges of determining standardized costs for battery storage systems with different kWh durations.

Following the approach recommended by E3, we breakdown the costs as follows: Costs by storage costs in $/kWh (the actual battery racks in case of a battery system), and BOS costs in $/kW (inverter, utility interconnection, BMS, and installation). This approach is documented below.

Table C-100: Commercial and Industrial Battery Storage Cost and Performance

Input field	LBNL Synthesis Value	Other Estimates/ Bounds on Assumption	Notes
Cost Assumptions			
cost_unit_var			
cost_site_enab			
cost_fix_init	$550/kW installed	2015 cost estimates	2015 costs, average of BOS costs from Zakeri and Syri (2014) report
cost_var_init	$324/kWh	2015 cost estimates	Average battery cell price per kWh from DOE handbook and E3 calculations
cost_fix_opco	$34/kW	2015 cost estimates	E3 estimates based on Zakeri and Syri (2014) report
cost_var_opco	0		Default Assumption
cost_fix_ … co_benefit	0		Default Assumption
cost_var_ … co_benefit	0		Default Assumption
cost_margin_ … dispatch_day	0		Default Assumption
tech_lifetime	5 years		LBNL Estimate
Performance Assumptions			
T_delay_local (seconds)	1		LBNL Estimate
T_ramp (seconds)	120		LBNL Estimate
t_resolution_ …	15		LBNL Estimate

local_control (seconds)			
Shed_peak (Fraction of end use sheddability)	1		LBNL Estimate
Shed_1_hour (Fraction of end use sheddability)	1		LBNL Estimate
Shed_2_hour (Fraction of end use sheddability)	0.5		LBNL Estimate
Shed_4_hour (Fraction of end use sheddability)	0.25		LBNL Estimate

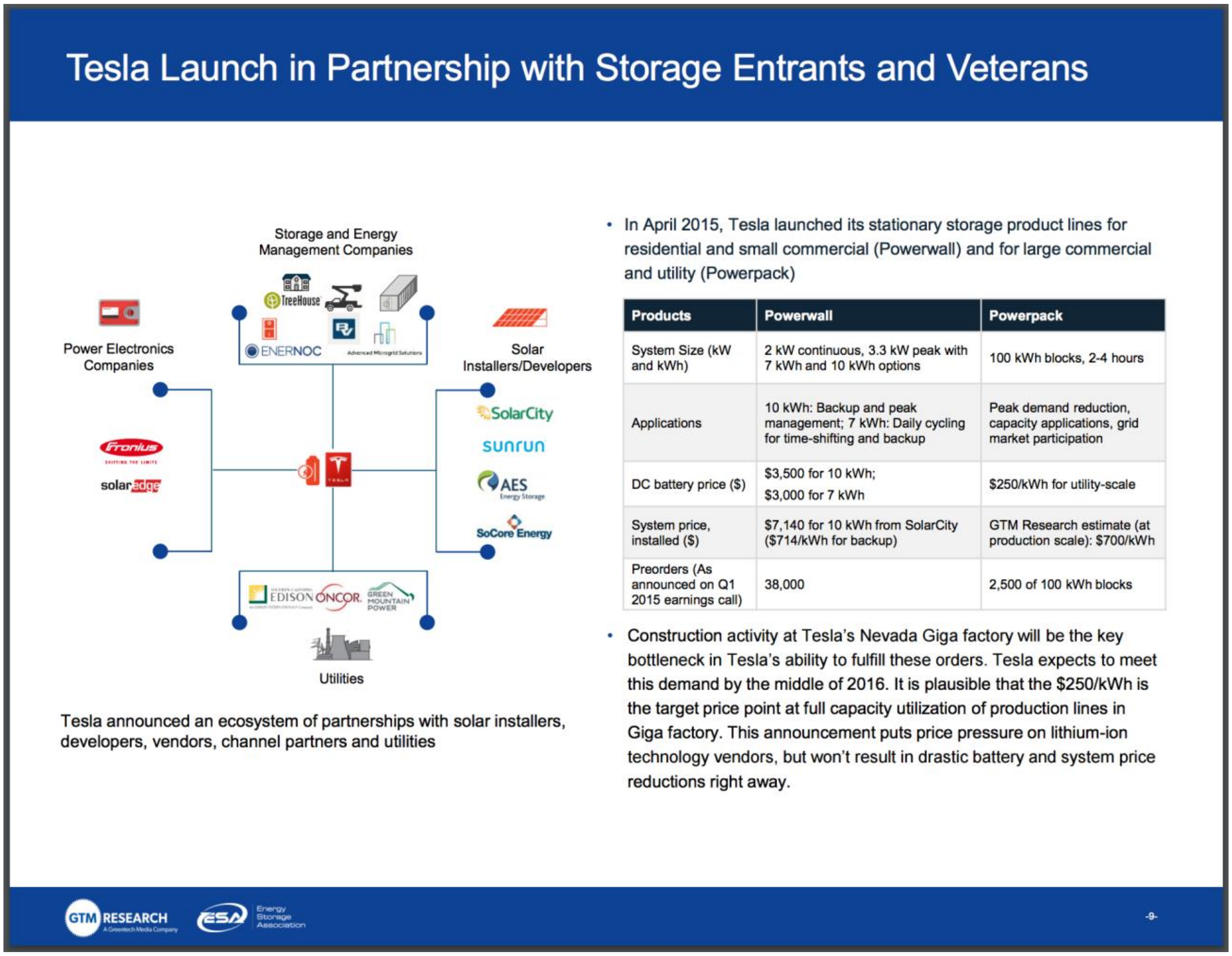


Figure C-6: Slide from http://www.eenews.net/assets/2015/05/28/document_cw_01.pdf

C-15. References

2010 Statewide Residential Appliance Saturation Study (RASS). Prepared for California Energy Commission by Gilmore Research group, 2010. Print.

2011 California Building Energy Efficiency Standards, Measure Information Template – Demand Responsive Lighting Controls. California Utilities Statewide Codes and Standards Team, 2011. Print.

Akhil, Abbas et al. *DOE/EPRI 2013 Electricity Storage Handbook in Collaboration with NRECA*. N.p., 2013. Print.

Churchill, Candice. *Executive Summary: 2015–2025 Demand Response Portfolio of Southern*

California Edison Company. Prepared for Southern California Edison by Nexant, Inc, 2015. Print.

Demand Response Enabled Pool Pump Analysis. Prepared for SDG&E by NegaWatt Consulting, Inc., 2013. Print.

"Energy Incentive Programs, California | Department of Energy." N.p., n.d. Web. 22 Mar. 2016.

Evaluating Electric Vehicle Charging Impacts and Customer Charging Behaviors: Experiences from Six Smart Grid Investment Projects. Department of Energy, Office of Electricity Delivery and Energy Reliability, 2014. Web.

Final Evaluation for San Diego Gas & Electric's Plug-in Electric Vehicle TOU Pricing and Technology Study. Prepared for San Diego Gas & Electric by Nexant, Inc., 2014. Print.

Fitzgerald, Garrett et al. *The Economics of Battery Energy Storage: How Multi-Use, Customer-Sited Batteries Deliver the Most Services and Value to Customers and the Grid. Rocky Mountain Institute, September 2015.* Rocky Mountain Institute, 2015. Web.

George, Stephen, Jonathan Cook, and Andrew Kramer. *2014 Load Impact Evaluation for Pacific Gas and Electric Company's SmartAC Program*. Nexant, Inc. Prepared for PG&E, 2015. Print.

Ghatikar, Girish, Aimee McKane, et al. *Assessing the Control Systems Capacity for Demand Response in California Industries*. Lawrence Berkeley National Laboratory, 2012. Print.

Ghatikar, Girish, Venkata Ganti, et al. *Demand Response Opportunities and Enabling Technologies for Data Centers: Findings From Field Studies*. PG&E/SDG&E/CEC/LBNL, 2012. Print.

Information & Energy Services, Inc. Multi-Family Residential Variable Speed Swimming Pool/Spa Pump Retrofit. Prepared for SDG&E by NegaWatt LLC, 2012. Web.

Katipamula, Srinivas et al. *Small- and Medium-Sized Commercial Building Monitoring and Controls Needs: A Scoping Study*. Pacific Northwest National Laboratory (PNNL), Richland, WA (US), 2012. *www.osti.gov*. Web. 22 Mar. 2016.

Lekov, Alexander et al. "Opportunities for Energy Efficiency and Automated Demand Response in Industrial Refrigerated Warehouses in California." N.p., 2009. Web.

Liu, Zhenhua et al. "Data Center Demand Response: Avoiding the Coincident Peak via Workload Shifting and Local Generation." *Performance Evaluation* 70.10 (2013): 770–791. *CrossRef*. Web.

22 Mar. 2016.

Navigant Consulting. *Assessing Demand Response (DR) Program Potential for the Seventh Power Plan: Updated Final Report*. Prepared for Northwest Power and Conservation Council, 2015. Web.

Olsen, Daniel et al. *Opportunities for Automated Demand Response in Wastewater Treatment Facilities in California - Southeast Water Pollution Control Plant Case Study*. Lawrence Berkeley National Laboratory, 2012. Print.

Olsen, Daniel, Arian Aghajanzadeh, and Aimee T. McKane. *Opportunities for Automated Demand Response in California Agricultural Irrigation*. N.p., 2015. Web.

Pacific Gas and Electric Company Monthly Report On Interruptible Load and Demand Response Programs for January 2015. Pacific Gas and Electric Company, 2015. Print.

Piette, Mary Ann et al. *Costs to Automate Demand Response – Taxonomy and Results from Field Studies and Recent Programs*. Lawrence Berkeley National Laboratory, 2015. Print.

San Diego Gas and Electric (A Sempra Utility) Monthly Report On Interruptible Load and Demand Response Programs. 2015. San Diego Gas and Electric, 2015. Print.

Sezgen, Osman. “PG&E Demand Response Programs: An Overview.” IEEE conference. San Francisco. 2009.

Sullivan, Michael et al. “Using Residential AC Load Control in Grid Operations: PG&E’s Ancillary Service Pilot.” *IEEE Transactions on Smart Grid* 4.2 (2013): 1162–1170. Web.

Thompson, Lisa et al. “Automated Demand Response Opportunities in Wastewater Treatment Facilities.” N.p., Nov. 2008. Web.

Wei, Joy et al. *Wireless Advanced Lighting Controls Retrofit Demonstration*. Lawrence Berkeley National Laboratory, Prepared for the General Services Administration, 2015. Print.

Zakeri, Behnam, and Sanna Syri. “Electrical Energy Storage Systems: A Comparative Life Cycle Cost Analysis.” *Renewable and Sustainable Energy Reviews* 42 (2015): 569–596. *ScienceDirect*. Web. 22 Mar. 2016.

Appendix D: Demand Response Product Framework

Appendix D: Demand Response Product Framework

System-level needs for flexibility and curtailment are what drive the development of existing and new DR capabilities. In this study we use a **DR Products Framework** to match these needs with the capabilities of DR. Each discrete DR product has characteristics that can qualify to meet particular (or a set of) system needs, and through this framework we determine what the level of flexibility for each DR product. Our analysis builds a bottom up approach where technologies and end uses are matched with product requirement and characteristics to determine the capability of providing grid service, and then to assess the costs and benefits.

The Figure C-1 below presents an illustration of grid support products and their nested relationship. The two larger **blue** boxes depict two types of DR: Load Modifying DR and Supply-Side DR. Within each of these **blue** boxes, grid service products are presented in three different colors, indicating how these products are currently, or proposed to be integrated and compensated in the power system. The **purple** boxes indicate a DR product that can be physically delivered to the grid and are be modeled separately by LBNL as a DR product. The **green** boxes illustrate a forward capacity credit, which represents an additional monetary incentive that is available to aggregators, generators, and LSE’s if they are capable of meeting the capacity obligation.

The nesting of the products within each box illustrates the various products’ interrelationships. For example, the **purple** boxes within the supply-side DR box are partially contained within the Peak Capacity (System RA) box, but also transcend this box. This indicates that some Economic (Energy) DR is *not* Peak Capacity DR because it may not meet all of the administrative requirements to be credited with supply capacity but is able to participate in energy markets, similar to today’s Proxy Demand Response (PDR) Resources. The Economic DR box contains three DR products. Spinning Reserve and Regulating Reserve fall within the Non-Spinning Reserve DR product. This illustrates that if an LSE/generator/aggregator can provide Regulating Reserve DR, then they can also provide Spinning and Non-Spinning Reserve DR, and ultimately Economic DR.

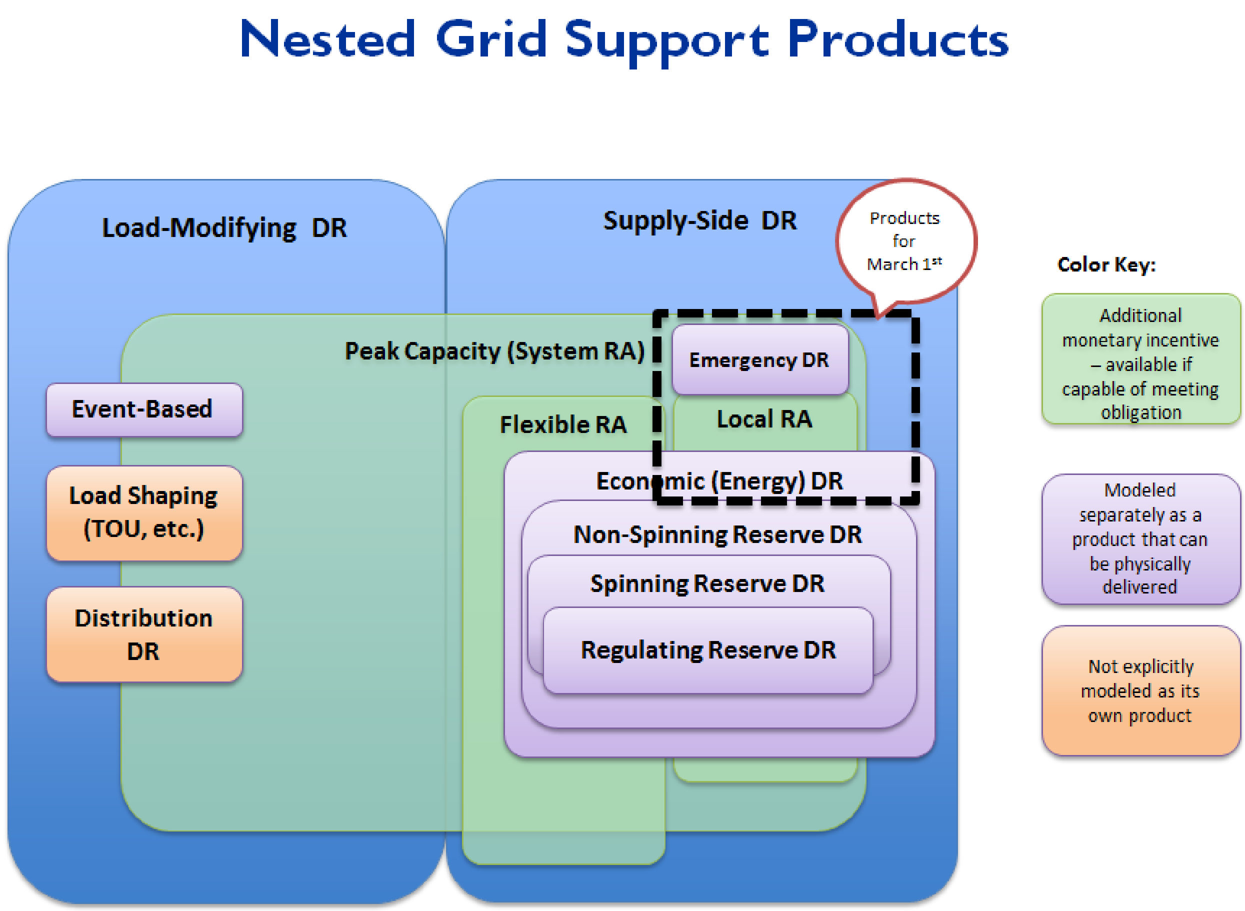


Figure D-1: Nested Grid Support Products. Classification of DR products by Resource Adequacy Capacity Credit, Supply-side, and Load-Modifying Demand Response, illustrating the interrelationship of grid support products.

D-1. Classification of DR Capabilities and System Needs

D-1.1. Defining System-Level Needs

DR is capable of meeting a range of needs in the current and future energy system, including:

- Annual capacity - reduce peak system load to avoid constructing peaking units or purchasing peak power.
- Local capacity - support distribution system operation with local services that defer or eliminate the need to build distribution infrastructure.
- Short-run (seconds to minutes) load-following - reduce instability and provide frequency and voltage support.

- Medium-run (minutes to hours) ramps and curtailment - reduce reliance on unscheduled import / export (area control error) and need for overbuilding flexible conventional generation to match a net load with steep ramps.

The discrete products are defined through a set of qualitative and quantitative **harmonized dimensions of DR**. These dimensions become the foundations for how to describe "products" based on market rules or "programs" that are administered and have a set of rules for participation. Our analysis is agnostic to the choice of market-based or administratively determined products. This framework will allow legacy DR programs (like summer peak shaving or time-of-use pricing) to be described along the same terms as new market- or program-based opportunities for supporting the grid.

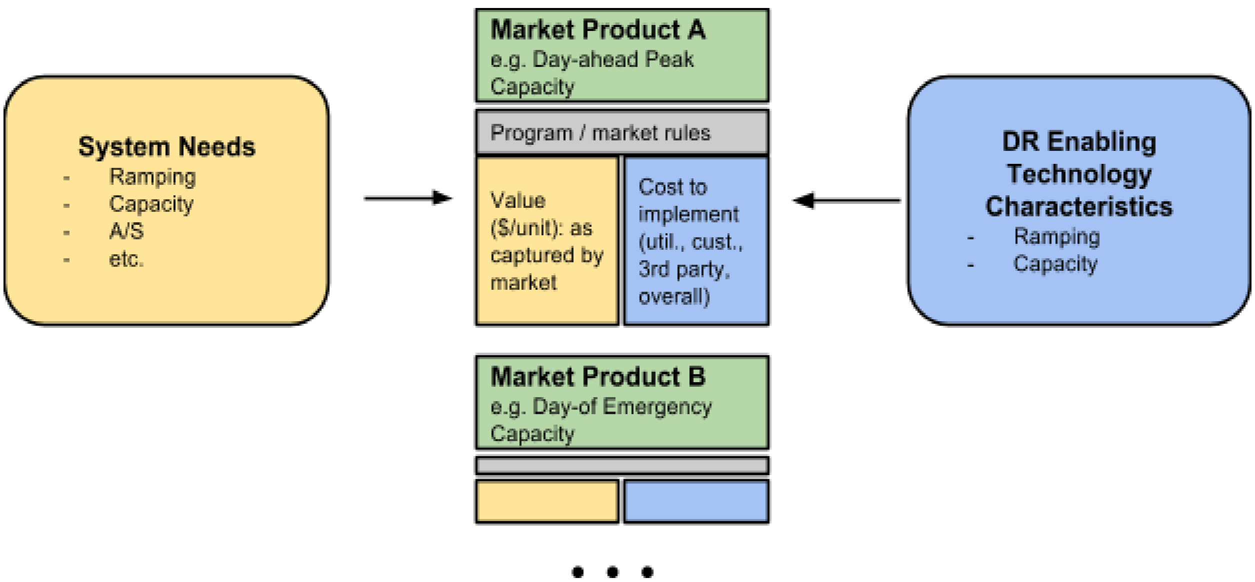


Figure D-2 Framework for markets linking system needs with DR capabilities.

D-1.2. Defining Demand Response Product Technical Characteristics

Table D-1 identifies the end-use technical characteristics, dimensions of DR, and examples of system needs mapped to each technical characteristic.

Table D-1: Mapping of technical characteristics to example system needs.

Technical Characteristic	DR Capabilities Definition	Measurement Categories or Units	Example match to system need
Response Duration	The minimum and maximum duration of time that an event is sustained	Time: e.g., at least in state for 15 minutes and at most for 3 hours	Match duration of need and responsiveness requirements for ramp, peak, or load-following instance
Response Frequency	The number of instances that DR is able to be called in a given period	Number of calls per time period (e.g., 10 air-conditioner curtail events per summer)	Determines whether option value for future performance is important in decision to engage
Response Speed	Time elapsed between system need identification and start of response	Time, e.g., 0	Determines whether valued for frequency / short-run stability support
Ramp Rate	Time elapsed between the beginning of response and full response achieved	Time, e.g., ~0.1 seconds for switched loads, 1 minute for ramped HVAC, etc.	Determines whether valued for frequency / short-run stability support
Charge Requirements - Recovery	The time until the full resource is available again after an event	Hours to 50%, 99% magnitude available	Defines degree to which system needs after event are influenced

D-2. Overall Framing

The technical baseline analysis provides estimates of end-use capabilities to provide DR resources. We classify those end-uses into DR products to meet bulk power system and utility grid needs. The DR products identify what end-uses are capable of providing the system need (based on the technical potential), notification and response requirements, and the types of customer response factors (e.g., response signal, automated or manual response). The DR product characteristics be used to build the supply curves and conduct the economic analysis, where we apply the appropriate costs, benefits, customer enrollment, and customer response assumptions.

DR has traditionally been used to meet system capacity needs during a limited number of hours each year (e.g., 100 to 250 top load hours). Our analysis considers the capabilities of DR to meet both current and future system needs, with both event-driven and everyday DR. Building on current needs, the future need for DR will be driven by integration of variable generation with increasing levels of visibility, connectivity, and control on the demand side.

At a high-level, our classification approach is composed of three steps for each scenario:

1. First, we will **define the system level needs** that DR is capable of providing (e.g., bulk power system and local capacity, intra-hour ramping). These needs lead to requirements for a "product", defined by a particular set of characteristics and a response to meet them (e.g., duration, control signal type).
2. Second, we **map results from the technical potential to match the system needs,** using technology system data that includes (1) the hourly technical potential by end use, (2) their DR performance characteristics (e.g., response duration, ramp rate and control capabilities)[11]. These characteristics are compared with the system needs identified in the previous step to identify times when the technical potential provides system value with the required characteristics, which is a key assumption for the economic analysis.
3. Third, we **identify factors that drive adoption of demand response.** These factors include eligibility, enrollment and investment decisions, different levels of information to support, and day-to-day operational factors. These structural and behavioral factors determine the potential for adoption of "products" that are delivered through markets or programs with certain sets of rules for participation.

A simple example of how system needs translate into a market product that can be matched with DR capabilities is shown in Figure D-3 below. Phase 1 market products and their identified DR characteristics are given in Table D-2.

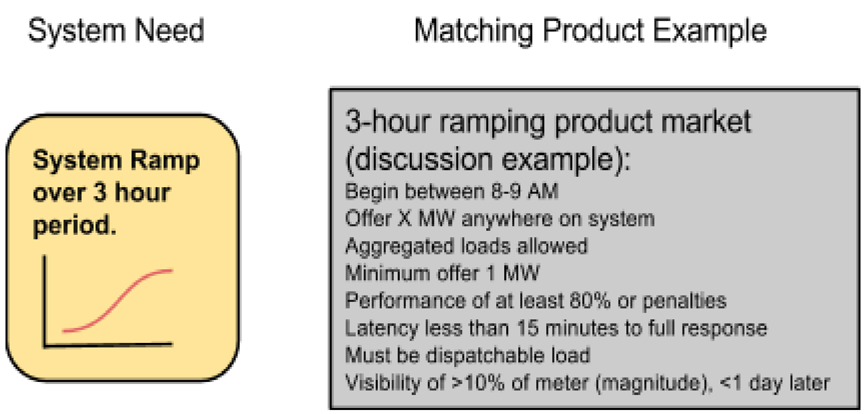


Figure D-3 Example system need and matching product characteristics.

This DR product framework allows legacy DR programs (e.g., residential A/C load control) to be described in similar terms as future DR resources for supporting the grid. This analysis emphasizes evaluating existing market products and how DR fits into the wholesale market.

[11] It is important to note that in step two, the technical potential for each end use is calculated within the DR-PATH model definitions for each end use and DR technology pathway. Detail on the processes of qualifying for a DR product is explained in Appendix C.

D-3. DR Product Market Factors

DR products considered in the study include characterizations of market factors and serve as the foundation of product or program rules and requirements. Existing DR program rules are typically specified through rate tariffs and may define eligibility (e.g., customer class), ability for aggregator enrollment and AutoDR, event signals and triggers, and compensation for participation and event response.

D-3.1.1. Phase 1 & 2 Products

Our study addresses the potential of two supply DR market products for Phase 1:

- Economic Energy Market Participation (aka: Proxy demand resource (PDR))
- Emergency & Reliability Resources (aka: Reliability Demand Response Resource (RDRR))

We assess Local & System Resource Adequacy capacity credits within our framework, quantifying the capacity of RA for each product. We also examine the impact of load modifying demand response, which is evaluated as Time-of-Use tariff.

The DR market product approach is a classification framework to bridge the results of end-use technical baselines and forecast through the supply curve potential assessments.

D-4. Market Products Framework: Phase 1

The DR product approach is intended to serve as an organizational and classification framework to bridge the results of technical potential by end-use and the economic and market potential assessments by products that are more similar to DR programs and the manner in which DR is implemented. Table D-2 shows example DR products organized by system need and with some of the characteristics we will include in the final DR product classification. Where possible, we identify examples of current California IOU DR programs and where they likely fit within the product classification. At a minimum existing wholesale market products will meet CAISO and CPUC RA regulations.

Table D-2: Demand Response Market Products and requirement characteristics modeled in Phase 1.

	Emergency & Reliability Resources (aka: Reliability Demand Response Resource (RDRR))	Economic Energy Market Participation (aka: Proxy demand resource (PDR))
Minimum load curtailment	0.5 MW (500 kW)	Loads may be aggregated together to achieve the minimum participation thresholds below: 0.5 MW (500 kW) for the Non-Spinning Reserve market 0.1 MW (100 kW) for day-ahead & real-time energy
Bid Type	At 95%+ of the price ceiling	Economic bid above Net Benefits Test price
Response time –	Deliver reliability energy in real-time reaching full curtailment within 40 minute.	Energy Market: 5 minutes
Metering & settlement	Not required for market participation	Using AMI
Minimum run time	1 hour.	1 hour
Sustained run time	Up to 4 hours sustained service	Up to 4 hours sustained service
Dispatch type	Discrete (full on/off) dispatch allowed.	Dynamic within ramping constraints
Maximum dispatch for discrete loads	50 MW	N/A
Availability	Must be available for up to 15 Events and/or 48 hours per term during a 6-month summer & winter period running from June through September & from October through May, respectively.	May be called relatively frequently (several times a month or year)

D-4.1. Economic Energy Market Participation (aka: Proxy demand resource (PDR))

Demand response that is bid into the energy market at competitive prices can be thought of as operational or day-to-day DR. It may be called relatively frequently (several times a month or year) depending on the economics of the energy and/or ancillary services market in which it participates. Current CPUC and CAISO rules define an economic market participation product called Proxy Demand Resources (PDR). These PDRs can participate in Day-Ahead (DA) Energy, Real-Time Energy, and Non-Spinning Reserve markets like a generator resource and are valued for RA if they meet certain criteria for performance. For Phase 1 of the study (March 1st) LBNL is modeling participation in Energy markets; in Phase 2 Ancillary Services markets will be included.

Based on the California case and in general terms, we are defining the parameters of Economic DR with respect to modeled technical potential for flexibility in terms of a set of technical and administrative requirements. These are summarized below, with the current set of rules in CAISO noted.

D-4.2. Emergency and Reliability Resources (aka: Reliability Demand Response Resource (RDRR))

Other DR resources may be run less frequently but can still provide important critical operations value to grid operators. These emergency and reliability resources are often entire factories or commercial operations that can be shut down, or may represent other load shed types as well.

In California, RDRR is a wholesale DR product that enables emergency response DR resources to integrate into CAISO market & operations. It is bid into CAISO Day-Ahead Market in response to a reliability event for Real-Time, "reliability energy" delivery. An RDRR may participate in the Day-Ahead and Real-Time markets like a generator resource, but may not submit Energy Self-Schedules, may not Self-Provide Ancillary Services, and may not submit RUC Availability or Ancillary Service bids.

D-4.3. RA Credit

While some payments are available for providing DR resources into energy and ancillary services markets, the bulk of the value of the service is from avoiding the need to procure additional generation capacity. For each of the pathways to RA credit, economic and emergency, the quantity of capacity credit is based on the estimated availability to provide service (as defined by the products above). There are two methods that will be included in the model:

- **Hourly match with expected critical hours (in the version used for this report):** RA credit based comparing hours of product resource availability with loss of load expectation or net load peaks.
- **Simulated market process (planned for future work):** RA credit based on market rules. The flexible DR capabilities are qualified for RA based on the expected ability to bid into market(s) in ways that conform to market obligations, perform compared to market-defined baseline, and perform during expected verification periods

Appendix E: Economic Evaluation

Appendix E: Economic Evaluation

DR benefits are conventionally identified through capacity and energy needs in utility resource and operational plans. In order to thoroughly assess the potential value of avoided generation, transmission, and distribution capacity costs and avoided energy costs due to these DR products, they should be modeled within production cost and operational planning tools representing the full electricity system. However, such a modeling exercise is beyond the scope of our economic assessment. We will instead rely on avoided cost values provided by the California IOUs and explore alternative assumptions in the scenario analysis.

The results of the economic assessment will provide an indication of whether or not particular DR products are likely to be cost-effective given our assumptions and the relative impact of each cost and benefit category on the overall cost-effectiveness assessment. Therefore, the results will not necessarily screen and remove possible DR products based on whether or not they are cost-effective, but instead identify what retail and wholesale market opportunities may be necessary to make the DR products cost-effective.

E-1. Economic Valuation Analysis- Determining the Value of Demand Response

The value of demand response for offsetting capacity depends on how the DR resource lines up with times of system need on the grid. The approach for defining these periods of need in DR-PATH is based on the estimated system wide net load peaks, including any expected load and uncontrolled renewable generation.

Our estimates for the contributions of renewables in future years are based on current-day operations data for utility-scale solar and wind that are reported publicly on the CAISO OASIS service. These are paired with the coincident estimates for weather in each weather case. In the model, for each year and weather case, the generation from the statewide fleet of utility-scale solar and wind renewables estimated based on the expected growth in generation capacity for renewables.

We base the expected trajectory of renewable energy generation on current RPS requirements as interpreted by the CEC (listed below), which were most recently updated with SB350 to put California on track for 50% renewable electricity in 2050.The current (circa 2015) baseline is around 20%, which is a mix of utility scale solar and wind, geothermal, biomass, and small hydroelectric power. About half of that is the utility-scale renewables in the CAISO data. To achieve a ~40% RPS by 2025, the fleet is grown by a factor of four.

The following are CEC defined trajectories for renewables in California[12].

- An average of 20 percent in 2011-2013
- 25 percent by the end of 2016
- 33 percent by the end of 2020
- 40 percent by the end of 2024
- 45 percent by the end of 2027
- 50 percent by the end of 2030
- No less than 50 percent in each multi-year compliance period thereafter

The summary renewable power generation for the model cases we present in this report are shown in figures below.

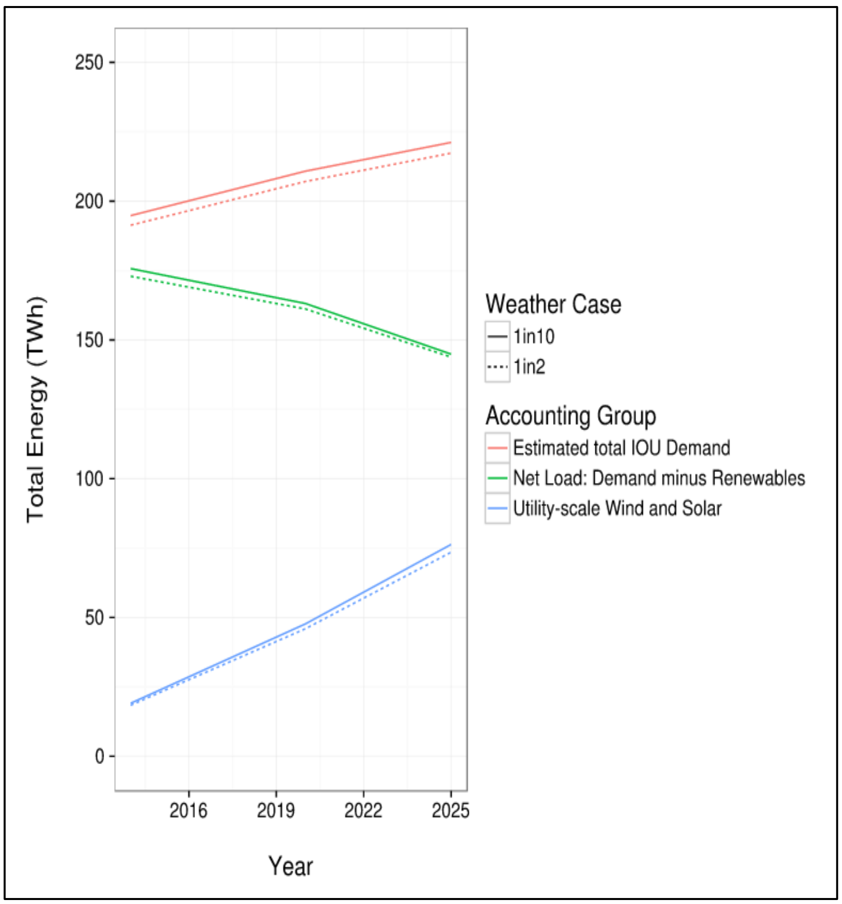


Figure E-1: Total system level (CAISO) energy forecast in MWh for years 2014 through 2025.The lines depict the following groupings: red line: IOU energy demand; green line: net load; blue line: utility scale wind and solar. The dotted line depicts a 1:2 weather scenario, and the solid represents a 1:10 scenario

[12] http://www. energy. ca. gov/renewables/tracking_progress/documents/renewable. pdf

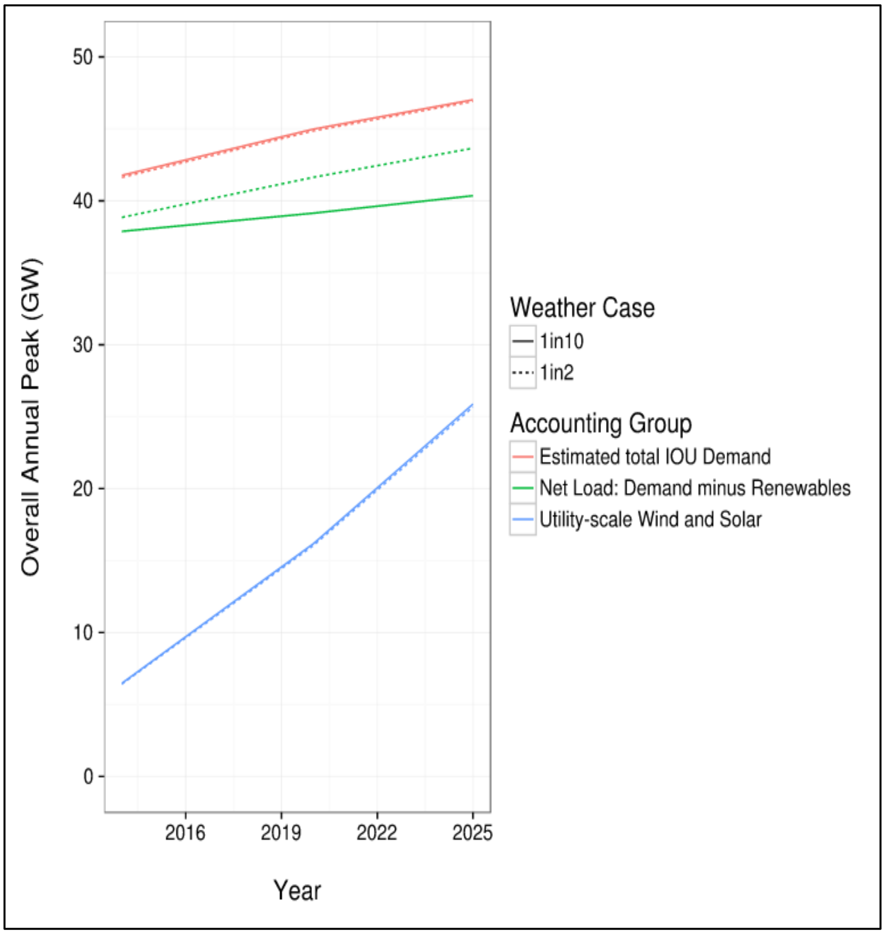


Figure E-2: Total system level (CAISO) peak demand forecast in GW for years 2014 through 2025.The lines depict the following groupings: red line: IOU total demand; green line: net load; blue line: utility scale wind and solar. The dotted line depicts a 1:2 weather scenario, and the solid represents a 1:10 scenario.

In the plots below that detail the daily net load profiles for 2014, 2020, and 2025 (with red dots on the top 250 net load hours), it is notable that while the shape of the net load is radically changed with increasing renewable energy loads the months when the top load hours occur stay the same, albeit with some shuffling of the timing for those hours.

In 1-in-10 weather years the top load hours remain concentrated in the summer months, while the 1-in-2 year includes some peak hours in the winter (a handful from November through February).This suggests that future capacity needs will be determined by year-round possibility of grid needs, but that capacity shortages are still concentrated in the summer, coincident with high peak loads. For additional details as to the development of the Ex Ante Weather and Renewable Generation Forecasts, please see Appendix H.

The DR-PATH model estimates the RA value of DR using the top 250 hours in the net load for each run, using a weighted average value of DR capacity available for bid into supply markets (or expected load impacts for load modifying DR) during those hour. The weights are variable among the top hours depending on the relative net load magnitude, and the ratio in weight between the top hour and the 250th hour is approximately 4:1.

Using this approach is a simplified and useful approximation for the capacity value of DR that could be estimated through more complex models like "loss of load probability" or "estimated load carrying capability" approaches. Ultimately, the value of DR in the market (i. e., the quantity that is paid for) is determined through administrative processes that define how DR is measured and settled, which may or may not match exactly with model-based estimates.

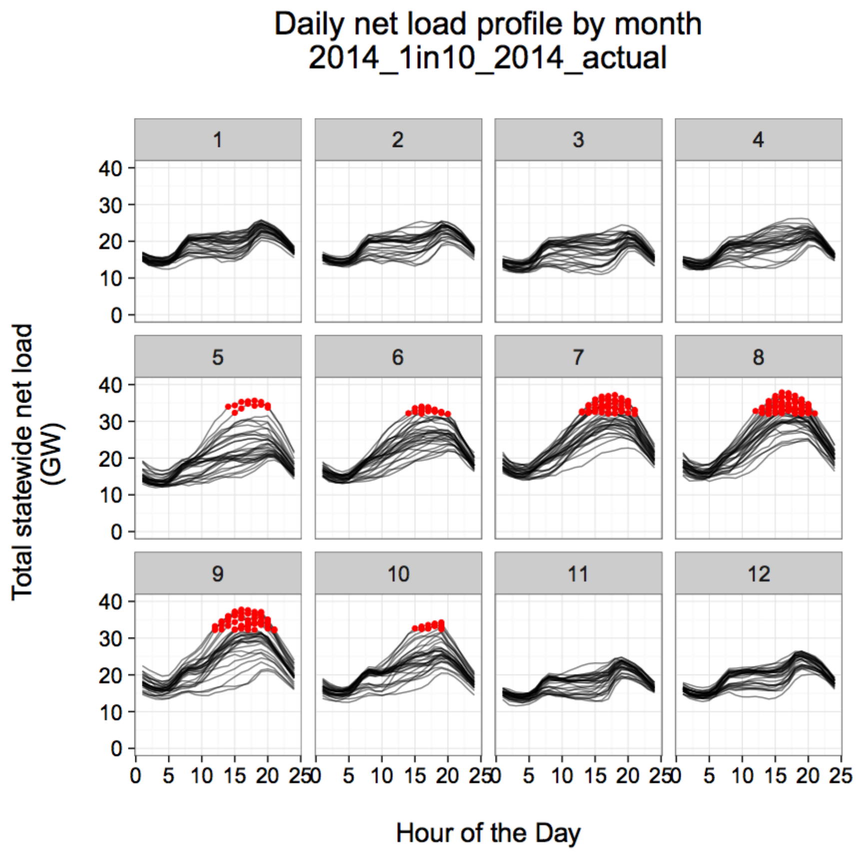


Figure E-3: Daily system level (CAISO) net load forecast in GW for 2014.The red dots depict the top 250 used in the model to calculate RA credit. The graphics depict a 1:10 weather scenario.

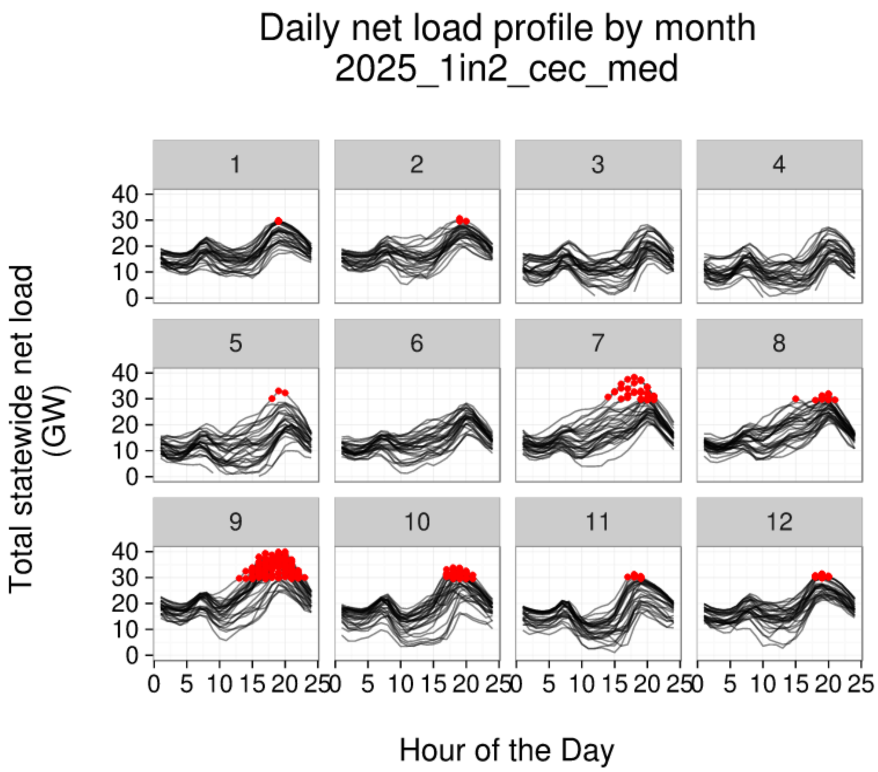


Figure E-4: Daily system level (CAISO) net load forecast in GW for 2020. The red dots depict the top 250 used in the model to calculate RA credit. The graphics depict a 1:10 weather scenario.

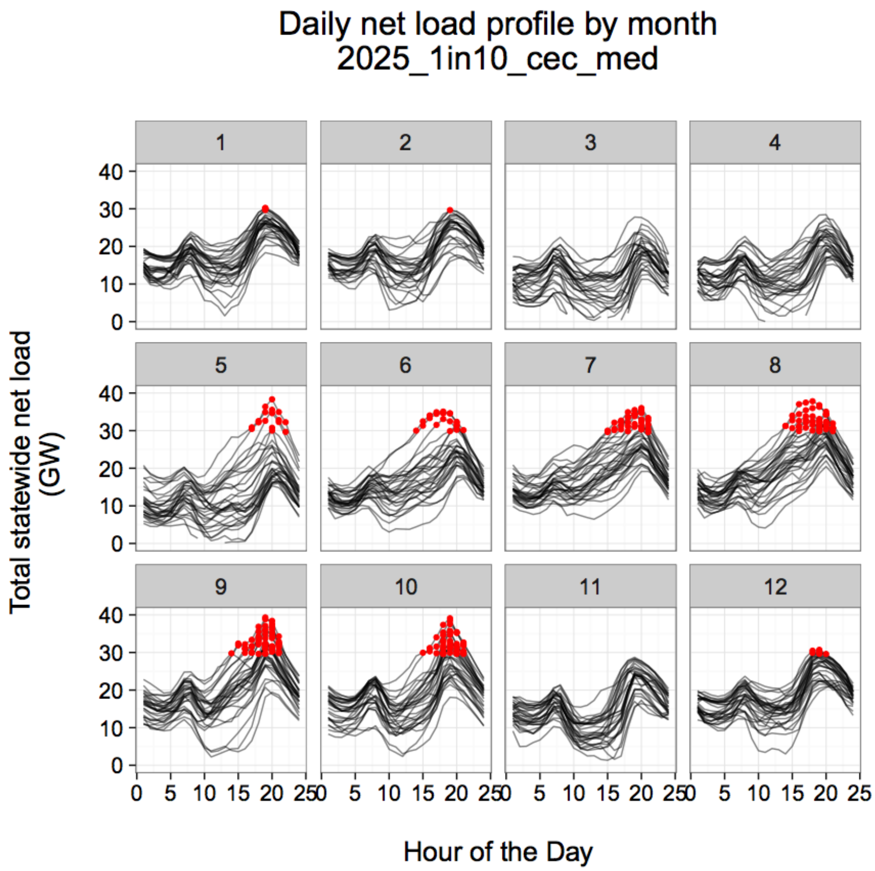


Figure E-5: Daily system level (CAISO) net load forecast in GW for 2025.The red dots depict the top 250 used in the model to calculate RA credit. The graphics depict a 1:10 weather scenario.

Notes on figures above: The progression of the duck curve by 2025, in the 1in2 year, indicated there are peak capacity hours spread throughout the year, concentrated in September. None in June but some in January.

E-2. Economic Valuation Inputs

Once we have identified the top 250 hours in the net load profile as described in the previous section, we assign weights to each of these hours for each year: 2014, 2020, and 2025.These hours are assigned resource adequacy capacity credit weights, or value, for which we assume represent the capacity needs for each year. For each of the DR Products, we match their hourly availability and load reduction capability, effectively determining the capacity for each to contribute to the grid needs. Once the DR products have this capacity value in kW, we are then able to determine what capacity benefits should be assigned, including avoided energy, adjustments for line losses, and T&D benefits.

For the PDR and RDRR DR Products, (i. e. Phase 1 supply DR), the quantity of RA credit (in kW/yr), is calculated by multiplying the 4-hour filter sheddable load fraction for each end-use 8760 hourly load profile. This vector of sheddable load values is multiplied by the vector of relative capacity weights, in this case the weighted top 250 hours (conventional RA calculation), which is based on net system load. These hourly values are summed and adjusted for dispatch reliability, operating reserves, T&D, improvements in performance within the scenarios (BAU, medium, and high), and for changes in the year to year trajectory, (i. e.2020 - 2025).As the source of DR capacity is at the end-user, the RA credit is adjusted for T&D and operating reserves to be consistent with capacity from conventional generation.

E-2.1. Adjustments to performance

- CE Protocols: The protocols include performance adjustments for Operating Reserves and T&D to capture the benefits of DR in the supply market. For example, this adjustment captures the fact that a MW of DR is not equal to a MW from a generator, because the MW from a generator will lose energy/capacity over transmission and distribution lines.
- Adjusted for scenarios: The performance ratios within the BAU, Medium and High scenarios include technology performance improvements for forecasting DR Potential in 2020 and 2025.The performance improvements are captured as increases in the shed factors for each technology.
- Adjustments for year-to-year trajectory: From 2015-2025, the performance of technology for some technologies is expected to improve beyond 2015 levels, which require additional adjustments outside of those performance adjustments made within the scenarios.

E-3. Assigning Economic Value to DR Performance

LBNL utilizes an interim economic analysis methodology that incorporates cost and benefit adjustments from the cost effectiveness protocols that are not already included in our model approach. This methodology provides economic potential values for demand response that meets System and Local RA needs on the grid. The outputs of the analysis detail the influence of expected load-modifying demand response on RA needs and what combinations of DR enabling technologies and targeted end uses can provide economic (energy) DR as a cost effective supply resource. The Phase I study adjusts the avoided costs in the model to account for external benefits as appropriate, based on the benefits and characteristics of each product and technology implementation.

The list below provides a high level overview of the economic potential analysis process, starting with the outputs of the supply curve analysis, which are summarized by an expected quantity of capacity credit (MW-year) available for each cluster at an expected cost level that includes the cost of administration, marketing, transactions, and site-level technology investment, and incentives as appropriate.

1. Identify cost and benefit categories that are external to the expected capacity value of DR, based on existing cost effectiveness protocols
2. Adjust the expected cost of each available DR resource at the cluster level, (e. g., avoided costs of energy, T&D avoided costs, etc.) for hour, month, and year per kW or MW.
3. Adjust the expected quantity of DR available so capacity value is on the same basis as system-level generation (e. g., T&D losses, etc.)
4. Compare the resulting unit cost of DR ($/kW-year) to a price referent benchmark for long-run average capacity cost (e. g. , combustion turbine/capacity value).The DR that is available below this cost threshold is considered to be the "Economic Potential" DR for the given scenario.

Additional adjustments and valuation inputs for determining the benefits for PDR and RDRR are required to appropriately estimate the value of DR in the sub-LAPs and IOU territories. The application, or exclusion, of the various cost-effectiveness protocols, (factors), and the values we used in the model are mapped in Table E-1 below.

Appendix C and Appendix D provide details on the methodology of estimating the costs and value of DR within the DR-PATH model.

Table E-1: The 2015 C/E protocol factor mappings, explanations, and application of these factors for the valuation of DR supply curves and products.

Data used to estimate the Supply Curves & conduct Economic Valuation Analysis	Data Sources & Notes
Availability, dispatch trigger speed, and controllability of DR resource	These are implicitly calculated for each cluster & end-use in the model, based on a weighting function approach.
Avoided transmission capacity costs ($/kW-year)	2020 & 2025 values provided by NEM Public Tool. PG&E-$19. 39; SCE-$23. 34; SDG&E- $21. 34
Avoided distribution capacity costs ($/kW-year)	2020 & 2025 values from the NEM Public Tool. PG&E- $67. 70; SCE-$30. 10; SDG&E- $52. 24
T&D right time-right place adjustment [D Factor]	LBNL assumes that this factor is 100%, with no additional adder. LBNL does not have sufficient information about the needed investments in the IOUs service territories that would enable us to determine whether

Data used to estimate the Supply Curves & conduct Economic Valuation Analysis	Data Sources & Notes
	the locational DR sufficiently defers T&D investments.
Avoided energy and ancillary services' cost ($/kWh-year) by each Sub-LAP	Avoided energy & ancillary services costs based on expected hourly dispatch for DR. Time & weather dependent avoided costs are estimated based on the input data year with historical data from the CAISO.
Payments &/or avoided costs for flexible capacity & other advanced DR products.[F Factor & similar]	Not included in Phase 1; Completed in Phase 2 in integrated investment optimization approach.
Geographic adjustment of capacity value for Sub-LAPs in local capacity constrained areas [G Factor]	Based on CPUC-provided factors from cost effectiveness protocols, by local capacity area: SDG&E-110%; SCE-for Local dispatch in Big Creek-Ventura or the L. A. Basin, the G Factor will be 105%; PG&E- 100%
System-level avoided cost of peak capacity ($/kW-year)	Avoided capacity costs & capabilities to model alternative price referents for sensitivity analysis & to benchmark the model against other scenarios for future avoided cost.2025 capacity costs is modeled at $143 /kW-yr data, as reported in the 2015 CE Protocols.* *The 2014 California Net Energy Metering Public Tool reports the "Net CONE of a marginal capacity resource" as $175 kW/yr*
Avoided GHG costs	GHG price based on the expected future price in California markets. Added to energy prices ~$13/MWh
Avoided Line Losses	Line losses are assumed to be approximately 10%

E-4. Demand Response Valuation Price Referent

The final step in our economic analysis in setting a price referent in the supply curves to estimate the quantity of demand response that is cost competitive. DR that falls beneath the price referent line is considered cost competitive, as it can clear in the market at prices less than the all-in costs of a new CT generator, plus the capacity values for T&D, specific to each utility. The price referent is set at a value of $200/kW within this model, and is comprise of capacity values that were developed in collaboration with the CPUC staff. These values are developed from the recent public tools, including the 2014 California Net Energy Metering Public Tool, E3's avoided costs calculator, and the 2015 C/E protocols.

The price referent is developed by summing the following values:

- **System-level avoided cost of peak capacity ($/kW-year):** The model incorporates the 2025 capacity costs of $143 /kW-yr, as reported in the 2015 CE Protocol
- **Avoided distribution capacity costs ($/kW-year):** 2020 & 2025 values from the NEM Public Tool. For PG&E = $67. 70; For SCE = $30. 10; For SDG&E = $52. 24
- **Avoided transmission capacity costs ($/kW-year):** 2020 & 2025 values provided by NEM Public Tool. For PG&E = $19. 39; For SCE = $23. 34; For SDG&E = $21. 34

E-5. Incorporating the Cost Effectiveness Protocols

LBNL utilized and interim economic analysis methodology for the Phase one deliverable. This methodology provides the CPUC with economic potential values for the PDR, System RA, and Local RA DR products. The outputs of the analysis detail what combinations of DR enabling technologies and targeted end uses for each DR product are cost effective and capable of meeting grid needs at the bulk power system.

The Phase 1 deliverable focuses on the Total Resource Costs Test which include:

- Administrative and capital costs incurred by the LSE
- Participant costs (capital costs to participant + value of service lost + transaction costs)
- Increased supply costs, if any

The economic potential analysis employs hourly energy and avoided cost data. The methodology retains the application of the existing protocols, including the Factors A,B, D, E, F, G, however the manner in which they are applied differs from the cost calculator that has historically be used in the DR cost effectiveness tests. The manner in which the protocols and factors are applied is described below.

The A Factor: The A factor is address in the LBNL model by capturing the DR resource availability by evaluating each hour (8760) for availability. The DR product supply curve method captures: (1) if the end use is in use and available to participate in a DR event, (2) if the technology is able to reduce load per the requirements of the DR product, and (3) how much of the load can be reduced. The available load that can be reduced for each DR product is summed up for each hour. It is then multiplied by the hourly avoided energy and capacity costs. This factor is accounted for in the following equation:

Sum of Load Impacts for each end use in each hour (reduced by DR event) x sum of hourly avoided costs= total benefits.

For phase 1, we applied the costs and benefits hourly to the top 250 hours for each utility, thus approximating the hourly System RA needs.

The B Factor: Our model captures the ability of a resource to respond based on the enabling technology and the end use, which is captured in each product's 8760-hour supply curve. The requirements for each product (e.g. response time, notification, etc.) are built into the assumptions around controllability and availability of the resource when developing the supply curves. This factor is applied during the development of the 8760 for each DR product, which are developed based on the requirements for that DR product to participate in the market.

The C Factor: This factor was removed during recent modifications to the C/E protocols.

The D Factor: Represented as a factor that is computed by comparing the non-coincident peak for each IOU service territory to the coincident system peak using CEC system load forecasts. For DR that can address both system and T&D peaks, and can avoid or defer T&D investments the D factor can be greater than 100%.In as much, the valuation of these DR supply curves should capture the right time and right place for each DR product and grid need combination. LBNL will assume that this factor is 100%, with no additional adder. LBNL does not have sufficient information about the needed investments in the IOUs service territories that would enable us to determine whether the locational DR sufficiently defers T&D investments.

The E Factor: The LBNL model incorporates hourly avoided energy price data provided by each utility. LBNL incorporates this as an hourly avoided energy calculation where hourly load impacts are multiplied by the hourly energy prices. It is treated as a benefit that offsets the costs of providing DR in the market.

The F Factor: Not included in Phase 1; to be incorporated in Phase 2 in integrated investment optimization approach.

The G Factor: The D Factor accounts for those DR resources that can be called locally in the resource constrained regions. For each IOU Sub-LAP, each supply curve evaluates DR at that level, and therefore, considers the available DR resource within that geographic area, and it does assume the ability to trigger the resource with geographic specificity. LBNL's model uses the G-factor adder for augmenting local capacity value in areas where DR provides additional local benefit as described in protocol update. The factors are applied as the adders defined below:

Table E-2 G Factor Adder from 2015 CE Protocols

Utility	G Factor Adder from 2015 CE Protocols
SDG&E	110%
SCE	0% for DR programs that can only be dispatched in the entire service territory.

	For Local dispatch in Big Creek- Ventura or the L. A. Basin, the G Factor will be 105%.
PG&E	For PG&E, there is no adder for the G Factor. Thus the G Factor is 100%

LBNL evaluates the economic value of the System and Local RA (Peak Capacity) Supply- Side Energy DR product (PDR and RDRR) by creating supply curves (8760) for each product. These supply curves incorporate the above C/E factors and avoided costs, as specified above. The methodology for determining the economic potential for each DR Product is done by applying the avoided costs and the adjustment factors from the C/E protocols to each of the supply curves as hourly benefits. LBNL then determines how much DR is available given a range of dollar values (i. e., where the supply curve of DR meets a given price of capacity; below that price is "cost effective"). LBNL believes that this is a transparent and accurate methodology of determining the quantity of DR available in the market for each specific price.

Appendix F: Enrollment rates

Appendix F: Enrollment Rates

The magnitude of DR resources that can be acquired is fundamentally the result of customer preferences, program or offer characteristics (including incentive levels), and how programs are marketed. How predisposed are specific customers to participate in DR? What are details of specific offer and how do they influence enrollment rates? What is the level of marketing intensity and what marketing tactics are employed? Enrollment rates are a central element of estimating achievable DR potential.

Many DR potential studies rely on top down approaches which benchmark programs against enrollment rates that have been attained by mature programs. This approach, however, has several drawbacks in the context of California.

- The study is designed to the next generation of DR applications, which not only includes meeting peaking capacity, but also new and recent applications such as resources to meet longer and larger sustained ramps (ramping capacity), fast response to address renewable volatility and multiple up and down ramps throughout the day, and shifting of loads to avoid over-generation in the middle of the day. For most of these applications, there are no mature existing programs against which to benchmark.
- Aggregated program results often do not provide enough detail to calibrate achievable market potential. In many cases, programs are not marketed to all customers, either because of it is not cost-effective to market to all customers or budgets are limited. Enrollment rates are a function of specific offers and the extensiveness of marketing over many years. They also vary based on the degree to which DR resources are utilized. Enrollment rates tend to be higher when payments are high but actual events are infrequent, particularly among large C&I customers.
- Many jurisdictions rely on back-up or behind the meter generation for DR. California customers are required to deliver reductions and are not allowed to fire up back-up generators in response to curtailment events. Many jurisdictions including PJM, NYISO, and ISO-NE, a substantial share of DR, roughly 30–40%, is delivered via backup generation and not delivered through load reductions.
- DR programs have been exhaustively marketed to large C&I customers. Every large customer at PG&E, SCE, and SDG&E has been offered several types of DR options and has made a decision about whether or not to participate.[13] As a result, approximately 35% and 70% of large non-residential customers and loads,

x

respectively, are enrolled in some type of DR program. On the other hand, mass market programs for residential customers and small and medium businesses have relied on highly targeted efforts due to the substantial differences in climate and end-use saturation across California.

The optimal approach for estimating enrollment levels is to rely on choice models that quantify three main components: which customers are more predisposed to enroll, how the offer/program characteristics influence enrollment rates (e.g., number of events, penalties, incentive levels, need to install devices, etc.), and how specific marketing tactics such marketing approach (i.e., direct mail, phone, or door-to-door), number of times a customer is contacted and other marketing factors influence participation rates.

The approach employed to estimate participation rates involved five general steps, the details of which are explained in the following sections;

1. Estimate an econometric choice model based on who has and has not enrolled in DR programs. The goal of this model is to estimate the pre-disposition or propensity of customers to participate in DR based on their characteristics.
2. Incorporate information about how different offer characteristics influence enrollment likelihood. What is the incremental effect of incentives? How do requirements for on-site installation affect enrollment rates? The two questions above have been analyzed using California specific data for residential customers. In each case, regression coefficients describe the incremental effect of each of the above factors on participation rates.
3. Incorporate information about how marketing tactics and intensity of marketing influence participation rates. What is the effect of incremental acquisition attempts? Is there a bump in enrollment rates when phone and/or door-to-door recruitment is added to direct mail recruitment?
4. Calibrate the models to reflect actual enrollment rates attained with mature programs. To calibrate the models the constant is adjusted so that the model produces exactly the enrollment rates observed by mature programs used for benchmarking.
5. Predict participation rates using specific tactics and incentive levels for programs with and without installation requirements. The enrollment estimates were produced for low, medium, and high marketing levels, where specific marketing tactics are specified for each scenario. All estimates reflect enrollment rates for eligible customers. For example, if 25% of eligible customers can be enrolled but only 40% have central air conditioners, the attainable penetration rate for AC load control is 10% (25% x 40%). The assumptions about marketing tactics underlying the enrollment projections are not prescriptive. Utilities can attain the enrollment levels in a number of ways.

Appendix A provides a conceptual overview of probit models and background to understand how coefficients can be extracted from aggregate level tests.

F-1. Key Assumptions and Data Sources

Table F-1 summarizes the data sources employed for each step of the estimation and model calibration. The data used to estimate enrollment predisposition and to calibrate results reflect a compromise between incomplete data and the need to produce the results given those constraints. Data was not available for all programs and utilities and did not include information regarding acquisition marketing attempts and offers to customers. It relied exclusively on participation among the eligible population, which inherently assumes that all customers received the same amount of acquisition marketing offers.

Table F-1 Data sources and calculations employed.

Step		Residential	Small and medium businesses	Large C&I
1	Econometric choice model to establish pre-disposition or propensity to participate	- SCE air conditioner load control program and opt-in Peak Time Rebate data - Adjusted for eligibility by including air conditioner likelihood variable in econometric model - PG&E and SDG&E residential participation data was incomplete or unavailable	- Granular data about participation and acquisition marketing for SMB customers was not available. - The pre-disposition of specific industries/building types to participate was estimated using customers with less than 400 kW in annual max demand.	- Large customer participation data at PG&E, SCE, and SDG&E. - Enrollments from default CPP were screened out since the focus was on program enrollment. - Assumes all large customers have been offered DR options by account representatives or aggregators
2	Effect of offer characteristics	- Effect of incentive level is based on PG&E publicly available choice analysis of various incentive levels.[14] - Effect of installation requirements on enrollment assessed by comparing SmartAC and SmartRate	- Incentive level coefficient from residential model used and adjusted downward by 25% - The effect of the installation requirement was doubled. This was a judgmental adjustment based on experience with field	- Effect of incentives and average number of events derived by comparing customers with enough load to be eligible for BIP on their own (>100 kW on a 24/7 basis) versus incentives and participation by customers too small to participate on BID on their own.

[14] George, Bode, Perry, and Goett (2010). 2009 Load Impact Evaluation for Pacific Gas and Electric Company's Residential SmartRate, Peak Day Pricing, TOU Tariffs, and SmartAC Programs: Volume II. PG&E implemented a number of marketing tests. The analysis and results are detailed in Section 4.1 of Volume II.

	Step	Residential	Small and medium businesses	Large C&I
		enrollment after controlling for customer characteristics, incentive levels and marketing offers.	recruitment.	
3	Influence of marketing tactics and intensity of marketing	- Decreasing effect of incremental touches is derived from publicly available choice analysis. - Effects of phone, and door-to-door marketing were derived from field experience from PG&E's ancillary service pilot.[15]	- Incentive level coefficient from residential model used and adjusted downward by 40%	No known variation in marketing techniques. Assumes phone calls plus in-person follow up by account representatives or aggregators.
4	Calibration and benchmarking	- Models were calibration to participation levels attained by mature DLC programs, after controlling for AC saturation.	- Calibrated to SDG&E Summer Saver non-residential program. It is one of the SMB programs with the highest penetration in the U.S.	No calibration used. This approach assumes that additional reductions and grid applications will come from increasing reductions and/or DR automation from existing participants.

The data sets used and the propensity scores will be updated for the final report with more comprehensive data, if it is provided.

For residential customers, we only relied on SCE air conditioner load control and peak time rebate program data to estimate customer's predisposition to participate based on their characteristics, including geography, size, and their low income status as identified by participation in CARE. PG&E and SDG&E data regarding residential load control data wasn't available or was incomplete. Developing the estimates required controlling for eligibility based on the likelihood of owning air conditioning (a variable estimated by LBNL). The propensity scores were estimated using a probit model that took in to account both the likelihood of owning

[15] Sullivan, Bode, and Mangasarian (2009). 2009 Pacific Gas and Electric Company SmartAC Ancillary Services Pilot. See section 4.4 Enrollment/Recruitment.

air conditioning and an indicator variable that identified if a customer was in a grouping of customers within a particular climate zone, decile of annual usage, and whether they were enrolled in CARE. The estimated constant and coefficient from the customer grouping can be interpreted as the propensity of that group to enroll in a DR program, adjusted for eligibility. The models were subsequently calibrated to data regarding penetration as a percentage of eligible sites based on a survey of large mature load control programs.

Enrollment rates for SMB customers (<200 kW) were the most challenging. Until recently, most SMB customers were not eligible for most DR programs, with the exception of AC load control, because they lacked smart meters. Both SDG&E and SCE have marketed load control to SMB customers with package air conditioning units for multiple years, but the granular data for those programs and acquisition marketing campaigns was not available. As a result, the pre-disposition of customers to participate was estimated using customers with annual max demand below 400 kW as a proxy. We then incorporated coefficients quantifying the influence of marketing tactics from residential studies, and calibrated the models based on SDG&E SMB load control penetration. SDG&E has enrolled roughly 4,800 customers and over 11,000 package air conditioning units. In total, we estimate that 6% of SMB eligible customers have enrolled.[16] Historically, enrollment rates for SMB customers have been lower than in any other segment for DR and energy efficiency programs.

Large customer enrollment rates were estimated based on actual participation data. As noted earlier, every large customer at PG&E, SCE, and SDG&E has been offered several types of DR options and has made a decision about whether or not to participate. This approach assumes that additional reductions and grid applications will come from improving or increasing DR automation from existing participants rather than adding a large number of new participants. Enrollments from default CPP were screened out when possible, since the main topic of interest was program enrollment. To assess how the number of expected dispatch hours affects enrollment levels, we incorporated information from the 2012 FERC DR survey, which canvassed utilities that make up over 90% of loads in the U.S.

Table F-2 summarizes key assumptions about marketing tactics associated with different marketing levels. Different marketing levels – low, medium, and high – were constructed to allow customization of marketing tactics and intensity for specific customer types. This allows

[16] We estimate that roughly 85,000 of SG&E's 130,000 SMB account are eligible for load control. Many accounts are not buildings (e.g., sprinkler systems, utility boxes, bill boards, etc.), not all buildings with SMB customers have air conditioning, and not all non-residential air conditioners are package units.

for value-based targeting approach were segments with a high expected benefits may receive more extensive marketing. The specific tactics included in the low, medium, and high marketing scenarios are not prescriptive but are instead designed to provide concrete details about the assumptions used. There is a wide range of strategies and tactics that can attain the same enrollment levels and utilities should be encourages to develop, test, and optimize their own marketing strategy. In each instance enrollment rates were modeled under a wide range of incentive amounts to allow the potential model to quantify achievable potential with different incentive levels.

Table F-2 Summary of Marketing Tactics Underlying Enrollment Rate Projections.

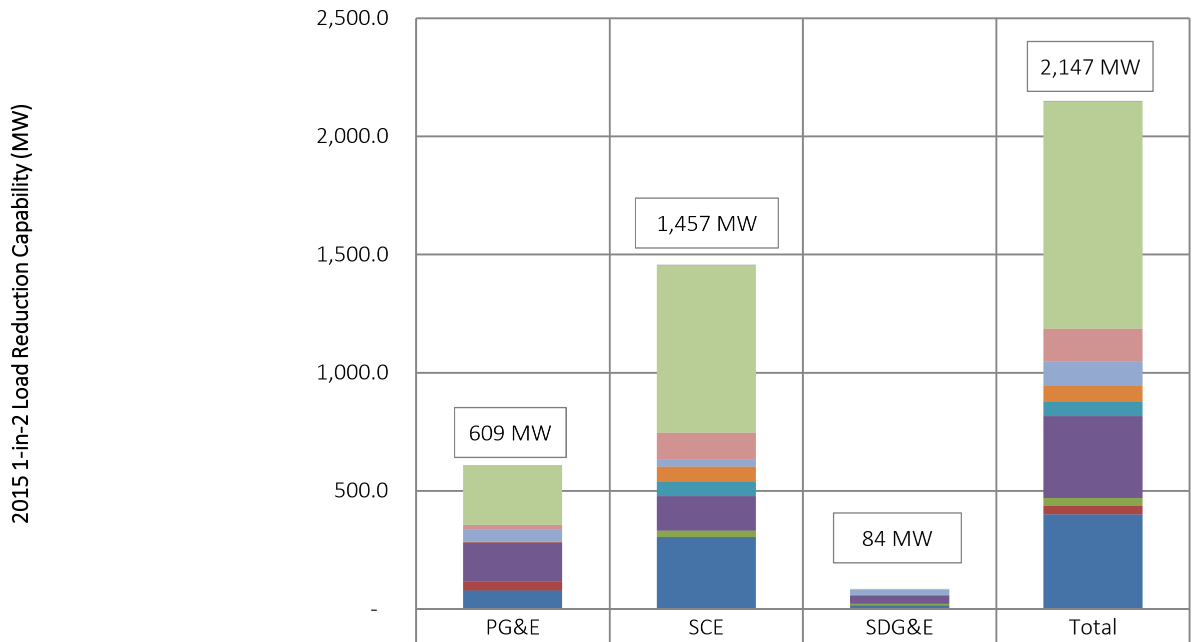
Sector	Marketing Component	Marketing Level		
		Low	Medium	High
Residential	Incentive	0-$200 per customer per year	0-$200 per customer per year	0-$200 per customer per year
	Number of marketing attempts	3	5	5
	Outreach mode	Direct Mail	Direct Mail	DM + Phone
	Years to Reach Achievable Potential	3	5	5
SMB	Incentive	0-$200 per control device	0-$200 per control device	0-$200 per control device
	Number of marketing attempts	5	5	8
	Outreach mode	Direct Mail	DM + Phone	DM + Phone
	Years to Reach Achievable Potential	5	5	8
Large C&I	Incentive	0-$200 per kW-year	0-$200 per kW-year	0-$200 per kW-year
	Number of marketing attempts	8		
	Outreach mode	In-person account reps or vendors		
	Years to Reach Achievable Potential	7		

F-2. Current Participation Rates and Benchmarking

California has several unique aspects that affect DR penetration – a very diverse climate, limited humidity during heat waves, a ban on use of back-up generators for demand response, and TOU rates with large on-peak price signals (for large C&I). For the purpose of this study, it is useful to assess the level of penetration of DR in California, benchmark it with other programs in the U.S. and identify key differences.

Figure F-1 summarizes the demand reduction capability in August 2015 under 1-in-2 weather year conditions. For some programs, such as air conditioner load control, the resources available are substantially larger under extreme conditions when they are needed most. Across the three major investor owned utilities, 2,147 MW of load reduction capability was available in 2015. This represents 4.6% of the 1-in-2 weather peak loads in CAISO (47,188).[17]

[17] CAISO. *2015 Summer Loads and Resources Assessment.* Available at: www.caiso.com/Documents/2015SummerAssessment.pdf



	PG&E	SCE	SDG&E	Total
Non-Res - Real time pricing		2.5		2.5
Non-Res - Interruptible rates	252.1	707.8	1.0	961.0
Non-Res - Demand bidding	21.0	114.5	2.6	138.1
Non-Res - Critical peak pricing	51.5	29.8	20.9	102.2
Non-Res - Air conditioner load control	2.7	64.3	3.1	70.1
Non-Res - Agricultural pump control		59.4		59.4
Non-Res - Aggregator programs	165.7	147.2	34.7	347.6
Residential - Peak time rebates		27.0	5.3	32.3
Residential - Critical peak pricing	36.9			36.9
Residential - Air conditioner load control	78.9	304.5	17.0	400.3

Figure F-1 Existing Demand Reduction Capability at California Investor Owner Utilities. Source: Utility Monthly reports on interruptible load and demand response programs. Filed with the CPUC (A.11-03-001).

As part of its annual *Assessment of Demand Response and Advanced Metering*, FERC compares the potential peak reductions in organized markets in the U.S. Table F-3shows this summary for 2014. In comparison to the reminder of the U.S., participation in California is lower than what has been achieved elsewhere. However, the comparisons should not be made directly because of differences in what gets classified as Demand Resources (versus Demand Response). Two of the markets with the highest penetration – the ISO-NE and PJM – both include a substantial amount of behind-the-meter generation and energy efficiency. In MISO, over 4,200 MW or roughly 40% of resources are behind the meter generation. Once these adjustments are incorporated, the overall penetration at ISO-NE, MISO, and PJM are 2.5%, 5.3%, and 4.1%, respectively, and are comparable or lower than penetration in California. With the exception of ERCOT, participation of DR is mainly as capacity resources. ERCO is unique in that it relies on DR primarily to deliver synchronized contingency reserves.

Table F-3: Potential Peak Reduction from U.S. Independent System Operators

	2014 Potential Peak Reduction (MW) [1]	% Peak Demand [1]		Includes behind-the-meter generation?	Includes energy efficiency?
California ISO (CAISO)	2,316	5.1%		No	No
Electric Reliability Council of Texas (ERCOT)	2,100	3.2%		Yes, but the amount is not publicly posted	No
ISO New England (ISO-NE)	2,487	10.2%		Yes, approximately 300 MW [2]	Yes, approximately 1600 MW [2, 3]
Midcontinent Independent System Operator (MISO)	10,356	9.0%		Yes, 4,200 MW [4]	No
New York Independent System Operator (NYISO)	1,211	4.1%		Yes, but the amount is not publicly posted	No
PJM Interconnections, LLC (PJM)	10,416	7.4%		Yes, approximately 2,700 MW [5]	Yes, approximately 1100 MW [6]
Southwest Power Pool, Inc. (SPP)	48	0.1%			
Total ISO/RTO	**28,934**	**6.2%**		Over 7,200 MW	Approximatey 2700 MW

[1] FERC (2015). *Assessment of Demand Response and Advanced Metering* . Page 12. Available at: http://www.ferc.gov/legal/staff-reports/2015/demand-response.pdf

[2] ISO-NE Demand Resource Enrollment Statistics as of February 24, 2016. http://iso-ne.com/static-assets/documents/2016/02/a01_intro_drwg_mtg_02_24_2016.pptx

[3] ISO Key Grid and Market Stats. http://www.iso-ne.com/about/what-we-do/key-stats

[4] https://www.misoenergy.org/Library/Repository/Market%20Reports/Demand_Response_Participation.pdf . Publish date 2/02/2016.

[5] PJM 2015 Load Response Activity Report , February 2016. https://www.pjm.com/~/media/markets-ops/dsr/2015-demand-response-activity-report.ashx

[6] Neme, C., Energy Futures Group, and Cowart, R., Regulatory Assistance Project. (2014) *Energy Efficiency Participation in Electricity Capacity Markets – The U.S. Experience.* Montpelier, VT: The Regulatory Assistance Project. Available at: http://www.raponline.org/document/download/id/7303

Comparisons of aggregate resources across utilities are also challenging. We caution against drawing strong conclusions from aggregate program results. Programs are not always marketed to all customers and strategies and incentives to recruitment customers vary substantially. But perhaps most importantly, the share of customers with specific end-uses, such as air conditioners, and the magnitude of those loads can vary substantially. Nowhere is this more evident than for residential air conditioner load control programs.

F-3. Achievable Participation Rates

Figure F-2 summarizes achievable enrollment rates for residential customers as a function of incentive levels and marketing intensity. Attainable participation rates range between 20% and 30% for eligible customers, with higher levels of marketing intensity. The participation estimates are linked the eligibility, which is often related to whether a customers have a specific end use.

In a territory like SDG&E's, where approximately 50% of customers have central air conditioners, the achievable penetration as a percentage of the population would be half as large as shown in the figure because only half of the customer meet pre-requisite criteria. The participation rates increase with higher incentives, but higher incentives have diminishing returns. Overall enrollment rates reflect the cumulative effect of repeated attempts to enroll customers.

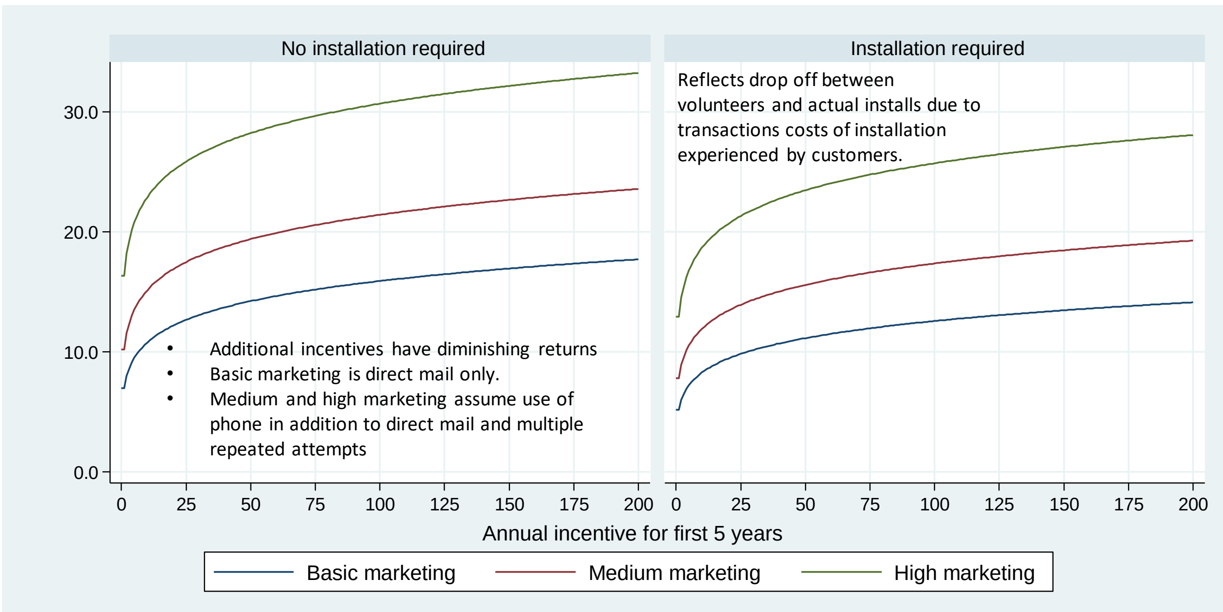


Figure F-2: Achievable Residential Participation Rates by Incentive and Marketing Level.

Figure F-3 also summarizes achievable enrollment rates for small and medium customers as a function of incentive levels and marketing intensity. At the highest, the projections for SMB customers are roughly half of residential achievable participation rates. They are substantially lower when installations are considered. It is important to note that the estimates rely heavily on assumptions since data on SMB programs was available for the initial draft estimates. Historically, small and medium businesses have been difficult to enroll in demand response, energy efficiency, or pricing programs. They tend to lack dedicated energy managers, often are busy and thus difficult to engage, and prefer to avoid interruptions to their businesses.

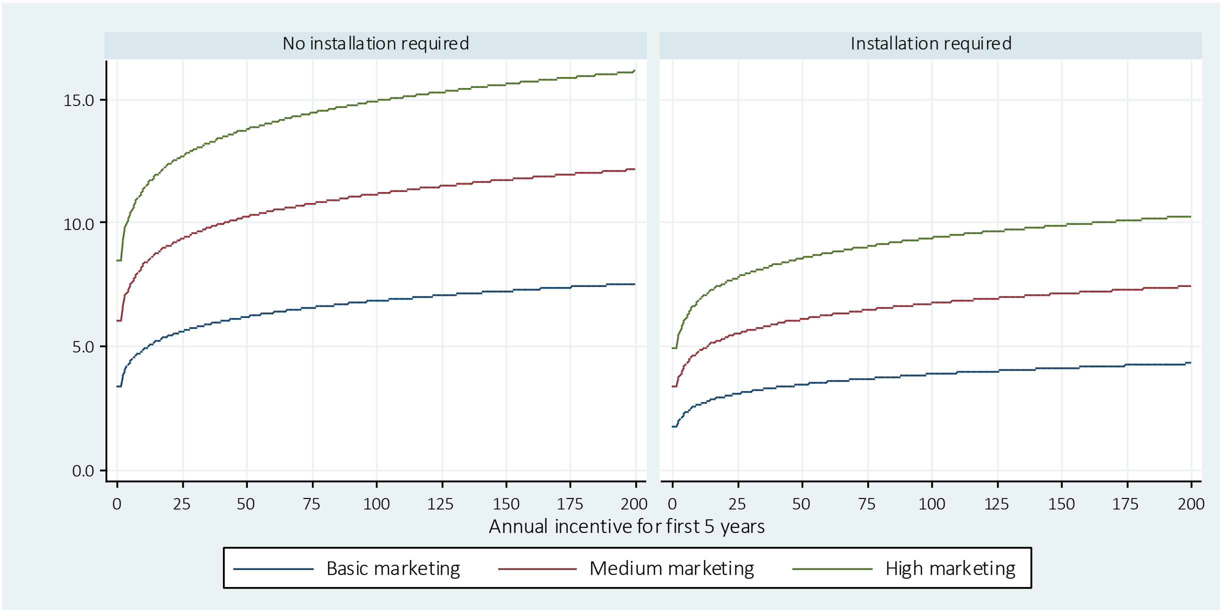


Figure F-3: Achievable Small and Medium Business Participation Rates by Incentive and Marketing Level.

Figure F-4 show how the projected achievable enrollment rates vary by building type, assuming high marketing efforts, and incentives of $50 and $100 per device. Projected participation rates are highest for water pumps and sprinklers, retail stores, and light industrial facilities.

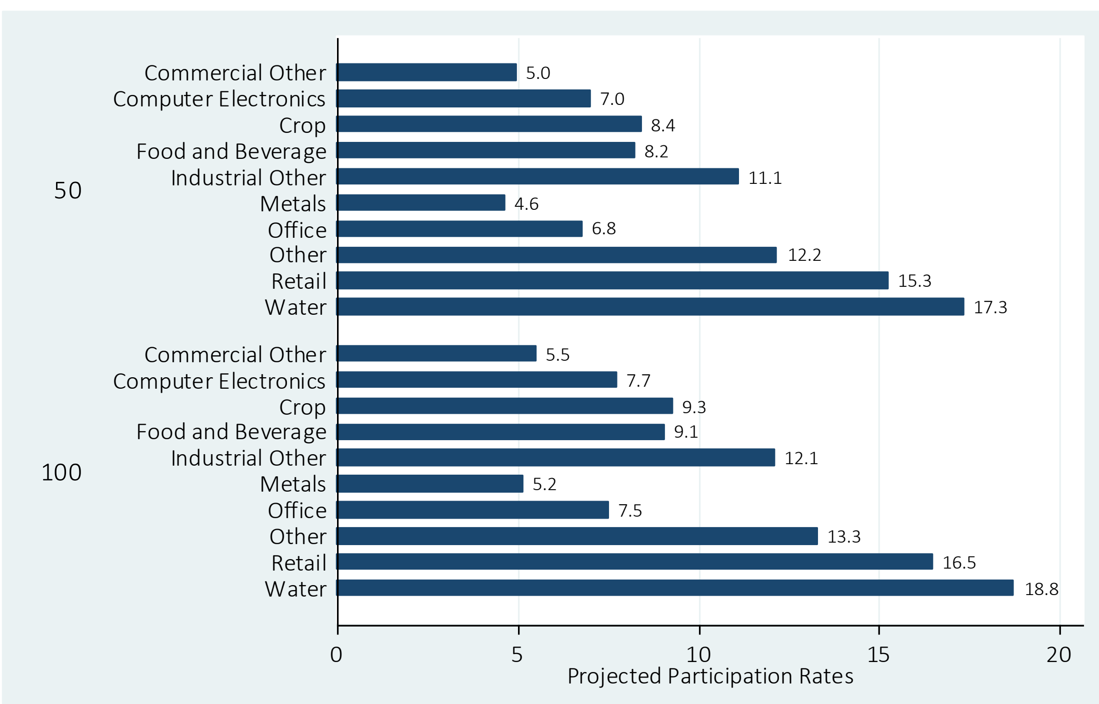


Figure F-4: Comparison of Participation Rates by Industry (High Marketing Scenario).

For large C&I customers (>200 kW), the achievable participation rates vary based on a number of factors: industry, customers size, incentive levels, and the expected number dispatch hours (which is different than a cap on annual dispatch hours). Figure F-5summarizes overall enrollment rates a functions of incentives, in $kW-year, and different expected number of dispatch hours. The projected participation rates do not reflect policies such as default critical peak pricing and simply reflect opt-in participations rates into programs. Enrollment levels are lower when large customers are dispatched more frequently but are paid the same incentive.

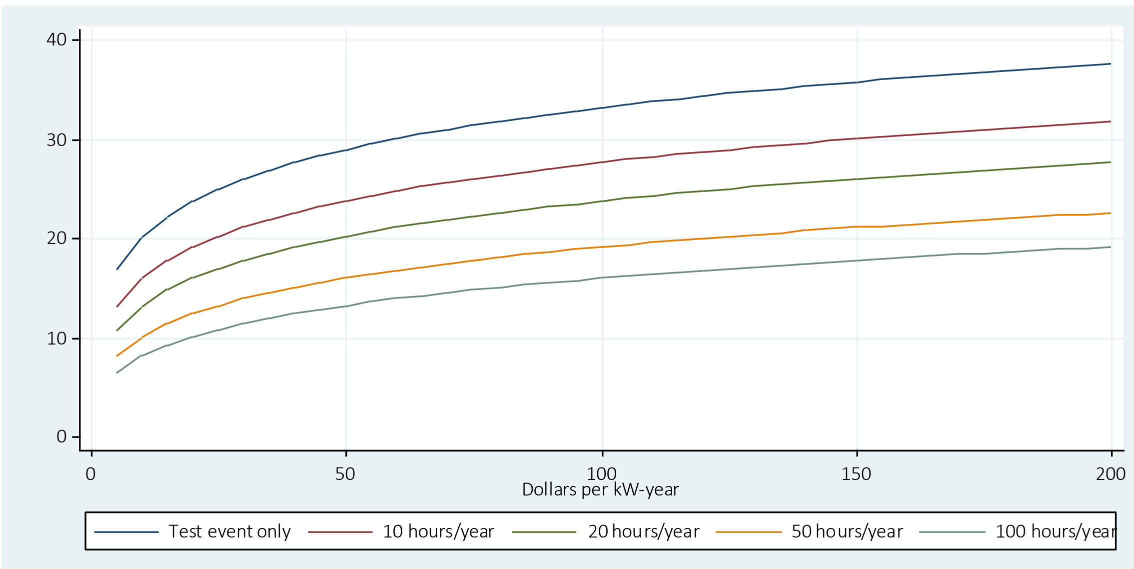


Figure F-5: Achievable Large C&I Participation Rates by Incentive and Average Annual Dispatch Hours.

Figure F-6 provides a different perspective and reflects that participation rates decrease when customers are called more often (holding all other factors constant). A key question is how to better integrate DR into markets without exhausting it prematurely. DR resources typically have low or no start-up costs and can deliver demand reductions for a short time period at little or no cost because of inherent storage in the form of heating, cooling or production stock. However, the more often and the longer DR is dispatched, the more expensive it becomes for businesses to sustain the reduction. Customers do not necessarily forego production when they reduce demand; more often than not, they either reduce a nonessential end-use load or are able to shift production to a different time period or day. Frequent or prolonged dispatch can inhibit the ability to shift or make up production for consumers who rely on this means to provide demand response.

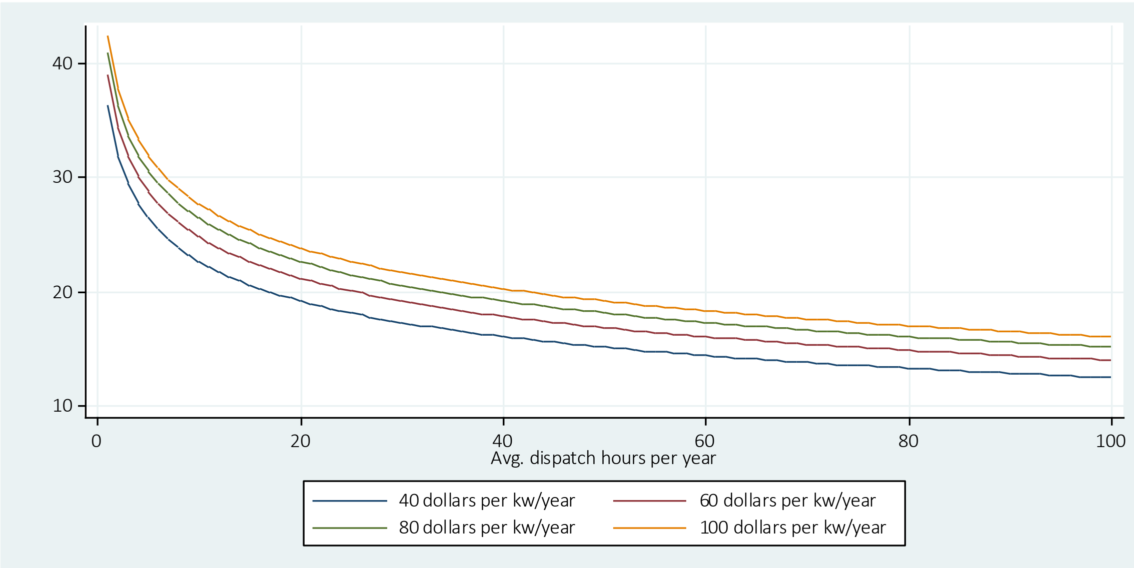


Figure F-6: Large C&I Effect of More Frequent Dispatch on Achievable Participation

Table F-4 summarizes achievable participation rates by industry and size if resources are dispatched on a limited basis, when the system is strained and capacity is needed or as contingency reserves. Table F-5 shows achievable participation rates with more frequent use, averaging 40 dispatch hours per year. In general industrial facilities are more likely to participate while offices are month the least likely to do so.

Table F-4: Achievable Participation Rates by Industry and Customer Size (Limited use scenario - $80/kW-year).

Building type or Industry	Less than 250 MWh	250-500 MWh	500-1,000 MWh	1-2 GWh	2-4 GWh	Over 4 GWh	All
Chemical	20.9%	32.8%	21.4%	22.7%	30.7%	36.3%	**27.0%**
Commercial Other	29.7%	45.9%	31.5%	30.9%	41.0%	47.4%	**37.5%**
Computer Electronics	14.8%	21.9%	14.1%	14.4%	22.3%	28.7%	**18.8%**
Crop	28.1%	46.0%	31.1%	27.4%	35.1%	35.9%	**34.3%**
Food and Beverage	26.4%	33.7%	23.9%	24.2%	32.5%	41.9%	**32.6%**
Industrial Gas			41.4%	40.6%	51.4%	79.6%	**67.1%**
Industrial Other	20.3%	32.8%	20.7%	21.7%	29.6%	38.9%	**26.3%**
Metals	20.9%	32.9%	21.2%	23.0%	33.3%	40.4%	**27.4%**
Offices	10.8%	17.0%	9.1%	9.6%	15.5%	19.8%	**12.1%**
Other		31.7%	15.4%	17.1%	25.3%	25.4%	**20.2%**
Petrol	32.9%	39.0%	22.1%	21.9%	30.2%	42.5%	**30.7%**
Plastics and Rubber	31.4%	47.1%	34.6%	32.7%	43.2%	52.9%	**42.1%**
Refrigerated Warehouses	41.5%	58.8%	45.3%	45.5%	48.8%	51.7%	**48.7%**
Retail	35.5%	52.4%	35.2%	36.7%	45.8%	49.7%	**40.3%**
Water	42.5%	60.5%	46.6%	43.5%	47.7%	46.3%	**47.4%**
Waste water facilities	28.8%	52.3%	33.2%	30.9%	32.0%	41.9%	**35.4%**
All	**30.5%**	**44.6%**	**26.6%**	**26.8%**	**34.8%**	**39.4%**	**31.9%**

Table F-5: Achievable Participation Rates by Industry and Customer Size (Frequent use scenario – Avg. 40 hours per year at $80/kW-year).

Building type or Industry	Less than 250 MWh	250-500 MWh	500-1,000 MWh	1-2 GWh	2-4 GWh	Over 4 GWh	All
Chemical	13.4%	22.8%	13.8%	14.8%	21.1%	25.8%	**18.2%**
Commercial Other	20.3%	34.4%	21.8%	21.2%	30.0%	35.8%	**27.0%**
Computer Electronics	9.0%	14.1%	8.5%	8.7%	14.5%	19.4%	**11.9%**
Crop	19.0%	34.5%	21.4%	18.5%	24.8%	25.4%	**24.3%**
Food and Beverage	17.6%	23.6%	15.7%	15.9%	22.6%	30.8%	**22.9%**
Industrial Gas			30.3%	29.6%	39.6%	70.1%	**56.9%**
Industrial Other	12.9%	22.8%	13.2%	14.0%	20.2%	28.1%	**17.7%**
Metals	13.4%	22.9%	13.6%	15.0%	23.3%	29.4%	**18.6%**
Offices	6.2%	10.6%	5.1%	5.5%	9.5%	12.6%	**7.1%**
Other		21.9%	9.4%	10.6%	16.7%	16.9%	**13.0%**
Petrol	23.0%	28.2%	14.3%	14.2%	20.7%	31.3%	**21.3%**
Plastics and Rubber	21.7%	35.5%	24.4%	22.7%	32.0%	41.0%	**31.1%**
Refrigerated Warehouses	30.4%	47.0%	33.9%	34.1%	37.1%	39.9%	**37.1%**
Retail	25.1%	40.6%	24.9%	26.1%	34.3%	38.0%	**29.4%**
Water	31.3%	48.8%	35.0%	32.2%	36.1%	34.8%	**36.0%**
Waste water facilities	19.5%	40.5%	23.2%	21.3%	22.2%	30.7%	**25.1%**
All	**21.2%**	**33.5%**	**18.2%**	**18.4%**	**25.1%**	**29.0%**	**22.7%**

Appendix G: Price Responsiveness to Residential Time Varying Rates

Appendix G: Price Responsiveness to Residential Time Varying Rates

Residential response to time-based pricing is primarily driven by end-uses that are temperature dependent, most notably air conditioning. For a given group of customers, the percent load change is highly dependent on the temperature conditions for a given day as well as the penetration of AC amongst those customers. Therefore, this study aimed to develop estimates of load modification as a function of AC saturation and average daily temperature. These results were generated for low income and non-low income customers in summer, winter, and shoulder months.

To understand how residential customers will respond to time varying rates, this study used empirical estimates of demand elasticity for a range of temperature conditions and calibrated them for a range of AC saturation levels. The key assumptions, data sources, and methodology are described in the following sections.

G-1. Key Assumptions and Data Sources

This study relied on estimates of price responsiveness from the SMUD SPO study's analysis of customers who were defaulted onto time of use (TOU) pricing. It was assumed that the price responsiveness (which is expressed in the form of elasticity) of these customers was representative of all California residents, though the values needed to be adjusted to account for a variety of AC saturation levels, which is described in more detail later in this section. These elasticity numbers are presented in Table G-1. In this table, EAPR refers to the Energy Assistance Program Rate (low income status).

Table G-1: SMUD SPO Elasticity Estimates for Default TOU.

EAPR	Quartile	All Electric	EOS	EOS_CDD	DAILY	DAILY_CDD
EAPR	1	0	-0.015	-0.001	-0.045	0.003
EAPR	2	0	0.043	-0.003	-0.229	0.012
EAPR	3	0	-0.038	-0.003	-0.097	0.005
EAPR	4	0	-0.048	-0.003	-0.144	0.008
Non-EAPR	1	0	0.007	-0.006	-0.298	0.017
Non-EAPR	2	0	0.002	-0.006	-0.175	0.011
Non-EAPR	3	0	-0.063	-0.005	-0.079	0.004
Non-EAPR	4	0	0.030	-0.007	-0.154	0.007
EAPR	1	1	0.053	0.000	-0.069	-0.003
EAPR	2	1	-0.004	-0.004	0.056	-0.005
EAPR	3	1	-0.045	0.002	-0.289	0.015
EAPR	4	1	0.029	-0.005	-0.221	0.004
Non-EAPR	1	1	-0.051	-0.006	-0.720	0.036
Non-EAPR	2	1	-0.071	-0.004	-0.347	0.018
Non-EAPR	3	1	-0.098	-0.003	0.053	-0.002
Non-EAPR	4	1	-0.115	-0.002	0.092	-0.001

Elasticity measurements are provided for each quartile of energy consumption and consist of four components: the elasticity of substitution (EOS) constant, the daily elasticity constant, and the cooling degree days (CDD) component of the EOS and daily elasticities. EOS is a measure of how much electricity usage will shift from the peak to off peak period of the day as a function of the intraday price ratio. Daily elasticity is a measure of how overall electricity usage for the day will change in response to the change in the average daily rate. Since this study is attempting to understand how electricity usage behavior will change compared to the status quo, we compare the average electricity rate under a TOU rate to the flat rate that customers are currently paying. For each of these elasticity measures, there is a constant component and a component that varies as a function of CDD, which is defined as either zero or the average daily temperature minus a base temperature value (in this case 65°F), whichever is greater. CDD is a common predictor of how much air conditioning will be used.

Because response to TOU is highly dependent on AC saturation while these elasticity measurements are only applicable to customers in the SMUD service territory (where AC saturation is 89%), a relationship between load impact and AC saturation was needed in order to adjust these elasticity measurements for a range of AC saturation levels. This relationship was derived by using publicly available load impact results from the 2012 evaluation of PG&E's SmartRate program. Though this is an opt-in CPP program, it was assumed that the relationship between load impact and AC saturation from this program could be applied to default TOU pricing.

G-2. Elasticity Estimation Methodology

Uncalibrated elasticity estimates were generated for a range of average daily temperatures (40°F to 94°F) by combining the constant and CDD components of the daily and EOS elasticities presented in Table G-1 for each temperature level. However, because these elasticity estimates from the SMUD SPO study were generated using a sample that only included average daily temperatures ranging from 57°F to 88°F, elasticities for temperatures outside of this range were capped to the max/min values observed.

These elasticity estimates were based on customers in the SMUD service territory, where AC saturation is approximately 89%. However, in areas with significantly lower AC saturations, customers will deliver far less load reduction on average. To understand how load reduction from time varying prices is a function of AC saturation, the estimated load impacts from the 2012 PG&E SmartRate program evaluation was used to build a regression model with load impact as a function of AC saturation. Load impact estimates from this study are presented in Table G-2. In this table, CARE refers to California Alternate Rates for Energy (low income status) and “CAC Ownership Likelihood” refers to customers who fall in different categories of likelihood of owning AC. Customers who are dually enrolled (also enrolled in the SmartAC program) necessarily own AC, and therefore have a likelihood of 100%.

By using the midpoint of each CAC ownership likelihood category, it was possible to derive a linear regression for percent load impact as a function of AC saturation. Using these regression outputs for each income class of customer, the load impact was estimated for customers at a variety of AC saturation levels, including 89%. For each AC saturation level, a scaling factor was calculated by dividing the estimated load impact by the load impact at an AC penetration rate of 89%.

Table G-2: 2012 SmartRate Load Impact by Likelihood of AC Ownership.

CARE	CAC Ownership Likelihood	Percent Impact
Non-CARE	0-25%	13%
Non-CARE	25-50%	12%
Non-CARE	50-75%	19%
Non-CARE	75-100%	20%
Non-CARE	Dually Enrolled	28%
CARE	0-25%	5%
CARE	25-50%	4%
CARE	50-75%	3%
CARE	75-100%	7%
CARE	Dually Enrolled	20%
All	0-25%	11%
All	25-50%	8%
All	50-75%	10%
All	75-100%	13%
All	Dually Enrolled	25%

These scaling factors were then applied to the uncalibrated elasticity estimates to produce EOS and daily elasticities for a variety of AC saturation levels. The resulting set of elasticities can be used to estimate change in load reduction using the following pair of equations. The first equation expresses the ratio of peak and off-peak energy use as a function of an intercept term and the ratio of peak and off-peak prices,

$$ln\left(\frac{Q_1}{Q_2}\right) = a_{12} + b_{12} * ln\left(\frac{P_1}{P_2}\right) \tag{1}$$

where Q_i is electricity use in period *i* in kWh/hour and P_i is the price of electricity in period *i*. The term a_{12} is the intercept and b_{12} is the EOS. Equation 1 captures tradeoffs in electricity consumption that occur between rate periods in the same day.

The second equation pertains to daily electricity consumption and has the following specification:

$$ln(Q_d) = c + d * ln(P_d) \tag{2}$$

In this equation, Q_d is the total electricity consumed in a day and P_d is the average price for that day, which is a weighted average of the peak and off-peak prices. Equation 2 is often called the daily equation since it captures changes in electricity consumption at the daily level that result from changes in prices and the term *d* is the daily elasticity.

G-3. Load Impact Estimation Methodology

Once calibrated elasticity estimates were derived, it was possible to estimate load impact percentages at each AC saturation and average daily temperature level. This was done for rate option #2 for PG&E from the statewide TOU pilot that is currently being designed and implemented by the TOU Working Group, which was formed by the CPUC to help understand the impact of future TOU rates in California. This rate option is illustrated in Table G-3. Additional rate options can be evaluated, and will be considered in the future. However, for now, load impact estimates were just generated for this rate option, which includes a three part tariff in the summer, and a two part tariff in the non-summer months. This rate option was compared to a flat rate of $0.217/kWh, which represents the likely flat rate that will be in effect in PG&E's service territory in 2016 based on an advice letter that was submitted to the CPUC. This rate represents the alternate rate option that customers will have available to them, and is similar in structure to the rate that most residential customers are currently on in California.

Calculation of the load impact percentages was fairly straightforward, using the previously described equations. An hour-weighted average daily rate was calculated for the TOU tariff and used to find the percent change in rate compared to the flat rate. This was combined with the daily elasticity to find how much overall electricity consumption changed for the day. Price ratios between peak, part peak, and off peak periods were combined with EOS elasticities to find how much electricity usage was shifted between various periods of the day. The result was hourly percent changes in load for different income levels and seasons at various AC saturation and average daily temperatures.

Table G-3: Residential TOU Rate

Season	First Off Peak Period			First Part Peak Period			Peak Period			Second Part Peak Period			Second Off Peak Period		
	Rate ($/kWh)	Start Hour	End Hour	Rate ($/kWh)	Start Hour	End Hour	Rate ($/kWh)	Start Hour	End Hour	Rate ($/kWh)	Start Hour	End Hour	Rate ($/kWh)	Start Hour	End Hour
Summer	0.295	12am	4pm	0.402	4pm	6pm	0.459	6pm	9pm	0.402	9pm	10pm	0.295	10pm	12am
Non-Summer	0.241	12am	6pm	-	-	-	0.263	6pm	9pm	-	-	-	0.241	9pm	12am

Appendix H: Ex Ante Weather and Renewable Generation Forecasts

Appendix H: Ex Ante Weather and Renewable Generation Forecasts

Rather than use a single year of historical weather for modeling, which fails to capture the range of possible conditions in any given month, it is better to produce two sets of weather predictions: one that represents a "mild" year and one that represents and "extreme" year. This section describes the process by which "mild" (1-in-2) and "extreme" (1-in-10) weather forecasts were derived for the 54 weather stations involved in the study. To maintain consistency, renewable generation forecasts that align with the 1-in-2 and 1-in-10 forecasts were also produced, which is also described in this section.

H-1. Weather Forecasts

Weather data was downloaded from weatherspark.com for all 54 NOAA stations for a 20-year period, from 1996 through 2015. The main variables of interest were temperature, cloud cover fraction, and wind speed. Because some weather stations did not keep complete information of these variables, especially in the earlier years and during late night/early morning hours, data was restricted to a 15-year period, from 2001 through 2015. Even then, there were some weather stations with significant data gaps. These gaps were filled by using a combination of techniques, as described below, which was repeated for gaps in temperature, cloud cover fraction and wind speed separately.

First, the data was subset in to two equal and mutually exclusive samples by taking data from alternating days to create two datasets. This was done to ensure robust predictions of the missing weather. For the first of these two datasets, known as the in-sample dataset, the 2001 through 2015 weather variable of interest (either temperature, cloud cover fraction, or wind speed) for a particular weather station (the reference station) was regressed against the same variable for each of the other weather stations (the candidate stations) in sequence to generate regression models that could be used to make predictions. The model specification took the form of:

$$y_r = \alpha + \sum_{h=1}^{h=24} \beta_h * y_{h,c} + \sum_{m=1}^{m=12} \beta_m$$

In this equation, α is a constant and β_h is a coefficient that explains how the outcome variable of interest, y_r, changes with each unit of change of the candidate station for each hour h. For example, if β_h was equal to 2, and the regression was estimating a missing weather station temperature, the coefficient would indicate that for every degree Fahrenheit at the candidate station, the reference station would be twice as hot during that hour. By including β_m, the regression also takes in to account the monthly average temperature at the candidate station, which allows predictions to vary according to the season.

Each of the models were then used to predict the reference station's weather, and the candidate weather station was selected based on choosing the candidate model that resulted in the lowest root mean squared error (RMSE) between the prediction and the out-of-sample (or withheld) days. For each reference weather station, the candidate weather station's data with the lowest RMSE was used to predict the missing data from the reference weather station. Root mean squared error is a measure of goodness of fit of an estimate, and is calculated according to the following formula:

$$RMSE = \sqrt[2]{\frac{\sum_{i=1}^{i=N}(\hat{y}_i - y_i)^2}{N}}$$

Where N is the number of observations, $\hat{y}_i$ is the estimated variable of interest, and $y_i$is the observed value at the reference station. Large values of the RMSE indicate that there is a poor fit of the prediction, or a large difference between $\hat{y}_i$ and y_i. Because the difference between the predicted and observed variable is squared, RMSE does not take in to account the directional bias of an estimate. Values of the RMSE for temperature ranged from 1.6 degrees to 5.7 degrees, with a median RMSE equal to 2.7.

This process reduced the number of missing data points by one to two orders of magnitude. However, in some cases both the reference station and the selected candidate station had a missing data point at the same time, so a prediction could not be generated. In these cases, which represented about 1% of total observations, a multi-level approach was taken to interpolate these missing values. For days with only one missing data point, the missing temperature value was calculated by averaging the prior and subsequent hour's temperature. For reference weather station days that had more than one missing data point at this point, the missing data was filled in by taking the average of the prior and subsequent days' temperature at the missing hour(s). This process was iteratively repeated 5 times, reducing the number of missing values by two to three orders of magnitude. The small number of data points that were still missing – approximately 0.001% of all observations – was interpolated using that day's average value.

For each weather station, the average daily temperature was calculated for each month of each year, which was then used to calculate the average CDD (cooling degree days) and average HDD (heating degree days) with a base of 65°F for each. These values were used to identify which years exhibited moderate and extreme weather conditions for each month. CDD values were used to classify the months of April through October, while HDD values were used for the remaining months. These values were then averaged across all of the weather stations.

The ex ante weather forecasts were built by identifying individual months from different years that are representative of average and extreme conditions, and combining those individual months of weather data to create two full years (one for average, or 1-in-2, weather conditions and one for extreme, or 1-in-10, weather conditions). The year in which the median CDD/HDD value was observed for each month was identified, and the month of weather data associated with that year was used to build the 1-in-2 weather forecast. A similar process was used to identify the months that would build the 1-in-10 weather forecast, but by identifying the CDD/HDD values that fell in the 90th percentile rather than the median. The weather forecasts that were built for 1-in-2 and 1-in-10 conditions contained hourly temperatures, as well as hourly cloud cover fraction and wind speed.

H-2. Renewable Generation Forecasts

Renewable generation forecasts needed to be built that would match the weather forecasts. However, it was not possible to simply combine the historical renewable generation profiles that match up with the historical weather data in the 1-in-2 and 1-in-10 weather forecasts, since much of the renewable capacity in California had not yet been built in those historical periods. Instead, actual renewable data from 2014 was used to build the generation forecasts.

To do this, each day in the ex ante weather forecast was matched up with actual 2014 weather data for weather stations that were closest to major utility-scale renewable resources. Renewable generation profiles from those days in 2014 were combined to produce 8760 generation profiles for the 1-in-2 and 1-in-10 weather years. For this, utility scale renewable generation data was pulled from the CAISO website, which breaks down utility-scale renewables into five different profiles: solar profiles for northern California, southern California, and central California and wind profiles for northern California and southern California. Based on the location of these resources, weather stations were mapped to these profiles as indicated by Table H-1.

Table H-1: Renewable Resources Weather Station Mapping.

Renewable Type	Zone	Corresponding Weather Station
Solar	North (NP15)	Sacramento Exec. Airport
Solar	South (SP15)	29 Palms
Solar	Central (ZP26)	Meadows Field Bakersfield
Wind	North (NP15)	Livermore
Wind	South (SP15)	Edwards AFB

Matching between the ex ante forecasts and 2014 actual weather data was accomplished using a propensity score matching technique. In this process, certain weather metrics, called match variables, are calculated for each day of weather data for the ex ante and historical weather datasets. Each individual day from the ex ante forecast is then matched with the historical weather day that most closely resembles it based on those match variables by finding the historical day with the smallest aggregate difference in values for the match variables. In this study, the pool of historical days from which a match could be found allowed for individual historical days to be matched with multiple ex ante days (in other words, the matched historical days were not removed from the match pool after they were matched).

Match variables included day time cloud coverage for solar weather stations and average daily wind speed and night time average wind speed for wind weather stations. Each day in the ex ante weather forecasts was matched with the actual 2014 day that most resembled it within a given season (December through February, March through May, June through August, and September through November). Matches were restricted to days within the same season to ensure that solar profiles would match up with the sunrise/sunset times expected for that part of the year.

After matching up the ex-ante weather forecasts with the closest 2014 actual day, the hourly renewable profiles for the corresponding days of 2014 were combined to produce 8760 generation profiles for 1-in-2 and 1-in-10 weather years. Inter-day discontinuities in renewable generation (resulting from sudden changes going from midnight of one day to a nonconsecutive day, and mainly affecting the wind profiles) were smoothed out by using the rolling 3-hour average of the renewable profile between the hours of 10pm and 2am of each day, instead of the actual renewable output.

The final output was two sets of 8760 renewable generation profiles, a 1-in-2 profile and a 1-in-10 profile, for each of the three solar resource zones (SP15, NP15, and ZP26) and two wind resource zones (SP15 and NP15). These forecasts represent utility-scale wind and solar generation that could be expected under the weather conditions of the 1-in-2 and 1-in-10 weather forecasts, respectively. Figure H-1 and Figure H-2 show the average daily generation profiles in the month of September for solar and wind, respectively, that are associated with the 1-in-2 and 1-in-10 ex ante forecasts. These figures sum up all of the various wind and solar resource zones, so it represents all utility-scale wind and solar in the state of California.

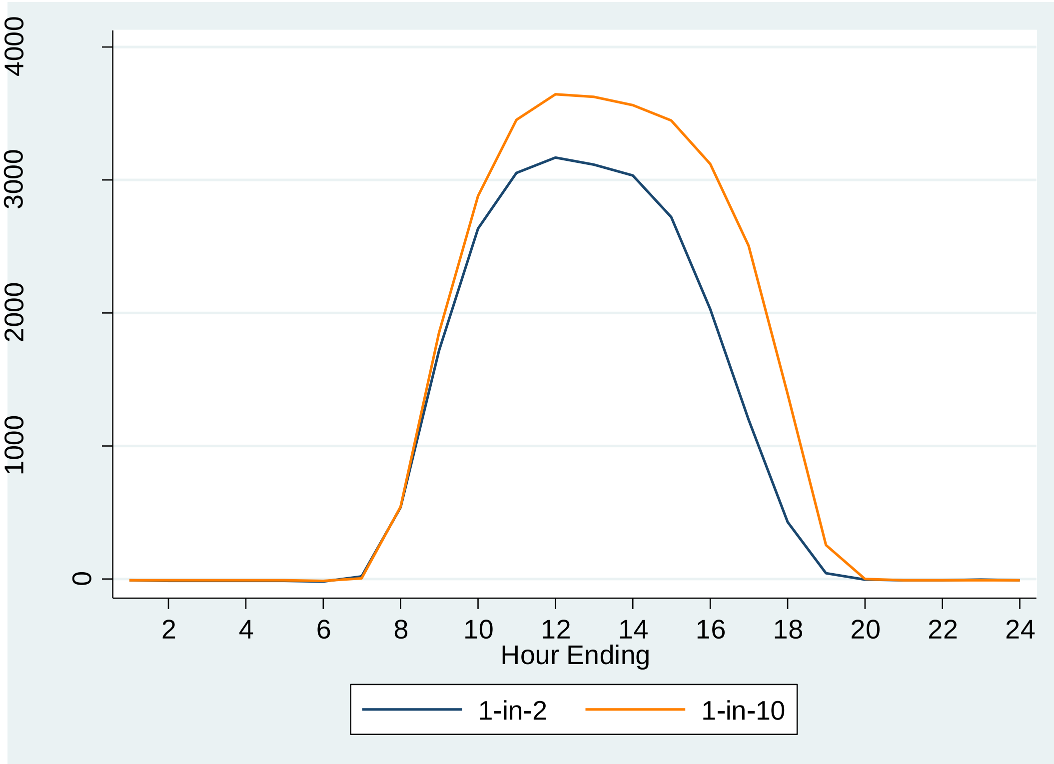


Figure H-1: Average Daily Solar Generation in September.

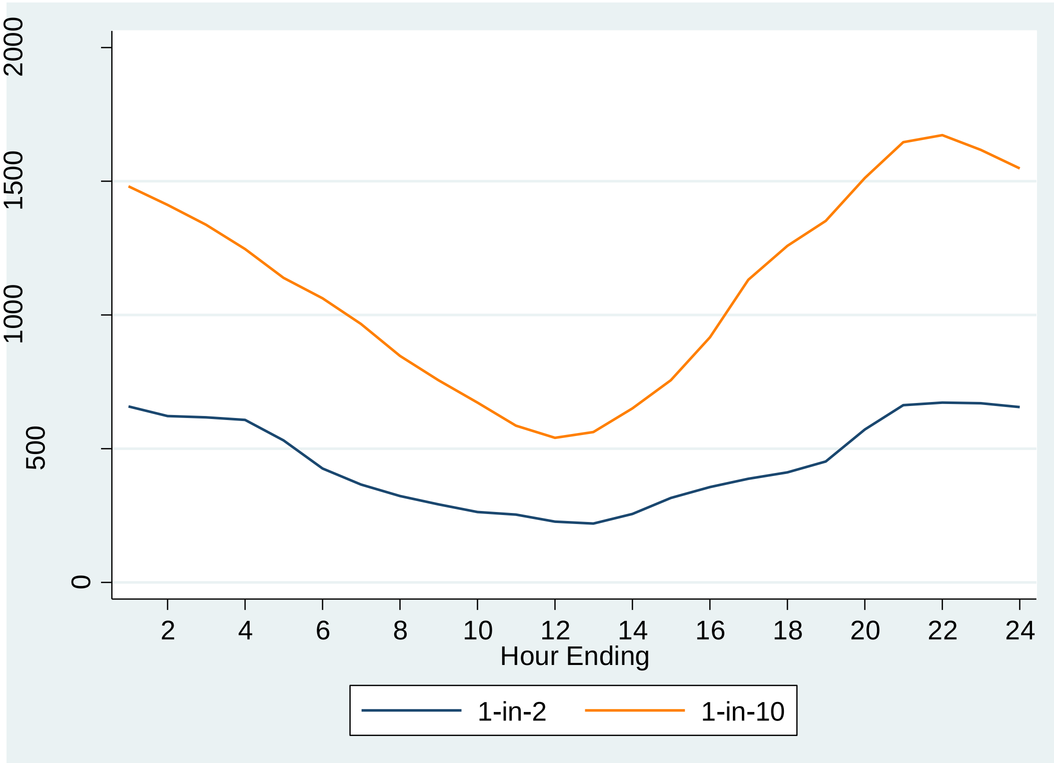


Figure H-2: Average Daily Wind Generation in September.

Appendix I: Conceptual Overview of Probit Models

Appendix I: Conceptual Overview of Probit Models

Probit models are non-linear choice models used to estimate the propensity or likelihood of participation. The basis of a probit model is a standardized cumulative normal distribution as shown in Figure I-1. The enrollment likelihood is non-linear and bound between 0% and 100% likelihood.

The coefficients reflect the change in standard deviations due to the explanatory variable. The model is non-linear and, as a result, the effect of specific external interventions, such as incentive level, depends on each customer's starting point. Customers who are highly predisposed against or for participation are less influenced by external factors than customer without strong pre-dispositions. The non-linearity is illustrated in figure. The same change in the standard deviation (equal to a coefficient of 0.5) leads to a different change in enrollment depending on the customers starting point or pre-disposition. For the customer with a strong predisposition against enrollment, the effect of the intervention is to increase the enrollment likelihood from 2.3% to 6.7%. For the customer who is not highly pre-disposed against participation, the same intervention boost the enrollment probability from 30.8% to 50%.

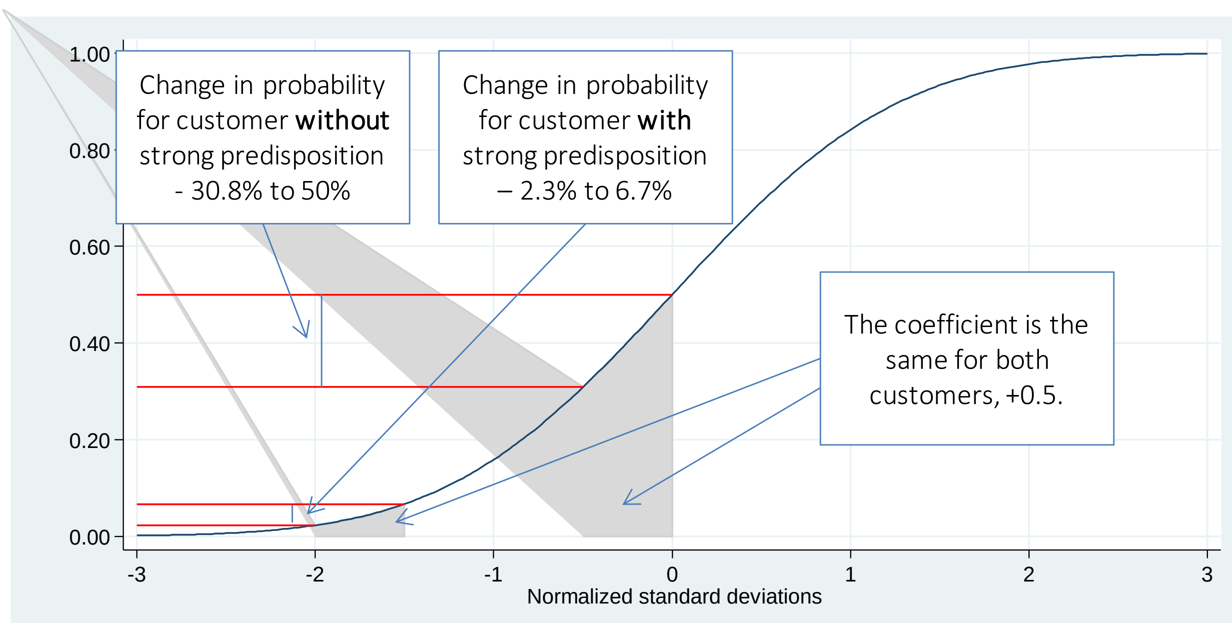


Figure I-1: Illustration of Non-Linear Pattern of Probit Choice Models.

Appendix J: CPUC DR Potential Study Technical Advisory Group (TAG)

Appendix J: CPUC DR Potential Study Technical Advisory Group (TAG)

Name	Party
▪ Kenneth Abreau	PG&E
▪ Fabienne Arnoud	PG&E
▪ Rick Aslin	PG&E
▪ Barbara Barkovich	CLECA
▪ Serj Berelson	Opower
▪ Eric Borden	TURN
▪ Jennifer Chamberlin	Joint Parties
▪ Fred Coito	DNV-GL
▪ Paul DeMartini	Newport Consulting
▪ Chris Ann Dickerson	DAWG
▪ Kent Dunn	Comverge
▪ James Fine	EDF
▪ Debyani Ghosh	Navigant
▪ John Goodin	CAISO
▪ Marcel Hawiger	TURN
▪ Don Hilla	CFC
▪ Eric Huffaker	Olivine
▪ David Hungerford	CEC
▪ Mike Jaske	CEC
▪ Xian (Cindy) Li	ORA
▪ Mona Tierney Lloyd	EnerNOC
▪ Alex Lopez	Opower
▪ David Lowrey	Comverge
▪ Carol Manson	SDG&E
▪ Mark Martinez	SCE
▪ Ali Miremadi	CAISO
▪ Neda Oreizy	PG&E
▪ Sam Piell	PG&E
▪ Jill Powers	PG&E
▪ Heather Sanders	SCE
▪ Nora Sheriff	CLECA
▪ Mike Ting	Itron
▪ Greg Wikler	Navigant
▪ Gil Wong	PG&E