The Los Angeles 100% Renewable Energy Study

Chapter 3. Electricity Demand Projections

FINAL REPORT: LA100—The Los Angeles 100% Renewable Energy Study

March 2021

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Los Angeles Department of Water & Power

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Lead Author of Chapter 3: Elaine Hale[1]

Residential Buildings: Anthony Fontanini,[1] Eric Wilson,[1] Janet Reyna,[1] Rajendra Adhikari,[1] Chioke Harris,[1] Scott Horowitz,[1] Dalton Jones,[1] Noel Merket,[1] Maharshi Pathak,[1] Joseph Robertson,[1] Andrew Speake,[1] David Roberts[1]

Commercial Buildings: Henry Horsey,[1] Andrew Parker,[1] Carlo Bianchi,[1] Eric Bonnema,[1] Matthew Dahlhausen,[1] Marlena Praprost,[1] Liang Zhang,[1] David Roberts[1]

Transportation: Matteo Muratori,[1] Eric Wood,[1] Dong-Yeon Lee,[1] Christopher Neuman[1]

Industrial Systems: Colin McMillan,[1] Meghan Mooney,[1] Ricardo Oliveira[1]

Water Systems: Kelly Sanders,[2] Angineh Zohrabian[2]

dsgrid: Elaine Hale,[1] Meghan Mooney,[1] Jane Lockshin,[1] Noel Merket[1]

[1] National Renewable Energy Laboratory
[2] University of Southern California

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Context

The Los Angeles 100% Renewable Energy Study (LA100) is presented as a collection of 12 chapters and an executive summary, each of which is available as an individual download.

- The **Executive Summary** describes the study and scenarios, explores the high-level findings that span the study, and summarizes key findings from each chapter.
- **Chapter 1: Introduction** introduces the study and acknowledges those who contributed to it.
- **Chapter 2: Study Approach** describes the study approach, including the modeling framework and scenarios.
- **Chapter 3: Electricity Demand Projections** (this chapter) explores how electricity is consumed by customers now, how that might change through 2045, and potential opportunities to better align electricity demand and supply.
- **Chapter 4: Customer-Adopted Rooftop Solar and Storage** explores the technical and economic potential for rooftop solar in LA, and how much solar and storage might be adopted by customers.
- **Chapter 5: Utility Options for Local Solar and Storage** identifies and ranks locations for utility-scale solar (ground-mount, parking canopy, and floating) and storage, and associated costs for integrating these assets into the distribution system.
- **Chapter 6: Renewable Energy Investments and Operations** explores pathways to 100% renewable electricity, describing the types of generation resources added, their costs, and how the systems maintain sufficient resources to serve customer demand, including resource adequacy and transmission reliability.
- **Chapter 7: Distribution System Analysis** summarizes the growth in distribution-connected energy resources and provides a detailed review of impacts to the distribution grid of growth in customer electricity demand, solar, and storage, as well as required distribution grid upgrades and associated costs.
- **Chapter 8: Greenhouse Gas Emissions** summarizes greenhouse gas emissions from power, buildings, and transportation sectors, along with the potential costs of those emissions.
- **Chapter 9: Air Quality and Public Health** summarizes changes to air quality (fine particulate matter and ozone) and public health (premature mortality, emergency room visits due to asthma, and hospital admissions due to cardiovascular diseases), and the potential economic value of public health benefits.
- **Chapter 10: Environmental Justice** explores implications for environmental justice, including procedural and distributional justice, with an in-depth review of how projections for customer rooftop solar and health benefits vary by census tract.
- **Chapter 11: Economic Impacts and Jobs** reviews economic impacts, including local net economic impacts and gross workforce impacts.
- **Chapter 12: Synthesis** reviews high-level findings, costs, benefits, and lessons learned from integrating this diverse suite of models and conducting a high-fidelity 100% renewable energy study.

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Key Findings

The LA100 study identifies and evaluates pathways that achieve a 100% renewable electricity supply for Los Angeles while maintaining acceptable reliability for both the grid and end users. This chapter focuses on the customer—how electricity is consumed by customers now, how that might change through 2045, and what opportunities there may be to better align electricity demand and supply.[1] Through historical data analysis, sector-specific (e.g., residential, commercial, transportation) simulations, data coordination, and demand response resource modeling across three demand projections, we evaluate how end-user demand could evolve differently depending on level of effort put toward energy efficiency, electrification, and demand response. We focus on addressing the following questions: given the same expected levels of population and economic growth, what are the ranges of possibilities for total electricity demand, peak electricity demand, and load shape? How does a high level of demand-side effort (e.g., energy efficiency, electrification, and demand response) compare to a moderate level of effort? How much more costly is it in terms of peak and annual electricity demand to "electrify everything" without putting similar levels of effort toward efficiency and demand response?

How might Los Angeles electricity demand evolve over the study period in response to technological change?

1. **All demand projections assume significant technology-driven change based on Los Angeles and California's historical track records and future ambitions regarding energy efficiency and electrification.**

   There are three LA100 load projections: Moderate, High, and Stress. The Moderate projection includes the least change as compared to today's electricity demand. However, between meeting LA's proportion of the California 2030 zero-emission vehicle (ZEV) goal,[2] keeping up with and even exceeding the buildings-sector energy efficiency gains expected in future versions of California's Title 24 building energy codes,[3] and achieving economic potential deployment of energy efficiency in the industrial and water system sectors, the Moderate projection is not a business-as-usual case. It projects about 1 million light-duty electric vehicles on LA's roads by 2045, more use of electric and heat pump technologies in the buildings sectors, and a continued focus on energy efficiency through all sectors of the economy.

2. **Weather-correlated cooling demand is an important driver of LADWP system-wide peak demand in all projections and all model years.**

   Today, LADWP is a summer-peaking system, and we project that will continue to be the case throughout the study period. In our modeling results, in all projections and all model years the system-wide peak day occurs in early August, on the hottest weekdays of the

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1 This analysis was performed based on electricity demand projections generated prior to the COVID-19 pandemic. It does not account for changes that occurred during the pandemic, nor does it consider potentially longer-lasting impacts, such as changes in work patterns.

2 CPUC, "Zero-Emission Vehicles," California Public Utilities Commission, https://www.cpuc.ca.gov/zev/

3 CEC, "Building Energy Efficiency Standards: Title 24," California Energy Commission, https://www.energy.ca.gov/programs-and-topics/programs/building-energy-efficiency-standards.

modeled weather year. Historically, the LADWP system peak day has occurred on various days in August or September. Cooling loads in buildings are a nonlinear function of outdoor air temperature—hotter temperatures mean not only increased cooling demand, but also increased energy needs to deliver the same amount of cooling.

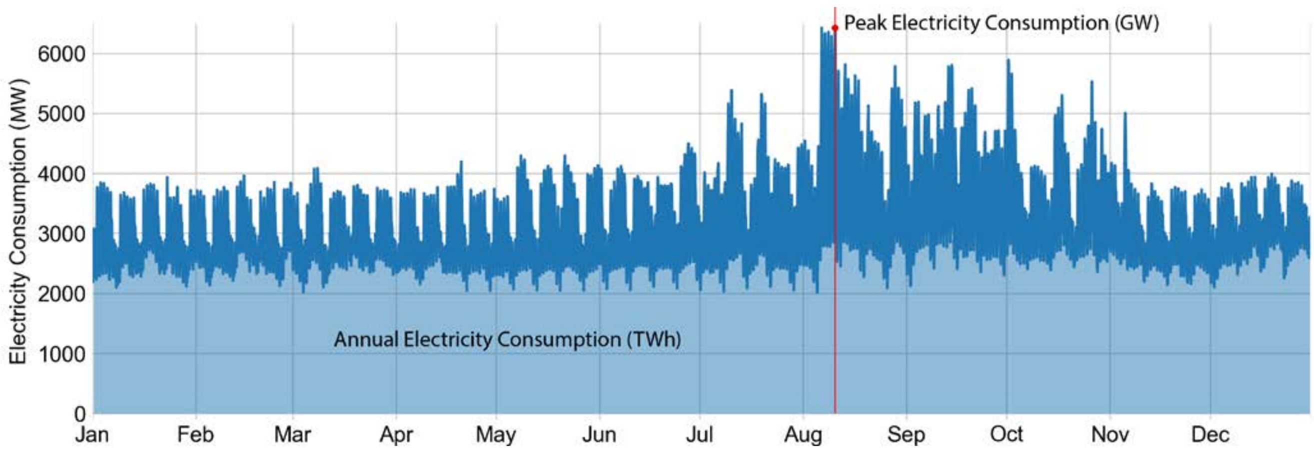

Figure 1. The key metrics of peak electricity demand (measured in GW) and annual electricity consumption (measured in TWh) illustrated with an example of a profile from LA100 modeling results

Peak demand is the maximum point of the demand profile. Annual consumption is computed by integrating the demand profile over the year. 1 GW = 1,000 MW. 1 TWh = 1,000 GWh = 1 million MWh.

Figure 1 shows the resulting system peak demand in the context of a full year of demand data. The magnitude and timing of peak electricity demand drives power system planning, because there must be enough generation capacity available to meet that demand at that time (and at other near-peak times), with some power in reserve to manage forecast errors and outages on the power system. The amount and timing of electricity use throughout the whole year is important as well—how much total energy needs to be delivered, and how well those needs align with wind, solar, and other generation resources.

3. **With high electrification of the light-duty vehicle fleet, system peak days are still driven by cooling loads, but EV charging may influence the timing of the peak by 2045.**

   Although LA100 peak demand always hits on an August day with high cooling loads, the timing of the 2045 demand peak is significantly different across our three projections. The Moderate projection shows the same peaking pattern as today—peak demand occurs around 4 p.m.—but the High and Stress projections, which both include significant light-duty vehicle electrification, show peak demand occurring at 2 p.m. and 7 p.m., respectively (Figure 2). In those projections, the time of system peak is influenced by where, and therefore when, EV charging takes place. The High projection assumes more workplace charging, which is better aligned with solar generation. The Stress projection continues today’s trend of mostly residential charging starting in the evening hours.

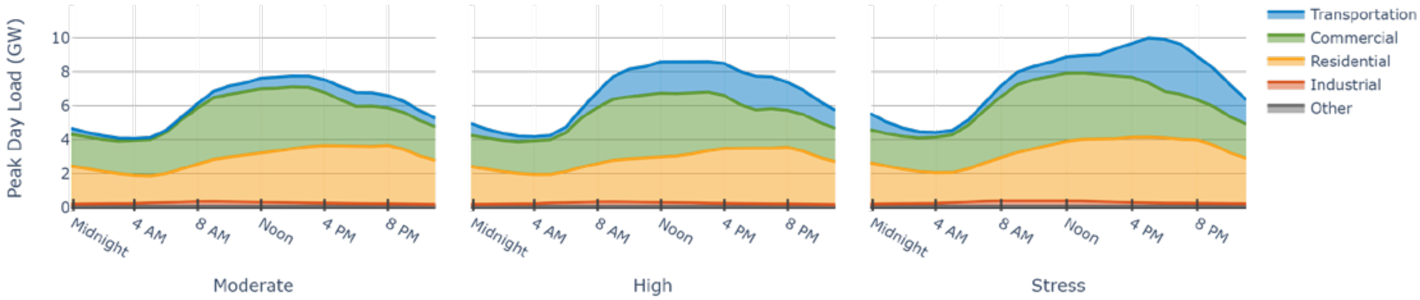

Figure 2. Peak demand profiles in 2045

EV charging shifts the time of system peak earlier in the High projection and later in the Stress projection, compared to both today's system and the Moderate projection in 2045.

4. **High levels of energy efficiency and electrification would drive significant change in the buildings sector that is difficult to see in peak demand and annual energy consumption metrics.**

   For example, the annual energy use in the buildings sectors is similar between the Moderate and High projections in all model years (Figure 3), but this is only because high levels of electrification and efficiency largely cancel each other out at this high level of aggregation. By 2045 the High projection achieves 90%–100% electrification of all key end uses, while the Moderate projection end uses only reach electrification levels of about 50% (residential water heating, space heating, and cooking) to about 80% (commercial space heating). The High projection significantly mitigates the associated increases in electricity use through 100% sales shares of the highest efficiency equipment models in the residential sector and efficiency adoption up to 15 years ahead of Title 24 codes in the commercial sector. The Stress projection illustrates how much additional electricity could be needed if buildings electrify but do not pursue efficiency as aggressively. Overall greenhouse gas emission results shown later in this report (Chapter 8) demonstrate the importance of pursuing the twin goals of electrification and efficiency in the service of decarbonization.

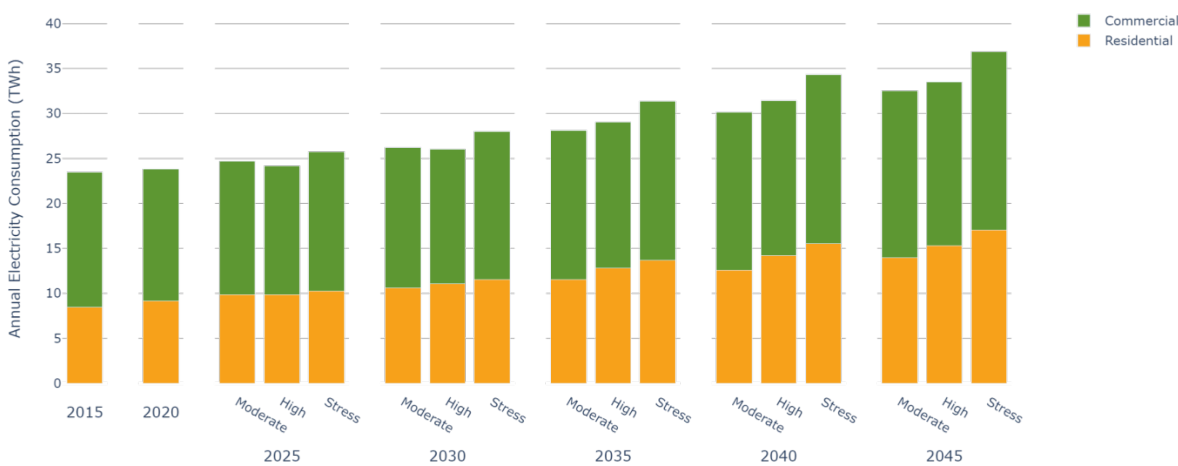

Figure 3. Annual electricity consumption for commercial and residential building sectors

5. **Key public infrastructure such as the water system, school buses, and transit buses are expected to use significantly more electricity; however, these will remain small loads from a system-wide perspective.**

   In line with the City of LA's goals to locally source 70% of its water and recycle 100% of its wastewater by 2035, all LA100 load projections have water system electricity use increasing from about 260 GWh to 360 GWh today to 1,200 GWh to 1,250 GWh by 2050. Although this represents a three to five-fold increase in electricity use in that sector, the water systems' proportion of projected load is only expected to grow from about 1.3% to somewhere between 2.5% and 3.2% over the study period. Our demand estimates for a fully electrified bus fleet are even more modest, just 130 GWh annually in total.

6. **All projections show higher annual energy consumption, driven most prominently by EV charging, but with contributions also from economic growth, the water system, miscellaneous electric and process loads in buildings, and building electrification.**

   Starting from 2020, Moderate projection demand grows at a compound rate of 1.6% year-on-year, starting at 26,500 GWh and reaching 38,900 GWh by 2045. The High projection reaches 46,200 GWh by 2045, corresponding to a 2.2% growth rate. The Stress projection, with high electrification and reference efficiency, experiences an annualized growth rate of 2.6% based on a projected 2045 annual consumption of 50,200 GWh. Transportation demand grows from about 580 GWh in 2020 to 4,300 GWh, 10,800 GWh, and 11,100 GWh in 2045 in the Moderate, High and Stress projections, respectively.[4] The corresponding annual growth rates are 8.3% for the Moderate projection, 12.4% for the High projection, and 12.5% for the Stress projection (Figure 4).

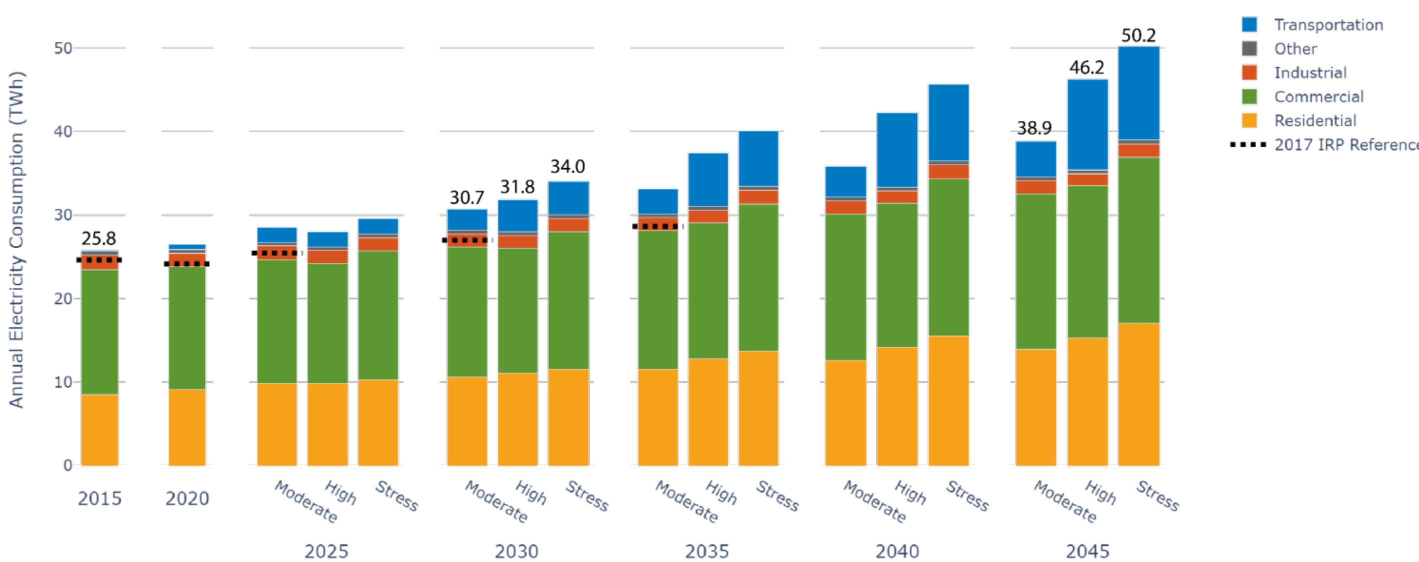

Figure 4. Annual electricity consumption by projection-year and sector

[4] The number of electric vehicles is the same in the High and the Stress projections, but because the High projection has more DCFC and less L1/L2 charging than the Stress projection, it avoids some AC-to-DC conversion losses and therefore uses less electricity to fulfill the same mobility demands.

Throughout this chapter, electricity demand is presented as at-the-meter consumption; that is, pre-distribution and transmission losses.

7. **7. Peak electricity demand also grows in all projections, but at a rate slower than annual electricity consumption. This reflects the tendency of electrification to add load at all times, not correlated with system peak, and results in an overall demand profile that is less peaky.**

   In LA100, the 2020 peak electricity demand is 6,020 MW and grows to 7,810 MW, 8,660 MW, and 10,100 MW in the Moderate, High, and Stress projections, respectively. This corresponds to annualized, compound growth rates of 1.0%, 1.5%, and 2.1%. Because these peak demand growth rates are lower than the corresponding annual demand growth rates, LA100 projects 2045 load profiles that are less peaky compared to today. The ratio of average to peak demand increases from 50% in 2020 to 57% in 2045 for the Moderate and Stress projections, and 61% in 2045 for the High projection (Figure 5).

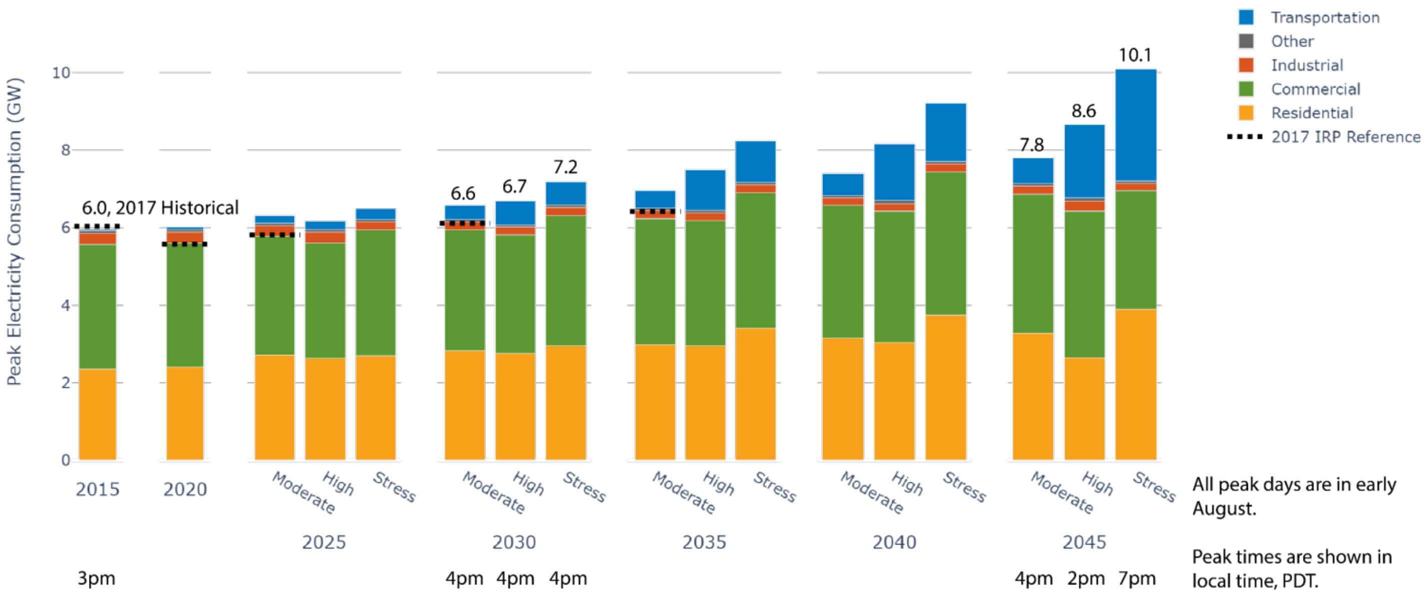

Figure 5. Peak electricity demand by projection-year and sector

What strategies can be used to better align electricity supply and demand?

8. **EV charging can be better aligned with solar generation by ensuring access to workplace charging infrastructure.**

   EVs in the High projection have 50% access to workplace charging and 60% access to home charging, whereas the Stress projection assumes 15% access to workplace charging and 90% access to home charging. This results in charging profiles that on average are more (High projection) or less (Stress projection) aligned with solar generation in the daylight hours (Figure 6).

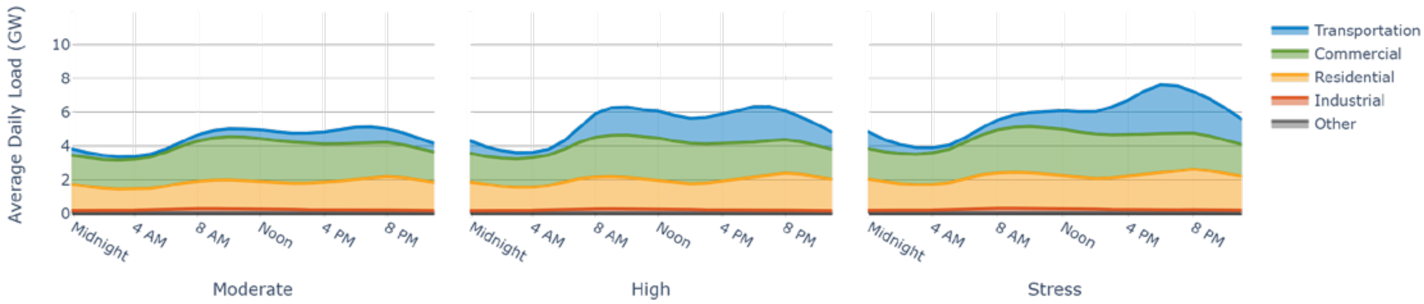

Figure 6. Average daily profiles for 2045 by projection-year and sector

9. **With high electrification of the light-duty vehicle fleet, schedulable EV charging may be able to provide significant demand response opportunities even if LADWP's incentive levels and marketing efforts are modest.**

   The Stress projection puts significantly less effort toward demand response in terms of automation, marketing, and incentives than does the Moderate projection. Despite this, the two projections have similar absolute ability (in MW) to reduce load at the system peak time because EV charging is a large, schedulable load in high-electrification futures (Figure 7).

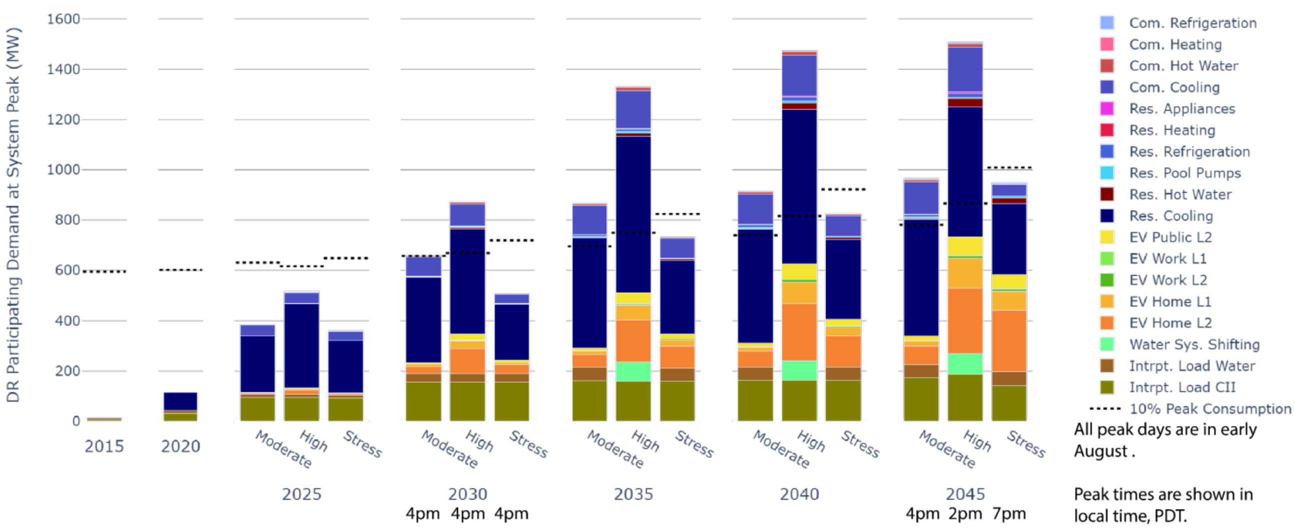

Figure 7. Summary of participating DR demand available at system peak times

10. **If demand response technology becomes plug-and-play and LADWP provides a wide range of well-marketed and sufficiently incentivized demand response programs, up to 18% of peak demand (Figure 7) and 12% of total annual demand (Figure 8) could be avoided or shifted from high- to low-price times.**

    The High projection assumes that the demand response industry generally and LADWP particularly, aggressively develop and promote demand-side flexibility across all sectors, and transitions from a primary focus on peak load reduction to also include regular demand shifting that explicitly aligns demand with available supply from, for example, wind and solar. In addition to residential, commercial, and industrial programs across a wide variety of end uses, including EV charging, the High projection assumes that LADWP water and power system operations could be coordinated to unlock water system electricity demands as a significant source of demand-side flexibility.

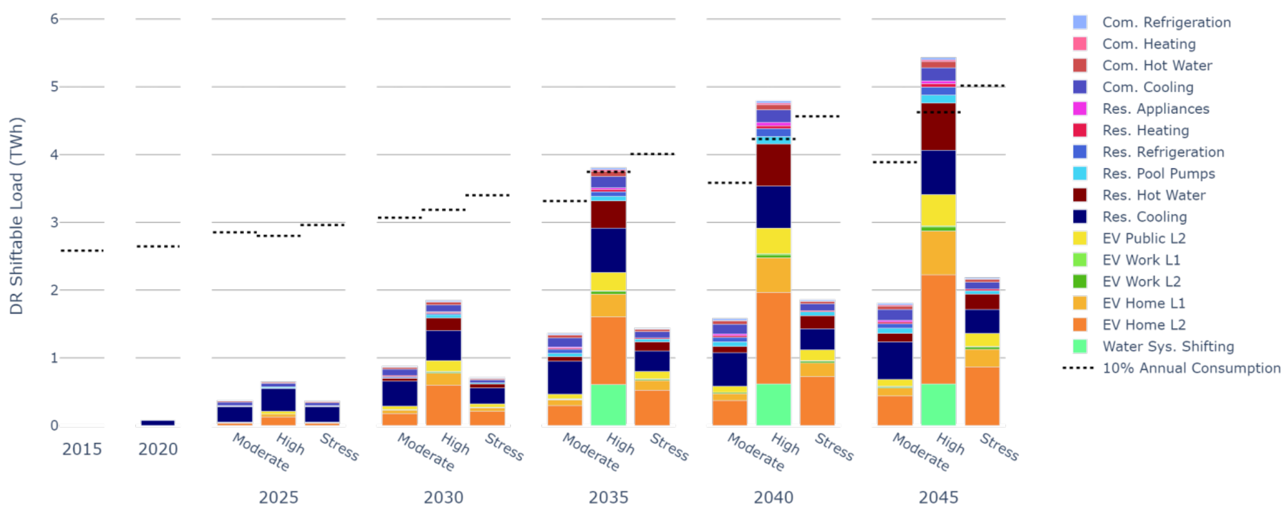

Figure 8. Summary of DR-participating, shiftable demand

11. **The LA100 demand response analysis used the best data and modeling methods available at the time, but there is more to learn.**

The LA100 demand response projections in all cases assume continuation plus significant growth of LADWP's current programs focused on peak demand reductions from large commercial, industrial and institutional (CII) customers, and from residential cooling via a programmable communicating thermostat (PCT) program. Capacity growth and new capabilities are envisioned—the CII program is projected to grow from 44 MW in 2020 to 215 MW in 2030, and also to transition from being semi-automated to fully automated, which will allow for load response even quicker than the current minimum 2-hour-ahead notification. The High projection further assumes coordinated operations between LADWP power and water systems. Programs like the residential PCT program are projected to proliferate, expanding into multiple end uses in in both residential (cooling, heating, hot water, pool pumps, refrigeration, and major appliances) and commercial buildings (cooling, heating, hot water, and refrigeration), providing load shifting in addition to reductions at peak times, and expanding to widespread adoption of scheduled EV charging.

While the outline of where demand response could be moving is clear, exactly what level of transformation will be achievable is highly uncertain. There are open questions concerning infrastructure buildout (e.g., how much automation, how much EV charging infrastructure and where, what additional capital equipment and controls would be needed to coordinate water and power system operations), precise technical capability (e.g., how far can demand be shifted and what are the energy costs, if any, for doing so), and human behavior and preferences (e.g., what are the behavioral tolerances and economic trade-offs involved with shifting demand, how many customers can be incentivized to participate in demand response programs). Market structures and business models (e.g., can demand flexibility be incentivized and delivered in efficient ways that are worthwhile for all involved) are also active areas of innovation. In this study, we used current understanding of technical capability and demand response participation rates, we had to make assumptions about the availability of more-automated technologies, and we did not explicitly account for the potential impact of different business models. We also limited demand response shifting to within a day and did not evaluate multiday strategies that could help reduce the need for power system capacity in managing longer-term events. Research is ongoing in all these areas.

One critical question that this study leaves unanswered is, “What proportion of the EV fleet could be effectively incentivized to participate in managed EV charging programs?” Based on historical demand response participation rates, LA100 assumes that no more than 30% participation would be achieved, but the actual upper bound could be much higher. Another unanswered question that could be important for LADWP and other power system operators is, “How much multiday demand shifting is possible?” Some CII premises may be able to schedule demand over longer time periods and long-range EVs may only need to charge once or twice a week. Would it be possible to tap into such resources to improve power system reliability at lower cost? Such strategies might be especially helpful in the face of longer-term outages, extreme weather, or prolonged lulls in renewable generation.

Important Caveats

1. LA100 demand projections relied on state and local planning documents for projections of population and economic growth, and those assumptions were held constant across the scenarios.
2. None of the component demand models is currently capable of capturing relationships between, for example, income and demographic factors, and decision-making and habitual behaviors that drive energy use outcomes. Nor were income and demographic factors available in detailed parcel- and customer-level data used to spatially disaggregate modeling results.
3. Technology adoption was modeled exogenously, based on various planning documents, state and local policies and goals, and engineering judgement. The overarching goal of demand scenario construction was to provide a small number of demand projections that approximately bracket possible outcomes from a power system (total and peak load) perspective. Notably, the City of LA’s 2019 electrification and efficiency targets came out mid-project—we were able to incorporate most, but not all, of the City’s demand-side goals; namely, we were not able to include electrification of medium- and heavy-duty vehicles (a qualitative description of impacts of medium- and heavy-duty vehicle electrification on load charging and other areas of the LA100 study is included in Chapter 9, Appendix A).
4. LA100 models different electrification scenarios for the Port of Los Angeles, but electrification of the airport is not captured, nor is industrial decarbonization. There are also many commercial premises in Los Angeles that do not map to standard commercial building types—as with industrial manufacturing (including refining, which could be impacted by high electrification of the transportation sector), demand for those premises was projected to continue largely as-is.

5. LA100 captures average monthly temperature increases from climate change but does not capture heat island effects or extreme weather events such as heat waves.

1 Introduction

As the backdrop for all power systems analysis and the original source of power system variability and uncertainty, customer electricity consumption must be the starting point for understanding the City of Los Angeles's 100% renewable energy future. However, the historical planning practice of projecting LADWP's current demand with year-on-year load growth factors is not sufficient. To provide a realistic picture of how LADWP's system is changing, the LA100 project must explore transformed energy futures up to and including the city's vision,[5] which includes significant demand-side change that will impact the magnitude and shape of future electricity demand. Driven by technology progress, state and local policies, and customer preferences, Los Angeles is already experiencing significant adoption of passenger electric vehicles and continuous ratcheting of building-level energy efficiency expectations. State and city targets to significantly electrify more end uses, especially space and water heating, are also expected. The LADWP water system has its own aggressive goals that are likely to increase the amount of electricity used to treat water and convey it locally. To ensure that these and other impacts are properly captured in the LA100 power system modeling, the team uses a highly resolved, bottom-up modeling approach referred to as the demand-side grid model (dsgrid)[6] to project, compile, and geospatially distribute sector-level demand estimates.

The dsgrid model is composed of multiple detailed models that each represent one major electricity load sector, plus additional gap models and other adjustments required to compose a complete, time-synchronized, and spatially resolved electricity load data set. The detailed models provide hourly or subhourly load profiles at a fine geographic resolution and with end-use specificity (Hale et al. 2018). The results of all sector models plus gap models are summed to reach the total load. Each of the sector models captures details related to technology stock quantities, usage patterns, performance, and evolution over time. In addition to electricity, some of the detailed sector models account for other fuels such as natural gas. Although electric utility load forecasting typically only considers electrical loads, analyzing the impacts of large-scale electrification requires models that can accurately assess the impacts of switching fuels for some end uses.

Context within LA100

This chapter is part of the Los Angeles 100% Renewable Energy Study (LA100), a first-of-its-kind power systems analysis to determine what investments could be made to achieve LA's 100% renewable energy goals. Figure 9 provides a high-level view of how the analysis presented here relates to other components of the study. See Chapter 1 for additional background on LA100, and Chapter 1, Section 9, for more detail on the report structure.

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[5] "L.A.'s Green New Deal: Sustainability pLAn 2019," https://plan.lamayor.org/.
[6] "dsgrid: Demand-Side Grid Model," NREL, https://www.nrel.gov/analysis/dsgrid.html.

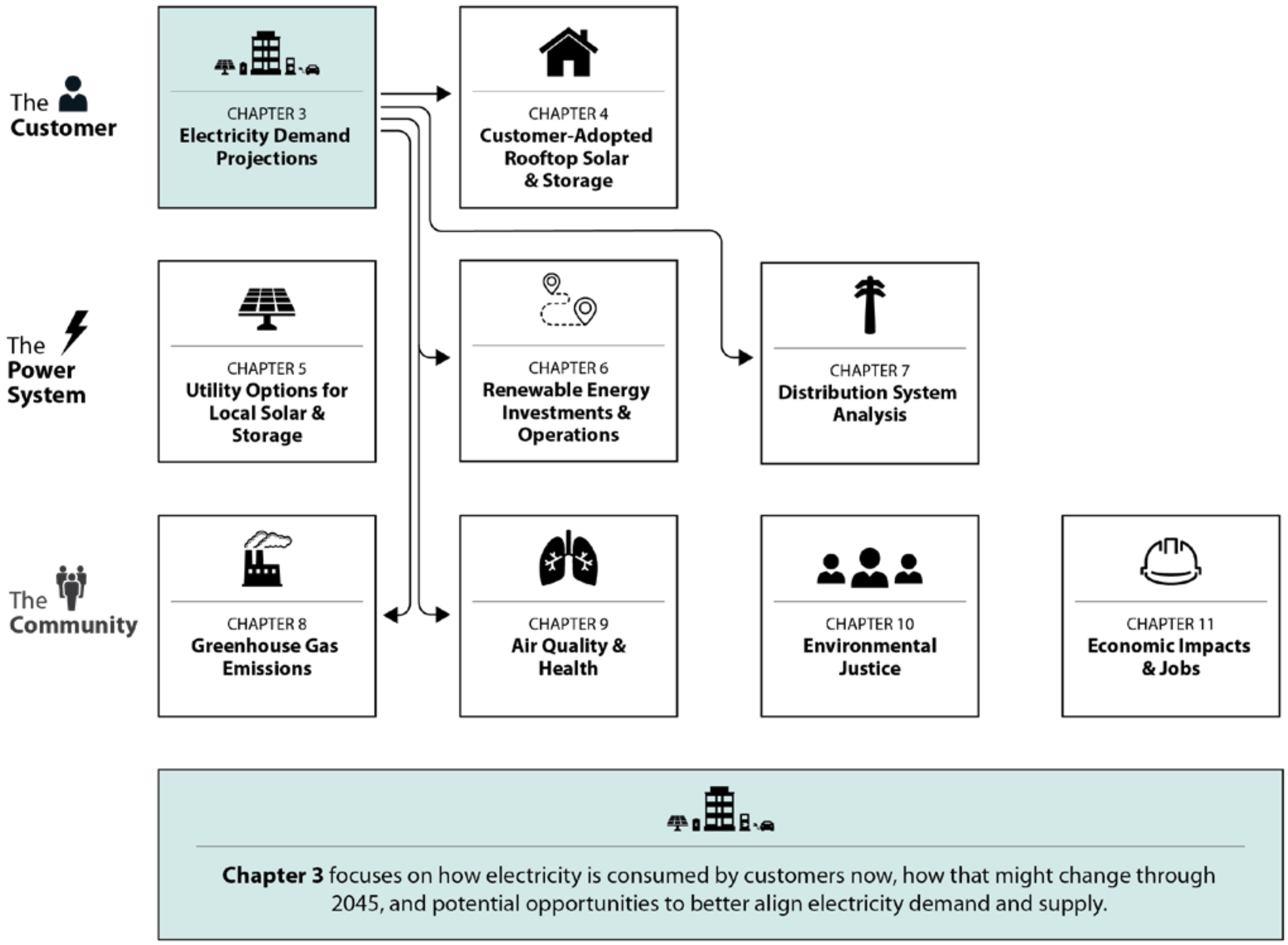

Figure 9. Overview of how this chapter, Chapter 3, relates to other components of LA100

This chapter provides time-series electricity demand projections and demand response, by location, which are used directly in the analyses in Chapters 4 (customer-adopted rooftop solar), Chapters 6 and 7 (power system analyses), Chapter 8 (greenhouse gas emissions), and Chapter 9 (air quality).

In particular, the analysis in this chapter focuses on projecting future customer electricity demand. While these electricity demand projections underpin all analyses throughout the study, the electricity projections are directly used by the modeling in Chapter 4 (customer-adopted rooftop solar) and the power system analyses of Chapters 6 and 7.

LA100 Scenarios

The LA100 scenarios are based on three separate demand projections, each of which provides a different narrative of how LA's electrical load may evolve over the study period (Table 1). Energy efficiency and electrification (i.e., adoption of electrified end uses) are both modeled at moderate and high levels to produce the Moderate and High LA100 customer demand projections, respectively. A third load projection, Stress, is created to explore the impact of high electrification but with significantly slower energy efficiency gains.

The projections also vary in the amount of demand response (DR) resource they provide to the LADWP system. In the LA100 project, we define demand response as any change in electricity demand that is made to provide a grid service. As described below, we focus on interruptible loads and load shifting in time that can be used to reduce bulk power system peaks and better align demand with supply. The three load projections vary in how ambitiously they pursue DR. The Moderate and High projections assume moderate and high DR. Because the purpose of the Stress projection is to present a worst-case growth challenge, this projection assumes the lowest levels of DR ambition in terms of incentives, marketing level, and automation.

For LADWP territory only,[7] dsgrid models were constructed for each of these projections and covering 7 model-years starting in 2015 and proceeding in 5-year increments through 2045: 2020, 2025, 2030, 2035, 2040, and 2045. Because the same data sets are used for all projections for the years 2015 and 2020, the team created a total of 17 subhourly, geographically resolved load data sets representing current and future LADWP load.

[7] Historical load data combined with per-balancing authority constant-growth projections that are uniform over all hours were used to represent load shapes throughout the Western Interconnection except for LADWP (WECC TEPPC 2011; FERC 2016).

Table 1. LA100 Customer Demand (Load) Projections, including Examples of Distinctions among the Projections regarding Efficiency, Electrification, and Demand Response

Load Projection	**Moderate**	**High**	**Stress**
Description	The Moderate load projection assumes easy, low-hanging-fruit electrification and above-code improvements to energy efficiency and demand response. Significant change, but short of the Mayor's Office's Green New Deal 2019 pLAn[a] goals.	The High projection is designed to match most of the electrification and energy efficiency goals set forth in the 2019 pLAn, and it includes 80% light-duty vehicle electrification by 2045 and significant demand response potential. Very high electrification results in significantly more demand, even with high levels of energy efficiency.	High electrification combined with low energy-efficiency improvements and demand response to create worst-case load conditions.
Energy Efficiency	Sales distributed across available efficiency levels; 80% of new and retrofit equipment is 5 years ahead of Title 24 commercial building energy-efficiency code-minimum	100% sales at highest efficiency levels	LADWP's 2017 SLTRP 10-year efficiency goals[8]
Electrification	30% electric light-duty vehicle share of market in 2045	100% electric sales share by 2030 (incl. HVAC and water heating; 100% electric homes by 2050	Same as "High"
Demand Response	75% access to residential charging; 25% access to workplace charging	60% access to residential charging; 50% access to workplace charging	90% access to residential charging; 15% access to workplace charging

[a] "L.A.'s Green New Deal: Sustainability pLAn 2019," https://plan.lamayor.org/.

[8] Target of 10%–15% energy efficiency to be achieved between 2017 and 2027.

Figure 10 summarizes the process flow for the overall dsgrid model, including geographic downscaling and demand response. Three sector-specific submodules submit load to dsgrid. The data are subsequently processed to create model-specific data sets that vary in spatial, temporal, and sectoral resolution. A key piece of the dsgrid workflow is to geographically downscale some sectors' loads to the agent-level, which is similar to a parcel or utility customer. From that geospatial resolution, the LADWP electrical connections are traced to yield data at the bulk power nodal level, which is what the capacity expansion, production cost, and dynamics models need. The distribution, solar adoption, and air quality models use the agent-level data directly. The dsgrid team creates DR resource estimates by analyzing the sector-level data by end use. Demand response is subsequently dispatched by power system models, thereby displacing alternative supply-side resources.

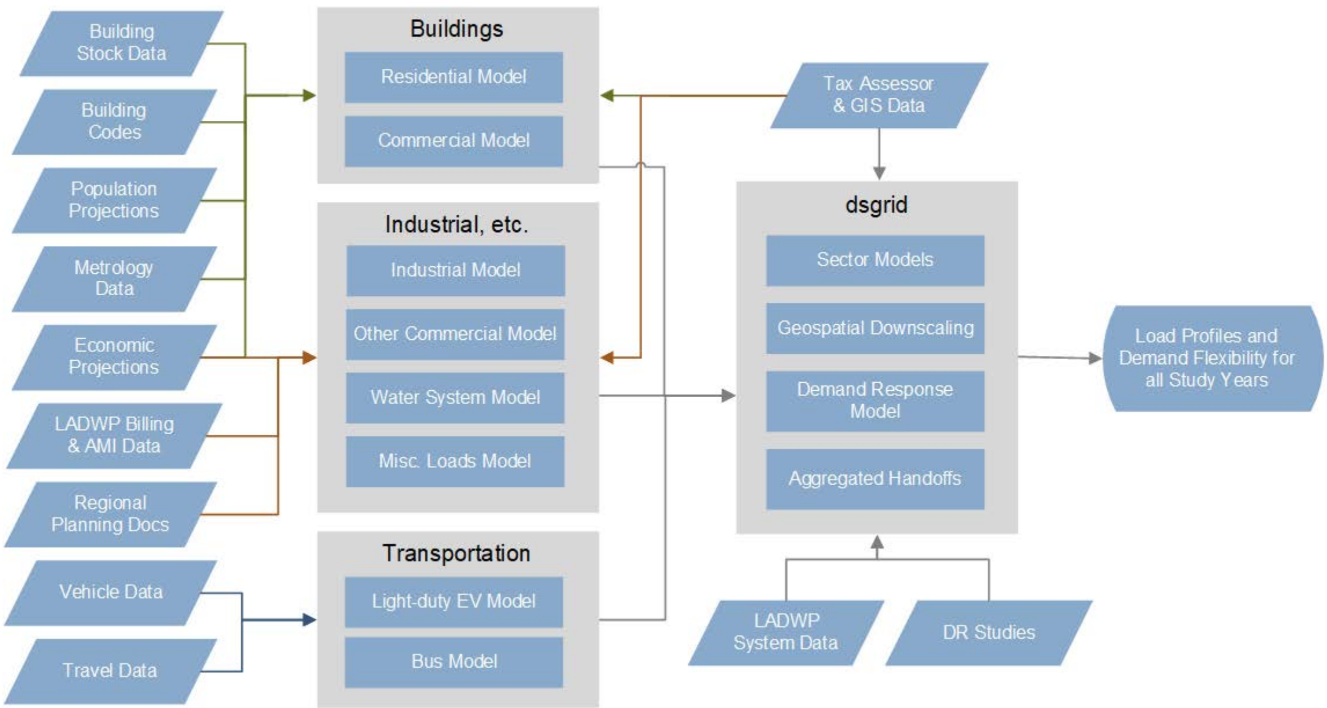

Figure 10. Process flow for generating load profiles and demand response (DR) potential

2 Sector Models

Within dsgrid's architecture, each sector's energy use was modeled with sector-specific methodologies informed by and calibrated to historical LADWP and other relevant data sets. Modeling the baseline load year (2015) provides a comprehensive representation of current energy demand calibrated to recent system peak, annual demand by sector, and load shape by sector metrics. This data set then provides a solid foundation for moving out to future-year projections, which are created by applying population growth, economic growth, and technology adoption assumptions. Brief descriptions of the sector-specific modeling methodologies follow.

Residential and Commercial Buildings

Building loads were estimated using ResStock™[9] and ComStock™,[10] which used statistical methodologies to represent Los Angeles's single-family, multifamily, and commercial building stocks. These models sampled from probability distributions that represent known characteristics of the building stock and used these characteristics to make tens of thousands of detailed, physics-based whole building energy models (using EnergyPlus™[11]) that represented the stock. *Future-year load* captured changes in the number, type, and size of buildings, as well as technology adoption, including energy efficiency and electrification options.

Transportation

Light-duty electric vehicle (EV) charging profiles were modeled using the Electric Vehicle Infrastructure Projection Tool (EVI-Pro) (Wood, Rames, and Muratori 2018). EVI-Pro simulates hourly charging profiles based on travel data and charging preference assumptions (i.e., residential, workplace, or public charging). The baseline number of EVs was determined using data on current vehicle registrations. **Future-year load** was estimated by creating three plug-in electric vehicle (PEV) adoption projections in line with Los Angeles and California goals and specifying alternative charging preference scenarios in line with demand response ambitions. Bus charging loads were developed assuming 100% electrification of all school, LA Metro, and LADOT buses serviced within LADWP service territory by 2030 and overnight depot charging.

Industrial and Other Commercial Loads

The magnitudes and shapes of industrial and other commercial loads (commercial customers with building types not modeled by ComStock) were modeled using LADWP billing and advanced metering infrastructure (AMI) data. For customers without AMI or other locatable direct data, the load shape was filled in based on the load shapes of other customers with similar North American Industry Classification System (NAICS) codes or with sector-level average load shapes (i.e., industrial or commercial). **Future-year load** for industrial and other commercial customers was projected based on LADWP and other regional planning documents.

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[9] "ResStock Analysis Tool," NREL, https://www.nrel.gov/buildings/resstock.html.
[10] "ComStock Analysis Tool," NREL, https://www.nrel.gov/buildings/comstock.html.
[11] EnergyPlus is a whole-building energy simulation program that engineers, architects, and researchers use to model energy consumption. Its development is funded by the U.S. Department of Energy's Building Technologies Office. See "EnergyPlus," https://energyplus.net.

Water System

The University of Southern California developed a detailed understanding of LADWP's water system in terms of water use, water supply, wastewater treatment, groundwater recharge, and water recycling, built up for the base year primarily from LADWP's 2015 Urban Water Management Plan (UWMP) (LADWP 2016). They also developed load shapes based on the assumption that energy use follows the hourly end-use water demand for the water supply subsector, and the hourly treatment plant inflows at the Hyperion wastewater treatment plant for the wastewater treatment subsector. **Future-year load** for water end uses was projected based on LADWP planning documents, other regional planning documents, and recent city-level announcements, as well as conversations with LADWP and the shared understanding that Los Angeles will be prioritizing locally sourced water over other considerations in the years to come.

Other Loads

The modeling described above covers most, but not all, of the electricity use in the LADWP service territory. Outdoor lighting loads and Owens Valley loads are estimated separately, consistent with LADWP's designation of these loads as "Other loads" (LADWP 2017a). Initial loads are estimated from LADWP data on annual demand and shape. **Future-year load** was estimated by assuming additional outdoor lighting efficiency gains and constant Owens Valley load.

Figure 11 shows how the sector models combine to represent the total load profile.

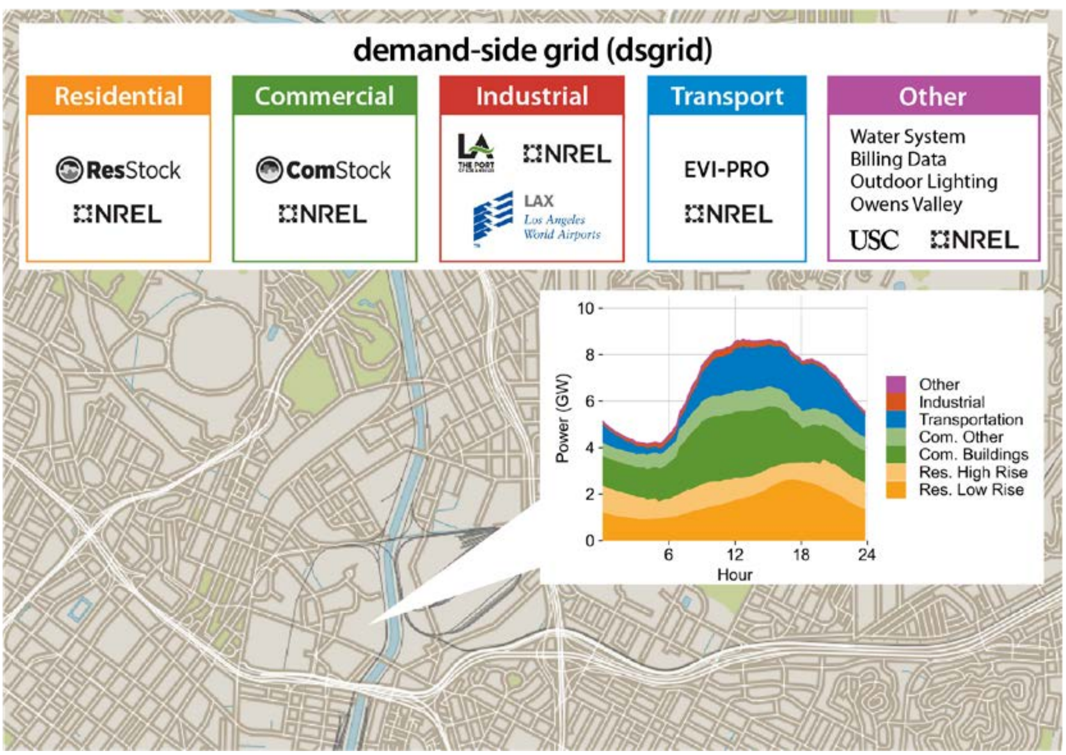

Figure 11. dsgrid provides a highly resolved spatiotemporal picture of LADWP electricity consumption

Load data are illustrative only.

For all loads, the future will depend on a variety of factors such as economic conditions, policy decisions, and incentives. These factors are all difficult to predict, especially over the long timespan under consideration. Rather than attempt to forecast these factors and their impacts, a project-level decision was made to model several different levels of technology change to help LADWP understand what the range of load growth might look like.

Given this approach, assumptions about adoption of technologies such as EVs, efficiency, and electrification were exogenous to the model. For each sector-level load model, these assumptions were made to be consistent with the projections described in Table 1.

2.1 Buildings

The ResStock and ComStock tools are used to create baseline and projection descriptions of LADWP's residential and commercial building electricity demand. Both tools follow a four-step process to create and validate the baseline model:

1. **Building Stock Characterization:** Existing data sources are used to create probability distributions of about 100 building characteristics (e.g., vintage, wall insulation, lighting, cooking range, building size, number of stories, HVAC system, heating fuel, foundation type) for each of the two models that statistically describe the building stock of the LADWP service area. Some probability distributions are conditional on the sampling outcome of upstream distributions. For example, the probability that a commercial building is 10 stories tall is conditioned on building type—this outcome is reasonably likely for office buildings, but very unlikely for restaurants.
2. **Statistical Sampling:** For the LADWP service area these distributions are sampled 75,000 times: 50,000 times for ResStock using quota-based sampling and 25,000 times for ComStock using low discrepancy Sobol sequences to create sets of building characteristics. The characteristics from each building in the sample are translated into building energy models in the U.S. Department of Energy's flagship building energy simulation platform, OpenStudio®/EnergyPlus. Weighting factors are used to scale the results from thousands of simulations to represent the millions of households and commercial buildings in the LADWP service area.
3. **Baseline Building Simulations:** Each building energy model produces subhourly load data for the statistically representative building covering one year of operations. End uses modeled in ResStock include heating, cooling, water heating, cooking, dish washing, clothes washing and drying, lighting, refrigeration, ceiling fan, fans and pumps, plug loads, and pool pumps. ComStock models include heating, cooling, ventilation, water heating, lighting, pumping, refrigeration, and plug and process loads.
4. **Validation:** Steps 1–3 are completed to produce representative residential and commercial building energy profiles for 2015, 2016, and 2017; these were compared to LADWP data provided for each of those years, and then the models were adjusted to match expected annual demand, peak demand, and load shapes.

Once the baseline stock is determined, a set of projections are developed to capture changes in building stock due to population growth, economic growth, the adoption of more energy efficient appliances and building practices, and fuel-switching to electric equipment. These projections consider building and equipment stock turnover rates, as well as estimates of equipment performance and likely adoption. Additional Los Angeles and California-specific data for building stocks and energy codes (i.e., Title 24) were used to determine the relevant technologies, their applicability to the local building stock, and their costs and performance characteristics. In addition to electricity, ResStock and ComStock model consumption of other fuels such as natural gas. This enables us to report each projection's fuel use and estimate the emissions impacts of fuel switching.

The building model outputs of ResStock and ComStock provide a highly resolved description of future building stocks in terms of number, type, and size of buildings; technology adoption, including energy efficiency and electrification options; and energy use, especially electricity and natural gas; all at the representative building, end-use level. Overall, the models output 15-minute timeseries data for about a dozen end uses for 75,000 building energy simulations per projection-year. The final data set covering 17 projection-years consists of results from 1.28 million simulations.

Detailed information on how the residential and commercial baseline models were assembled may be found in Appendix A, Appendix B, and Appendix C. In the remainder of this section, we describe the validation process, climate change adjustments, and stock turnover models.

2.1.1 Building Stock Turnover Models

The building stock turnover models first project the building stock, and then project how the technology within both new and existing buildings evolves over time. The residential stock model tracks existing building demolition rates, as well as the construction of new residential buildings to replace demolished buildings and provide for LA County increases in population projected by the CA Department of Finance. The commercial stock model projects growth differentiated by building type using 2002 to 2017 historical data and projections through 2022 provided by Dodge Data and Analytics Metropolitan Construction Insight (Dodge Data & Analytics, 2nd Quarter, 2018).

Both models differentiate growth rate by building type, and model technology adoption by replacing equipment and systems at end-of-life based on technology sales shares that are differentiated by LA100 load projection and evolve over time. Detailed descriptions of stock turnover models are provided in Appendix C.

Across all projections, building stock as represented by number of housing units and commercial building floor area, differentiated by building type, is held constant. Number of housing units by vintage is shown in Figure 12; floor area by Dodge Data commercial building type is shown in Figure 13.

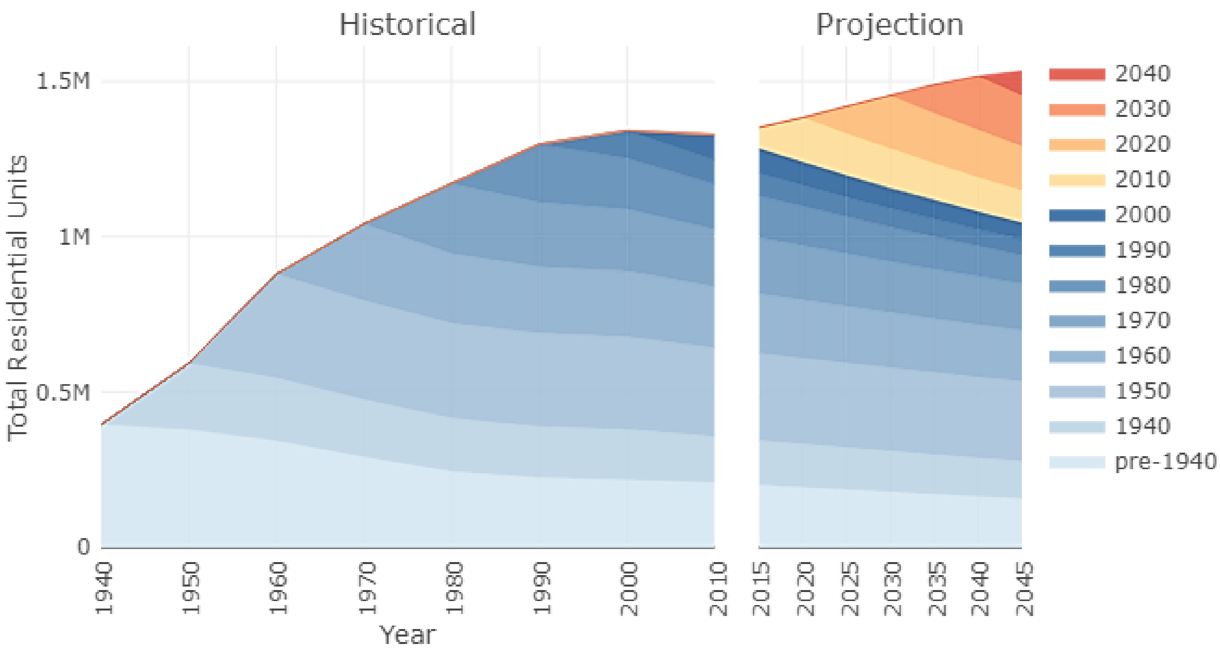

Figure 12. LADWP service territory historical and projected future residential building stock by vintage

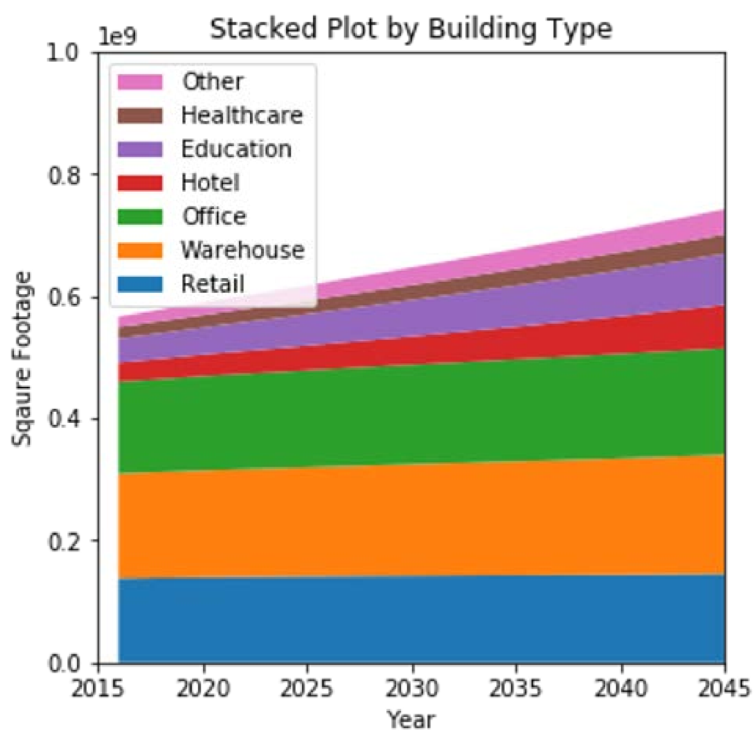

Figure 13. Growth in square footage of commercial buildings by building type

2.1.1.1 Efficiency Projections

The residential building models construct efficiency projections by assigning different sales shares to the range of performance levels available for different equipment and envelope technologies. Original fuel types and performance levels are estimated using 2009 RASS survey data,[12] only existing technologies are considered, and for the most part the highest-efficiency options correspond to the ENERGY STAR "Most Efficient" specification. The Stress efficiency projections was designed to match 2017 IRP 10-year efficiency goals. High efficiency projection assumes that equipment sales shares will be dominated by (greater than 90%) or exclusively to (100%) the highest-efficiency unit available. The Moderate efficiency projection uses sales shares that fall between the Stress and High projections.

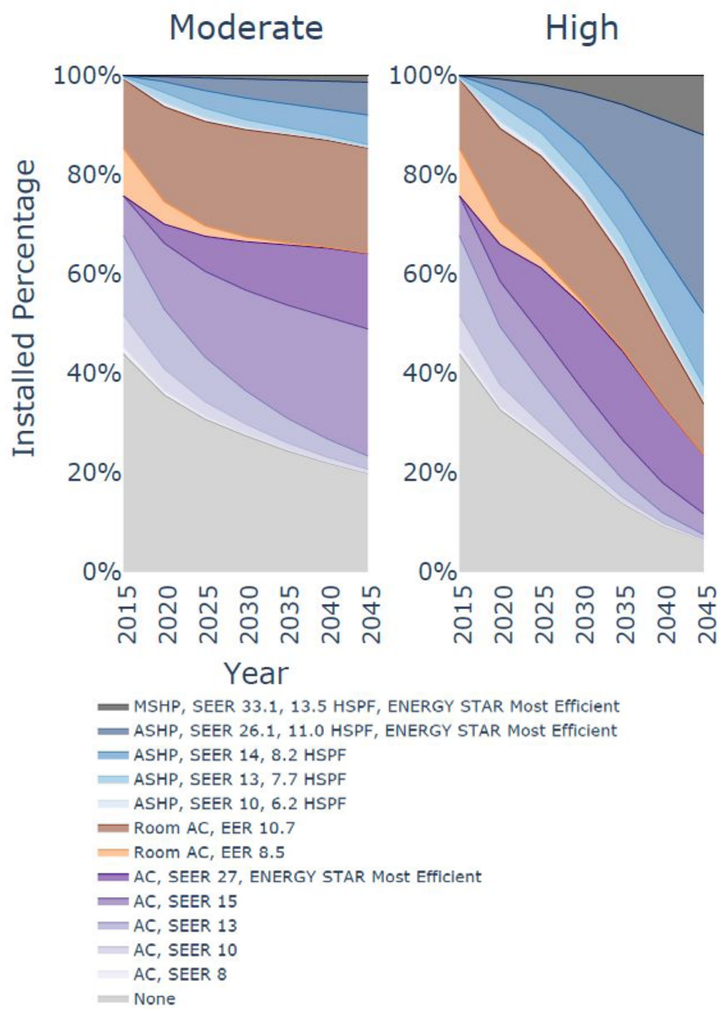

Figure 14. Installed percentage of cooling system types and efficiency levels, by projection-year

The resulting technology adoption for cooling systems is shown in Figure 14. The dominant cooling technologies in the Moderate projection in 2045 are None (over 25% of households), SEER 15 air conditioners (one level short of ENERGY STAR Most Efficient), and EER 10.7 room air

[12] CEC, "2019 Residental [sp.] Appliance Saturation Study," California Energy Commission, https://www.energy.ca.gov/appliances/rass/.

conditioners. The Moderate projection also introduces a sizable number of SEER 27 (ENERGY STAR Most Efficient) air conditioners, as well as more heat pumps of several different performance levels. The High projection, which includes high electrification in addition to high energy efficiency assumptions, has heat pumps comprising over half of the cooling technology stock by 2045, compared to about 10% in the Moderate case. This has the additional effect of driving down the number of households with no air conditioning. A sizable fraction of households still have cooling-only systems, most at the highest efficiency levels (SEER 27 for central units, EER 10.7 for room units).

The commercial building stock model relies on historical and projected energy code descriptions to modulate efficiency across the LA100 load projections. The code descriptions are grouped into five major system categories: envelope, exterior lighting, HVAC, interior lighting, and service water heating; and the technologies in those categories are updated to a more-recent building code when the system reaches the end of its effective useful life (EUL). EUL varies by system—envelopes have the longest EUL (70 years) and are usually not upgraded within a building's lifetime, whereas interior lighting is upgraded every 13 years. ComStock is initialized by running the representative building samples through a series of system upgrades as dictated by its original vintage and the system and building-level EUL. Equipment type specifications, including primary fuel, are aligned with the California Commercial Saturation Survey (CCSS) (Itron, Inc. 2014).

Each load projection then has a different specification concerning what range of codes should be applied in a given model year. The Stress projection randomly assigns upgrades to be below code (20% assigned to an earlier code-year), at code (70% assigned to the current code-year), or beyond code (10% assigned to a code-year 5 years in the future). The Moderate and High projections assign all upgrades to be at or beyond code, up to 20 years ahead in some of the High projection samples.

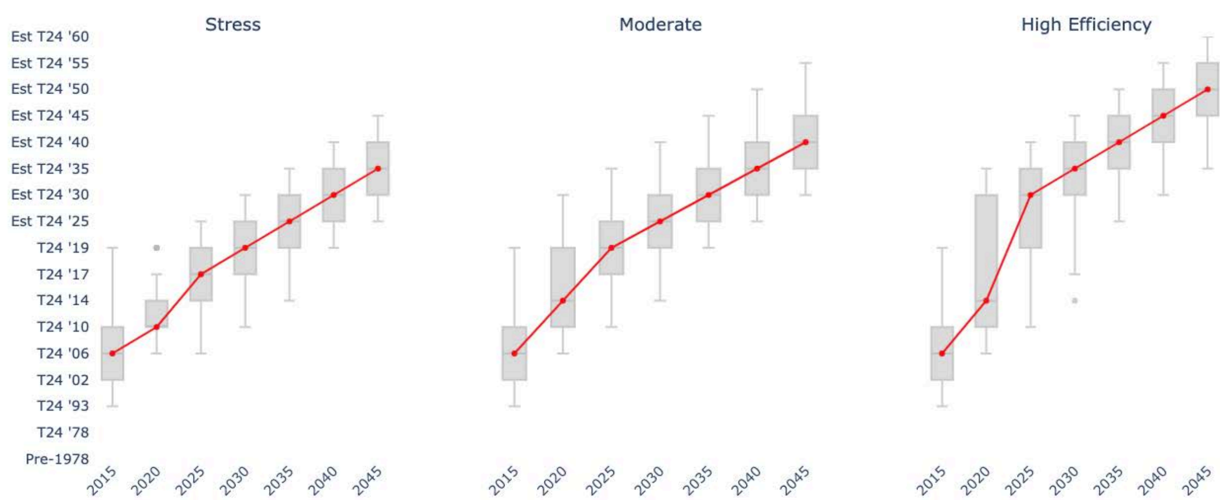

Figure 15. Interior lighting energy efficiency adoption rate

The y-axis lists all of the modeled (historical) and projected codes used in ComStock, in order of increasing energy efficiency. The box-and-whisker plots provided for each projection-year demonstrate the distribution of buildings existing in that year in terms of with which code their interior lighting complies.

The impact of these differing code-level assumptions is most apparent for interior lighting, because of its relatively short EUL. Even before the projection model is applied, ComStock starts with all pre-1993 buildings having had at least one interior lighting upgrade. Then median applied code levels progress to 2035 in the Stress projection and 2050 in the High projection, both by 2045 (Figure 15).

2.1.1.2 Electrification Projections

For the base year of 2015, large quantities of both electricity and natural gas were consumed by buildings in LADWP's territory. Increasing electrification of building equipment could substantially reduce emissions intensity and impact the temporal demand profile of building electricity use. Current trends suggest a consumer preference toward electrification of residential technologies.[13] However, the actual adoption of electric equipment in both the residential and commercial sectors will be influenced by policy and utility incentives, as well as market conditions such as equipment cost and differing fuel type tariffs. Therefore, we evaluate a range of possible electrification adoption outcomes. These electrification projections are exogenous to the model and are meant only to cover the range of possible electrification levels; they should not be interpreted as a modeling result indicating what might be most economically competitive or likely.

Some electrification insights were drawn from the Electrification Futures Study (EFS). EFS is a wide-ranging study led by NREL exploring the impact of electrification on all economic sectors across the United States.[14] The scenarios described by EFS cover a wide range of adoption futures, ranging from little to no movement from pre-2017 policies to complete replacement with electrification technologies as they become available (Mai 2018, Mai et al. 2018). These scenarios are executed at a Census Division scale, and as a result do not entirely encapsulate the unique regulatory environment faced by California and the City of Los Angeles specifically.

The LA100 study models increased electrification of four building end uses: space heating, water heating, clothes dryers, and cooking ranges. All four end uses are modeled for residential buildings; only space heating and water heating are considered for commercial buildings. The EFS scenarios were used to inform the technology sales shares of commercial buildings. The Moderate projection uses the High EFS scenario electric technology sales shares to construct electric and natural gas equipment market shares, renormalized to the current LADWP technology stock baseline. The High projection starts with the Technology Potential EFS scenario but ramps up ambition even further to align with the 100% net carbon neutral by 2050 goal defined by the Mayor's Office in its 2019 pLAn. Given the expected component lifetimes of the HVAC and service water heating (SWH) systems, it was necessary to force 100% electrification of replacements starting in the 2035 model year, in addition to building only all-electric new buildings starting in 2030.

The residential High electrification assumptions support the pLAn's carbon-neutrality targets: all new construction has electric appliances by 2030 and all existing buildings are fully electric by

[13] EIA, "Everywhere but Northeast, Fewer Homes Choose Natural Gas as Heating Fuel," U.S. Energy Information Administration, *Today in Energy*, September 25, 2014, https://www.eia.gov/todayinenergy/detail.php?id=18131.
[14] "Electrification Futures Study," NREL, https://www.nrel.gov/analysis/electrification-futures.html.

2050. To achieve the pLAn targets using end of life equipment turnover, all equipment sales must be 100% electric by 2030. The residential Moderate assumptions assume that some end uses (i.e., clothes drying and water heating) would be easier to electrify than others (i.e., space heating and cooking ranges).

Figure 16 shows the impact of both efficiency and electrification assumptions on the residential modeling results for heating systems. The High projection phases out electric resistance technologies (in response to Title 24 and the guidance of LADWP), and greatly favors high-efficiency heat pump technologies. The Moderate projection favors some higher-efficiency gas furnaces, as well as increased adoption of heat pumps, but short of the efficiency and electrification changes associated with High.

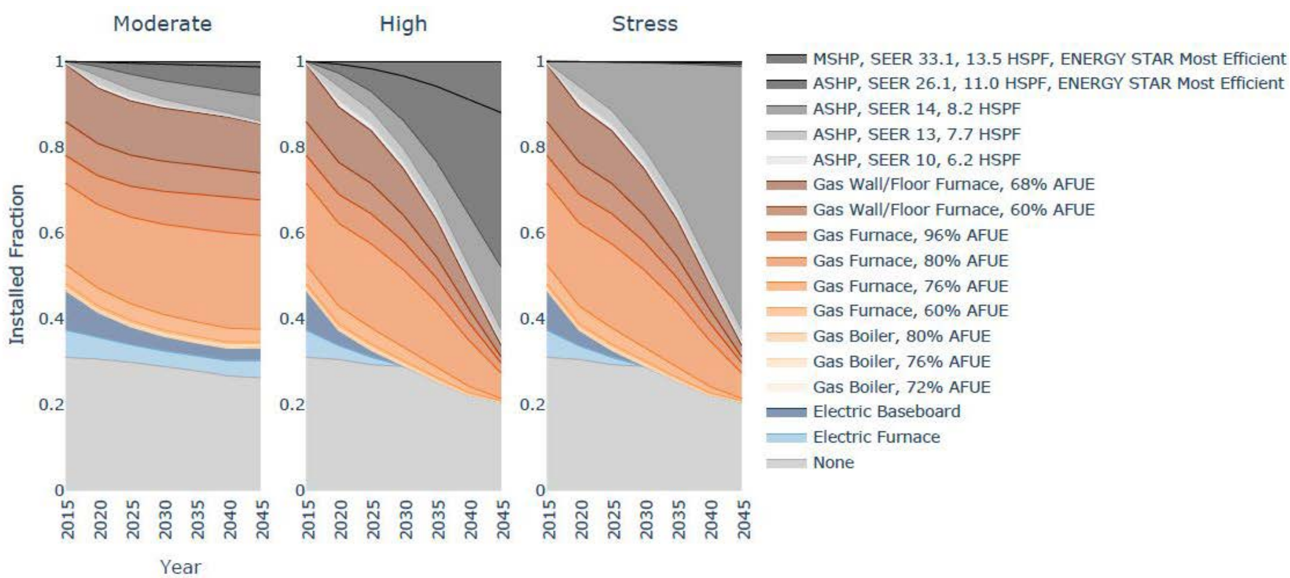

Figure 16. Installed residential heating systems by projection-year

Commercial service water heating starts at 62% electrified by building count in the 2015 baseline year and is completely electrified by 2045 in the High projection. Moderate assumptions attenuate the outcome such that service water heating only reaches about 75% electrification in the same time frame. The story for HVAC electrification is similar. Starting at 53% electrified in 2015, we estimate that commercial building HVAC would be completely electrified by 2050 in the High projection. The Moderate projection reaches about 80% electrification by 2045.

2.1.2 Climate Change Adjustments

To address impacts of hotter temperatures due to climate change, LA100 captured expected changes in air conditioning demand based on projected increases in average and peak temperatures. Higher daily maximum temperatures were estimated using the Intergovernmental Panel on Climate Change (IPCC) Representative Concentration Pathway (RCP) 8.5 scenario ("emissions continue to rise strongly through 2050 and plateau around 2100") as represented in the UCSD Scripps Institute of Oceanography Localized Constructed Analogs statistically downscaled climate projection data set.[15] The changes in monthly average high temperatures from the Los Angeles area RCP 8.5 scenario data, for the three climate zones used in the study, were used to increase the dry bulb temperatures in the 2012 weather files that drive the ResStock and ComStock simulations, starting in model year 2025. The impact of the dry bulb temperature modifications is seen in the weather dependent end-use loads (heating and cooling) produced by the physics-based building energy models. The study did not look at other potential impacts such as changes to precipitation, fires, technology performance, air quality, among others. The study also did not look at uneven distribution of heating due to neighborhood-level impacts of climate changes, for example, in areas with significant paved surfaces.

For consistency throughout the project, 2012 weather data—revised to reflect projected increases in temperature associated with climate change—is used for each simulation. In addition, given that observed peak temperatures (and associated loads) in recent years substantially exceeded the peak in 2012, adjustments to the peak temperature and load week were made to capture the more recent extreme summer temperatures and loads. Specifically, the temperature-adjusted loads for the week of peak demand in 2012 were increased to match the 2017 peak demand in the LADWP system (i.e., the load based on 2012 weather and 2015 building stock was increased to match load in the peak week of 2017). This results in a modified 2012 peak-week consistent with the recent observed extremes in temperatures and associated loads. This modification is maintained throughout future projections, such that future load-years reflect both this modification to capture observed current extremes and further increases in temperatures associated with climate change.

2.1.3 Building Projection Results

Figure 17 shows the predicted annual electricity consumption for the commercial and residential building sectors for the three projections out to 2045. Comparing the Moderate and High projections, one can see that the annual consumption impact of electrification called for in the pLAn Green New Deal can largely be mitigated through aggressive energy efficiency. On the other hand, the Stress projection which combines low energy efficiency with aggressive electrification shows over a 10% increase in predicted annual electrical usage for these buildings sectors.

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[15] CEC, "Exploring California's Climate Change Research," California Energy Commission, https://cal-adapt.org/.

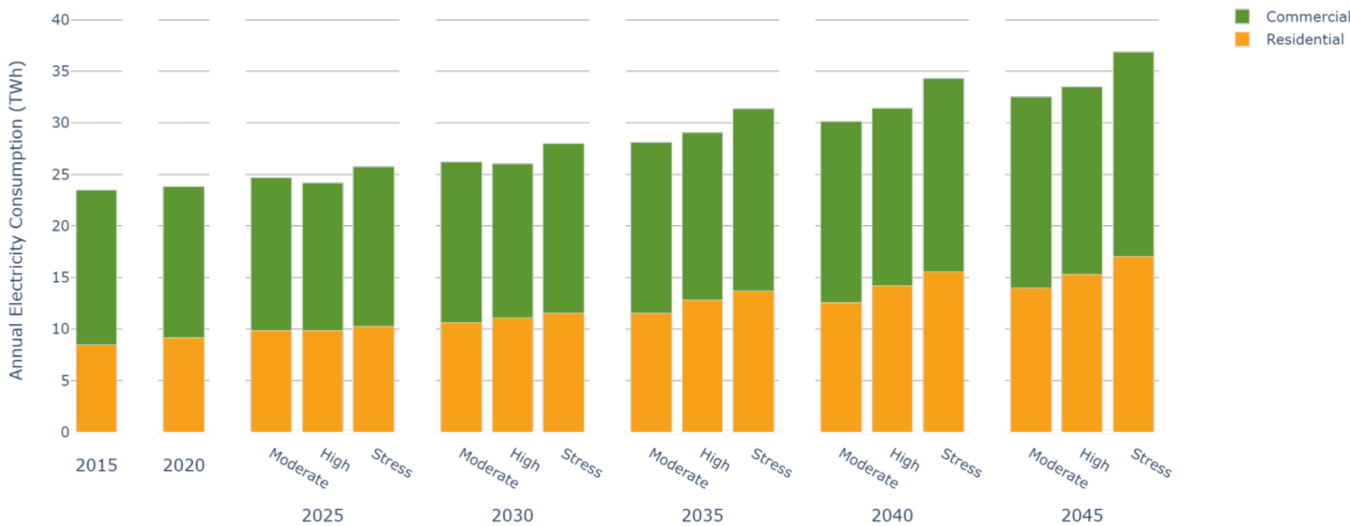

Figure 17. Annual electricity consumption for commercial and residential building sectors

Figure 18 shows the predicted demand for the commercial and residential building sectors for the three projections out to 2045. Similar to the annual electricity usage in Figure 17, comparing the Moderate and High projections in Figure 18 indicates that aggressive energy efficiency offsets the peak demand impact of electrification.

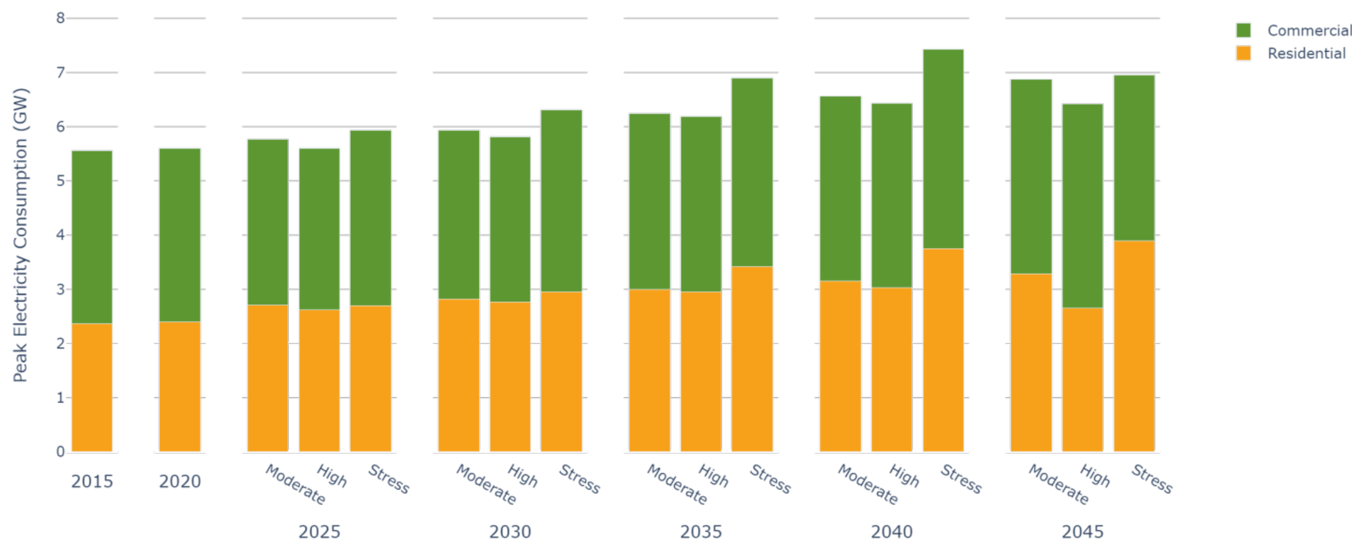

Figure 18. Peak demand for commercial and residential building sectors

Figure 19 shows the average daily and peak day load shapes for commercial and residential building sectors. Similar to figures above, comparing High to Moderate projections shows that energy efficiency can largely offset aggressive electrification. Interestingly, the time of the combined peak from the commercial and residential sectors moves to mid-day under the Stress projection. This is largely a result of increased cooling demand within the commercial and residential building stock, paired with limited additional thermal envelope efficiency upgrades, as well as increased electric water heating loads.

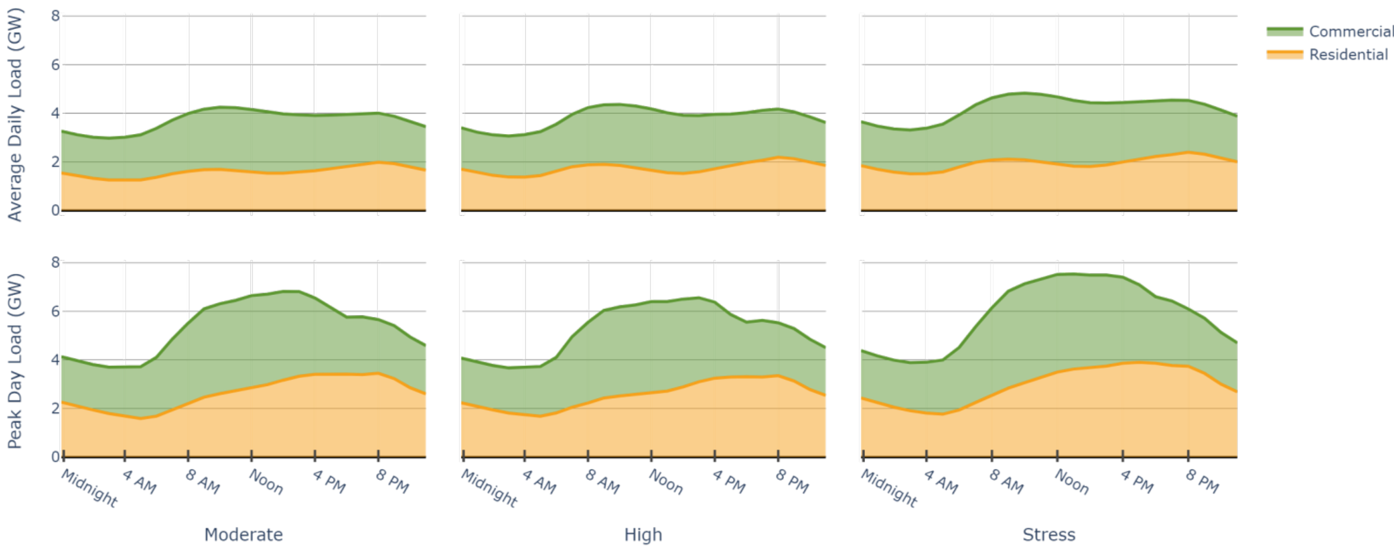

Figure 19. Load shapes for commercial and residential building sectors, 2045

Figure 20 and Figure 21 show the average and peak-day end-use load shapes for the Stress projection for the residential and commercial building sectors, respectively, along with the changes in load shapes between Stress and High projections. The bottom row in each figure shows the savings in energy due to energy efficiency, which are positive for the end-use loads for nearly all hours. For example, efficiency improvements to cooling offer the greatest savings in electricity use, especially on the peak day in the afternoon (bottom, right panel of both figures). This result highlights that without additional energy efficiency, growth and electrification will add substantial load from these building sectors, principally from space cooling and associated delivery, although plug and process loads as well as lighting still contribute significantly to the increased energy use of the building stock.

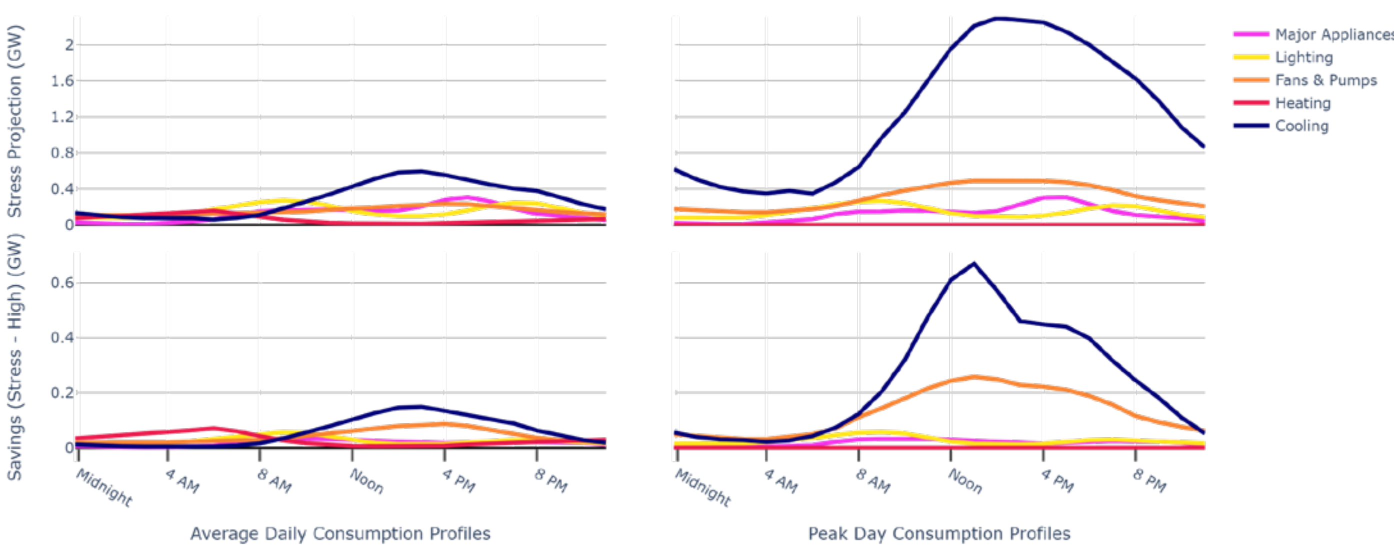

Figure 20. Average (left) and peak (right) daily end-use load shapes for residential building sector, 2045

Top row is Stress projection and bottom row shows reductions in consumption due to energy efficiency (difference between Stress and High projections). Positive values in the bottom row indicate electricity savings due to efficiency improvements at that hour, on an average day (left) and on the peak day (right).

In the residential model (Figure 20) on the peak day (right), the dominant residential load (top) and the dominant source of potential energy savings (bottom) is residential cooling. Under both projections, increased electrification of space heating causes the adoption of heat pumps, which can both heat and cool spaces. Indirectly, this increases the saturation of fully cooled homes. In the Stress projection, the adopted heat pumps tend to be minimally efficient models, whereas the High projection adopts heat pumps with higher efficiency levels. The savings from these higher efficiency heat pumps are realized most strongly in the middle of the day, when cooling demand is the greatest. For the average day (left), efficient heat pumps reduce energy use for heating prior to 8am, thereby better aligning load and solar generation during winter months.

In residential buildings, fans and pumps are typically an integrated part of the heating and cooling systems, and so we see energy savings from this end use in the High, as compared to the Stress, projection as a companion effect to increased heating and cooling energy efficiency. Fan and pump savings in the High projection are further driven by greater adoption of mini-split heat pump systems that do not circulate air through the whole house.

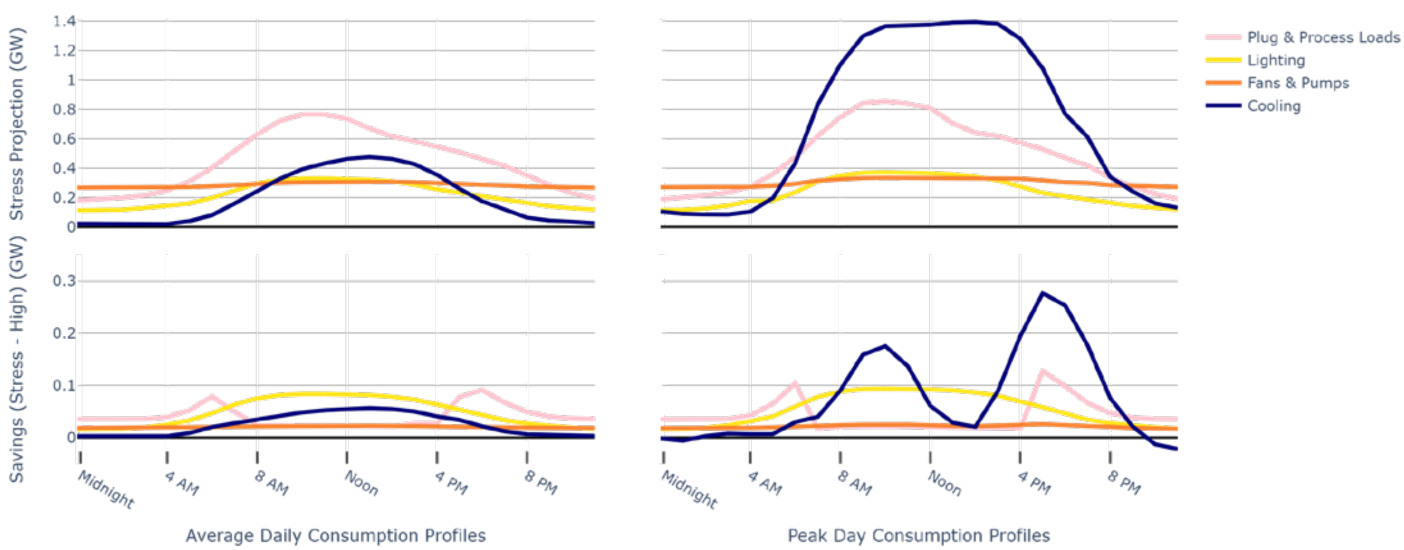

Figure 21. Average (left) and peak (right) daily end-use load shapes for commercial building sector, 2045

Top row is stress projection and bottom row shows reductions in consumption due to energy efficiency (difference between Stress and High projections). Positive values in the bottom row indicate electricity savings due to efficiency improvements at that hour, on an average day (left) and on the peak day (right).

Similar to the residential sector, commercial building cooling demand and energy efficiency savings are dominant on the peak day, and more efficient fans and pumps (which deliver cooling and heating services to building occupants) are important peak day energy savers as well (Figure 21). However, the commercial cooling savings shape is significantly different from that for residential buildings. Significantly better window, wall, and roof construction in the High projection leads to significantly reduced cooling loads during low sun-angle periods (i.e., in the morning and evening when the east or west faces of buildings receive direct solar radiation). This, paired with increased part-load efficiency of many cooling systems in the high scenario, leads to almost 20% savings in the cooling end use at 5 p.m. on the peak day. Plug and process loads also show a noticeable decrease in energy use in the High as compared to the Stress projection, particularly during parts of the day when buildings have low occupancy levels. This is primarily achieved through more automated control of plug loads, as well as some increase in overall efficiency. Finally, the High projection assumes that higher-efficiency LED technologies will replace current generation LED technologies across the commercial building stock.

Figure 22 shows the difference in annual electricity consumption between Stress and High projections for the commercial and residential building sectors. The height of the bar indicates annual energy savings from contributing end uses due to improvements in efficiency. Similar to load shape figures above, the changes are positive for nearly all end uses. These results show that building energy efficiency saves almost 3 TWh of electricity in the 2045 High, as compared to the Stress, projection. The largest savings come from cooling, lighting, and fans and pumps; but plug and process loads, heating, and major appliances (residential only—commercial appliances are grouped into the overall plug and process load category) are not far behind. Overall, we see that a holistic approach is needed to achieve the full benefits of energy efficiency in the buildings sectors.

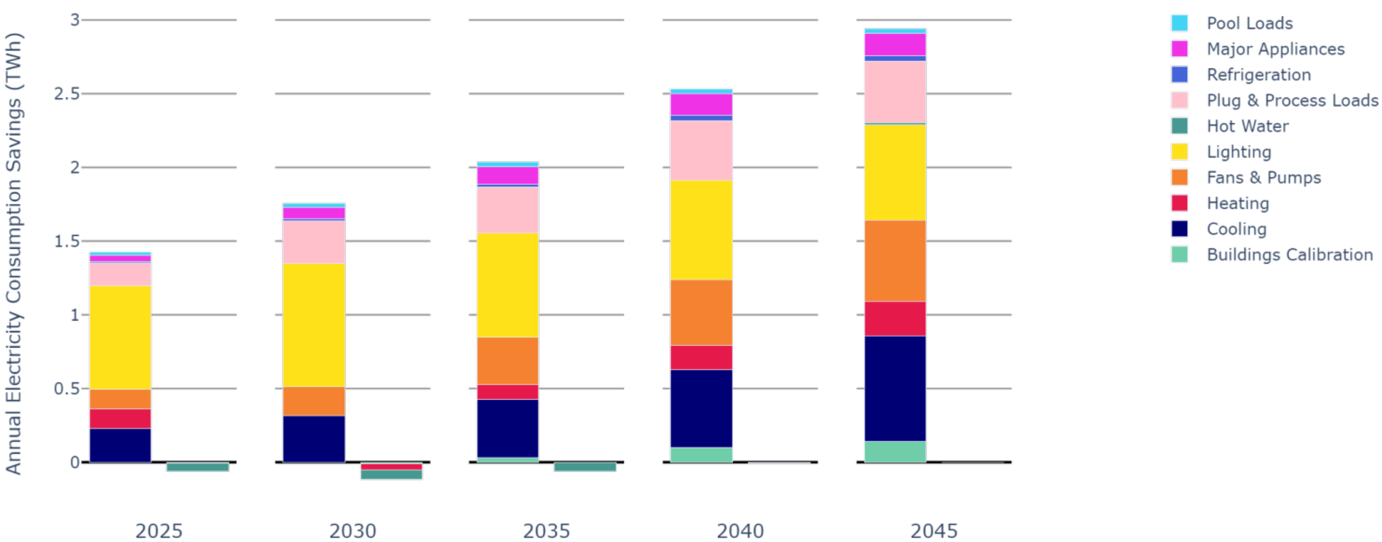

Figure 22. Difference in annual electricity consumption between High and Stress projections for the commercial and residential building sectors

Positive value indicates the annual savings in electricity due to the improved efficiency of end uses in the High projection compared to Stress.

The dynamics of the residential sector adoption model decreased electric heating saturation in 2030, leading to lower-than-expected electric heating load in that year and an inconsistent comparison between the High and Stress projections. Other model years were not impacted.

Figure 23 shows the difference in peak electricity demand between Stress and High projections for the commercial and residential building sectors. Positive values indicate peak demands under the Stress projection are higher than under the High projection. Prior to model year 2045, the

High and Stress scenarios' times of peak demand are all in mid to late afternoon, and the contribution of individual end-use contributions to peak demand savings are straightforward. Cooling is the main contributor to peak demand savings, with more modest contributions from fans and pumps, lighting, plug and process, and major appliance. In model year 2045 however, the High Scenario peaks around 2 p.m., whereas the Stress Scenario peaks around 7 p.m. This causes the composition of peak demand, in terms of which end uses are using electricity at that time, to be quite different. Thus, the bar charts for 2045 show that there are a lot fewer residential appliances and a lot more plug and process loads (primarily associated with commercial building types) operating in the High scenario at 2 p.m. as compared to the Stress scenario at 7 p.m. Cooling is still the single largest contributor to peak savings, however, increases in efficiency for fans and pumps as well as major appliances play a far greater role in the efficiency mix across those hours.

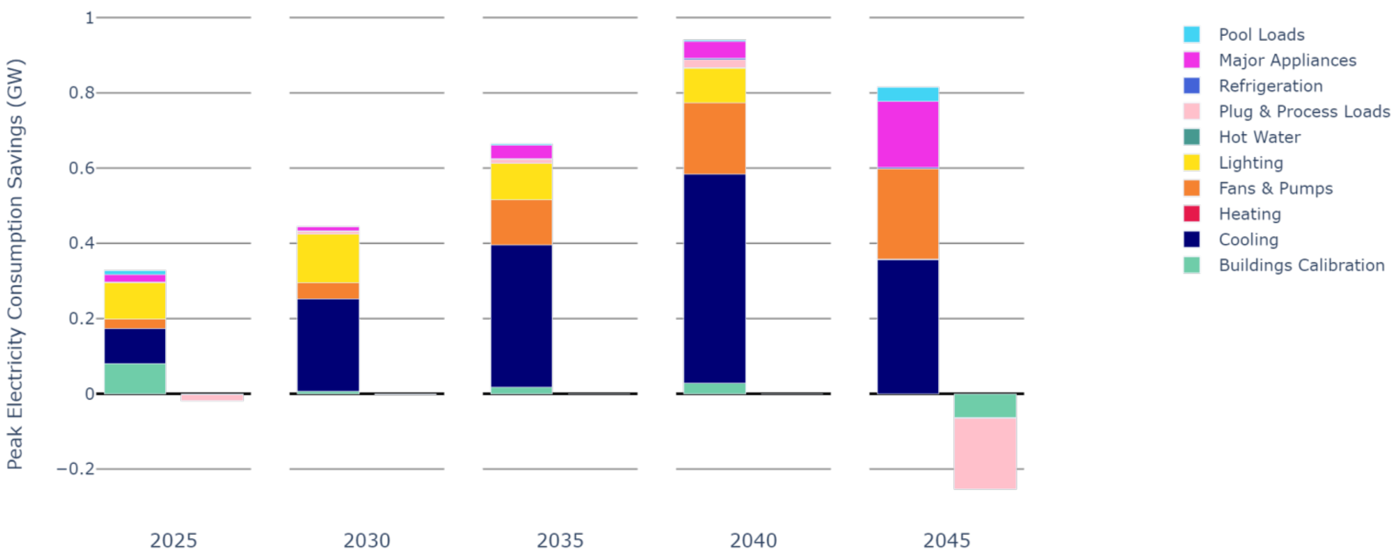

Figure 23. Difference in peak demand between High and Stress projections for the commercial and residential building sectors

Positive value indicates the annual savings in electricity due to the improved efficiency of end uses in the High projection compared to Stress.

Additional modeling results of the residential and commercial buildings sectors are included in Appendix D.

2.2 Transportation

Electric vehicle (EV, in this study meaning plug-in electric vehicle, or PEV, which includes battery electric vehicles [BEVs] and plug-in hybrid electric vehicles [PHEVs]) adoption has the potential to create significant load growth and profoundly change load shapes, impacting distribution, transmission, and generation systems. Moreover, EV load is intrinsically flexible, creating major demand response opportunities. EV charging load, however, is particularly difficult to model because a) EV adoption is still in its infancy and data are scarce and incomplete; b) EV charging is dictated by consumer preference for when and where to charge as well as available charging options (e.g., workplace charging); and c) it is unclear what level of charging flexibility vehicle owners are willing to provide, and what business models can best incentivize demand response participation. In this study we developed different projections of light-duty passenger EV adoption, consistent with California and City of Los Angeles goals, and charging availability to properly represent EV charging in Los Angeles. We also modeled full electrification of the school, LA Metro, and LADOT fleet serviced within LADWP service territory by 2030.

2.2.1 Light-Duty Vehicle Electrification

Modeling EV charging load requires an understanding of how many and what kind of EVs are present, where and when the vehicles are used, and thus the locations and times at which they can be charged. NREL's EVI-Pro tool uses LDV travel information based on how vehicles (mostly conventional gasoline vehicles) are driven today to produce estimates of the number of EV chargers required to support mobility needs and the resulting EV charging load profiles. EVI-Pro has been developed by NREL in collaboration with the California Energy Commission (CEC) and with additional support from the U.S. Department of Energy. EVI-Pro uses detailed data on personal vehicle travel patterns, EV attributes, and assumed residential and workplace charging availability and consumer charging preferences in bottom-up simulations to estimate the quantity and type of charging infrastructure necessary to support various levels of regional EV adoption, and the resulting charging load profiles. In a subsequent step these charging loads are disaggregated to the LA100 agent level to assess impacts on the distribution systems (Figure 24). Vehicle travel patterns (in the form of representative trips) and options for the prevalence of different charging options (low-powered level 1 [L1], medium-power level 2 [L2], and highest-power DC fast-charging [DCFC]) are based on available data and scaled to represent the number of EVs in each projection-year for the different LA100 projections. EVI-Pro has been used for detailed studies in Massachusetts; Columbus, OH; California; Maryland; and for a national analysis of U.S. communities and corridors.[16]

[16] Eric Wood, Sesha Raghavan, Clement Rames, Joshua Eichman, and Marc Melaina, *Regional Charging Infrastructure for Plug-In Electric Vehicles: A Case Study of Massachusetts* (NREL, 2017), NREL/TP-5400-67436, https://www.nrel.gov/docs/fy17osti/67436.pdf.
Eric Wood, Clément Rames, Matteo Muratori, Sesha Raghavan, and Stanley Young, *Charging Electric Vehicles in Smart Cities: An EVI-Pro Analysis of Columbus, Ohio* (NREL, 2018), NREL/TP-5400-70367, https://www.nrel.gov/docs/fy18osti/70367.pdf.
Abdulkadir Bedir, Noel Crisostomo, Jennifer Allen, Eric Wood, and Clément Rames, *California Plug-In Electric Vehicle Infrastructure Projections, 2017-2025: Future Infrastructure Needs for Reaching the State's Zero-Emission-Vehicle Deployment Goals* (CEC, 2018) staff report, https://www.nrel.gov/docs/fy18osti/70893.pdf.
Matthew Moniot, Clément Rames, and Eric Wood, *Meeting 2025 Zero Emission Vehicle Goals: An Assessment of Electric Vehicle Charging Infrastructure in Maryland* (NREL, 2019). NREL/TP-5400-71198. https://www.nrel.gov/docs/fy19osti/71198.pdf.
Eric Wood, Clément Rames, Matteo Muratori, Sesha Raghavan, and Marc Melaina, *National Plug-In Electric Vehicle Infrastructure Analysis* (DOE, 2017). DOE/GO-102017-5040. https://www.nrel.gov/docs/fy17osti/69031.pdf.

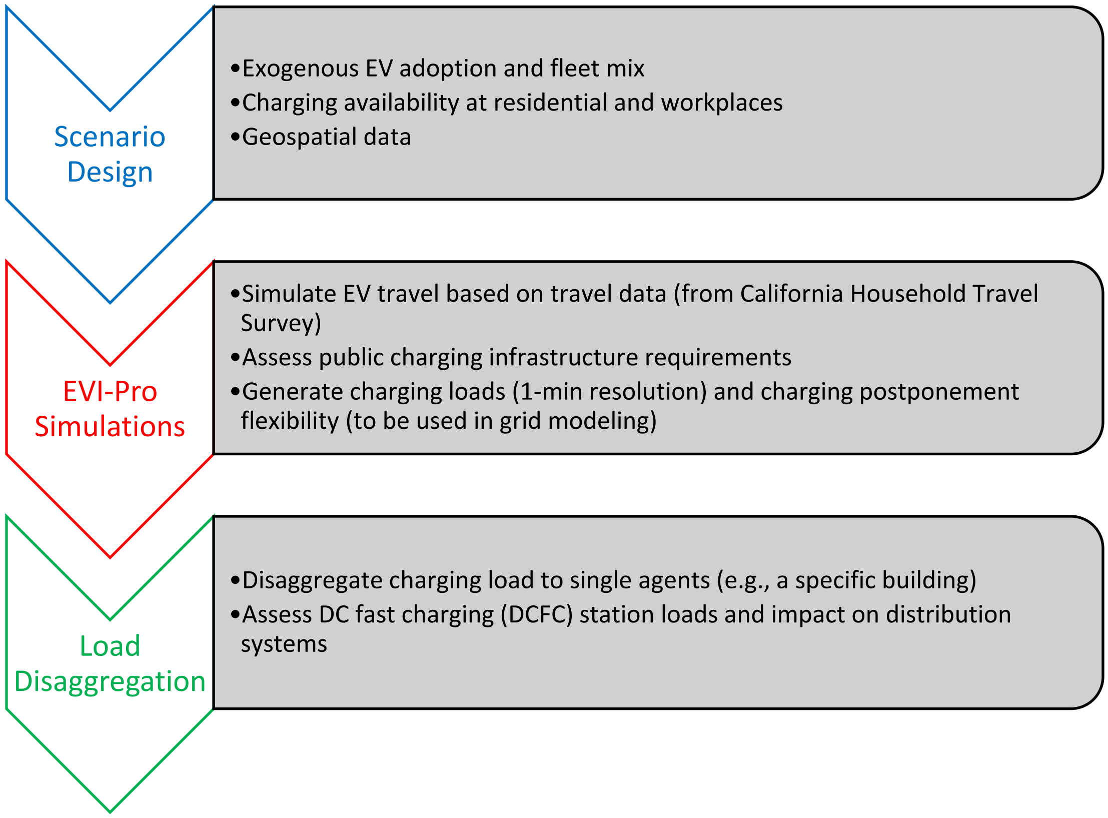

Figure 24. EV load modeling methodology

Adoption projections for light-duty personal vehicles over the planning horizon (2020–2045) are shown in Figure 25 (number of vehicles) and Figure 26 (market share). These projections assume that ~10% of California vehicles are located in the LADWP service territory, based on consultation with LADWP staff. This estimate includes vehicles adopted by residents of the LADWP territory and does not account for vehicles that enter or exit the City of Los Angeles during the day, which could provide additional/reduced opportunities.

Both Moderate and High EV projections are consistent with the California ZEV 2025 and 2030 goals.[17] The Moderate projection is based on the "high case" EV adoption from the LADWP 2017 SLTRP. This projection exceeds the California Zero Emission Vehicle (ZEV) mandate in 2025 and achieves the 2030 ZEV goal (assuming the City of Los Angeles is responsible for 10% of the EV adoption prescribed in the CA ZEV goal). The High electrification projection follows the 2017 SLTRP "high case" until 2025, and then assumes more aggressive adoption from 2026 onward based on the High electrification scenario in NREL's EFS study (Mai et al. 2018).[18] This

[17] CARB, "Zero-Emission Vehicle Program," California Air Resources Board, https://ww2.arb.ca.gov/our-work/programs/zero-emission-vehicle-program/about.
[18] The EFS High adoption scenario represents "a combination of technology advancements, policy support and consumer enthusiasm that enables transformational change in electrification." For all electrification technologies and scenarios, adoption is modeled in terms of sales share trajectories that "were developed through expert judgement from the authors based on analysis of current trends and insights from other studies as well as from consumer choice

projection exceeds both California ZEV goals and reaches a total EV market share of approximately 80% in 2045.

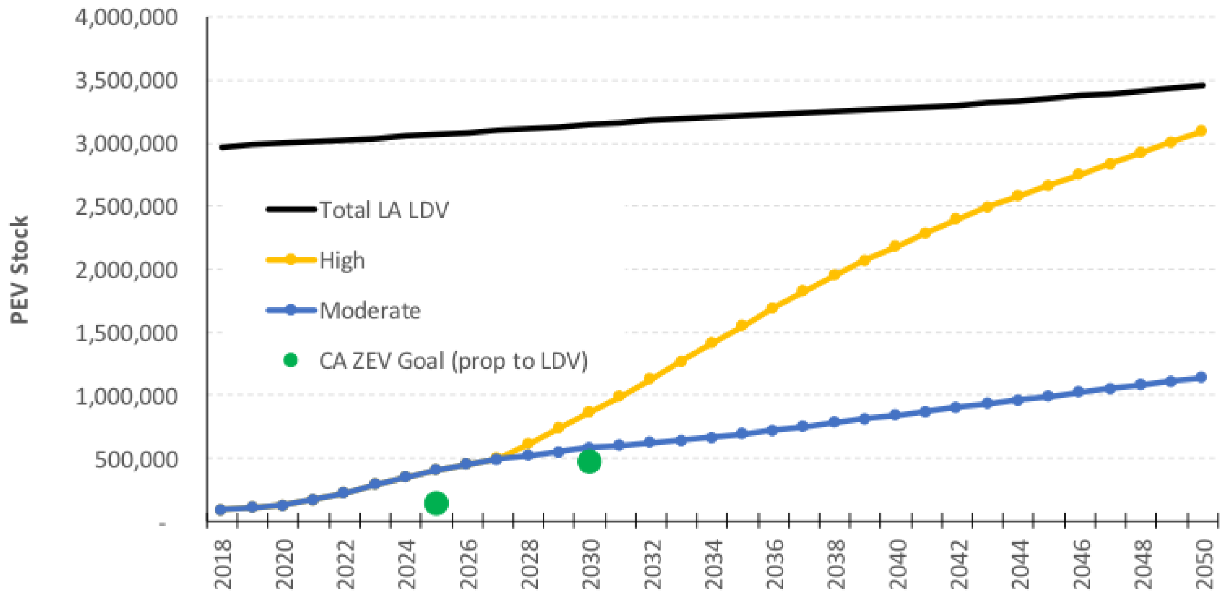

Figure 25. Projections of EV stock by electrification projection

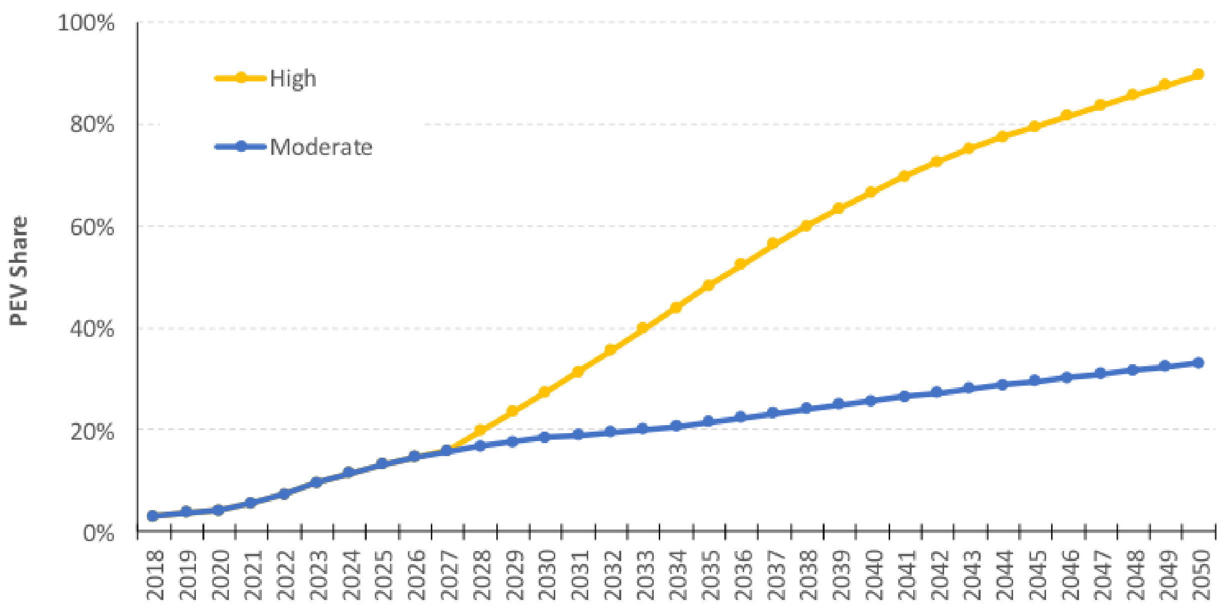

Figure 26. Projections of EV stock as a share of LA light-duty vehicles, by electrification projection

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models." For the High scenario, light-duty plug-in electric vehicle (PEV) sales shares were estimated using the ADOPT model (with rapid battery advancement, EV component "Program Success case," and non-EV component "No Program Success case" assumptions) through 2033. A linear adoption trend from 71% PEV sales shares in 2033 to 100% PEV sales shares in 2050 was assumed for years 2033-2050 (Mai 2018).

Vehicle fleet composition (e.g., PHEV/BEV ratio and vehicle ranges) are taken from (Wood et al. 2017) (with the exclusion of SUVs that have not been considered here) and are reported in Table 2. One fundamental assumption in EVI-Pro is that consumers prefer residential charging, when available, and maximize the miles driven on electricity (for PHEVs). To determine charging loads, individual travel days from available travel surveys are simulated in the model. Each travel day is simulated multiple times for each potential combination of charging behavior (e.g., Level-1 Home, Level-2 Home, Level-1 Home plus Level-1 Work, etc.) and the lowest-cost option is then selected, considering different levels of consumer preference for alternative charging solutions.

Table 2. Light-Duty Electric Vehicle Fleet Mix by Vehicle Type

Vehicle Type	Electric Range (miles)	Fleet Mix (%)
PHEV20	20	15%
PHEV50	50	35%
BEV100	100	15%
BEV250	250	35%

In this analysis, we vary the availability of EV chargers in different types of locations based on the overall LA100 load electrification and DR assumptions. In particular, we assume that access to residential charging decreases as more EVs are adopted as a consequence of EVs being adopted by more people who live in residences that would be difficult to equip with dedicated chargers (e.g., residents with on-street parking). Access to residential charging is assumed to be 75% and 60% for the Moderate and High electrification projections, respectively.

We also assume that access to workplace charging and higher levels of demand response are positively correlated, under the assumption that conditions that result in LADWP investments in demand response would also incentivize investments to align EV charging with middle-of-the-day solar electricity generation. Access to workplace charging is assumed to be 25% and 50% for the Moderate and High demand response projections, respectively. This translates to as many as 1.3 million workplace chargers in 2045 for some projections.

The Stress projection charging assumptions are constructed differently, to assess the maximum impact/stress of widespread home charging of EVs. This projection assumes that 90% of EVs have access to residential charging and only 15% have access to workplace charging. This allocation of infrastructure produces a large demand every evening when people come home from work and plug in. This projection aligns with the current behavior of early EV adopters (Greene et al. 2020), capturing a possible future in which most EVs charge at home, and providing one bookend for highly uncertain charging infrastructure developments.

All projections estimate the amount of public L2 and DCFC infrastructure required for all simulated trips to be successfully completed. That is, public infrastructure is added to supplement the initially assumed home and workplace charging to make all trips feasible.

EV adoption and the EVI-Pro charging profiles are geographically downscaled to capture the impact of EV charging on distribution networks and to provide output data on the different charger types (i.e., Home L1, Home L2, Work L1, Work L2, Public L2, and DCFC). Home, work, and public charging loads are placed at agents that match those categories. DCFC station locations are sampled from large nonresidential parking lots within 0.3 miles of the 34.5-kV distribution network.

Finally, EVI-Pro estimates two uncoordinated charging load profiles that are both available at the agent-level: minimum delay and maximum delay. The two profiles bookend the timing of charging once a vehicle is plugged in. Minimum delay starts charging right away when a vehicle arrives at a location where charging is needed and stops when the vehicle battery is full or the vehicle is unplugged, whichever comes first. Maximum delay postpones charging as long as possible subject to the constraint that the vehicle must have sufficient charge for its next trip when it is unplugged. The minimum-delay profile is assumed to be the default behavior and is used in all uncoordinated load profiles. By combining the two profiles, we bound flexible charging opportunities and realistically model the impact of demand response participation by charger type respecting mobility needs (i.e., making sure that vehicles can complete all their trips).

The different EV adoption and charging availability projections result in aggregate vehicle charging totals with different overall electricity use, peak demand, and load shapes. Figure 27 summarizes the annual EV charging energy (x-axis, in GWh) and the EV charging peak (y-axis, in MW) for all the projections considered in 2045. Note that because different vehicles plug in at different times, and it is not generally the case that every electric vehicle has a single dedicated charger, the EV charging peak is an emergent, aggregated phenomenon with a total power much less than multiplying the total number of EVs times the maximum power draw of any particular type of charger.

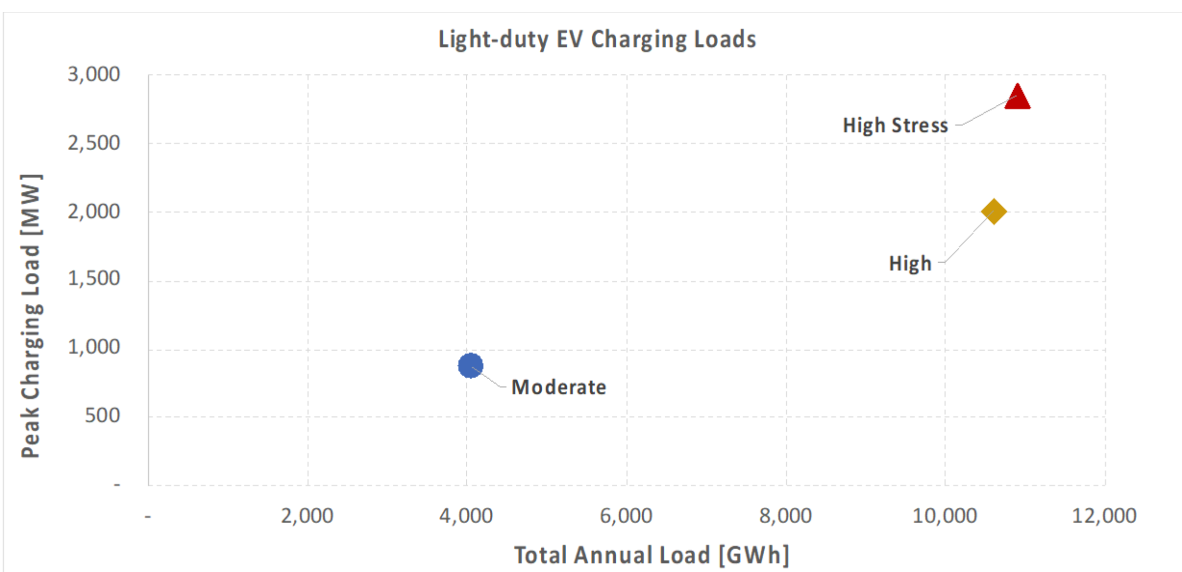

Figure 27. Summary of LDV EV charging annual energy consumption and peak demand, by projection, in 2045

On average, personally owned LDVs use ~4,000 kWh of electricity per year, and lead to an average system-level per-vehicle peak demand of 0.75–1.07 kW (total EV charging load divided by number of EVs). This translates to an average of 3 hours of charging per day. Average energy consumption per vehicle is mainly driven by travel behavior and varies minimally across projections. Peak demand is driven by the number of vehicles and the charging infrastructure available, which results in different shares of charging happening at different locations and at different power levels.

To better visualize load shapes (and peak demand) for each projection, Figure 28, Figure 29, and Figure 30 report the aggregated LDV charging load profiles for the three projections. In particular, for each projection four aggregate charging load profiles (the sum of all the charging events from all the EVs considered in that projection) are reported:

- Top left: Typical weekday aggregate charging load assuming “uncontrolled” charging: vehicles start charging as soon as plugged in and continue to consume power until fully charged or if another trip is initiated.
- Top right: Typical weekend day aggregate charging load assuming “uncontrolled” charging: same as top left but for weekend days, rather than weekdays.
- Bottom left: typical weekday aggregate charging load assuming “maximum delay” for home and workplace charging: at public locations, vehicles start charging as soon as plugged in and continue to consume power until fully charged or if another trip is initiated. At home and work, vehicles delay charging start time as much as possible under the constraint of equivalent energy transfer compared to the uncontrolled scenario.
- Bottom right: typical weekday aggregate charging load assuming “maximum delay” for home and workplace charging: same as bottom left, but for weekend days, rather than weekdays.

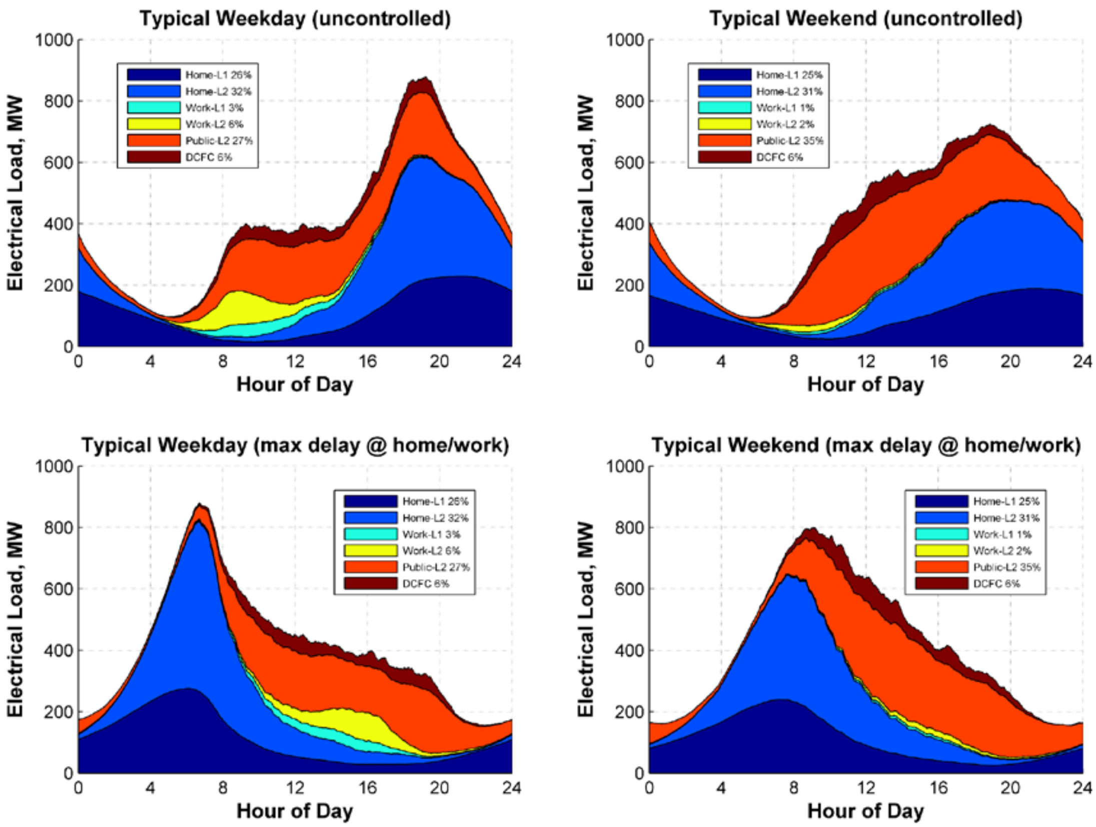

Figure 28. Light-duty electric vehicle charging profiles for the Moderate projection, 2045

Top row: Vehicles charge immediately upon arrival and charge until fully charged or another trip initiated. Bottom row: Vehicles charge as late as possible and still achieve the same total energy charge as top row. Left half—weekdays; right half—weekends.

The "uncontrolled" and "maximum delay" scenarios provide insights on the time windows during which EVs can be charged without affecting mobility needs (i.e., how early can charging start and how late can it be postponed guaranteeing that each vehicle is fully charged every day and that trips are completed). This window is critical in assessing the ability of EVs to participate in DR programs without compromising their primary mobility mission. While personally owned electric LDVs are shown to be charging an average of 3 hours per day, in these scenarios they are plugged in for an average of 13 hours per day (15 on weekends), leaving room for significant charging rescheduling and optimization.

Comparing the charging load profiles in Figure 28, Figure 29, and Figure 30 reveals significant differences in charging load profiles and load shapes beyond the simple "scale-up" of load associated with different levels of EV adoption assumed in the different projections. This variability is mainly driven by the different charging availability assumed in each projection that accounts for alternative futures of residential and workplace charging infrastructure development (public charging is estimated in EVI-Pro, as a last resort solution and charging at public locations is computed endogenously on an as-needed basis). Other sources of uncertainty in EV charging load are related to many other variables that could evolve in different ways over time. For example, among other questions: Will residential/workplace chargers primarily be L1 or L2? What will be the future of public DC fast charging, and will extreme fast charging (e.g., 350 kW) become predominant? What will be the electric driving range of future EVs? At what locations will future EV owners prefer charging? Some of these uncertainties have been explored in (Wood et al. 2017), showing major impact on public infrastructure needs, and others remain interesting topics for future research.

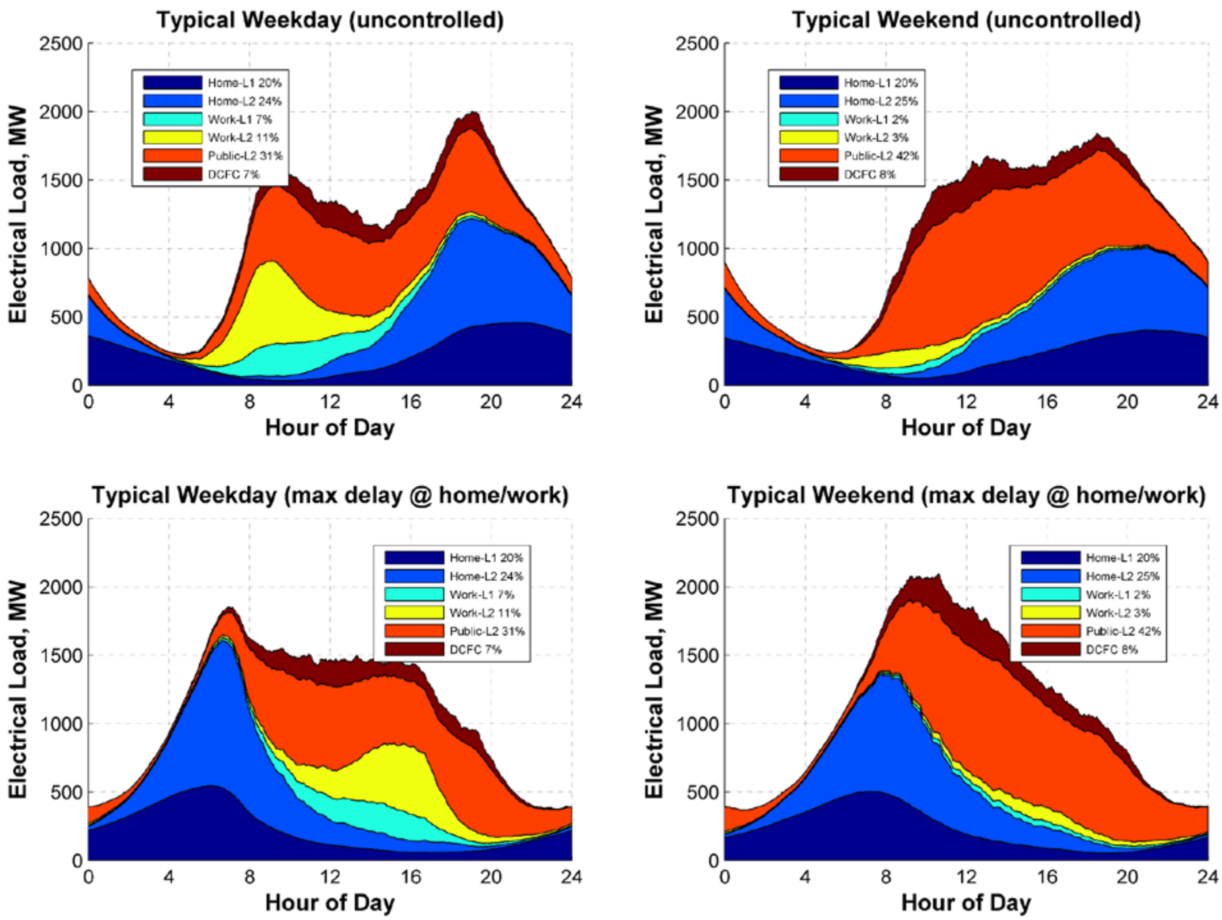

Figure 29. Light-duty electric vehicle charging profiles for the High projection, 2045

Top row: Vehicles charge immediately upon arrival and charge until fully charged or another trip initiated. Bottom row: Vehicles charge as late as possible and still achieve the same total energy charge as top row. Left half—weekdays; right half—weekends.

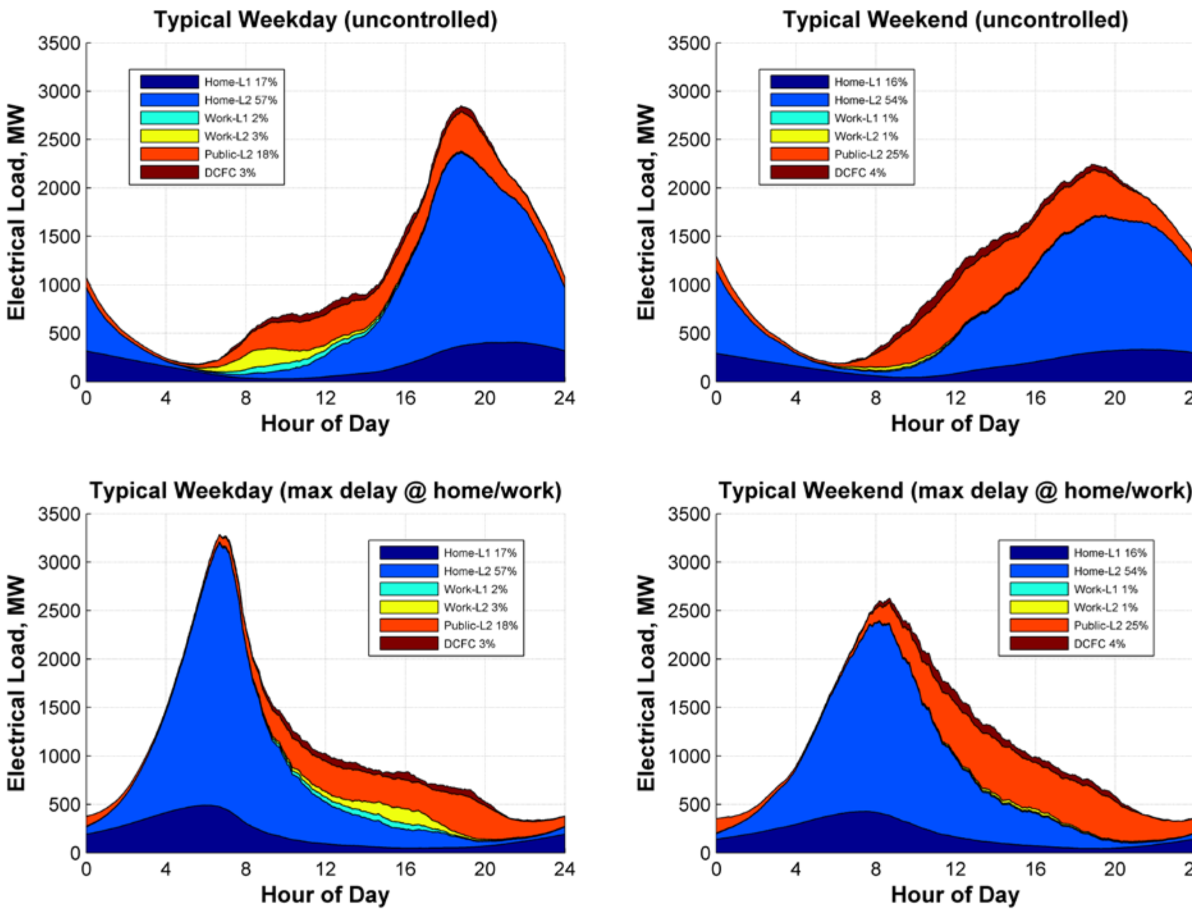

Figure 30. Light-duty electric vehicle charging profiles for the Stress projection, 2045

Top row: Vehicles charge immediately upon arrival and charge until fully charged or another trip initiated. Bottom row: Vehicles charge as late as possible and still achieve the same total energy charge as top row. Left half—weekdays; right half—weekends.

2.2.2 Bus Electrification

Electrification of buses offers a great opportunity to address local air quality in urban areas, contribute to California carbon dioxide emissions reduction goals, and could provide more affordable mobility options (according to many claims that electric buses are rapidly becoming cheaper than their diesel counterparts).[19, 20, 21]

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[19] Judah Aber, *Electric Bus Analysis for New York City Transit*. (New York City: Columbia University, 2016).
[20] M. Pihlatie, S. Kukkonen, T. Halmeaho, V. Karvonen, N. O. and Nylund, "Fully Electric City Buses: The Viable Option," In *2014 IEEE International Electric Vehicle Conference (IEVC)* (2014, December: 1-8). IEEE. https://doi.org/10.1109/IEVC.2014.7056145.
[21] Matt Casale and Brendan Mahoney, *Paying for Electric Buses: Financing Tools for Cities and Agencies to Ditch Diesel* (U.S. PIRG Education Fund, 2018). https://uspirg.org/sites/pirg/files/reports/National%20-%20Paying%20for%20Electric%20Buses.pdf.

From the grid perspective, the adoption of electric buses has the potential to impact distribution, transmission, and generation systems by creating additional load and changing load shapes.

The LA100 study includes electric bus charging load profiles for the City of Los Angeles assuming that the entire fleet of school and transit buses that are currently serviced in the LADWP service territory will be fully electrified by 2030. Buses are assumed to continue to follow their existing schedules and routes, and to charge while not operated (typically overnight) at their respective depots (or yards). Charging at depots leverages downtime to perform charging so that bus operation does not have to be shifted to accommodate charging and charging infrastructure is concentrated in centralized locations owned or leased by bus operators. We also assume that each bus has access to a charging plug and charging is performed at constant power and at the lowest possible power level that guarantees meeting each bus charging requirements, making the peak power requirements (and the corresponding impact on distribution infrastructure) as low as possible.

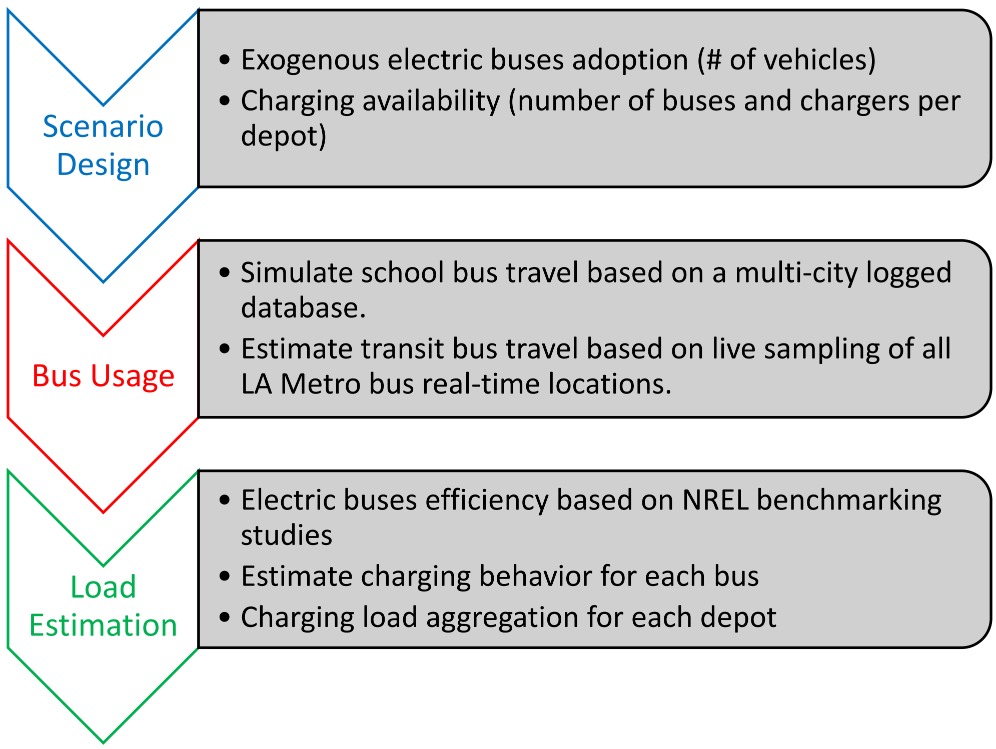

Figure 31. Electric buses load modeling methodology

Figure 31 illustrates the overall methodology used to estimate electric bus charging load by meter location and with 15-minute temporal resolution. First, the number of buses and charger locations are determined to fulfill the narrative of entire existing bus fleet electrification by 2030 with buses continuing to operate out of the depots that are currently used. Second, bus usage (driving data) for school and transit buses is used to project vehicle usage, including daily energy use and depot arrival-departure times, which determines charging requirements and a window in time during which each bus can be charged overnight. Finally, the charging load is estimated for each bus and aggregated to the depot level.

2.2.2.1 Bus Types and Locations

This analysis assumes that all the 1,287 school buses, 1,693 LA Metro, and 403 LADOT transit buses currently serviced within the LADWP service territory will be electrified (fully battery electric buses) by 2030. Fleets are assumed to not grow over time, and buses are assumed to continue to be operated in line with existing schedules (operated by diesel buses) and from the same depot. Bus depot locations and numbers of buses are summarized in Table 3. Further details are available in Appendix E.

Table 3. Summary of Buses by Depot within LADWP Service Territory

Bus Type	Depot	Address	Number of Buses
School Buses	Gardena Yard	18421 S Hoover Street Gardena, 90248	404
	Business Division	604 E 15th Street Los Angeles, 90015	400
	Sun Valley Yard	11247 Sherman Way Sun Valley, 91352	200
	Van Nuys Yard	16200 Roscoe Blvd. Van Nuys, 91406	250
	Sepulveda Yard	8920 Sepulveda Blvd. North Hills, 91343	33
		Total	**1,287**
LA Metro Transit Buses	Division 1	1130 E 6th St, Los Angeles, 90021	165
	Division 2	720 E 15th St, Los Angeles, 90021	410
	Division 3	630 W Ave 28, Los Angeles, 90065	178
	Division 5	5425 S Van Ness Ave, Los Angeles, 90062	281
	Division 8	9201 Canoga Ave, Chatsworth, 91311	186
	Division 10	742 N Mission Rd, Los Angeles, 90033	107
	Division 13	920 N Vignes St, Los Angeles, 90012	143
	Division 15	11801-11927 Branford St, Sun Valley, 91352	223
		Total	**1,693**
LADOT Transit Buses	Downtown	454-518 E Commercial St, Los Angeles, 90012	86
	Sylmar	12776 Foothill Blvd, Sylmar, 91342	154
	Washington	1950 East Washington Blvd, Los Angeles, 90021	163
		Total	**403**

Figure 32 shows the location of all school (five) and transit (nine LA Metro and three LADOT) bus depots within LADWP service territory as well as the number of buses served at each depot.

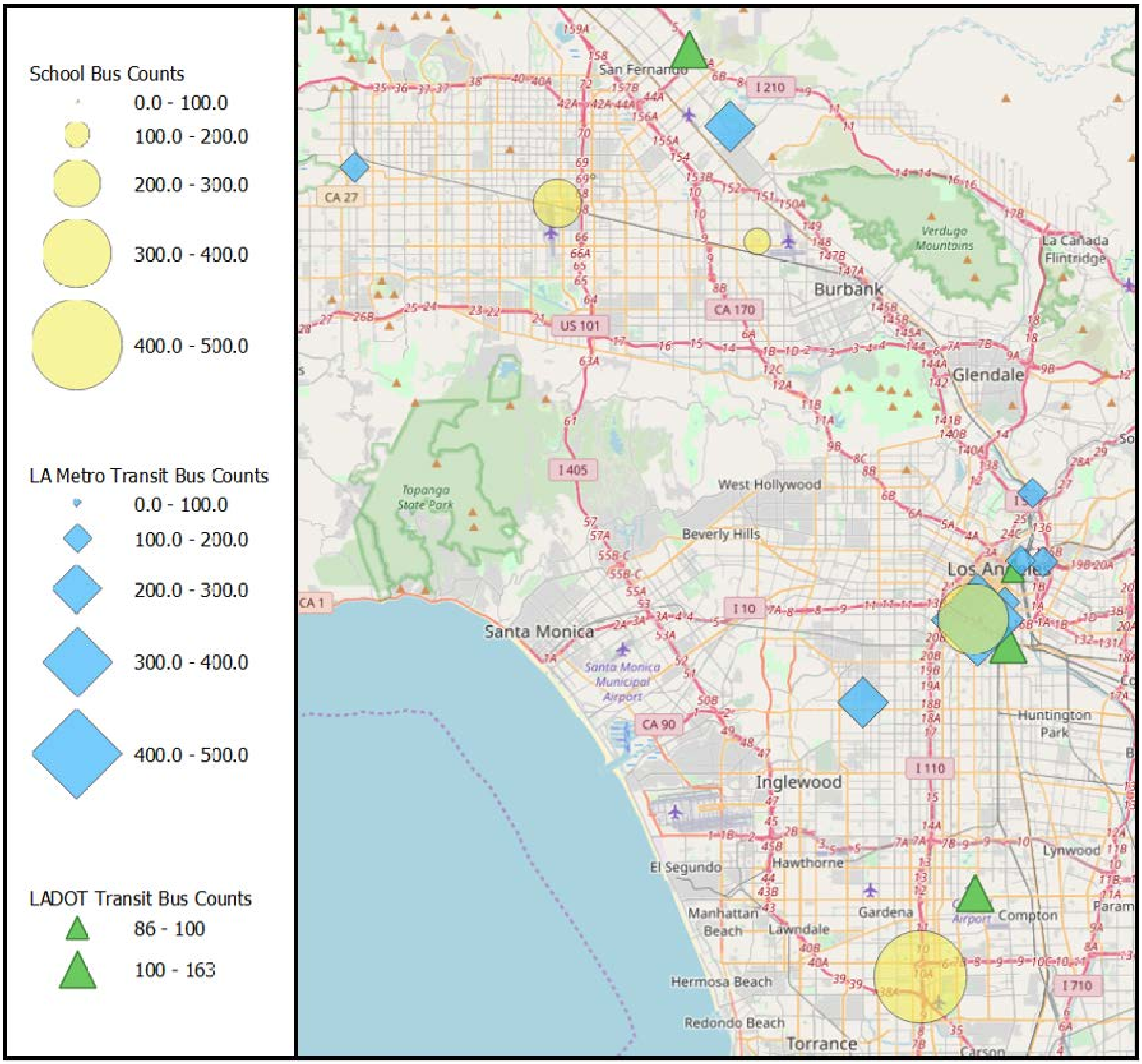

Figure 32. Map of bus depots and fleet sizes within LADWP service territory

2.2.2.2 Bus Demand Projections

Detailed descriptions of how the electrified buses are used and what we therefore estimate their charging profiles to be are provided in Appendix E. Key assumptions include energy requirements of 2.84 kWh/mile, 90% charging efficiency, and chargers sized to meet each day's required energy demand during bus depot dwell time.[22] Aggregate energy use and peak power demand are reported in Figure 33 and Figure 34, respectively. They show depots with up to about 20 GWh of demand per year, and with a maximum peak demand of a little under 10 MW. Table 4 summarizes these data, showing total annual bus charging loads of about 130 GWh.

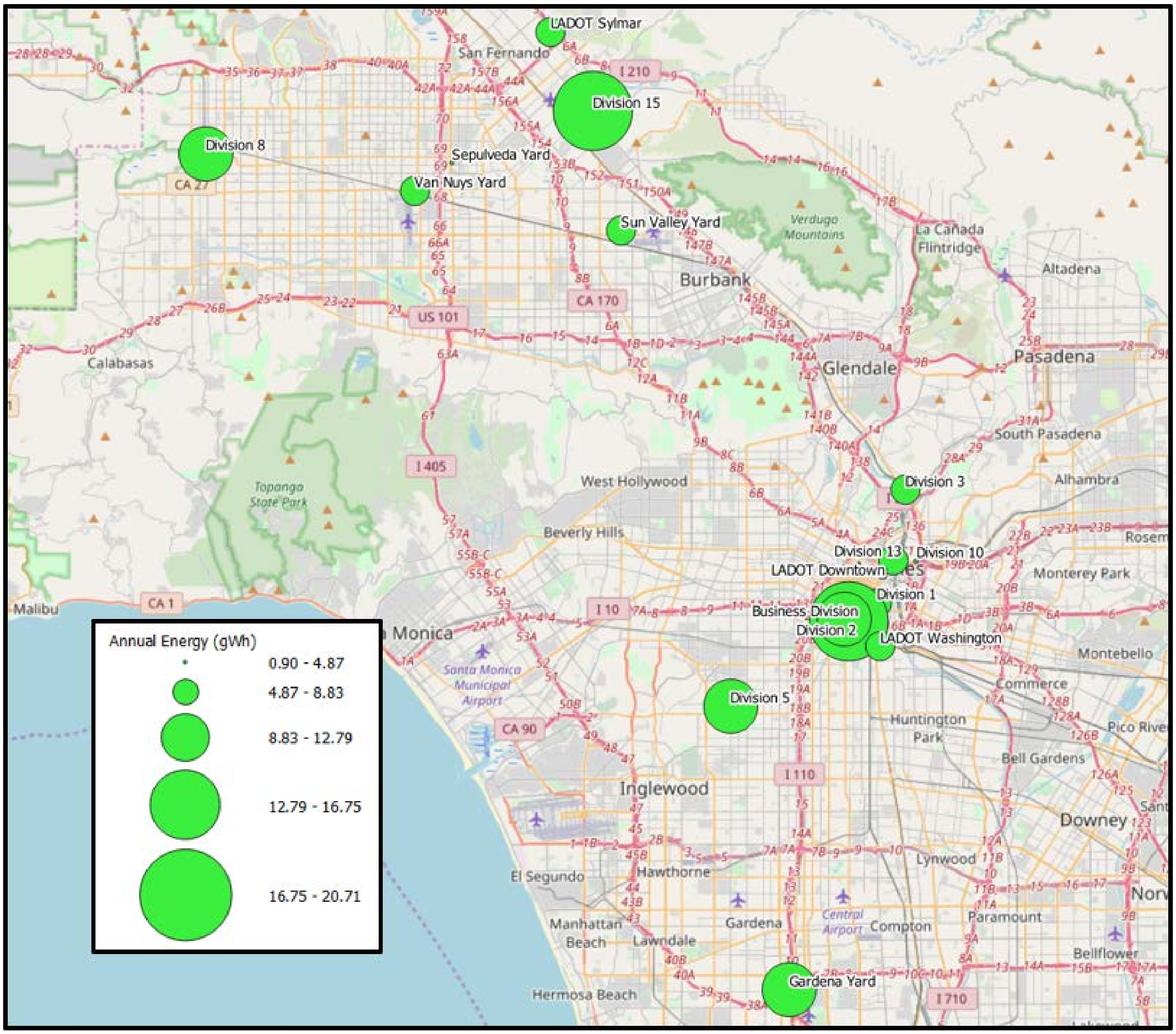

Figure 33. Annual aggregated energy use by bus depot

[22] Almost all school buses can be fully charged with a power consumption less than 50kW. Many transit buses require higher-powered chargers. Power consumptions of 100kW or less are sufficient for about 90% of transit buses.

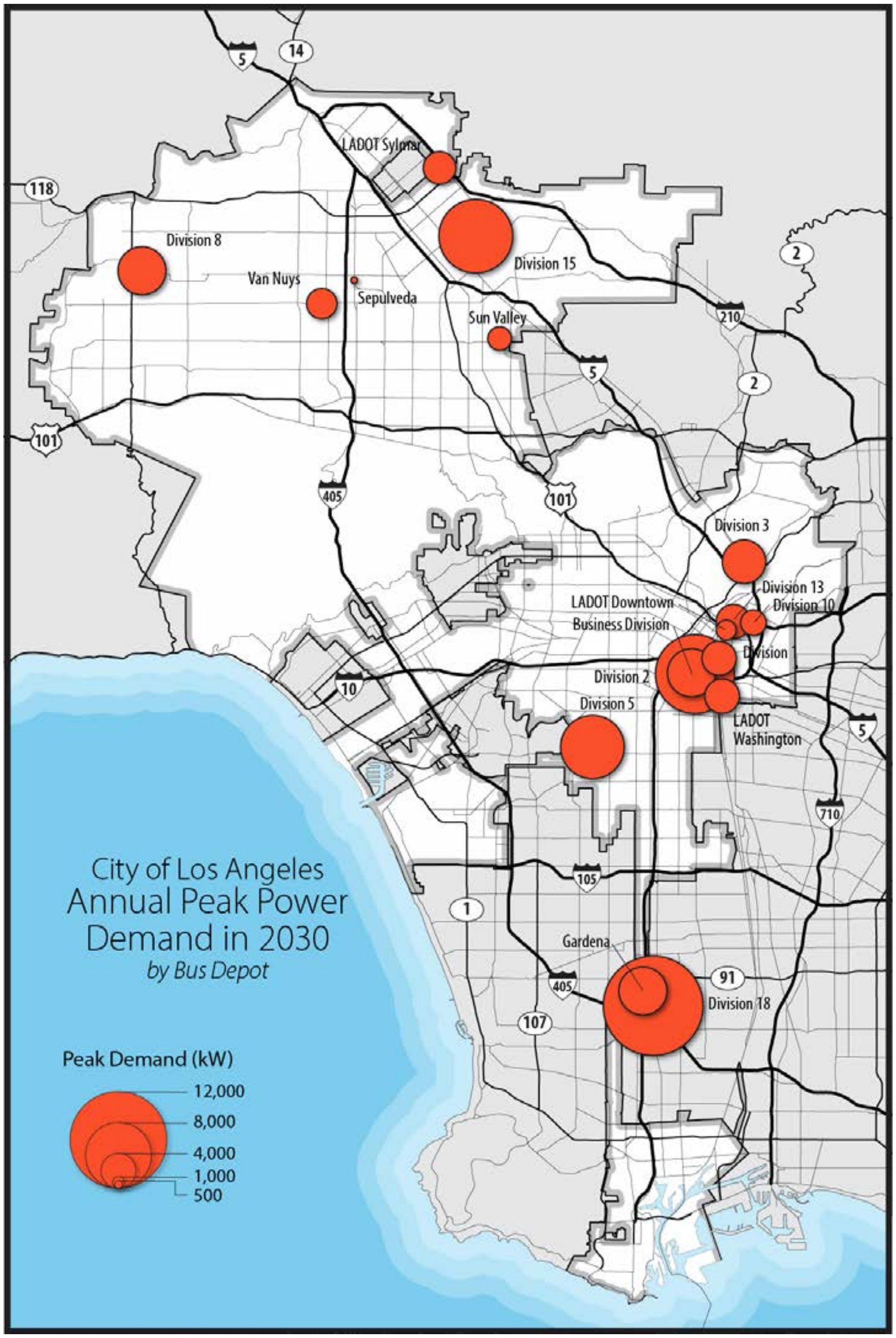

Figure 34. Annual peak power demand by bus depot

Table 4. Summary of Electrified Bus Annual Energy and Peak Demand, by Bus Type and Depot

Location	Type	Annual Energy (GWh)	Peak Power (kW)
Business Division	School Buses	11.0	5,800
Gardena Yard		11.1	5,820
Sepulveda Yard		0.90	470
Sun Valley Yard		4.98	2,670
Van Nuys Yard		6.85	3,540
Division 1	LA Metro	6.99	4,050
Division 2		16.4	9,800
Division 3		8.24	5,220
Division 5		12.0	7,830
Division 8		10.8	5,800
Division 10		4.77	2,920
Division 13		6.37	4,030
Division 15		13.6	9,150
LADOT Washington	LADOT	6.44	4,080
LADOT Downtown		3.71	2,180
LADOT Sylmar		6.21	3,820
	Total	**130.5**	**N/A**

2.3 Industrial and Other Loads

In addition to residential buildings, commercial buildings, and EV transportation, other significant electricity demands in the LADWP system include industrial customers, commercial customers not represented by prototypical commercial building models, the LADWP water system, unmetered outdoor lighting, and Owens Valley.

2.3.1 Industrial and Other Commercial

For the purposes of the LA100 study, "industrial and other commercial" refers to all industrial manufacturing loads, plus commercial loads not represented by prototypical commercial building models. All of these loads were analyzed using similar methods reliant on LADWP customer billing data and the Los Angeles County Assessor Parcels Database. However, a portion of the loads, namely,

- Industrial customers engaged in mining, manufacturing, or agriculture operations
- Airports and their supporting operations
- The Port of Los Angeles and its supporting operations
- The motion picture and video industry

were analyzed in greater detail based on NAICS codes and 15-minute AMI data. All of the other loads (industrial and commercial customers that were difficult to classify and/or that do not fall within these particular categories) we categorized as “gap agents” and analyzed using simplified methods that combined annual energy metrics compiled from the LADWP billing data with overall commercial and industrial load shapes and growth rates. Additional gap agent modeling details are provided in Appendix F. The remainder of this section focuses on the more-analyzed industrial and other commercial loads, which are spread over 12,132 premises and are modeled across 62 categories[23] of industrial and commercial activities. In what follows, these different groups are collectively referred to as industrial loads.

All premises with industrial NAICS codes in the customer billing data and a tax assessor industrial general property use type were identified as industrial loads. The other commercial loads modeled in this more-detailed way (i.e., airports, Port of Los Angeles, and motion picture and video industry) were identified using a similar process that also relied on tax assessor designations for specific property use type.

Baseline industrial demand is modeled using LADWP data. Monthly energy demand comes from customer billing data for fiscal years 2016 and 2017. LADWP data for calendar year 2016 were used to define baseline energy demand by month. Billing entries that spanned multiple months were disaggregated using the mean daily kWh for the period. We did not correct for any other billing irregularities. Hourly load profiles were aggregated from 15-minute interval data from 2016 provided by Energia. Load shapes were created for each day of the week for every month of the year as a fraction of monthly kWh and an identified load-shape match. Of the 12,132 premises identified as industrial, only 1% were matched by premise to 15-minute AMI data. The remaining premises were either matched to AMI data by an aggregated-NAICS code, or if no aggregate-NAICS was found, matched to a composite load profile created by averaging all industrial interval data.

Annual 2016 demand for these categories of load, which totals to 2,514 GWh, is shown by subsector in Table 5. The largest subsector by annual electricity demand is support for transportation—the 693 premises that include airport and port and harbor operations in LADWP’s service territory used 739 GWh in that year. The second-largest total load was associated with petroleum and coal products manufacturing.

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[23] North American Industrial Classification System (NAICS) codes—a hierarchical description of business operations—are used as the basis for identifying categories of industrial and miscellaneous large commercial loads (“North American Industry Classification System,” https://www.census.gov/eos/www/naics/index.html). The relevant NAICS codes include a mix of operational detail and use three-digit (e.g., NAICS 311 Food Manufacturing) and six-digit (e.g., NAICS 324110 Petroleum Refining) codes.

Table 5. Summary of 2016 Load Data for Industrial and Miscellaneous Large Commercial Loads Aggregated to Three-Digit North American Industrial Classification System (NAICS) Code

NAICS Code	NAICS Code Description	Premise Count	Total Load (MWh)	Average Monthly Load per Premise (MWh)	Standard Deviation of Monthly Load per Premise (MWh)
488	Support Activities for Transportation	693	739,052	80	239
324	Petroleum and Coal Products Manufacturing	64	322,975	447	3,250
332	Fabricated Metal Product Manufacturing	1,530	132,614	8	60
325	Chemical Manufacturing	467	113,026	21	296
336	Transportation Equipment Manufacturing	588	75,437	11	74
327	Nonmetallic Mineral Product Manufacturing	485	56,942	10	49
337	Furniture and Related Product Manufacturing	1,219	35,446	3	9
339	Miscellaneous Manufacturing	693	30,210	4	13
326	Plastics and Rubber Products Manufacturing	115	26,445	20	94
333	Machinery Manufacturing	450	17,059	3	17
313	Textile Mills	309	10,784	3	11
314	Textile Product Mills	92	4,104	4	13
316	Leather and Allied Product Manufacturing	78	983	1	4
	Total	**10,350**	**2,513,765**	**21**	**28**

[a] Data are taken from the once-through cooling (OTC) study.

2.3.1.1 Industrial Demand Forecasting Approach and Data

Moving from baseline energy use to projections, changes in industrial loads over the study period are based on the following assumptions:

- **Moderate:** Port of Los Angeles Moderate electrification is assumed to follow the "In Between" case in two ICF International and E3 reports.[24,25] Energy efficiency through 2030 assumes that industrial energy efficiency market potential is 80% of the commercial value as reported in the Navigant 2017 energy efficiency potential study;[26] after 2030 we use the economic potential estimates from the Navigant 2017 and Nexant 2014[27] energy efficiency studies.
- **High:** Port of Los Angeles High electrification is assumed to follow the "Aggressive" case in the ICF International and E3 reports. Energy efficiency improvements are based on the maximum achievable estimates in the Navigant 2017 and Nexant 2014 studies.
- **Stress:** High electrification for the Port of Los Angeles combined with lower energy efficiency, which assumes that industrial energy efficiency market potential is 80% of the commercial value as reported in the Navigant 2017 energy efficiency potential study.

Note that while energy efficiency is considered for all subsectors, electrification is only considered for the Port of Los Angeles. (About 9% of the terminal equipment for the Ports of Los Angeles and Long Beach are electric; planned air quality improvements are projected to increase this fraction to 14% by 2025.[28])

Load growth (excepting Port of Los Angeles electrification) is consistent across the three projections, and is defined separately for industrial, airport, port, and motion picture and video industries. Except for industrial demand—which was assumed to follow LADWP sales forecasts[29]—our approach assumes that load growth will follow projections of economic activity (e.g., passenger-miles, tons of cargo) for each of the agent categories.

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[24] ICF International and Energy+Environmental Economics, *California Transportation Electrification Assessment, Phase 1: Final Report* (San Francisco, CA, September 2014). http://www.caletc.com/wp-content/uploads/2016/08/CalETC_TEA_Phase_1-FINAL_Updated_092014.pdf.
25 ICF International and Energy+Environmental Economics, *California Transportation Electrification Assessment, Phase 3-Part A: Commercial and Non-Road Grid Impacts, Final Report*. (January 2016). https://www.icf.com/-/media/files/icf/reports/2016/caletc_tea_phase_3.pdf.
[26] Navigant, *Energy Efficiency in California's Public Power Sector, 11th Edition*, 2017. http://ncpasharepointservice20161117100057.azurewebsites.net/api/document?uri=https://ncpapwr.sharepoint.com/sites/publicdocs/Compliance/2017_Energy_Efficiency_Report.pdf.
[27] Nexant, *LADWP Territorial Potential Draft Report Volume I* (Cary, North Carolina, June 24, 2014). http://dawg.energy.ca.gov/sites/default/files/meetings/6.LADWP%20EE%20Potential%20Study%20Vol%20I%20Draft%20-%2024June14.pdf.
[28] Starcrest Consulting Group, *San Pedro Bay Ports Clean Air Action Plan 2017: Potential Emission Reductions for Select Clean Air Action Plan Strategies*. (July 2017). https://www.portoflosangeles.org/pola/pdf/caap_potential_emission_reductions_from_select_caap_2017_strategies-final.pdf.
[29] LADWP, *2017 Retail Electric Sales and Demand Forecast*. Los Angeles, CA: City of Los Angeles, September 15, 2017. http://ezweb.ladwp.com/Admin/Uploads/Load%20Forecast/2017/10/2017%20Retails%20Sales%20Forecast_Final.pdf.

Port load growth for port operations and port-supporting operations was assumed to follow cargo forecasts. Total twenty-foot equivalent (TEU) cargo was projected to grow at a constant annual growth rate (CAGR) of 5.5% from 2010 through 2020 and 4.7% from 2020 to 2030.[30] We assumed the growth rate from 2030 to 2050 to be 50% of the 2020–2030 CAGR.

We assumed airport load growth follows the Southern California Association of Governments (SCAG) projections for passenger miles for both airport operations and airport support operations. SCAG projects Los Angeles International Airport (LAX) passenger traffic to grow from 70.66 million passenger miles (MAP) in 2014 to between 82.9 MAP and 96.6 MAP in 2040.[31] For post-2040 projection years we assumed the midpoint of 2040 growth (0.924%).

2.3.1.2 Energy Efficiency Projections

Our assumptions regarding energy efficiency for the industrial and miscellaneous commercial sectors are informed by the LADWP 2017 retail sales forecast (LADWP 2017a), the Nexant 2014 energy efficiency potential study (Nextant 2014), and the Navigant 2017 energy efficiency potential study (Navigant, 2017). For the Stress projection, we assume efficiency projections from the LADWP 2017 retail sales forecast. However, industrial efficiency projections are not reported directly. As a result, we start with the commercial efficiency projections and apply a scaling factor derived from the Navigant 2017 study that indicates the industrial energy efficiency market potential is 80% of the commercial energy efficiency market potential. Efficiency assumptions were then scaled by industry segment based on results of the Nexant 2014 efficiency study; the motion picture and video industry sector was matched to efficiency potential data for the institutional sector.

Efficiency assumptions for the Moderate projection are equivalent to the Stress projection through 2030. After 2030, assumptions are developed from economic potential estimates available from the Nexant and Navigant efficiency potential studies. The High projection assumes efficiency improvements based on maximum achievable potential. Energy efficiency assumptions for each of the three projections are summarized in Table 6.

Table 6. Industrial Energy Efficiency Assumptions by Projection and Year (Cumulative Percentage of Sales, %)

Industry Segment	Stress		Moderate		High	
	2030	2045	2030	2045	2030	2045
Chemical Manufacturing	14	15	15	20	18	24
Electronic Equipment Manufacturing	20	21	21	26	25	31
Food Manufacturing	18	19	19	24	23	29
Industrial Machinery	17	18	18	23	21	27
Lumber Wood Products	22	23	23	28	28	34

[30] The Port of Los Angeles, *Port Master Plan* (Los Angeles, CA, February 2014). https://www.portoflosangeles.org/getmedia/2f2b99a8-f0c3-4e01-9bfe-ba34de05293d/amendment-28.

[31] Southern California Association of Governments, *2016-2040 Regional Transportation Plan/ Sustainable Communities Strategy*. (April 2016). http://scagrtpscs.net/Documents/2016/final/f2016RTPSCS.pdf.

Industry Segment	Stress		Moderate		High	
	2030	2045	2030	2045	2030	2045
Mining	2	2	2	7	3	8
Miscellaneous Manufacturing	18	19	19	24	23	29
Paper Manufacturing	17	18	18	23	21	27
Petroleum Refining	17	18	18	23	21	27
Primary Metal Manufacturing	11	11	12	17	14	20
Stone Clay Glass Products	15	16	16	21	19	25
Transportation Equipment Manufacturing	18	19	19	24	23	29
Airport and Port	18	19	19	24	23	29
Motion Picture and Video Industries	18	19	19	24	23	29

2.3.1.3 Electrification Projections

Electrification of the industrial and miscellaneous commercial sectors focused on the Port of Los Angeles. About 9% of the terminal equipment for the Ports of Los Angeles and Long Beach are electric; planned air quality improvements are projected to increase this fraction to 14% by 2025 (Starcrest Consulting Group 2017b). We assumed new load beyond baseline growth for the Port of Los Angeles based on different levels of electrification in the Stress, Moderate, and High load projections. We did not assume any energy efficiency impacts for electrification load. Port electrification demand was assumed to be distributed among 100 premises based on 2016 OTC total annual kWh. Premises related to the port and its operations were identified based on NAICS code, tax assessor data, and proximity to the port.

Electrification assumptions are based on existing analysis of port electrification (ICF International and Energy+Environmental Economics 2014). These reports contain data relating to the existing port equipment stock and operations, typical annual demand and hourly load profile for electric equipment, and projected electric equipment adoption. Data on equipment stock, vessel activity, and average time at dock (e.g., berth hoteling) were updated using the 2016 Port of Los Angeles Inventory of Air Emissions (Starcrest Consulting Group 2017a).

We assumed electrification to occur in three categories of terminal equipment: shore power[32] (tankers[33] and container ships), cargo handling equipment (yard tractors, forklifts, and rubber-tired gantry [RTG] cranes), and heavy-duty trucks. Adoption assumptions are aligned in our Moderate projection to the In Between case, and our High and Stress projections to the

[32] Shore power is the use of grid electricity to power auxiliary vessel systems (e.g., lighting, air conditioning) instead of auxiliary diesel engines while a vessel is at dock. Current California Air Resources Board regulations require that by 2020 80% of port visits for container vessel fleets, refrigerator-cargo vessel fleets, and passenger vessel fleets must be shore-power visits (CARB, "At Berth FAQs," California Air Resources Board, https://www.arb.ca.gov/ports/shorepower/faq/faq.htm).

[33] Tankers use shore power only in the High and Stress projections.

Aggressive case. Unlike the California Transportation Electrification Assessment, we do not account for turnover in equipment stocks.

Figure 35 summarizes the load implications of the port electrification projections. Shore power contributes a large portion of the new load in every projection; however, the increasing adoption of electrified yard tractors leads to a new source of load nearly equally as large starting in 2030.

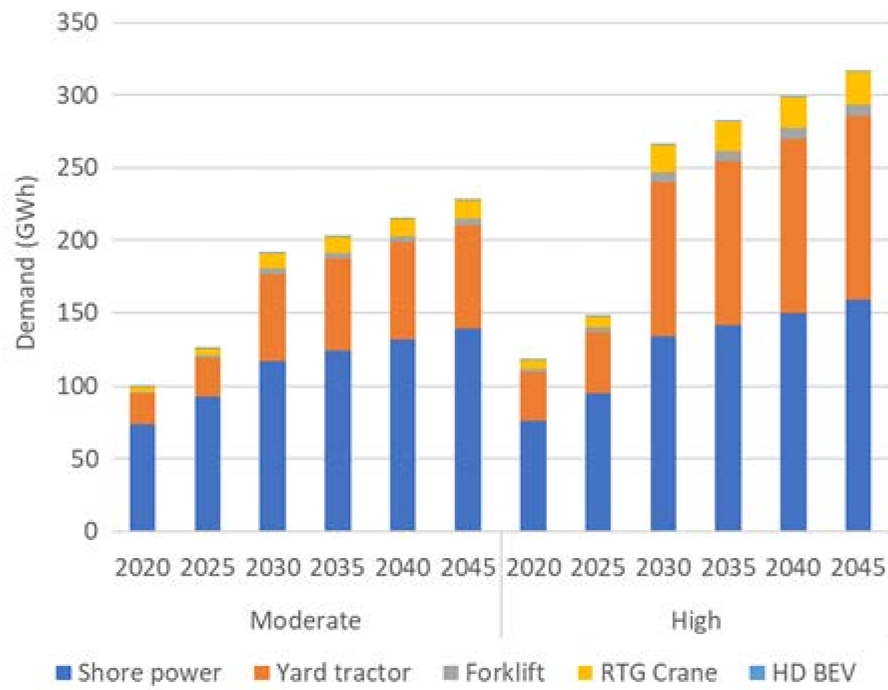

Figure 35. Assumed new load from Port of Los Angeles electrification

The Stress projection uses the same assumptions as High.

Along with additional load, expanded use of electric forklifts, as well as other cargo handling equipment, has implications for the hourly demand of port operations. Shore power contributes a large portion of the new load in every projection; however, the increasing adoption of electrified yard tractors in the Moderate, High, and Stress projections leads to a new source of load nearly equally as large. Along with additional load, expanded use of electric forklifts, as well as other cargo handling equipment, has implications for the hourly demand of port operations. Figure 36 shows the assumed load shapes for cargo handling equipment and shore power. Note that forklifts, yard tractors, and RTG cranes were assumed to have the same load shape. Shore power for tankers and for cargo vessels were also assumed to share the same load shape.

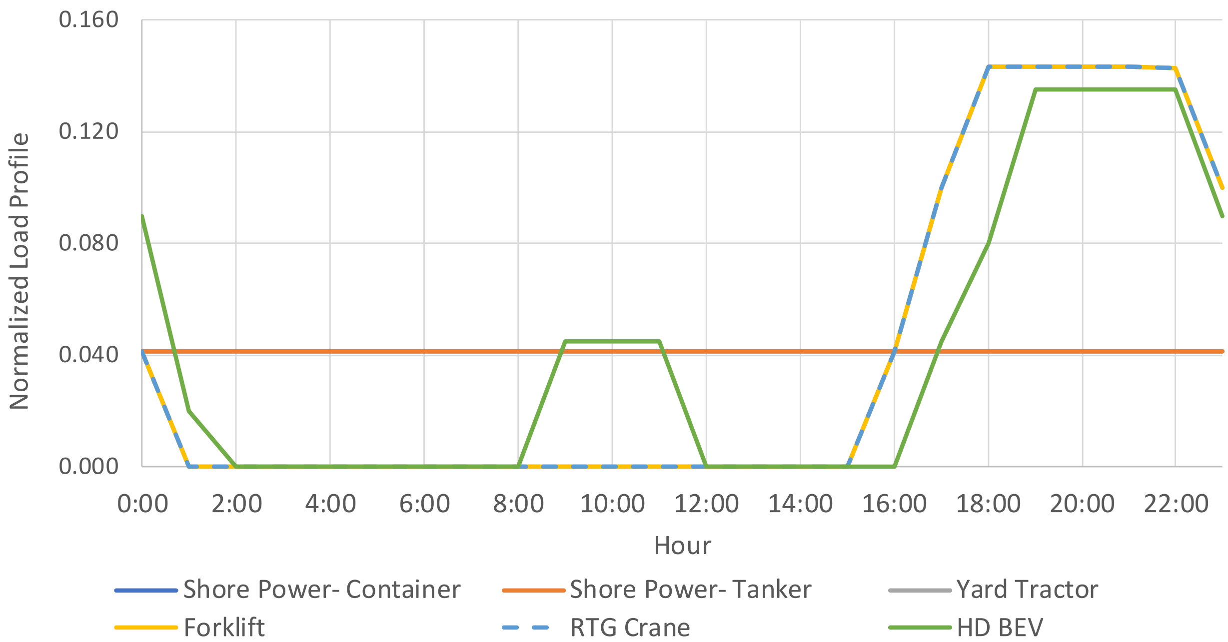

Figure 36. Normalized load profiles for port cargo handling equipment

Data inferred from ICF and Energy+Environmental Economics.[34]

2.3.1.4 Industrial Demand Projections

Industrial demand in 2045 grows from 2,585 GWh in 2015 to 3,013 GWh in the Moderate projection, 2,940 GWh in the High projection, and 3,290 GWh in the Stress projection (Table 7). These results represent increases over 2015 demand of 116%, 114%, and 127%, respectively. Demand growth in all projections is largely driven by port electrification efforts. Additionally, demand growth in the Stress projection is not moderated by energy efficiency programs, unlike in the two other projections.

[34] A load profile for shore power was not provided in the original report. We assumed a constant load factor for shore power as a result. Data inferred from figures published by ICF International and Energy+Enviromental Economics (https://www.icf.com/-/media/files/icf/reports/2016/caletc_tea_phase_3.pdf).

Table 7. Summary of Annual Industry Demand by Projection (GWh)[a]

Calendar Year	LADWP Sales or Forecast Sales	Moderate	High	Stress
2015	1,670	2,585	2,585	2,585
2020	1,798	2,451	2,469	2,469
2025	1,827	2,535	2,558	2,556
2030	1,851	2,727	2,693	2,818
2035	1,875	2,813	2,767	2,952
2040	no data[b]	2,908	2,850	3,113
2045	no data[b]	3,013	2,940	3,290

[a] Projection forecasts are based on OTC from calendar year 2016.
Sales to customers identified by this analysis as industrial totaled 2,514 GWh in 2016.

[b] LADWP sales forecasts end in June 2040.

2.3.2 Water System

2.3.2.1 Assumptions

The LADWP water system is subject to multiple sustainability priorities that are sometimes in conflict. For example, the City of Los Angeles's Green New Deal aims to source 70% of the city's water locally by 2035 and recycle 100% of the city's wastewater by 2035 (City of Los Angeles 2019).[35] Although developing more local water supplies through water recycling and storm water management could reduce volumetric water import purchases from the Metropolitan Water District, increased water recycling is likely to use more LADWP electricity overall because the treatment would happen within LADWP whereas the Metropolitan Water District conveyance energy occurs outside LADWP. Thus, for this sector, high sustainability effort actually corresponds to more electricity demand to be supplied by LA's 100% renewable system.[36]

The LA100 water system projections are created starting from a reference projection that leans heavily on LADWP projections regarding its future water supply portfolio based on a series of recently published documents including its 2015 Urban Water Management Plan (UWMP),[37]

[35] The report defines locally sourced water as "all local groundwater production, historical and future hardware-based conservation savings, centralized and distributed stormwater capture and recharge, and all recycled water produced in the City" (City of Los Angeles 2019).
[36] Although reducing water imports can increase net load across LADWP's electricity network, reductions in pumping energy would occur in other regions of CAISO due to less imported water deliveries to Southern California.
[37] LADWP, *Urban Water Management Plan: 2015* (2016), https://www.ladwp.com/cs/idcplg?IdcService=GET_FILE&dDocName=QOELLADWP005416&RevisionSelectionMethod=LatestReleased.

Water Conservation Potential Study,[38] and Recycled Water Master Plan,[39] as well as the City of Los Angeles' One Water LA plan.[40] In line with the load projections overall, energy efficiency and demand response interventions are more aggressive in High than Moderate, as defined in Table 8. The Stress projection is constructed by assuming high local water supply assumptions, but reference energy efficiency assumptions. The reference projection is not used in the LA100 projection framework but is listed here to provide information on the assumed alternative to high local water supply assumptions.

Table 8. Overview of LA100 Projections in Regard to LADWP's Water Supply, Water Distribution, and Wastewater Loads

LA100 Load Projection	Energy Efficiency[b]	Water Conservation[b]	Local Water Supply Assumptions
Reference[a]	Reference	Reference	Reference
Moderate	Moderate	Reference	High[d]
High	High	Reference	High[d]
Stress	Reference	Reference	High[d]

[a] Reflects water supply projections defined in LADWP's 2015 Urban Water Management Plan (LADWP 2016), using the water demand and supply definitions from "Exhibit ES-S: Service Area Reliability Assessment for an Average Weather Year."

[b] Over the analysis period, the cumulative savings are about 21.9 GWh, 36.5 GWh, and 53.7 GWh for the Reference, Moderate, and High projections, respectively, using insights from (Nextant 2014).

[c] Conservation is kept constant throughout all three projections, as the Reference projection already assumes aggressive conservation volumes.

[d] Assumes maximizing local supply resources including water conservation, groundwater, non-potable and indirect water reuse, and stormwater capture. These projections also include Los Angeles Mayor's recently announced plan for 100% water recycling from the Hyperion wastewater treatment plant (Office of Los Angeles Mayor 2019).

Because of the nature of the water system and limited data availability, the University of Southern California (USC) established a top-down methodology to estimate annual water system load, then disaggregated those annual data into hourly data, using water use profiles for establishing scaling coefficients. The electricity used by the system currently was estimated primarily by using LADWP's 2015 UMWP (LADWP 2016) combined with data on the energy

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[38] LADWP, *Water Conservation Potential Study* (2017), https://ladwp.com/cs/groups/ladwp/documents/document/mdaw/njiw/~edisp/opladwpccb620807.pdf.
[39] LADWP and Department of Public Works, *City of Los Angeles Recycled Water Master Planning Executive Summary* (2012), https://www.ladwp.com/cs/idcplg?IdcService=GET_FILE&dDocName=OPLADWPCCB381497&RevisionSelectionMethod=LatestReleased.
[40] City of Los Angeles, *One Water LA Progress Report: A Collaborative Approach to Integrated Water Management* (2017), https://www.lacitysan.org/cs/groups/public/documents/document/y250/mdiy/~edisp/cnt022236.pdf.

intensity of the major treatment and conveyance steps. USC's modeling results are summarized in Appendix H.

On-Site Generation Potential in Water Network

There are a few on-site electricity generation opportunities in LADWP's water network, which we treat as load reduction capacity. Hyperion's biogas co-generation plant has three 11.35-MW nameplate capacity (34 MW in total) combustion turbines that combust a mixture of collected biogas from the wastewater treatment plant and natural gas (up to 40% of the volume can be natural gas) (ENVIRON International Corporation. 2013). Currently the co-generation plant is used to reduce electricity purchases in the facility. Although the generation capacity is greater than the facility's peak demand (22 MW (ENVIRON International Corporation. 2013)), the plant is currently a net importer of electricity, as one to two turbines are operating at any given time. We assume the plant will become self-sufficient in terms of electricity use by 2025 (in all projections), and therefore the electricity demand from this facility will essentially be eliminated. Although LADWP's 2015 UWMP (LADWP 2016) predicts an increasing influent flow to Hyperion plant (which will increase electricity use), the co-generation plant capacity is still large enough to meet all electricity demand. We calculated the peak electricity demand of Hyperion using a representative influent flow curve shown in Figure 50 from Poosti et al. (2002). It is estimated that the peak load of this facility will increase to 31 MW by 2050, which is still less than its on-site generation capacity.

Additional on-site generation includes 1 MW of solar capacity installed at MWD's Jensen treatment plant, which has been operational since the end of 2017 (MWD 2016a). While this plant is not owned by LADWP, it consumes LADWP's electricity, and therefore the on-site annual solar generation of about 2,300 MWh will offset about 20% of the annual electricity demand of this facility (MWD 2016a).

2.3.2.2 Annual Growth and Hourly Load Profiles

Annual Water Supply and Wastewater System Load

Annual electricity load estimates for the water supply and wastewater systems are detailed in Table 9 and Figure 37. The energy associated with the wastewater system decreases in all cases due to high conservation levels, and most significantly due to the on-site co-generation plant at Hyperion. The water supply energy use increases significantly due to increases in recycled water volumes.

Table 9. Total Annual Electrical Load Estimates for LADWP's Water Supply and Wastewater Network Excluding Energy Efficiency for all Projections

All data are in GWh.

Year	Reference		Moderate		High	
	Supply	Wastewater	Supply	Wastewater	Supply	Wastewater
Base-Year (2010–2015)	157.8	203.2	157.8	203.2	157.8	203.2
2020	188.5	91.9	188.5	91.9	188.5	91.9
2025	268.5	144.5	268.5	144.5	268.5	144.5
2030	279.1	148.5	692.7	148.5	692.7	148.5
2035	291.9	152.9	1,115.7	152.9	1,115.7	152.9
2040	297.2	155.8	1,121.7	155.8	1,121.7	155.8
2045	294.3	155.8	1,119.7	155.8	1,119.7	155.8
2050	296.5	155.8	1,122.5	155.8	1,122.5	155.8

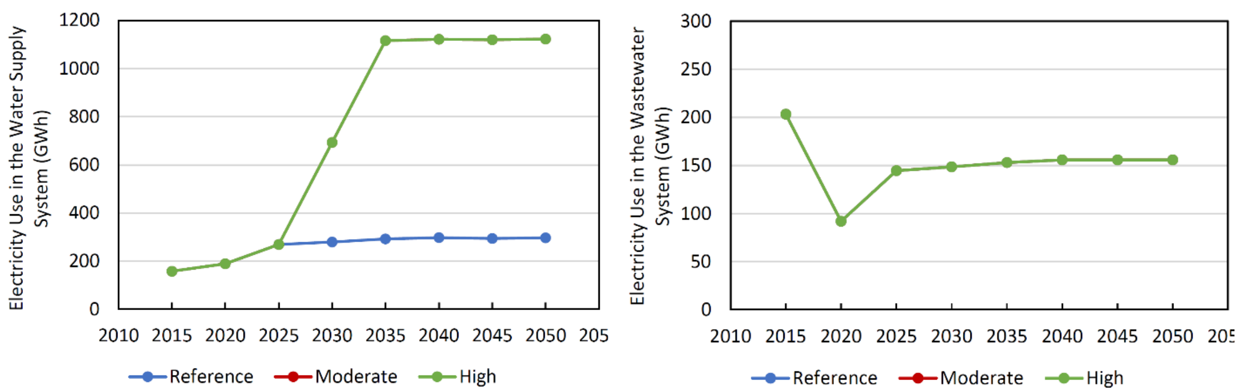

Figure 37. LADWP's annual electricity consumption dedicated to its water supply (left) and wastewater system (right) for the three projections studied

Energy Efficiency Impacts

Once annual electricity consumption was calculated for each year across all three projections, we used energy efficiency savings to update the baseline electricity demand for the water sector. We assumed that maximum achievable energy savings in the water sector is about 20% by 2035, as suggested in Nexant's LADWP Territorial Potential Study for the wastewater sector across a 20-year planning horizon (Nextant 2014). We assume 30%, 50%, and 70% of the maximum potential is realized by 2035 in the Reference, Moderate, and High projections, respectively. Then, we applied NREL's timeframe for energy efficiency savings for the entire planning horizon (see Figure 38 for details.)

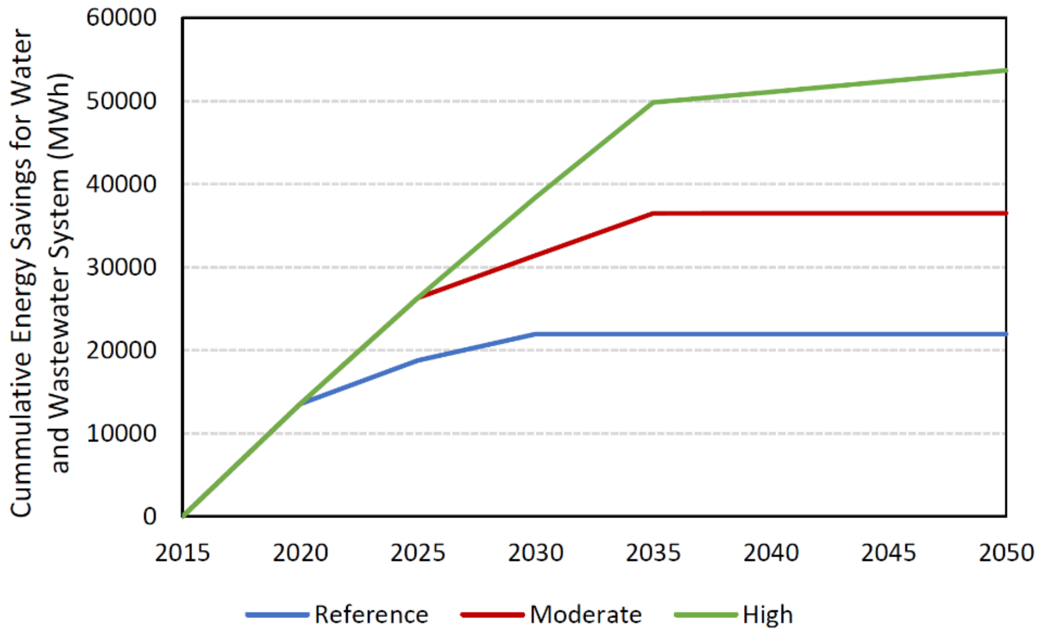

Figure 38. Cumulative energy efficiency savings for LADWP's water system for each projection

Annual Total Water-Related Load Results

The annual water-related load estimates show that electricity demand for water services increases over time after a decrease in 2020 mostly because of Hyperion's load reduction due to its co-generation plant operation (see Figure 39). The system-wide load increase is a result of aggressive non-potable and indirect potable reuse projects. This increase indicates the tradeoffs between reducing energy consumption versus increasing local water supplies in LADWP's service territory. (It should be noted that other regions across CAISO would experience reductions in pumping loads, as imports decreased.) However, increasing local water supplies is an important goal for improving water supply resilience in a future of increasing climate change and the risk of seismic events that can damage water import infrastructure. The net impact of conservation, energy efficiency, and more local water supplies causes a net increase in energy consumption for the most aggressive projection (High), while Reference and Moderate have relatively similar energy demand.

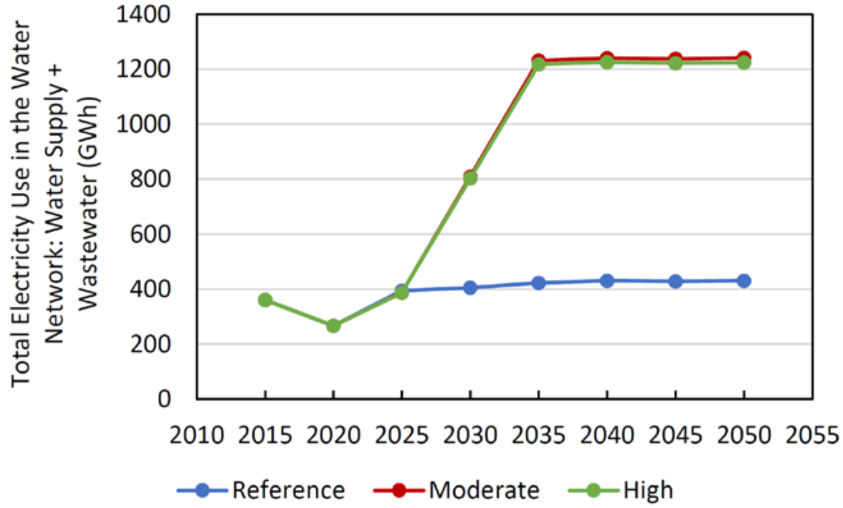

Figure 39. LADWP's annual electricity consumption dedicated to its water supply and wastewater system for the three projections studied

MWD's Jensen Treatment plant is included in load estimates, given the fact that this facility consumed LADWP's electricity.

Table 10 compares the results of this initial annual water load analysis to total annual LADWP load projections detailed in (LADWP 2017a). Results are presented in terms of total electricity load (GWh), as well as the percentage of total projected load from LADWP. The analysis shows that the water-related load accounts for ranges from about 1.2% to 4.7% of total electricity demand in any given year in LADWP's territory. It should be noted that LADWP's future system-wide load projections, last published in 2017, do not include the potential electricity demand increases that would be associated with these new energy-intensive water recycling projects. Thus, the percentage of water-related load shown might be a slight overestimation if total LADWP system-wide load were to increase.

Table 10. LA100 Water Load Analysis Results Compared to Total LADWP Demand as Projected in LADWP (2017a)

Year	Total Load	Reference		Moderate		High		Stress	
	GWh	GWh	(%)	GWh	(%)	GWh	(%)	GWh	(%)
2010–2015	23,094	361	1.6%	361	1.6%	361	1.6%	361	1.6%
2020	22,492	267	1.2%	267	1.2%	267	1.2%	267	1.2%
2025	23,537	394	1.7%	386	1.6%	386	1.6%	394	1.5%
2030	24,609	405	1.6%	810	3.3%	802	3.3%	819	3.3%
2035	26,015	423	1.6%	1,232	4.7%	1,218	4.7%	1,246	4.8%
2040	27,668	431	1.6%	1,240	4.5%	1,226	4.4%	1,255	4.5%
2045	—	428	—	1,238	—	1,222	—	1,253	—

Hourly Load Profiles

We summarize the resulting daily load profiles for dry and wet months in the High projection in Figure 40 and Figure 41, respectively. Daily load profiles are different from 2015 to 2030 (and 2050) due to the fact that much of the wastewater treatment load is eliminated because Hyperion wastewater treatment plant's load is met by an on-site cogeneration plant and the supply load increases significantly due to expansion of water recycling projects.

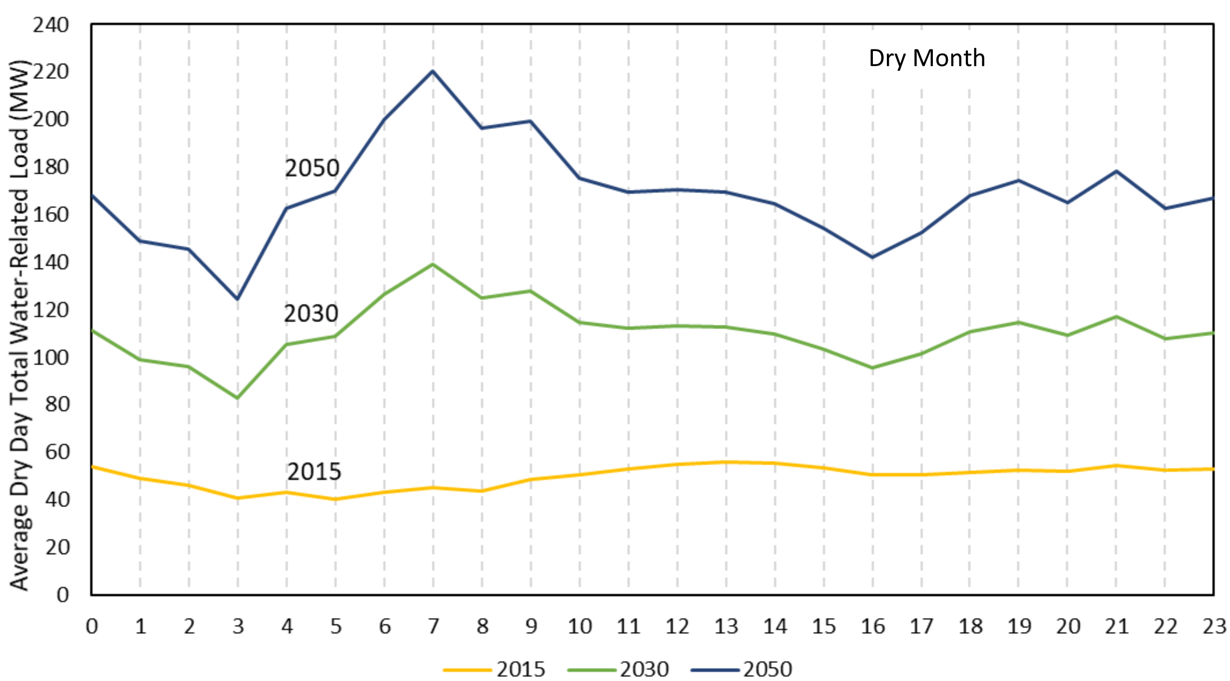

Figure 40. LADWP's estimated daily load for a dry month for 2015, 2030, and 2050 in the High projection

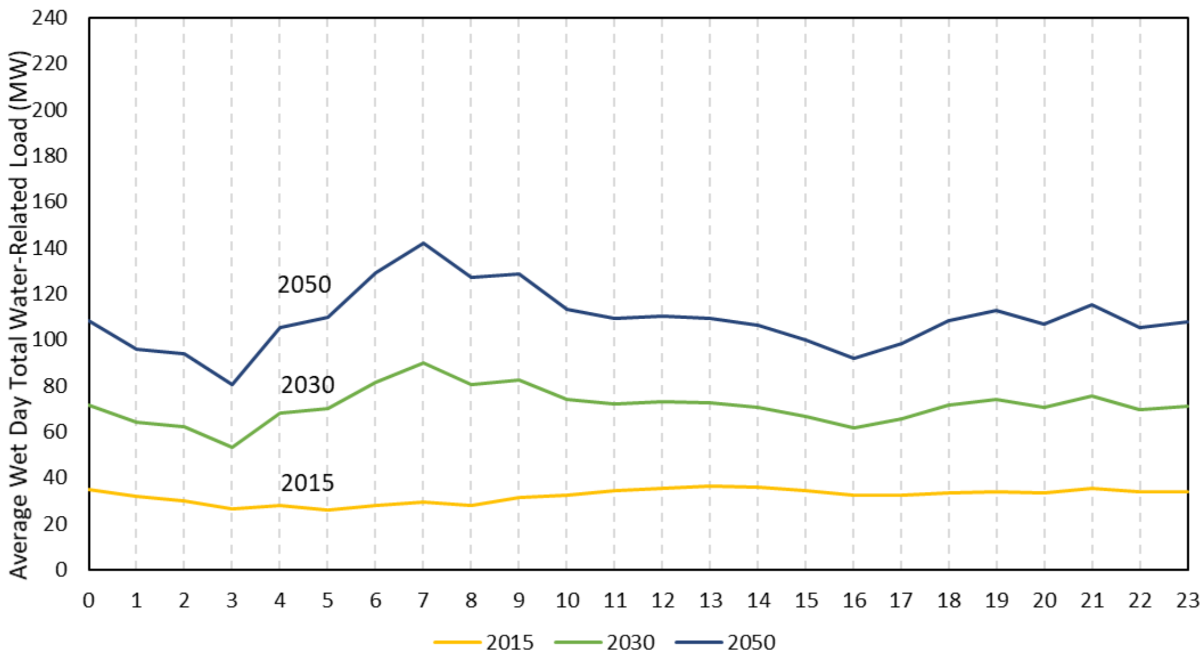

Figure 41. LADWP's estimated daily load for a wet month or 2015, 2030, and 2050 in the High projection

2.3.3 Other Loads

The modeling described above covers most, but not all, of the electricity use in the LADWP service territory. Following LADWP retail sales forecasts, we model unmetered outdoor lighting loads and Owens Valley loads as "Other" loads (LADWP 2017a). We estimate that outdoor lighting accounts for 85 GWh, and Owens Valley uses 137 GWh in 2015. Future-year load is estimated by assuming additional outdoor lighting efficiency gains, and constant Owens Valley load. Further details may be found in Appendix G.

3 dsgrid Outputs and Data Coordination

The dsgrid sector models have different native geographic resolution (Table 11). To provide a more comprehensive picture of Los Angeles electrical load, a firm basis for comparing modeled load to actual historical load at different levels of aggregation (e.g., distribution station, industrial station, receiving station, and system), and a high-resolution view of how Los Angeles's electrical load may evolve into the future, we combine a number of different data sets and use them to downscale most of the loads to what we call the "agent level." Some of the loads are also directly modeled at that level (e.g., industrial loads and gap agent loads).

Table 11. LA100 Geographic Resolutions

Geographic Resolution	LA100 Model
Agent	dGen, Distribution, dsgrid, EV, Gap agents, Industrial and Large Commercial loads
Circuit	Distribution
DS or IS	Distribution
RPM Nodes (same as RS within LADWP)	RPM, PLEXOS, PRAS, IGMS, Power Flow and Stability Analysis, GHG
LA City	Restock, Comstock, Electric Buses, Jobs and Economic Analysis
Census Tract	Environmental Justice
LADWP (LA City + Owen's Valley)	Water loads, dsgrid
2-km^2 grid cells (for South Coast Air Basin extent)	Air Quality

The LA100 geospatial analysis revolves around the concept of agents, which consolidates notions of LADWP customer meters, land parcels, and buildings into demand-side modeling units. The "agent" terminology is borrowed from the dGen model; the LA100 agents are an attempt to programmatically identify reasonable customer-level decision-making units; that is, it attempts to group electricity meters, buildings, and parcels together into something that might be reasonable to refer to as a single "site"—a home, an apartment complex, an office building, a hospital campus. Thus, in its simplest definition, the LA100 agent is a property which can be made up of one or more meters, buildings, and land parcels.

The identified agents are then classified into a load (or model) type and a dGen type. The former indicates what modeling team is responsible for providing data for that agent. The dGen type indicates whether the agent should be considered residential, commercial, or industrial for the purpose of modeling distributed PV adoption decisions. The load type classification and dGen type classifications are largely synonymous, however, there are some cases where they diverge. For example, multifamily residential buildings greater than four stories are modeled by the commercial buildings model, and thus, assigned a load type of commercial ("com"). dGen, however, classifies agent types based on their sector activity, so these agents are assigned a dGen type of residential ("res"). Further information about how the agents were created is provided in

Appendix I. Appendix J describes how each type of load was either modeled at or downscaled to the agent-level.

Load shape data generated by dsgrid will be used by other tools throughout the grid modeling process. A key function of dsgrid is that it helps to coordinate data inputs from its individual models and provides outputs at various geographic, temporal, and sectoral (subsector and end-use) resolutions. Figure 42 (next page) illustrates the data flow from the load-generating models, through dsgrid, and then out at the required levels of resolution to the downstream LA100 models. The load attributes vary in terms of geographic resolution, timescale, included sectors, and attributes.

Key outputs from this step are:

- Sector (e.g., residential, commercial, industrial, transportation, gap) and end-use-specific hourly load shapes for DR modeling and summary reporting
- Loads downscaled to the LA100 agent level, which is used by the dGen and distribution modeling teams to model individual customers
- Sector and end-use specific aggregations at the receiving station (RS) level, which is the nodal level of our bulk power system models. The mapping leverages LADWP electrical geography (i.e., how agents map to transformers; to circuits, commercial stations [CS], industrial stations [IS] and distribution stations [DS]; and then up to receiving stations [RS]).

All output load profiles are time-synchronous and in the LA100 Timeseries Format, as needed by the various other modeling steps and generated for 2020–2045 in 5-year increments. Output geographic resolution is chosen to best match with the receiving model's native resolution (Table 11, page 59). The mapping of agents to other geographic resolutions is described in Appendix K.

The data passed to and assembled by dsgrid is best thought of as meter-level data, that is, it does not include any distribution or transmission losses. Per the LADWP 2017 Load Forecast (LADWP, 2017a), LADWP estimates an annual average of about 12% combined distribution and transmission losses. The losses applicable to a particular power system model are either all modeled directly (e.g., distribution modeling) or are partially modeled and partially added by the dsgrid team. The latter happens in the handoffs between dsgrid and the capacity expansion and production cost modeling teams. Capacity expansion and production cost modeling requires load data at the receiving station level. Therefore, the dsgrid team adds 8% to cover distribution losses. The capacity expansion and production cost modeling teams are responsible for modeling transmission losses.

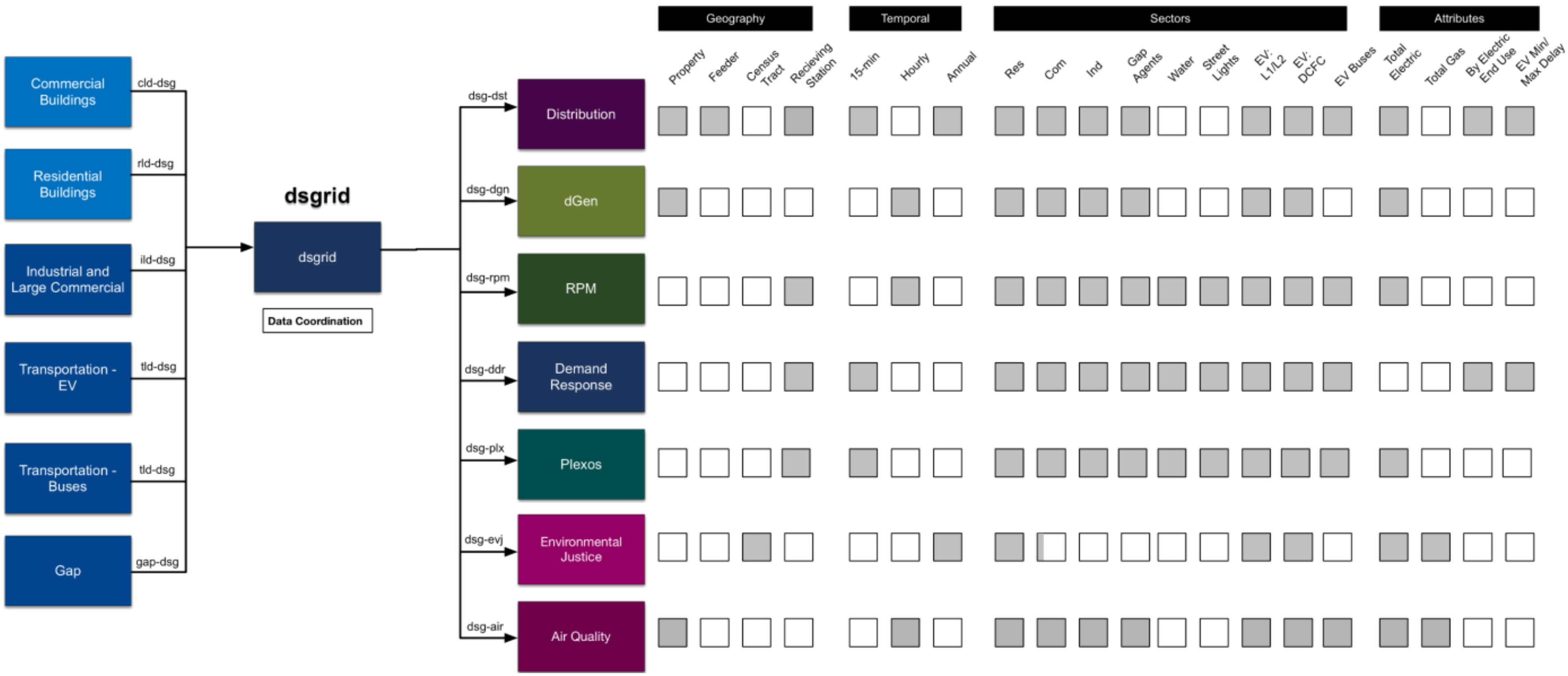

Figure 42. The dsgrid flow and model-specific load requirements

4 Load Projection Results

With the data from all the sector models gathered, we can analyze the three LA100 load projections. A very large amount of data is involved—tens of terabytes once we downscale to the agent level, where we have 15-minute timeseries by end use for 17 different projection-years; however, in this report we focus on the high-level findings—annual electricity consumption, peak electricity demand, and load shapes by sector, end use, and part of the city. We also focus on the key years of 2030 and 2045, while at times describing the overall transitions from today to 2030 and from 2030 to 2045.

As a reminder of key electricity demand metrics, we present Figure 43, which shows the modeled 15-minute load profile for all of LADWP territory in the Reference-2015 projection-year. LADWP typically experiences peak demand in the August-September timeframe. In our data set, the absolute peak demand occurs on August 6 at 2 p.m. PST/3 p.m. PDT, at a level of 5,951 MW. This peak demand level is LADWP consumption only, that is, no distribution or transmission losses are included, and there is no contribution from Glendale or Burbank.[41] The peak demand is a key metric—LADWP plans generation capacity to meet peak demand, despite significant uncertainty in both magnitude and timing. The annual consumption, as well as its typical shape and/or load duration curve,[42] are also important for determining what kinds of generation would be best suited to meeting load day-to-day and hour-to-hour in all seasons.

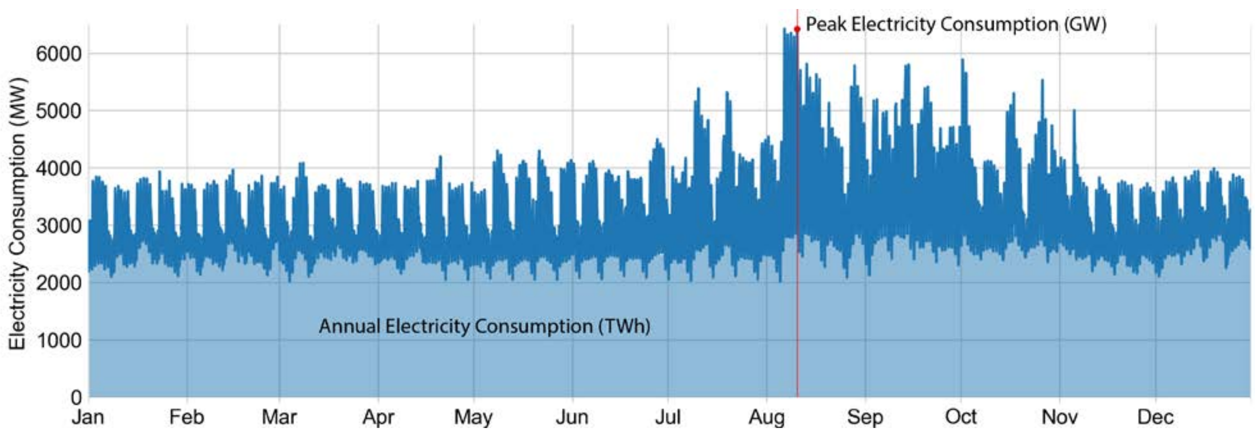

Figure 43. LA100 2015 aggregate 15-minute load data

The key metrics of peak electricity demand and annual electricity consumption are illustrated by marking the maximum energy demand for the year (red dot, time of peak demand marked with a red line) and shading the area under the annual consumption profile, respectively.[43]

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[41] LADWP (2017a) reports 12% losses. Per WECC TEPPC (2011) and assigning specific nodes in the LADWP BA to LADWP, Glendale, and Burbank, we estimate that approximately 90.1% of the BA's load is LADWP; that is, to get from LADWP load with losses to total BA load (which is the number that is often cited for "system peak") one would multiply by 1.1099.

[42] A load duration curve is formed by taking load data and sorting it in descending order, ignoring any timestamps. This monotonically decreasing curve is helpful for describing system "baseload" in fully dispatchable systems, as well as exactly how high the peaks are and how many hours they represent.

[43] Peak consumption is the maximum point of the demand profile. Annual consumption is computed by integrating the demand profile over the year. 1 GW = 1000 MW. 1 TWh = 1000 GWh = 1 million MWh.

Going beyond traditional planning use of load duration curves to approximately divide electricity demand into baseload, mid-level, and peaking energy, with high penetrations of variable renewable generation, hourly or subhourly data like those shown in Figure 43 are important for ensuring that generation and storage resources are sufficient to serve all load in all hours.

4.1 Overview

All three LA100 load projections demonstrate significant change from now until 2045. This is immediately evident in Figure 44, which shows annual meter-level consumption for each projection-year, broken out by sector. Significant load growth in the non-transportation sectors occurs in all projections, driven by population (residential) and economic (commercial and industrial) growth, although the aggressive efficiency assumptions in the High projection do show moderate growth as compared to the Moderate projection through 2030. After 2030, the impacts of building electrification result in High non-transportation loads that are higher than those in the Moderate projection. Because the Stress projection is identical to High except for much-attenuated efficiency assumptions, the Stress projection uses the most electricity in all projection-years.

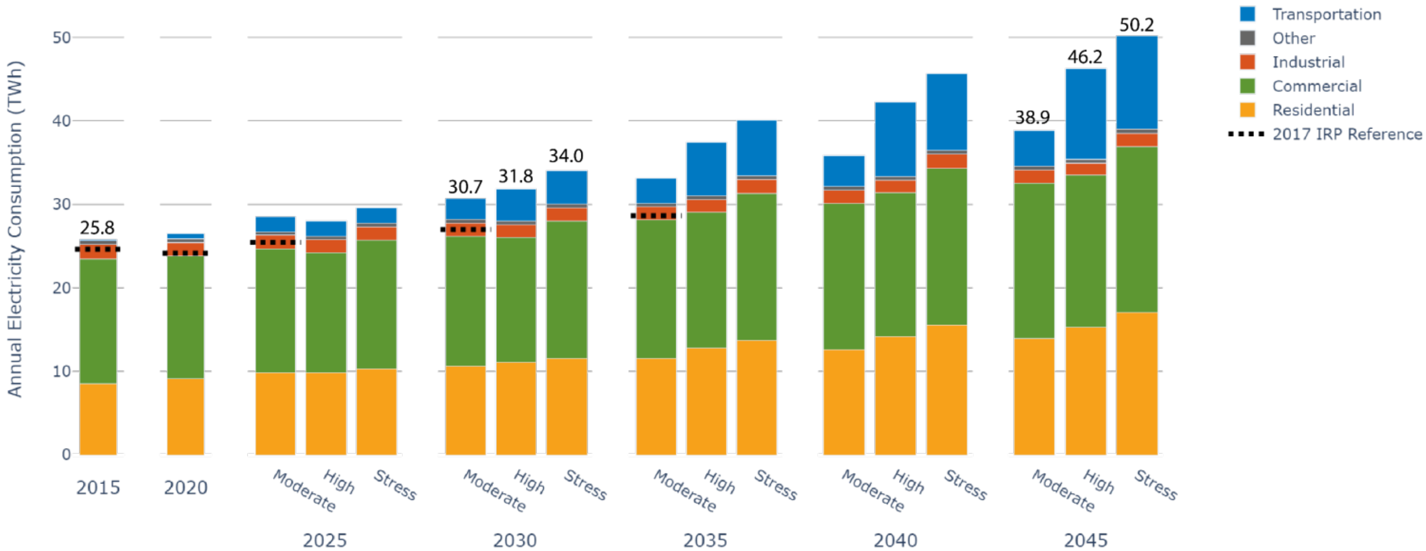

Figure 44. Annual electricity consumption by projection-year and sector

Transportation electricity demand becomes a significant source of load in all projections, larger than industrial demand as soon as 2030. Also in 2030, we see that while High projection non-transportation loads are smaller than the Moderate projection, the additional transportation load deriving from more aggressive electrification assumptions means that the overall High projection load is 31.8 TWh, already 1.1 TWh higher than the Moderate projection. With aggressive electrification but with less energy efficiency, the most electricity demand is seen in the Stress projection in 2045: a total of 50.2 TWh, nearly twice as much as our 25.8 TWh estimate for 2015.

Figure 45 shows the peak electricity demand for each projection-year. There is significant growth in peak demand as there was for annual load; however, the peak demand growth rates tend to be a smaller than those for annual load, see Table 12. Although the peak demand of non-transportation loads is smallest in the High projection for all study years due to aggressive energy efficiency assumptions for space cooling and other end uses, by 2030 transportation electrification contributes enough to peak for the High projection to surpass the Moderate projection's peak demand. The influence of transportation loads is especially significant in study year 2045, when EV charging shifts the peak demand times in both the High and Stress projections. Because the High projection places more emphasis on workplace charging, the peak demand time shifts up to 2 p.m. in that case; the Stress projection's emphasis on after-work residential charging pushes the peak demand time all the way to 7 p.m. These shifts in time are responsible for corresponding shifts in sectoral composition—High and Stress 2045 peak demand is least influenced by building loads, as compared to all other projection-years.

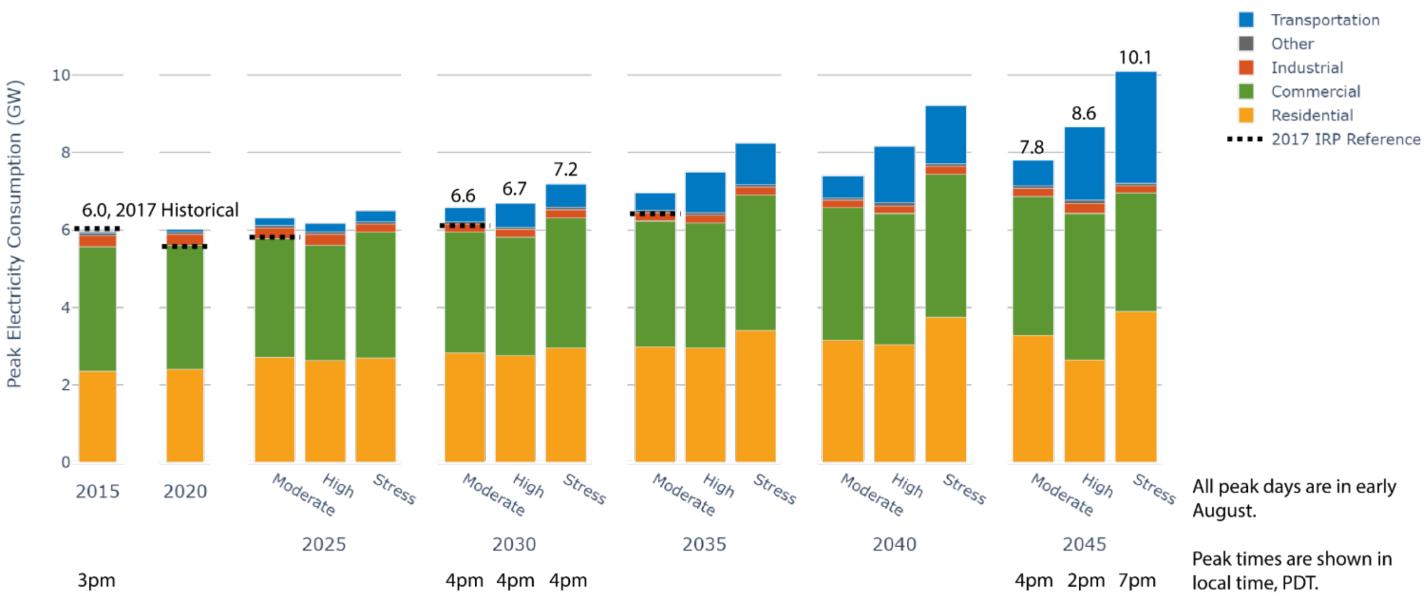

Figure 45. Peak electricity demand by projection-year and sector

Table 12. Summary of Annual and Peak Demand Growth Rates from 2015 to 2045

Metric	Quantity	Moderate	High	Stress
Annual Demand	2015 TWh	25.83	25.83	25.83
	2045 TWh	38.88	46.26	50.17
	Overall growth (%)	51	79	94
	CAGR[a] (%)	1.37	1.96	2.24
Peak Demand	2015 GW	5.95	5.95	5.95
	2045 GW	7.81	8.66	10.09
	Overall growth (%)	31	45	70
	CAGR (%)	0.91	1.26	1.77
Load Factor	2015	0.50	0.50	0.50
	2045	0.57	0.61	0.57

[a] Compound annual growth rate (CAGR)

Changes in load shape can be seen by looking at average and peak day load shapes side-by-side for the different load projections. The average load shape is computed by averaging demand for each unique time that occurs during one standard-time day (every 15 minutes, or 96 data points altogether) over all 365 modeled days. As such, it contains the average load for all end uses, including seasonal end uses like space heating and cooling. In contrast, the peak day falls in early August for all projection-years, therefore its shape is composed predominantly of space cooling plus the many kinds of loads that occur every day (e.g., lighting, water heating, industrial loads, electric vehicle charging).

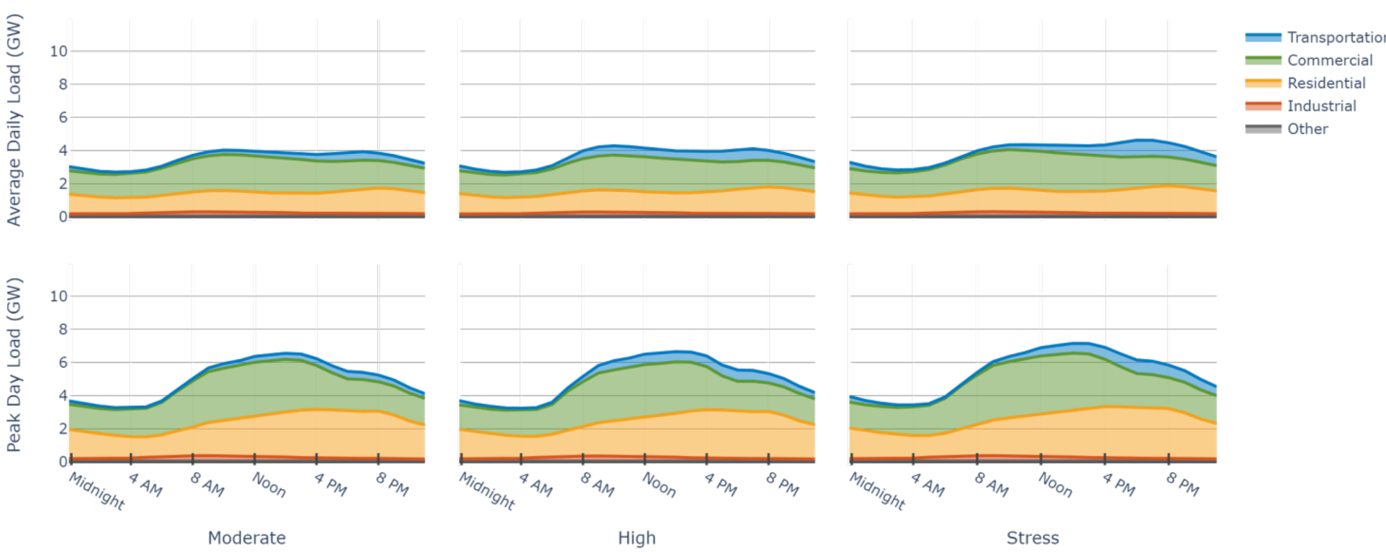

Figure 46. Average and peak day load shapes for 2030

All projections shown by sector.

The 2030 load shapes show modest differences between projections (Figure 46). Stress residential and commercial loads mostly show increased magnitude compared to the other projections. The most noticeable shape-only differences have to do with electric vehicle charging—especially in the average load shape, the Stress projection's emphasis on evening residential charging is evident.

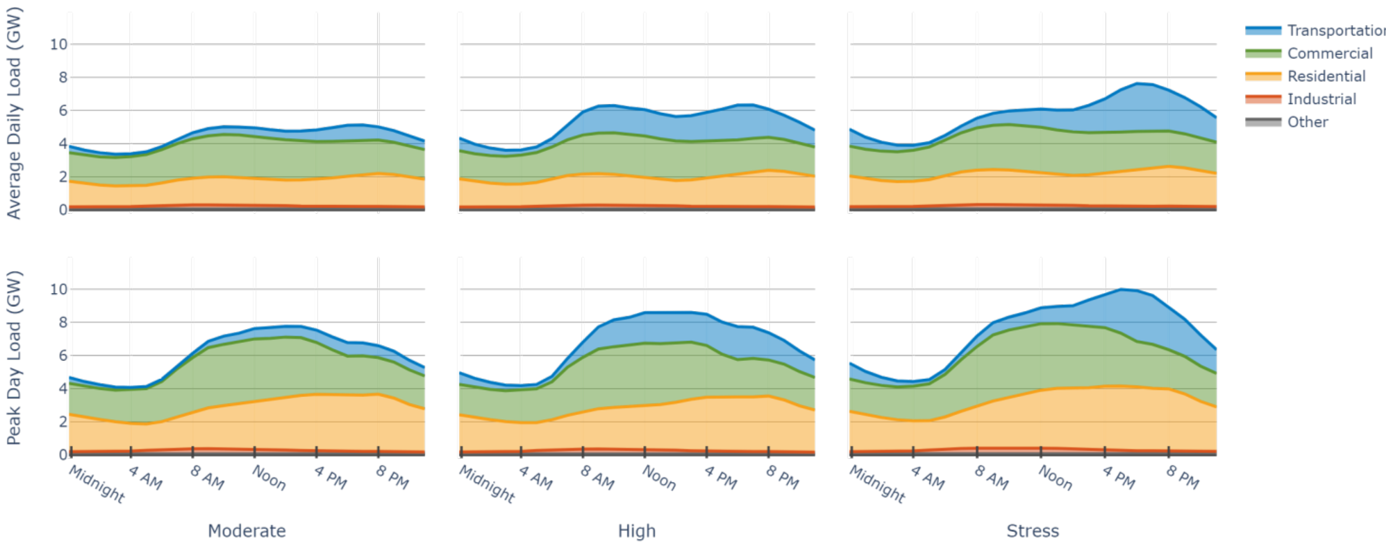

Figure 47. Average and peak day load shapes for 2045

All projections shown by sector.

Comparing the 2045 load shapes in Figure 47 to those in Figure 46 demonstrates how much the projections diverge between 2030 and 2045. Average morning residential and commercial loads are higher in the High and Stress projections than they are in the Moderate projection due to electrification of water and space heating. The overall larger amount of demand in the Stress projection is easy to see, as is the impact of efficiency on the High projection's non-transportation loads, especially compared to the Moderate projection on the peak day. The Stress projection's charging assumptions also distinguish its load shape from the Moderate and High projections.' The Stress average and peak days both have distinct daily peaks around 6 p.m. standard time, whereas the High projection average day follows a two-peak pattern and the High projection peak day peaks between noon and 4 p.m.

In addition to varying by projection, load shape also varies by location. Figure 48 shows average load shape by day type (i.e., weekday or weekend) for three different locations at the receiving station (RS) level that were chosen because they each have more load from one particular sector (commercial [C], residential [R], or industrial [I]) as compared to other aggregation points at this level.[44] Although none of the locations serves load of only one type, the sector-specific load shapes for commercial, residential, and industrial loads manage to show through for each of

[44] RS-level sector percentages were estimated using OTC customer billing data for 2016 and the GIS analysis that defined agents as well as their connection point with the LADWP system (Appendix I). Those data gave us an estimate of each agent's annual load, sector, and RS, from which we computed how much of an RS's annual load could be assigned to each sector—residential, commercial, and industrial. The resulting percentages are reported in Table 39.

these locations: RS-P (84% commercial), RS-U (59% residential), and RS-Q (39% industrial). Comparing the 2015 load shapes to all the projections in 2045, the efficiency and electrification differences per projection and sector are visible.

For example, the LA Port is served by RS-Q, and so we see weekday daytime demand increasing significantly in all projections, especially High and Stress. Residential building electrification is visible in the RS-U High 2045 shapes; RS-U residential EV charging is visible in all projections in the evening hours in 2045 but is especially acute in the Stress projection. RS-P shows relatively modest differences between years and projections. Nevertheless, there is load growth between 2015 and 2045; efficiency and electrification differences mostly cancel each other out in moving from Moderate 2045 to High 2045; and less energy efficiency results in more load moving from High 2045 to Stress 2045.

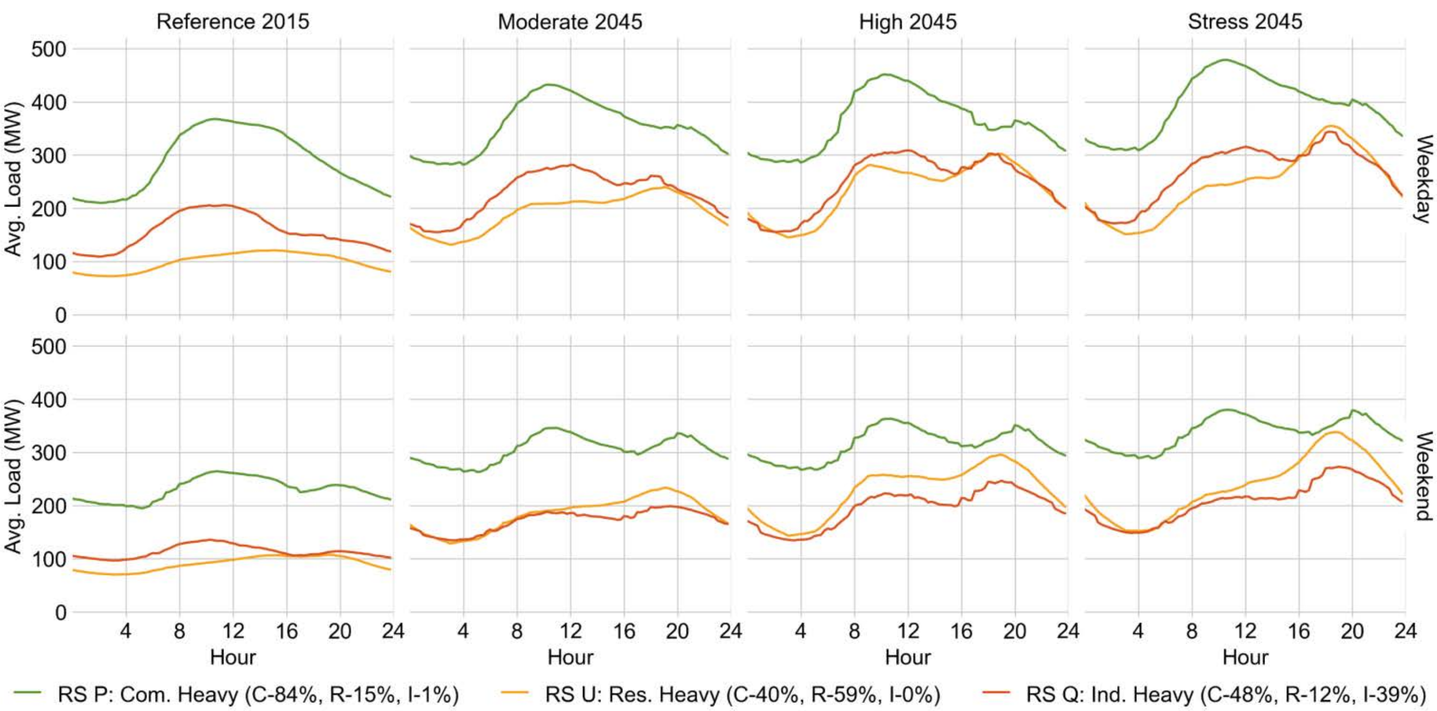

Figure 48. Average load shapes by day type for three different locations in LADWP territory

Each location (RS P, RS U, and RS Q) was chosen because it has more load from one particular sector (commercial [C], residential [R], or industrial [I]) as compared to other aggregation points at this level. The percentage breakdowns correspond to the OTC billing data for 2016 assigned to LA100 agents, which are tagged with sector and subsector information.

4.2 Demand by End Use

LA100 annual consumption by end use is shown for the Moderate projection in Figure 49. In this view, we get more specificity in terms of both building loads (with like-type loads combined across residential and commercial buildings) and electric vehicle charging types. We can also see the contributions from industrial loads, other commercial loads that do not map to the commercial building types modeled by ComStock, municipal water loads, and "other" loads which here include uncategorized billing data customers, unmetered outdoor lighting loads, and Owens Valley.

Regarding the building end uses, pool loads, major appliances (dishwashers, clothes washers and dryers, and cooking ranges), and household refrigerators and freezers are broken out from plug and process loads for low-rise residential buildings (i.e., those modeled by ResStock as opposed to high-rise residential buildings in ComStock). The refrigeration end use includes those ResStock-modeled refrigerators and freezers, as well as commercial refrigeration systems such as those found in grocery stores and refrigerated warehouses. Plug and process loads, which are modeled as increasing between now and 2045, consist of all other loads that are not water heating, lighting, or HVAC-related; for example, computers, televisions and monitors, other office equipment, commercial cooking equipment, and hospital equipment. Building calibration is an artificial end use that was used by the ComStock team to fill in nighttime loads that were revealed by the calibration process but for which the end use is unknown, and by the ResStock team to shift some energy to account for time lags.

Turning to transportation, we see that Level 1 and Level 2 light-duty EV charging is the predominant transportation load captured by the study.[45] Although we assume that all LA Metro, LADOT, and school buses are electrified by 2030, this results in a very small additional demand. DC fast charging is also a fairly small slice of the transportation loads. Overall, however, EV charging grows from being a nearly insignificant share of total demand in 2015 to over 10% of demand by 2045, even in the Moderate projection.

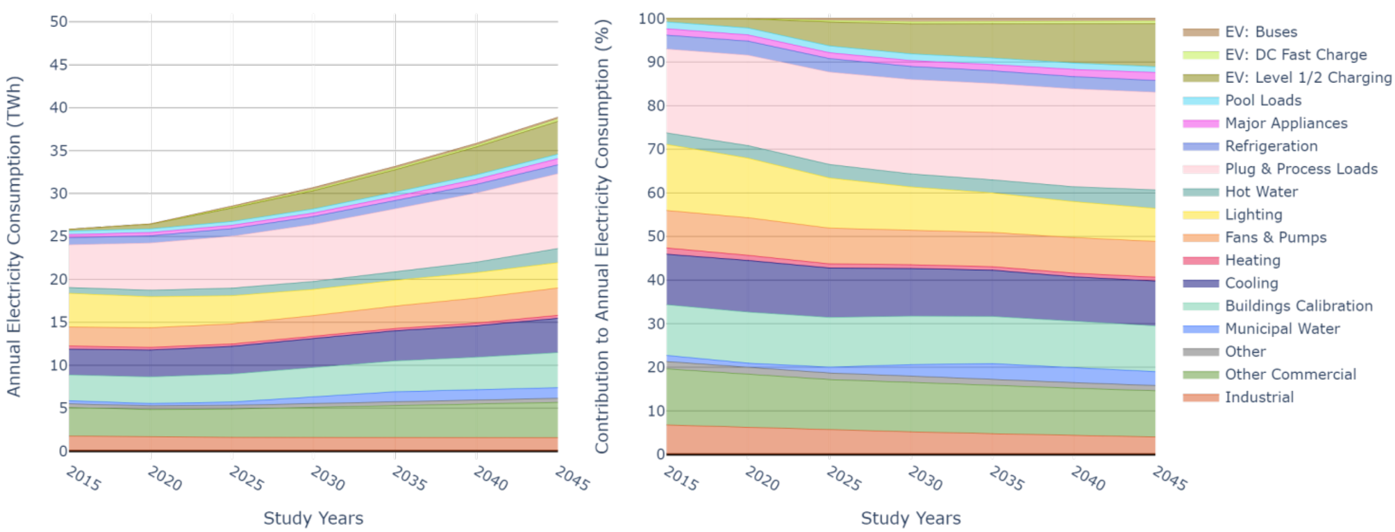

Figure 49. Moderate projection annual electricity consumption by end use and study year: Absolute quantities (left, TWh) and proportions (right, %)

The High projection breakdown of annual consumption by end use (Figure 50) shows even greater EV charging demands, an attenuation of end uses easily addressable by energy-efficiency, and significant growth in hot water electricity use. There are also some trends that are consistent across all three projections: significant growth in municipal water demands based on Los Angeles's plans for more-local water supplies and water recycling; fairly flat industrial and other commercial loads.

[45] Medium- and heavy-duty vehicle electrification was not modeled in detail, but Chapter 9, Appendix A provides a qualitative description of potential impacts, for charging, the power grid, and air quality and health.

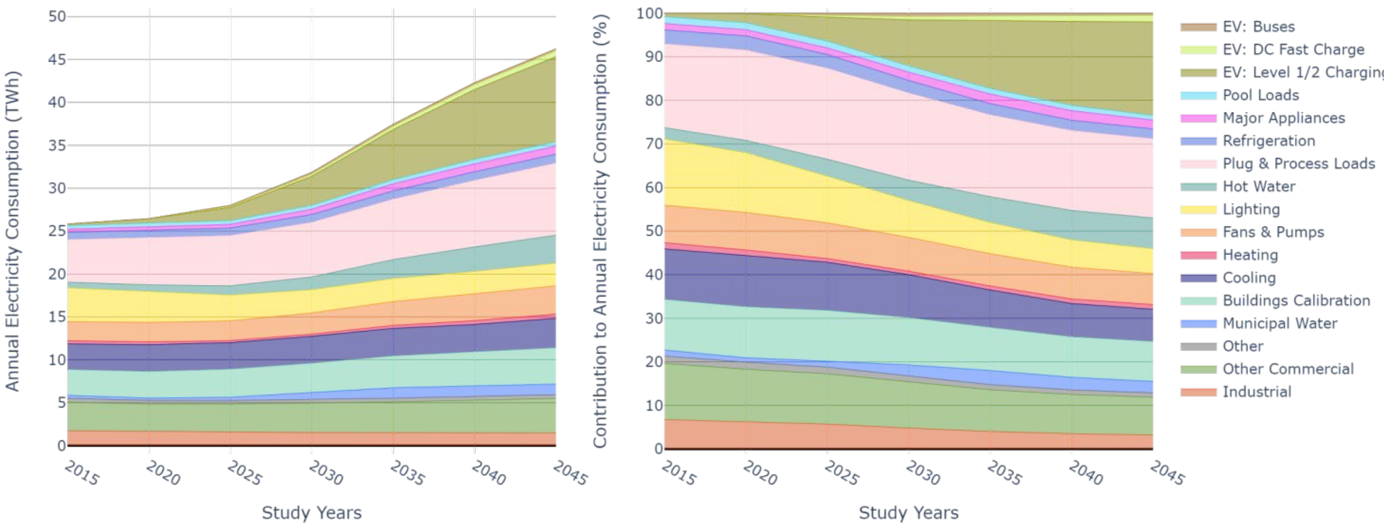

Figure 50. High projection annual electricity consumption by end use and study year: Absolute quantities (left, TWh) and proportions (right, %)

The Stress projection (Figure 51) uses about the same amount of electricity for EV charging as does the High projection. End uses subject to significant energy efficiency measures, meanwhile, simply use more energy to provide the same level of service achieved in the High projection.

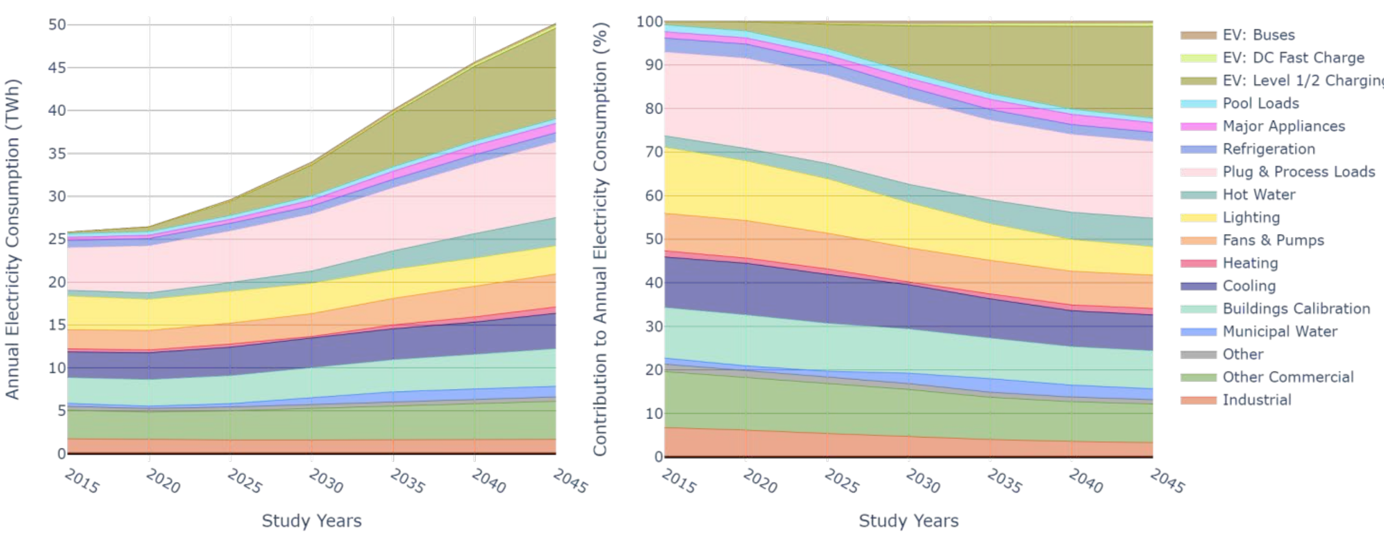

Figure 51. Stress projection annual electricity consumption by end use and study year: Absolute quantities (left, TWh) and proportions (right, %)

Similar stories can be told across projections when looking at end-use contributions to peak demand, with the main difference being a shift from looking at all end uses across the year to those aligned with LADWP's summer peak. Figure 52 shows those data for the Moderate projection. Building space cooling is the main driver behind the summer peak—building cooling loads increase nonlinearly with outdoor temperature, demanding both more energy over the whole day (longer run times) and more power at the hottest times (compressors actually pull more power to push the refrigerant through the system). Because the peak time typically happens on a weekday summer afternoon, other significant loads at that time include industrial and other commercial loads, lighting, plug and process, fans and pumps. By 2045, electric vehicle charging is also a significant demand at the system peak time, albeit one that can potentially be mitigated with demand response programs or time-of-use pricing.

The peak demand by end use for the High projection (Figure 53), as compared to the Moderate projection (Figure 52), shows energy efficiency and electrification impacts through 2040. In 2045, there is a discontinuity associated with the peak time moving from 4 p.m. PDT to 1:45 p.m. PDT, relative to other years and Moderate 2045. This shift is caused by unmanaged EV charging being a larger contributor to peak; because the High projection has significant workplace charging, the peak time actually moves earlier, and is therefore composed of significantly less building cooling demand and significantly more EV charging demand, including DC fast charging.

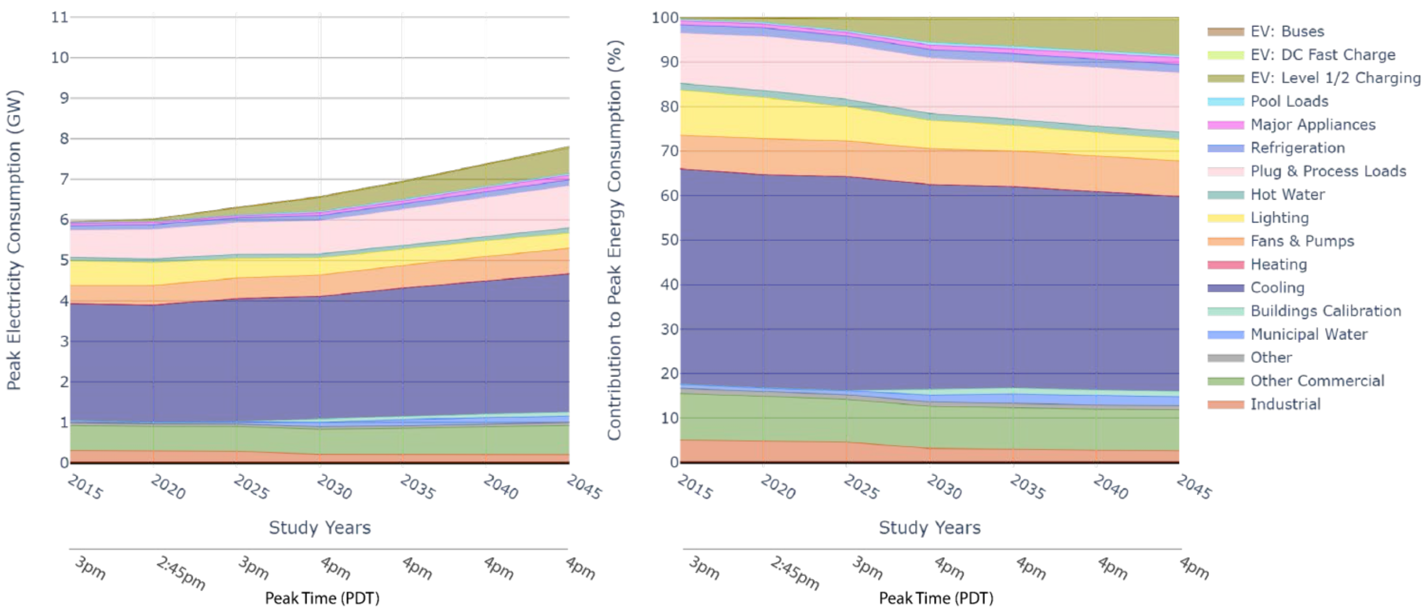

Figure 52. Moderate projection peak electricity demand by end use and study year: Absolute quantities (left, TWh) and proportions (right, %)

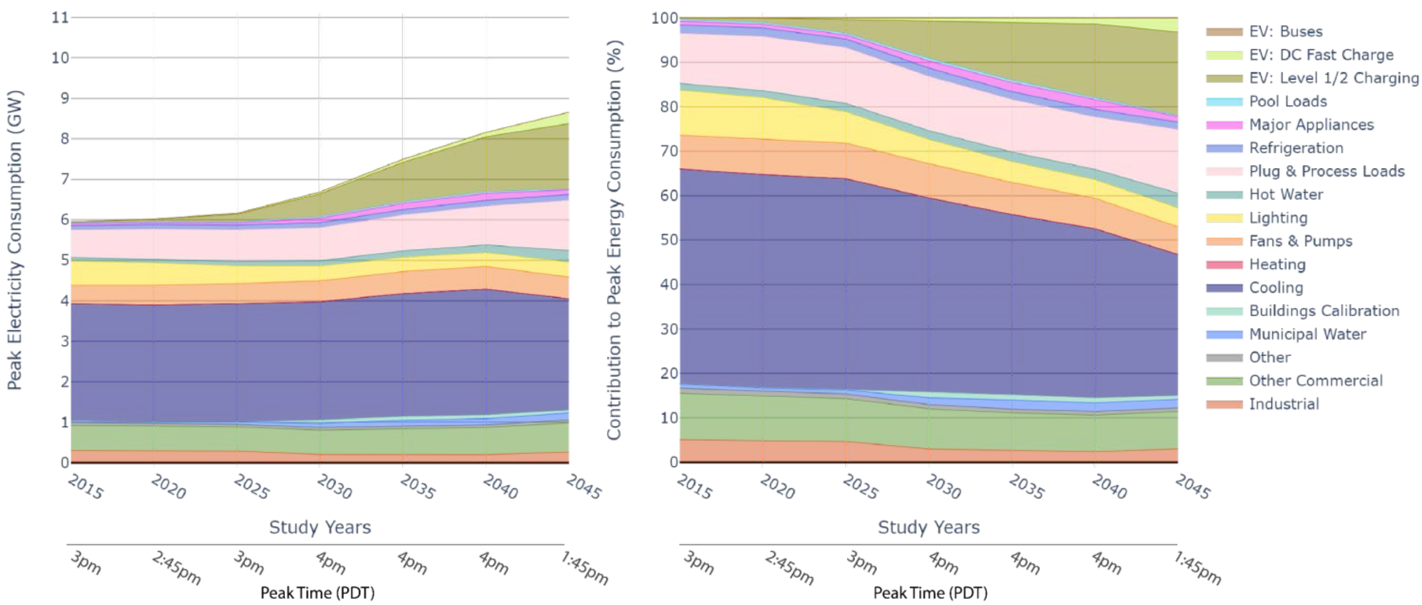

Figure 53. High projection peak electricity demand by end use and study year: Absolute quantities (left, TWh) and proportions (right, %)

A similar discontinuity happens in the Stress projection (Figure 54), but with the peak shifting later, to 6:45 p.m. PDT in 2045. Unlike in the High projection, the Stress projection actually shifts the peak time later in 2025, 2035, and 2040 as well. However, the pre-2045 shifts are modest—15 minutes to an hour; compared to the 2-hour 45-minute difference with Moderate and 5-hour difference with High in 2045. Those differences impact both solar integration and demand response availability.

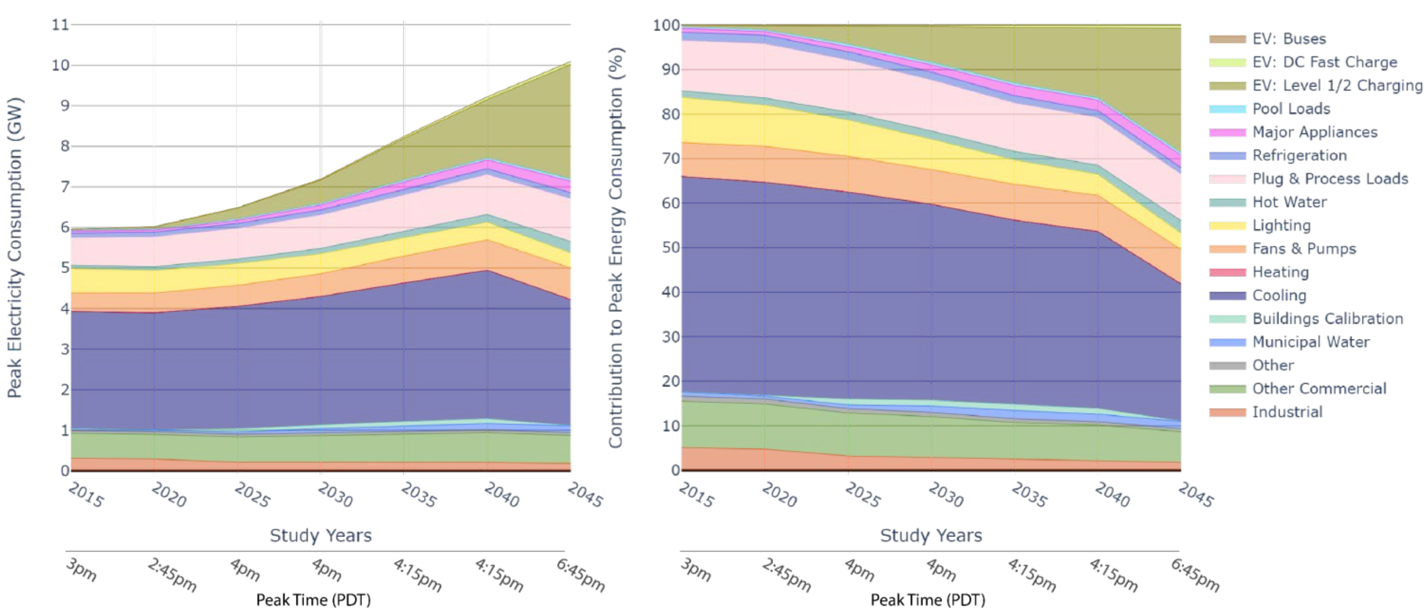

Figure 54. Stress projection peak electricity demand by end use and study year: Absolute quantities (left, TWh) and proportions (right, %)

4.3 High vs. Stress Projections: Energy Efficiency Differences

Digging a little deeper into the energy efficiency differences between the High and Stress projections, we see in Table 13 that the assumptions underlying those projections are quite different across residential buildings, commercial buildings, industry, and the water system. For example, the High projection assumes that all new residential appliances bought for LA residences are the most efficient available starting in 2030 (with significant uptake of energy efficient appliances in years prior, starting from recent actual outcomes), and more than half of commercial buildings (new and major system retrofits) are expected to implement technologies commensurate with 15-year-ahead expected code requirements.

Table 13. Summary of Energy Efficiency Assumptions

Sector	Moderate	High	Stress
Residential	Sales shares distributed across efficiency levels	100% sales share of highest efficiency models by 2030	2017 SLTRP Efficiency Goals
Commercial	80% adoption of 5-year-ahead Title 24 Code	70% adoption of 15-year-ahead Title 24 Code	2017 SLTRP Efficiency Goals
Industrial	Navigant 2017 and Nexant 2014 – Economic potential	Navigant 2017 and Nexant 2014 – Maximum achievable	Navigant 2017 – 80% of commercial market potential
Water System	Nexant 2014 – 50% of maximum potential for wastewater sector by 2035	Nexant 2014 – 70% of maximum potential for wastewater sector by 2035	Nexant 2014 – 30% of maximum potential for wastewater sector by 2035
Transportation[a]	75% access to residential, 25% access to workplace charging	60% access to residential, 50% access to workplace charging	90% access to residential, 15% access to workplace charging

[a] The transportation assumptions are not efficiency related, but they do underlie differences between the High and Stress projections.

The actual resulting energy use differences are shown in Figure 55 (absolute annual consumption by end use) and Figure 56 (differences between Stress and High). From Figure 55 we see that the impact of the High energy efficiency assumptions is significant (saving 3.9 TWh or about 7.8% of Stress 2045 annual demand), while not fundamentally changing how electricity is used across end uses. Figure 56 demonstrates more clearly where those energy savings come from, in addition to the greater emphasis in the High projection as compared to the Stress projection on DC fast charging, by showing which end uses use more energy in the Stress projection (positive quantities) and which use less (negative quantities).

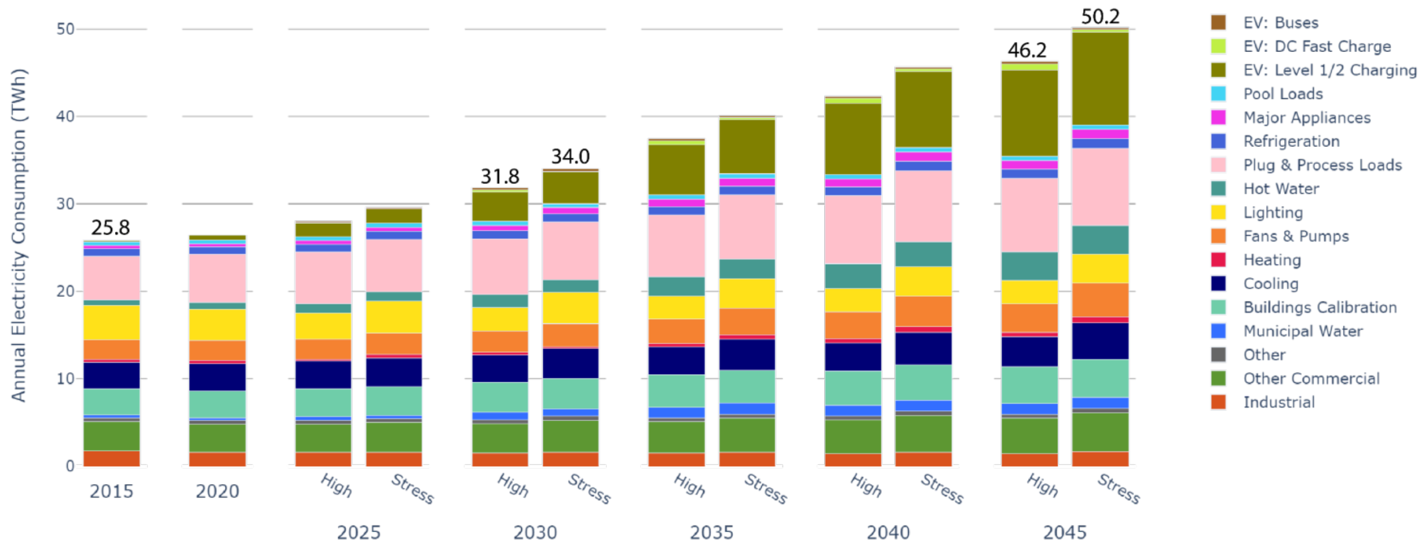

Figure 55. High and Stress projection annual consumption by year and end use

Figure 56 thus shows that over the whole year, a variety of end uses contribute to the energy efficiency savings embedded in the High projection. HVAC loads such as cooling, heating, fans, and pumps are greatly reduced—but so are lighting, plug and process loads, and other commercial loads. Industry, major appliances, and pool pumps also make visible contributions. Notably, water heating is not significantly more efficient in the High projection, likely because of the expectation that Title 24 will require heat pump water heaters in all cases starting in 2030.

The EV charging loads differences are due to charger availability assumptions; because the High projection relies more on workplace and public charging than does the Stress projection, more DC fast charging (DCFC) is needed to power all simulated trips. The additional DCFC load is displacing L1/L2 load in the Stress projection, resulting in less energy being needed overall—because of avoided AC-to-DC conversion losses.[46]

[46] EVI-Pro applies a 10% efficiency penalty for on-board AC/DC conversion, which applies to L1/L2, but not DCFC, charging.

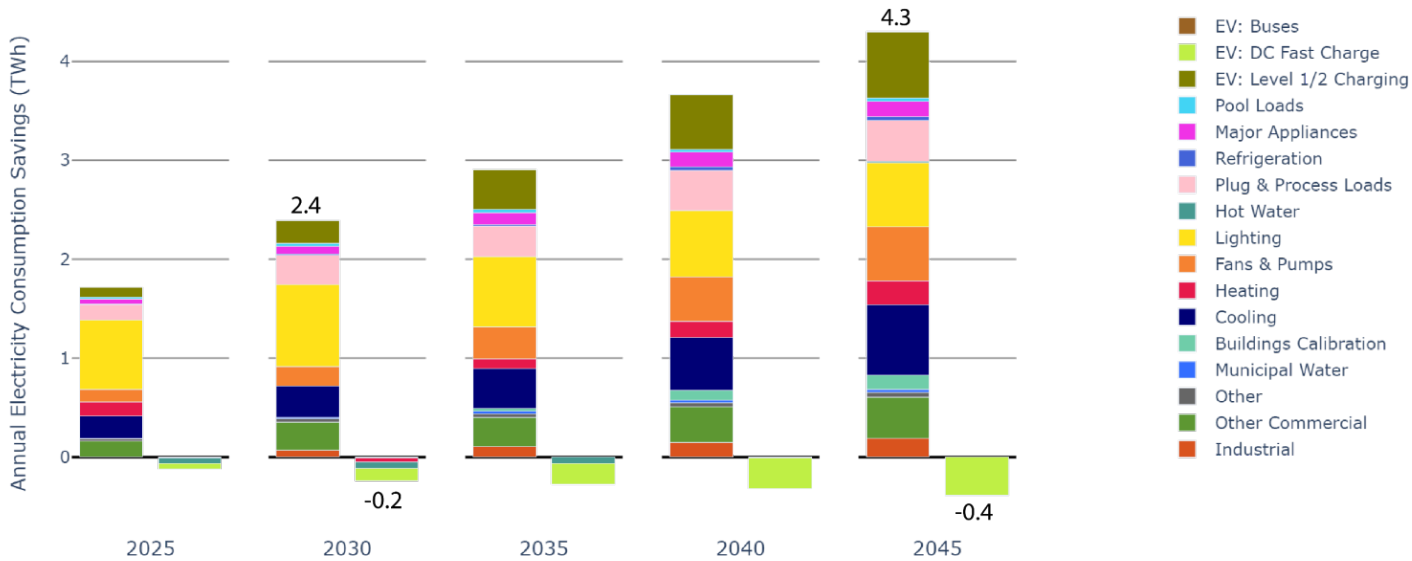

Figure 56. Stress minus High projection differences in annual consumption by year and end use

Energy efficiency and charging assumption differences have an even larger impact on peak demand, see Figure 57 and Figure 58. In this case, the High projection saves 1.42 GW, or 14.2% of peak demand, relative to the Stress projection and before demand response dispatch. This represents a potentially very large savings with regard to the supply-side resources needed to satisfy the equivalently electrified loads in the two projections.

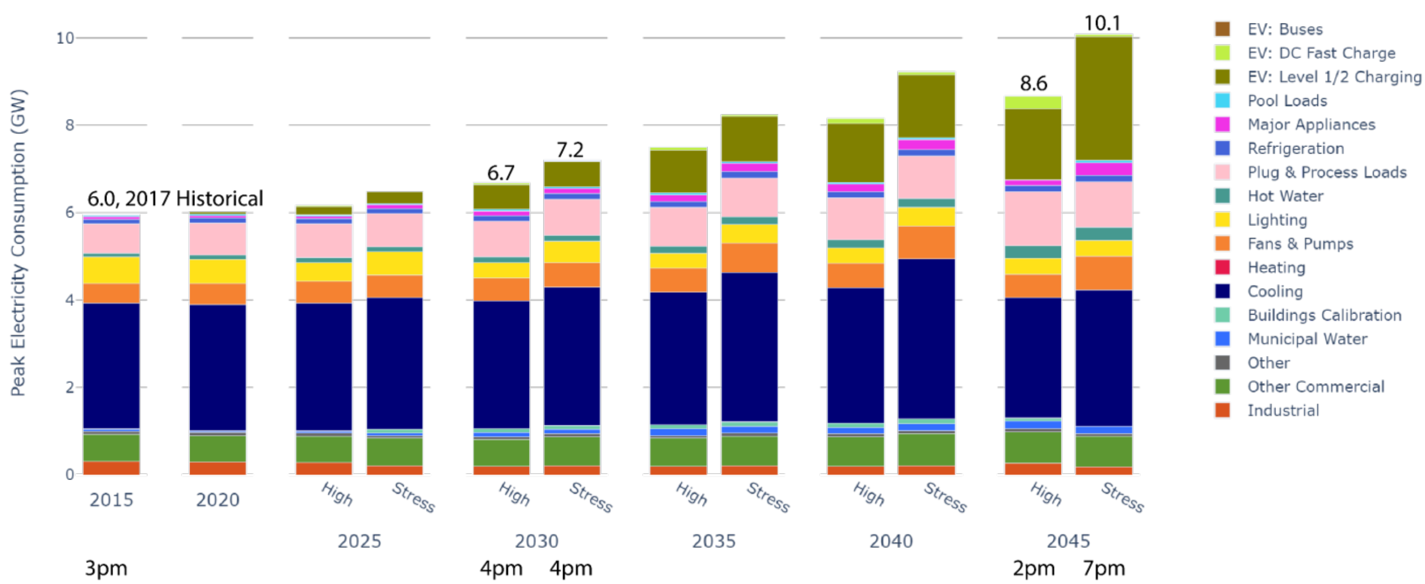

Figure 57. High and Stress projection peak demand by year and end use

In Figure 58 we see more precisely where these peak load savings come from. Focusing first on 2040, because for that study year the High and Stress projections peak at similar times, we see that most of the peak demand savings come from buildings—cooling especially, but also fans, pumps, and lighting. In 2045, the picture is complicated because of peak timing differences that maybe make the end-use comparisons not that meaningful. For example, because the peak times are 2 p.m. for the High projection and 7 p.m. for the Stress projection, we see in Figure 58 that the High projection peak demand contains more plug and process loads than does the Stress projection's peak demand (resulting in a negative Stress minus High difference for that end use in 2045). This occurs because there are more plug and process loads, spread across residential and commercial buildings, in the daytime as compared to the evening, more than making up for the energy efficiency effect evident in the pre-2045 model years (and Figure 56). However, the mismatch and the large contribution of L1 and L2 charging to the Stress projection peak are good reminders that in these two projections electric vehicle charging moves from being an almost insignificant electrical load today, in 2020, to being a main driver of key power system characteristics 35 years from now, in 2045.

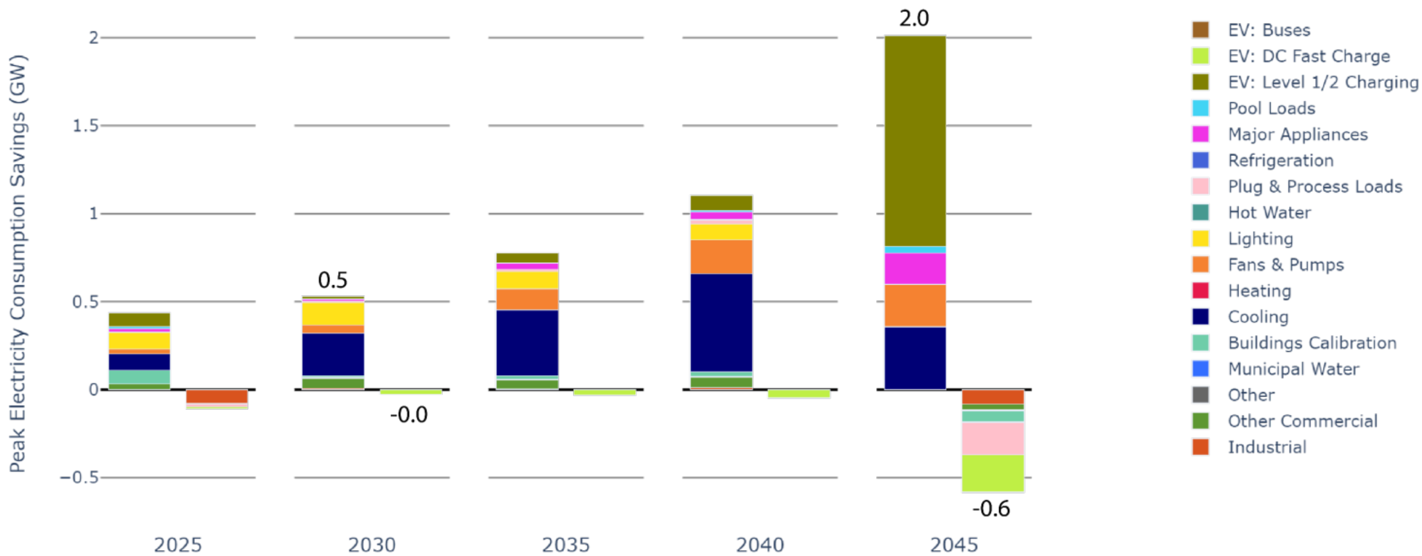

Figure 58. Stress minus High projection differences in peak demand by year and end use

4.4 Moderate vs. High Projections: Electrification and Energy Efficiency Differences

The Moderate and High projections differ along both the energy efficiency and electrification dimensions. Referring back to Table 13 on energy efficiency and to Table 14 for electrification, we see that the differences between Moderate and High are largely differences of magnitude, not kind. That is, the Moderate projection touches all of the same technology adoption decisions that the High projection does, but its implementation is markedly less ambitious, except in the limited areas of bus electrification and water supply localization.

That said it would be a mistake to underestimate the level of change embedded in the Moderate projection. That projection still assumes that 80% of commercial new buildings and major system retrofits adopt efficiency technologies ahead of the code schedule, industrial energy efficiency meets its full economic potential, 60% of residential water heater sales are electric by 2045, and 30% of the light-duty vehicle fleet is electrified by 2045. That is, the Moderate projection assumes current trends will continue and even accelerate, but in its realization demonstrates that doing more of the same is not enough to achieve the City of Los Angeles's ambitious multisectoral goals.[47]

Table 14. Summary of Electrification Assumptions

Sector	Moderate Stress	High Stress
Residential	Water and space heating electric sales shares, starting at ~7% and ~26%, increase to 60% and 40% by 2045	100% new construction electrification starting in 2030 100% electric sales share (HVAC and water heating) by 2030; nearly 100% electric homes by 2050
Commercial	By 2045, 43% of water heating and 85% of space heating systems are electrified	100% new construction electrification starting in 2030 100% electric sales share (HVAC and water heating) by 2030; close to 100% electric buildings by 2050
Transportation	100% bus electrification by 2030 30% light-duty vehicle electrification by 2045 Meet CA 2030 ZEV Goal and continue trajectory (2017 SLTRP "high case")	100% bus electrification by 2030 80% light-duty vehicle electrification by 2045[48]
Industrial	LA Port – ICF International and E3 reports on CA transportation electrification "In Between" case	LA Port – ICF International and E3 reports on CA transportation electrification "Aggressive" case
Water System	All projections maximize local water supply through groundwater replenishment, water recycling (non-potable and indirect potable reuse), and stormwater capture.	

What does the difference between Moderate and High projections look like in terms of LADWP electricity consumption? Figure 59 shows Moderate and High annual electricity consumption broken down by end use; Figure 60 shows the differences. Overall, by 2045 the High projection has 7.4 TWh or 19% more load than the Moderate projection. From Figure 60 we can see that if the High projection did not include increased energy efficiency, this difference would be even starker—8.8 TWh or 22% additional load.

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[47] "L.A.'s Green New Deal: Sustainable City pLAn, 2019," https://plan.lamayor.org/sites/default/files/pLAn_2019_final.pdf

[48] Following the EFS High scenario for light-duty vehicle electrification, which models 91% and 100% PHEV sales shares by 2045 and 2050, respectively, we do not reach 100% EV market share for that sector on the timeline assumed by the pLAn. Assuming that conventional internal combustion engine (ICE) vehicles are available on the market, adoption models calibrated with historical data (e.g., "ADOPT: Automotive Deployment Options Projection Tool," NREL, https://www.nrel.gov/transportation/adopt.html) generally do not show 100% EV market saturation by 2050; and the EFS had to go beyond ADOPT's projections to produce the High projection (Mai 2018, Appendix B). Overall, bottom up models that account for the diversity of driving behaviors and vehicle preferences, as well as the possibility that an easy charging option (i.e., home or work) just may not be available to everyone, are not going to show 100% market share by 2045 under typical assumptions of no early replacement and EV adoption primarily by higher-income residents at least in the near to mid-term.

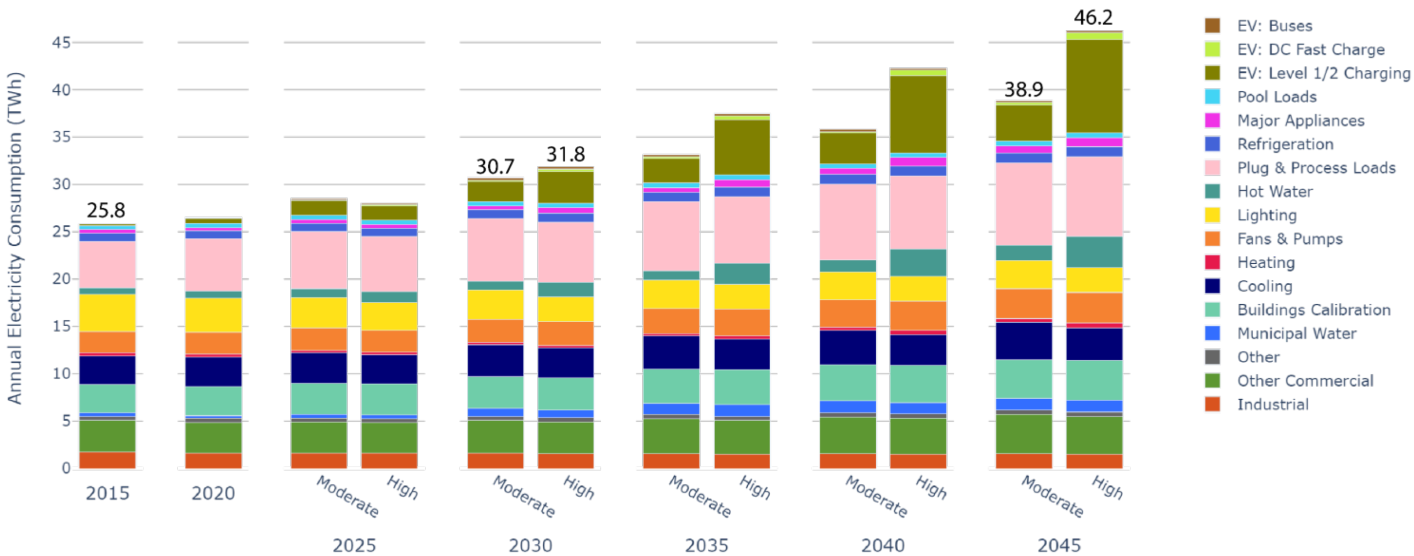

Figure 59. Moderate and High projection annual consumption by year and end use

In Figure 60 we also see that the biggest contributors to additional load in the High projection as compared to the Moderate projection are EV charging and water heating. Another contributor that may not be obvious is clothes drying (classified in the figure as a major appliance)—about 65% of clothes dryers in Los Angeles are powered by natural gas. Perhaps somewhat surprisingly, space heating is not a major factor; this is in large part because of the assumptions the team made (in response to LA100 Advisory Group feedback) around climate-change-induced increased outdoor temperatures. Thus, while the High projection assumes aggressive electrification of space heating, the actual demand for that energy service is attenuated by the climate change assumptions, and it does not end up having a large impact on annual demand or load shape.

Efficiency in the High, as compared to the Moderate projection, while technically coming from many sectors and end uses, is mostly provided by buildings loads: cooling, lighting, and plug and process.

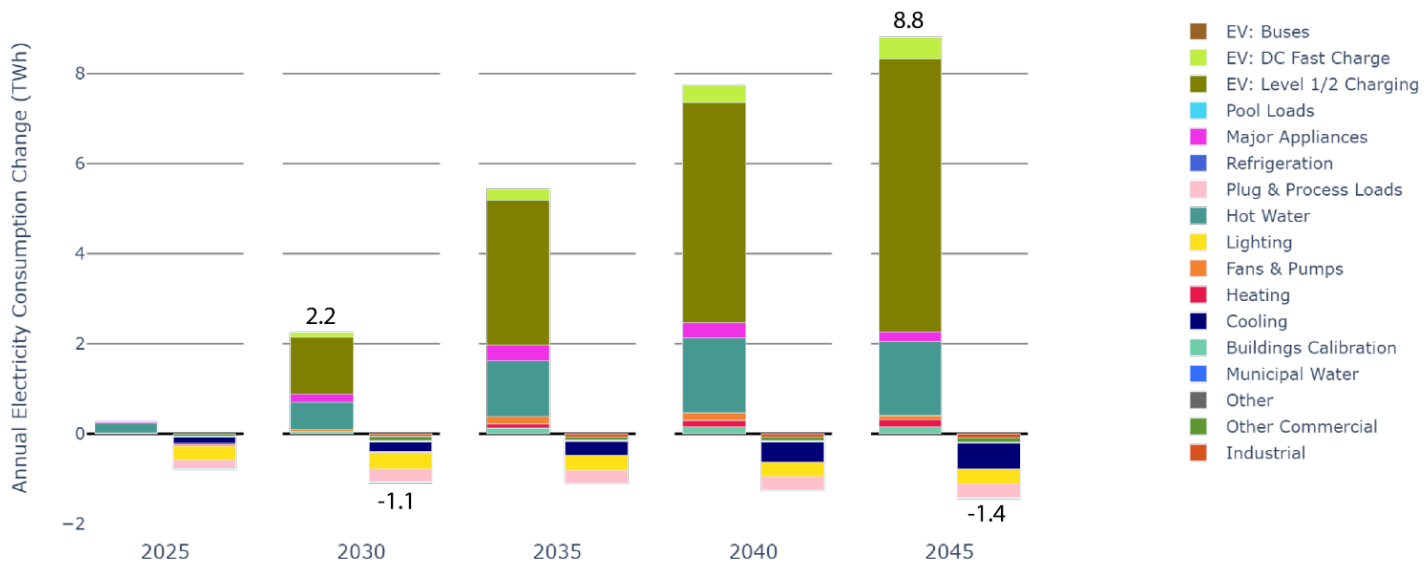

Figure 60. High minus Moderate projection differences in annual consumption by year and end use

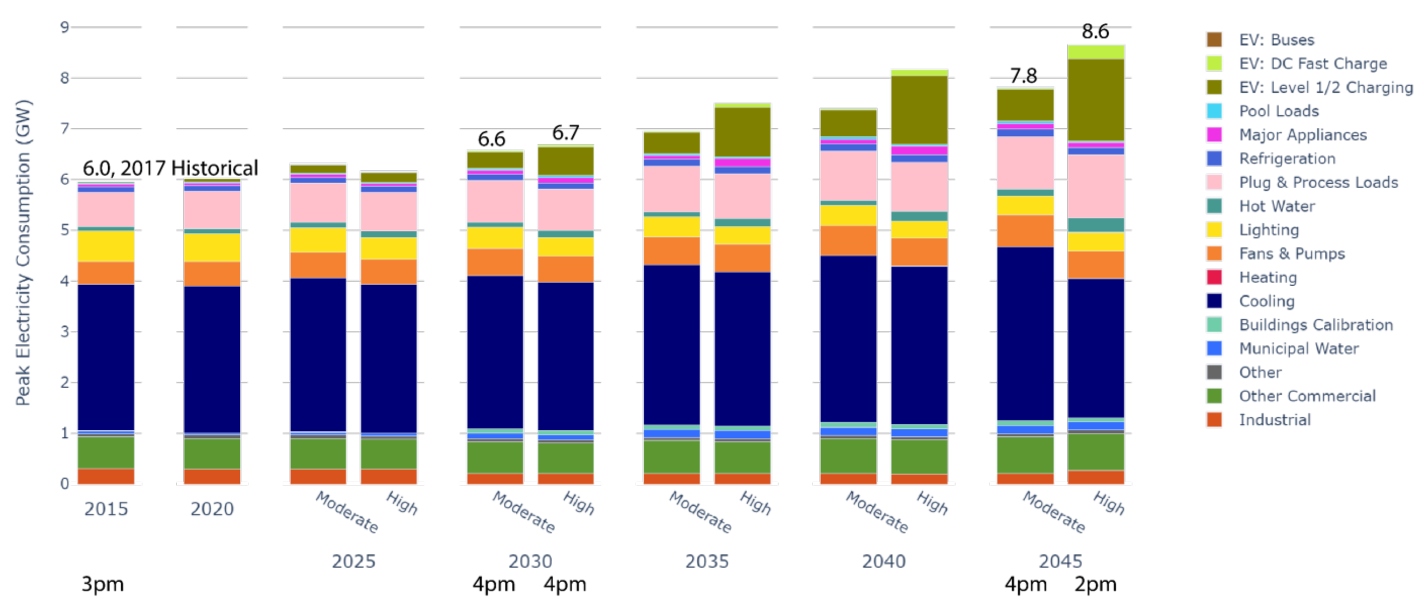

Figure 61. Moderate and High projection peak demand by year and end use

Although the annual electricity consumption differences between High and Moderate are quite large, 19% in 2045 relative to the Moderate projection, the peak demand differences are more attenuated. Figure 61 shows that the High projection's peak demand is only 11%, or 0.85 GW, higher than the Moderate projection's in 2045. This finding is in line with much of the High projection's additional demand coming from water heating and electric vehicle charging. While those loads are present during system peak times, they are not necessarily more likely to happen during those times than other times. For example, they are not seasonal, so they are spread out over the whole year, not piled up in the summer, and they are not necessarily more likely to occur during afternoon peak hours, as compared to morning or evening hours.

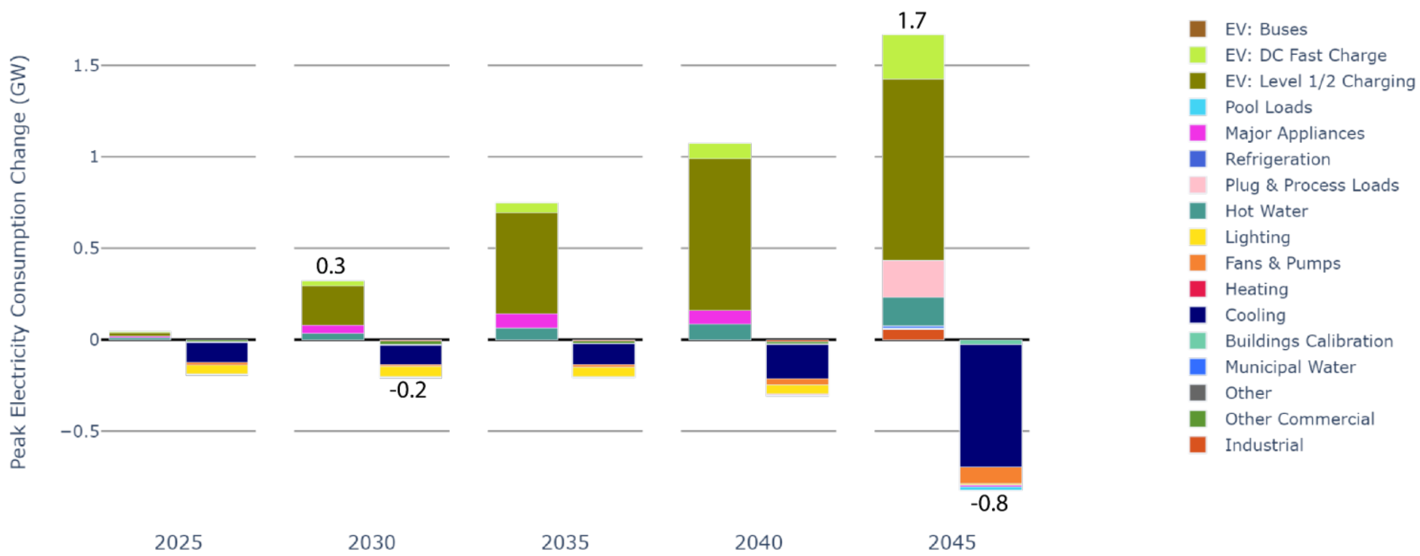

Figure 62. High minus Moderate projection differences in peak demand by year and end use

Examining the 2040 results in Figure 62 (because the peak times in that study year are the same between the High and Moderate projections) we see that EV charging, and to some extent water heating and clothes drying, causes the peak demand to go up in the High, as compared to the Moderate projection. Those increases in peak demand are in turn offset somewhat by efficiency realized from building cooling, lighting, fans, and pumps during the system peak time. As in Figure 58, the results for 2045 are more difficult to interpret because of the differences between when the peak happens (in this case, 4 p.m. for the Moderate projection and 1:45 p.m. for the High projection). What is clear is that if EV charging helps set the time of peak demand, that may change the degree to which different sector and end-use load should targeted for demand response.

5 Demand Response Projections

All load projections include demand response, starting from the programs currently in-place or rolling out,[49] and meeting an adjusted version of the goals outlined in the Demand Response 2014 Strategic Implementation Plan (DR 2014 SIP),[50] namely 500 MW of DR by 2030, of which 215 MW is interruptible load from large commercial, institutional, and industrial (CII) customers.[51] The remaining 285 MW (or more) consists of energy-shifting demand response from scheduled light-duty electric vehicle charging, and bring-your-own-device (BYOD) programs for residential cooling, water heating, space heating, pool pumps, and major appliances; as well as commercial cooling, water heating, space heating, and refrigeration. Water system load shifting is modeled only in the High projection, starting in 2035. All other projection-years assume that half of water system pumping loads are available to participate in the CII interruptible load program.

The amount of DR capacity varies by load projection based on assumed incentive, marketing, and automation levels that are least aggressive in the Stress projection, and most aggressive in the High projection. We exclude residential major appliance DR from the Stress projection altogether, because the small capacity per participant results in low incentive levels even in the Moderate and High projections. Incentive levels are set in part by converting $/participant to $/kW-yr and ensuring that the latter value does not exceed modeled capacity prices, which have been observed to be up to $150/kW-yr. Capacity per participant (kW/participant) is estimated by dividing end-use load coincident peaks[52] by the number of eligible participants (households, buildings, appliances, or electric vehicles), which are estimated by the detailed bottom-up load models.

Electric vehicle charging schedulability is estimated based on the EVI-Pro min-delay and max-delay profiles partitioned by charger type (i.e., Home L1, Home L2, Work L1, Work L2, and Public L2). DC fast-charging and electric bus charging are assumed to be inflexible demands, essentially operating at full capacity for as long as the vehicles they are serving are plugged in. We are very comfortable with this assumption for DC fast-charging—making such stations more flexible is possible (e.g., by co-locating stationary storage), but not by leveraging the vehicle batteries themselves, because doing so would fundamentally reduce the level of service being provided. Bus charging infrastructure, however, could be designed to provide more flexibility than we are capturing (e.g., by installing chargers with more power capacity than is strictly needed). We do not model such possibilities in the LA100 study because bus loads are at most only 0.8% of total LADWP load (Moderate Projection, 2030). Level 2 (L2) charging is incentivized to provide DR more than Level 1 (L1) charging, because the higher power and

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[49] LADWP's current demand response offering is a semi-automated interruptible load program for large customers (at least 100 kW of shed per customer). They are offering a residential programmable communicating thermostat DR program starting in 2020.
[50] LADWP and Navigant Consulting. *Demand Response 2014 Strategic Implementation Plan* (Los Angeles, CA: Los Angeles Department of Water and Power, 2014).
[51] Adjustments are derived from 2017 IRP language and personal communications with LADWP.
[52] Here, coincidence is within all end-use load eligible for a single DR program; we are not talking about coincident peak across multiple DR programs or at the whole system level.

faster charge times of L2 results in more scheduling flexibility than L1 charging given an equivalent amount of vehicle connection time.

Better aligning the DR shiftability assumptions used in bulk system grid models with what is physically realistic, especially for passive thermal storage resources like air conditioning loads, is an active area of research. In lieu of methods able to express all the time-varying aspects of demand shiftability, including non-unity round-trip efficiencies and dissipation, we assume that shifting has an efficiency of 100% and is not subject to dissipation (that is, the same amount of energy is required to fulfill demand at a shifted time or at the original time). Different end uses are modeled as having different levels of shiftability, however, by requiring loads to shift within specified windows, subject to constraints on allowable distance of the shift in both directions, and a capacity constraint (limit on the ability to increase load). Shiftability window size and capacity constraints are estimated exogenously based on engineering judgement.

Additional information on demand response modeling assumptions is available in Appendix L.

Based on detailed models of LADWP system demand through 2045 under three different load projections, we have developed data describing the amount of participating DR potentially available from:

- Large commercial, industrial, and institutional (CII) customers
- LADWP water system
- Residential end uses: Cooling, Heating, Hot Water, Pool Pumps, Refrigeration, and Schedulable Appliances
- Commercial end uses: Cooling, Heating, Hot Water, and Refrigeration
- Scheduled electric vehicle charging: Home-L1, Home-L2, Work-L1, Work-L2, and Public-L2.

The total demand response capacity by load projection and model year is shown in Figure 63. In all projections we easily exceed the 500 MW goal for 2030, in part because the capacity per program is measured non-coincidently. This allows us to show, for example, cooling and heating DR capacity on the same plot, but overstates the ability of DR to contribute to system needs in times of stress, because at no time will all of this capacity be available simultaneously.

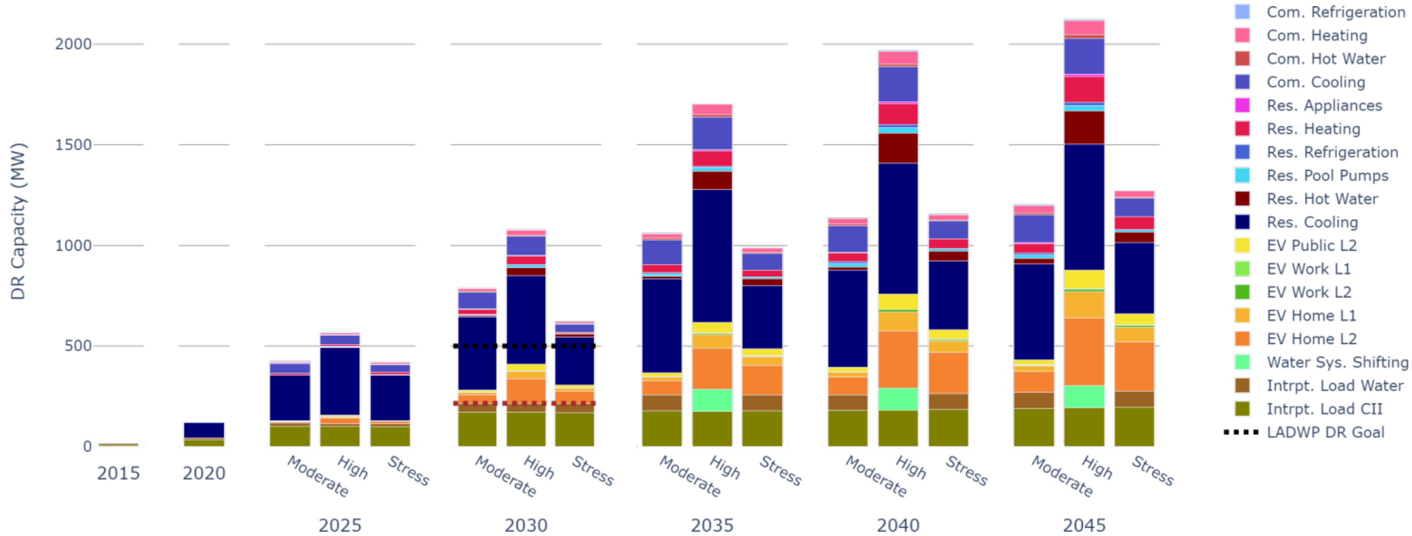

Figure 63. Summary of all DR capacity by load projection, year, and program

We therefore also show the amount of participating demand available at the system peak times, along with a reference point drawn at 10% of peak load in Figure 64. Taken together, these two summary plots show the current situation, in which CII interruptible load is the only active DR program, evolving quickly to grow CII capacity and add significant quantities of DR from residential cooling and schedulable EV charging. All projections also show significant capacity from commercial cooling, and residential and commercial space heating by 2035. Water heating and space heating capacity is significantly larger in the High projection starting in 2035—as compared to Moderate or Stress—because of its high electrification and DR assumptions.

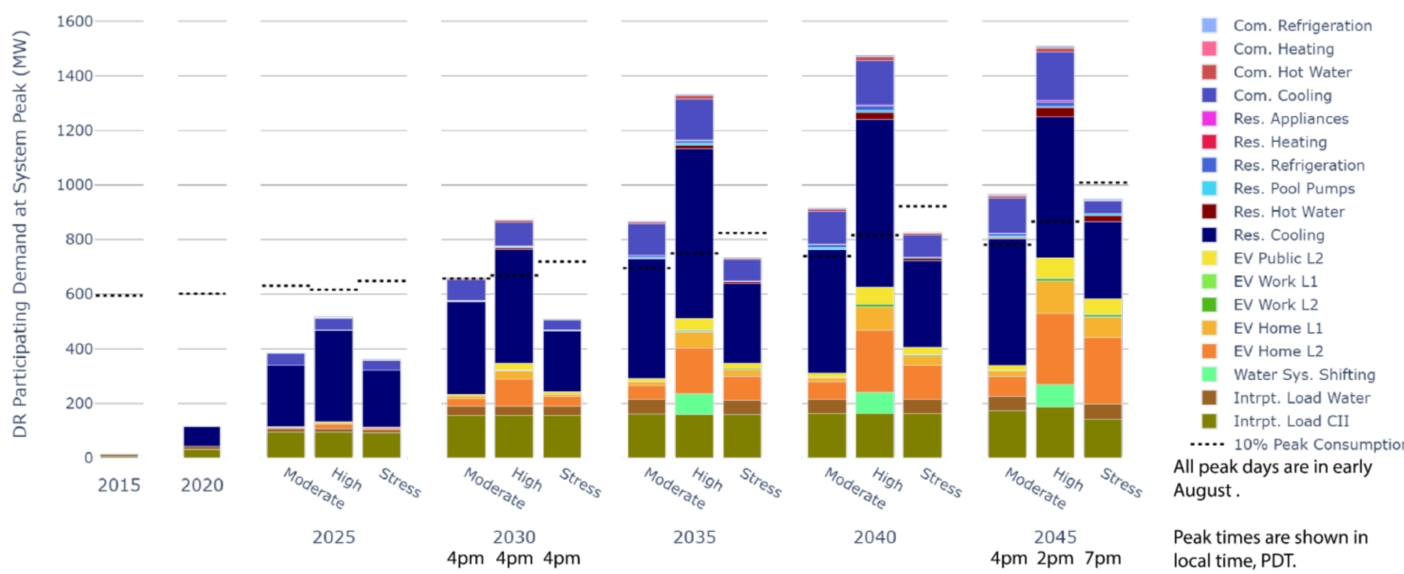

Figure 64. Summary of participating DR demand available at system peak times

We see in Figure 64 that space heating, hot water, and end uses like pool pumps are not able to provide a significant contribution to reducing system peak demand. However, some of these end uses, especially residential water heating, do provide large amounts of shiftable load throughout the year, especially in the High projection (Figure 65).

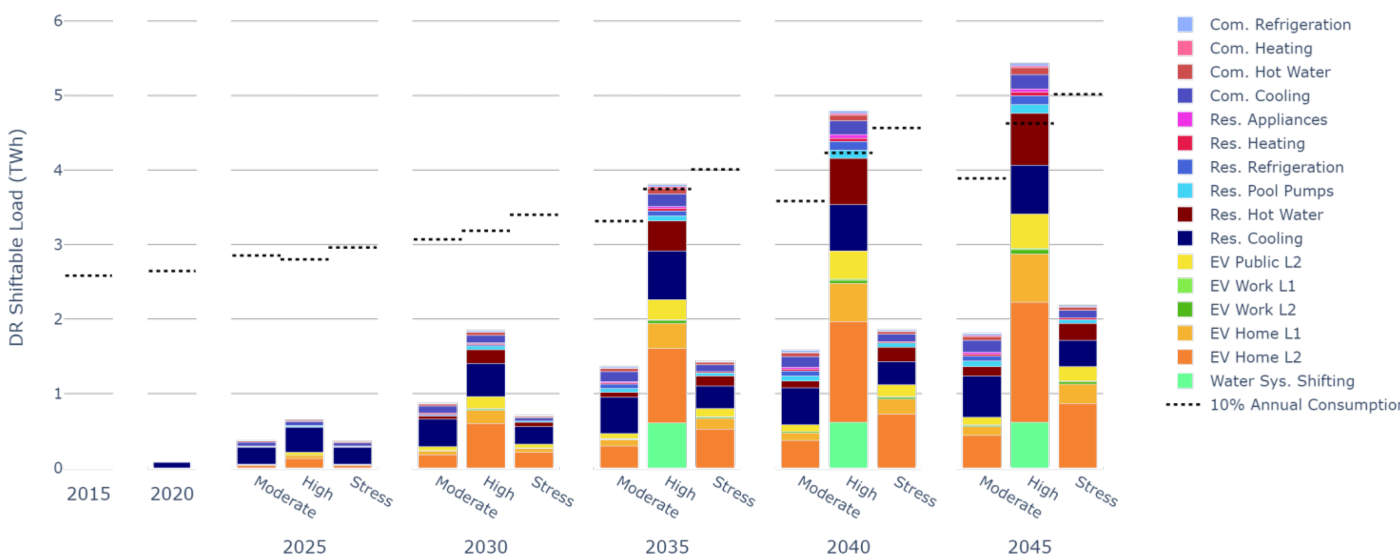

Figure 65. Summary of DR-participating, shiftable demand

Tabular summaries of DR resource, capacity, and related metrics are available in Appendix M.

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Appendix A. LA100 Common Data Elements

Table 15. Data Elements Used Across LA100 Study

Parameter	Value
Meteorological Year	2012
Area Served	LADWP service territory. Excludes areas within the balancing area but not served by LADWP
Solve Years	2020-2045 in 5-year increments, unless otherwise noted

Appendix B. High-Level Overview of Data Sources

B.1 Residential and Commercial Buildings

Table 16. Data Sources Used to Characterize Existing Residential Buildings in ResStock

Building Characteristics	Data Source
Garage, windows type, HVAC systems, HVAC setpoints, HVAC setpoint schedules, refrigerators, clothes washers, clothes dryers, dishwashers, ceiling fans, MELs, pool/hot tub	RASS 2009[a]*
Vintage, climate zone, building type, number of floors, number of units, unit size, bedrooms	LAC Assessor Parcels Database 2017[b]*
Building type, climate zone, neighbors, number of floors, unit size, number of units	LAR-IAC 2008[c]*
Hot water distribution, insulation, roof material, HVAC systems	California Title 24[d]
Plug loads, lighting, miscellaneous electric loads (MELs), pools and spas	CASE Plug Loads and Lighting[e]
Pools and spas	CASE Pools and Spas[f]
Plug loads, lighting, miscellaneous electric loads (MELs)	CLASS[g]
Lighting	Navigant Report – SSL study[h]
Dry-bulb temperature, relative humidity, solar insolation	White Box technologies,[i]* NSRDB,[j]* NOAA[k]
HVAC systems	Home Energy Saver[l]
Infiltration	ResDB – for LA County[m]
Orientation	OpenStreet Maps[n]*)

* Indicates Los Angeles DWP service territory-specific data sets

[a] Residential Appliance Saturation Study (RASS)

[b] Los Angeles County Assessors Database (Assessors DB)

[c] Los Angeles Region Imagery Acquisition Consortium (LAR-IAC)

[d] California Title 24

[e] Eric Rubin, Daniel Young, Maxmilian Hietpas, Arshak Zakarian, and Phi Nguyen, *Plug Loads and Lighting Modeling* (2016), 2016-RES-ACM-D. http://www.bwilcox.com/BEES/docs/Rubin%20-%202016%20T24CASE%20Report%20-%20Plug%20Load%20and%20Ltg%20Modeling%20-%20June%202016.pdf.

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[l] "Methods," Home Energy Saver, http://homeenergysaver.lbl.gov/consumer/documentation.

[m] "Residential Diagnostics Database," http://resdb.lbl.gov/.

[n] OpenStreet Maps

Table 17. Data Sources Used to Characterize Existing Commercial Buildings in ComStock

Characteristics	**Data Source**
HVAC system types, window to wall ratio, aspect ratios	CBECS[a]
Relative frequency of building types, aggregate statistics of square footage, number of stories, and vintage	CoStar[b]
As-built building characteristics, including envelope tightness, equipment efficiencies, baseline occupancy schedules, and space definitions	DEER reference buildings[c]
Dry-bulb temperature, relative humidity, solar insolation	NSRDB[d]
Heating fuel type	CEUS[e]
Heating fuel type	LA City Gas customer data (not yet acquired)
HVAC system types with efficiencies	California Commercial Saturation Survey[f]
New construction codes and standards	Title 24[g]
Inferenced gas consumption data using site to source conversion metrics	LADWP Existing Buildings Energy and Water Efficiency Program[h]
Location and varying high-level parameters of government, educational, health, and other buildings not covered by CoStar data	Department of Homeland Security Infrastructure Program[i]
Building occupancy characterization by building type	Itron MV90i data provided by LADWP for the LADWP service territory
Relative height of neighboring buildings by cardinal direction and neighboring building offset	LA County LIDAR Digital Elevation Data[j]

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[b] "About CoStar," http://www.costar.com/about. Because the CoStar database is not publicly available, the underlying data cannot be shared, but the results can.

[c] "Database for Energy Efficiency Resources (DEER)," http://www.deeresources.com/.

[d] Stephen Wilcox. *National Solar Radiation Database 1991–2010 Update: User's Manual* (NREL, 2012). NREL/TP-5500-54824, http://www.nrel.gov/docs/fy12osti/54824.pdf.

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[i] CISA, "Infrastructure Information Partnerships," Cybersecurity and Infrastructure Security Agency, https://www.dhs.gov/infrastructure-information-partnerships.

[j] County of Los Angeles, "2016 3-foot Digital Elevation Model (DEM): LARIAC 4," Los Angeles Regional Imagery Acquisition Consortium. https://egis3.lacounty.gov/dataportal/2017/10/11/2016-3-foot-digital-elevation-model-dem-lar-iac4/.

Table 18. ComStock Input Characteristics

		Dependencies						Data Sources							
	Characteristics	**Location**	**CoStar Bldg. Type**	**DEER Prototype**	**Vintage**	**Number of Floors**	**Building Shape**	**CBECS (EIA 2012)**	**RECS (EIA 2009)**	**CoStar (2017)**	**DEE R Prototypes**	**NREL Sector Model Assumptions**	**NREL NSRDB**	**LADWP MV90i**	**LARIAC [c]**
Meta	Location									X					
	CoStar Building Type	X								X					
	DEER Prototype Building		X								X				
	Vintage			X					X	X					
	Energy Code	X			X										
	Space Type Breakdown[a]										X				
	Weather Data	X											X		
Geometry	Rotation[b]											X			
	Number of Floors/Area			X					X	X					
	Floor to Ceiling Height			X				X							
	Building Shape			X											
	Aspect Ratio[c]						X					X			
	Neighboring Building Height[e]														X

		Dependencies						Data Sources							
	Characteristics	**Location**	**CoStar Bldg. Type**	**DEER Prototype**	**Vintage**	**Number of Floors**	**Building Shape**	**CBECS (EIA 2012)**	**RECS (EIA 2009)**	**CoStar (2017)**	**DEE R Prototypes**	**NREL Sector Model Assumptions**	**NREL NSRDB**	**LADWP MV90i**	**LARIAC [c]**
	Neighboring Building Offset[e]														X
Envelope	Construction Type, Wall and Window Properties[a]			X							X				
Internal Loads	People[a]			X	X						X				
	Lights[a]			X							X				
	Plug Loads, Elevators, Kitchen Equip.[a]			X	X						X				
Service Water Heating	Showers, Sinks, Laundry, etc.[a]			X							X				
Schedules	Operation Schedules[a]			X	X										
Occupancy	Occupancy Start/Stop time			X										X	
HVAC	HVAC System Type[d]			X				X							
	HVAC Controls, Efficiencies[a]	X		X							X				

[1] For energy simulations, values of these parameters are determined using EnergyPlus/OpenStudio defaults based on the dependencies shown (i.e., there are no probability tables associated with these characteristics).

[b] Rotation is defined as 8 orientation bins offset by 45 degrees, with a uniform probability distribution.

[c] Aspect is defined as 6 bins between about 0.5 and 6.5. Each shape uses only some of the bins.

[d] We infer HVAC system type based on a reanalysis of the California Commercial Saturation Survey (CCSS) conducted by Itron for the CPUC, published in August 2014 (http://capabilities.itron.com/WO024/Docs/California%20Commercial%20Saturation%20Study_Report_Final.pdf).

[e] These values are calculated for each of the cardinal directions and the underlying distributions are calculated on a census tract level.

Supplemental data, including data for comparisons and calibration, will be derived from:

- Historical electric metered consumption from the OTC study (using supplemental data matching in request bldg_4)
- LADWP load shapes (request bldg_1)
- Existing Buildings Energy and Water Efficiency (EBEWE) Program
- LADWP incentive programs
- Previous LADWP potential studies
- Lawrence Berkeley National Laboratory (LBNL) load component studies.

B.2 Electric Vehicle and Transportation Loads

EV data sources are summarized in Table 19.

Table 19. Transportation Data Sources

Data	Details	Data Source
Current light-duty vehicle (LDV) registration data	Make, model, year, fuel type, registrations by ZIP code	2018 IHS Automotive
Travel patterns	Vehicle usage patterns and household characteristics including trips/day, vehicle miles traveled (VMT)/day, origins and destinations, travel by time of day and demographics	2012 California Household Travel Survey
Plug-in EV (PEV) projections	Number of PEVs on the road over time for different projections	LADWP 2017 STLRP Base case and High case Distributed Energy Resource Integration Study (DERIS) NREL's Electrification Futures Study Medium scenario[a]
PEV characteristics	BEV/plug-in hybrid electric vehicle (PHEV) split, vehicle range	Wood et al. 2017[b]
EV supply equipment (EVSE) data	Chargers split by type (L1, L2) and power levels	CA PEV Infrastructure Projections[c]
Bus fleet info	Bus fleet size and location of parking lots	LADWP for school buses and Los Angeles County Metropolitan Transportation Authority for transit buses

[a] Trieu Mai, Paige Jadun, Jeffrey Logan, Colin McMillan, Matteo Muratori, Daniel Steinberg, Laura Vimmerstedt, et al. *Electrification Futures Study: Scenarios of Electric Technology Adoption and Power Consumption for the United States* (NREL, 2018). NREL/TP-6A20-71500, https://www.nrel.gov/docs/fy18osti/71500.pdf.

[b] Eric W. Wood, Clement L. Rames, Matteo Muratori, Seshadri Srinivasa Raghavan, and Marc W. Melaina. *National Plug-In Electric Vehicle Infrastructure Analysis* (DOE, 2017), DOE/GO-102017-5040. https://www.nrel.gov/docs/fy17osti/69031.pdf.

[c] Abdulkadir Bedir, Noel Crisostomo, Jennifer Allen, Eric Wood, and Clément Rames. *California Plug-In Electric Vehicle Infrastructure Projections, 2017-2025: Future Infrastructure Needs for Reaching the State's Zero-Emission-Vehicle Deployment Goals* (CEC, 2018) staff report, https://www.nrel.gov/docs/fy18osti/70893.pdf.

For this analysis, NREL developed multiple projections to explore alternative future EV adoption and charging behaviors. These projections include two levels of load electrification (moderate and high) in line with the overall LA100 approach to load modeling. Thus, EV adoption rates have been specified for two increasingly ambitious electrification projections. EV adoption in the Moderate projection is based on the "high case" EV adoption from the IRP. This projection exceeds the CA Zero Emission Vehicle (ZEV) mandate in 2025 and hits the 2030 ZEV goal (assuming LADWP is responsible for 10% of the EV adoption prescribed in the CA ZEV goal). The High electrification projection follows the 2017 IRP "high case" until 2025, and then assumes more aggressive adoption from 2026 onward based on the NREL's EFS study (Mai 2018). This level also exceeds the CA ZEV goals and mandates and reaches a total EV market share of approximately 80% in 2045 (90% in 2050).

Vehicle fleet composition (e.g., PHEV/BEV and vehicle ranges) are taken from a recent EERE report (Wood et al. 2017, with the exclusion of SUVs that have not been considered here):

Table 20. Vehicle Fleet Composition

Vehicle Type	Fleet Mix (%)
PHEV20	15%
PHEV50	35%
BEV100	15%
BEV250	35%

Residential and workplace charging are assumed to be equally split between Level-1 and Level-2. Public charging, which is computed endogenously in EVI-Pro and only relied upon when residential and workplace charging are not sufficient to satisfy travel needs, can be L2 or direct current fast charging (DCFC). Level-1 chargers are assumed to be 1.4 kW, Level-2 to be 7.2 kW (3.6 kW for plug-in hybrid EVs), and DCFC to be 150 kW.

B.3 Industrial, Large Commercial, and Other Loads

Table 21. Data Sources for Industrial and Large Commercial Loads

Characteristics	What Is Provided	Data Source
Monthly energy use (kWh) and demand (kW)	Energy use for particular customers and for customers grouped by North American Industry Classification System (NAICS) code; recent load growth rates by industry	LADWP billing data by customer account, ZIP code, or finer NAICS code
Time series of energy use	Load profiles by NAICS code (15 minute)	LADWP advanced metering infrastructure (AMI) data for select customers
Forecasts of cargo to be processed and port upgrades	Projections of Port of Los Angeles load growth rate.	Port of Los Angeles Master Plan[a]
Forecast of passenger air travel	Projections of Los Angeles International Airport load growth rate.	Southern California Regional Transportation Plan[b]
Port electrification projections	Projections of Port of Los Angeles loads from electrification	ICF International and Energy+Environmental Economics[c,d]
Energy efficiency market potential projections	Industrial energy efficiency measures and projections broken out from custom performance program	Nexant 2014 EE Potential Study,[e] Navigant 2017 EE Potential Study,[f] LADWP 2017 Load Forecast[g]

[a] Port of Los Angeles, *Port Master Plan* (2014), https://www.portoflosangeles.org/planning/pmp/Amendment%2028.pdf.

[b] Southern California Association of Governments, *The 2016-2040 Regional Transportation Plan/Sustainable Communities Strategy* (2016), http://scagrtpscs.net/Documents/2016/final/f2016RTPSCS.pdf.

[c] ICF International and Energy+Environmental Economics, *California Transportation Electrification Assessment, Phase 1: Final Report* (San Francisco, CA, September 2014), http://www.caletc.com/wp-content/uploads/2016/08/CalETC_TEA_Phase_1-FINAL_Updated_092014.pdf.

[d] ICF International and Energy+Environmental Economics, *California Transportation Electrification Assessment, Phase 3-Part A: Commercial and Non-Road Grid Impacts: Final Report* (January 2016), https://www.icf.com/-/media/files/icf/reports/2016/caletc_tea_phase_3.pdf.

[e] Nexant, *LADWP Territorial Potential Draft Report Volume I* (2014), http://dawg.energy.ca.gov/sites/default/files/meetings/6.LADWP%20EE%20Potential%20Study%20Vol%20I%20Draft%20-%2024June14.pdf.

[f] Navigant, *Energy Efficiency in California's Public Power Sector—11th Edition* (2017), http://ncpasharepointservice20161117100057.azurewebsites.net/api/document?uri=https://ncpapwr.sharepoint.com/sites/publicdocs/Compliance/2017_Energy_Efficiency_Report.pdf.

[g] LADWP, *City of Los Angeles Department of Water and Power 2017 Retail Electric Sales and Demand Forecast* (LADWP, 2017), http://ezweb.ladwp.com/Admin/Uploads/Load%20Forecast/2017/10/2017%20Retails%20Sales%20Forecast_Final.pdf.

Table 22. Data Sources for Other Sectors

Subsector	Characteristics	Spatial Resolution	Data Source
Water and wastewater treatment and supply	Water supply, treatment, and energy use	LADWP	2015 Urban Water Management Plan,[a] Water Conservation Potential Study,[b] and Recycled Water Master Plan,[c] as well as the City of Los Angeles' One Water LA plan,[d] Nexant 2014 EE Potential Study,[e] Mayoral announcement on water recycling,[f] UC Davis report on Water Utility Energy Intensity[g]
	Water treatment plant and pumping station locations	Customer	LADWP map of water system assets, LA100 agent attributes database
Outdoor lighting	Energy used by unmetered outdoor lighting, load shape for outdoor lighting	LADWP	LADWP 2017 Load Forecast,[h] communications with LADWP, LADWP 2012 Load Research Data outdoor lighting shape
Gap agents (commercial and industrial customers not otherwise modeled)	Monthly energy use	Customer	LADWP billing data by customer account
	Load shape, load growth including energy efficiency	LADWP	Load shapes and net growth (load growth + energy efficiency impacts) by sector from other LA100 commercial and industrial models

[a] LADWP, Urban Water Management Plan: 2015 (2016), https://www.ladwp.com/cs/idcplg?IdcService=GET_FILE&dDocName=QOELLADWP005416&RevisionSelectionMethod=LatestReleased.

[b] LADWP, *Water Conservation Potential Study* (2017), https://ladwp.com/cs/groups/ladwp/documents/document/mdaw/njiw/~edisp/opladwpccb620807.pdf.

[c] LADWP, and Department of Public Works, *City of Los Angeles Recycled Water Master Planning Executive Summary* (2012), https://www.ladwp.com/cs/idcplg?IdcService=GET_FILE&dDocName=OPLADWPCCB381497&RevisionSelectionMethod=LatestReleased.

[d] City of Los Angeles, *One Water LA Progress Report: A Collaborative Approach to Integrated Water Management* (2017), https://www.lacitysan.org/cs/groups/public/documents/document/y250/mdiy/~edisp/cnt022236.pdf.

[e] Nexant, LADWP Territorial Potential Draft Report Volume I (Cary, North Carolina, June 24, 2014). http://dawg.energy.ca.gov/sites/default/files/meetings/6.LADWP%20EE%20Potential%20Study%20Vol%20I%20Draft%20-%2024June14.pdf.

[f] "Mayor Garcetti: Los Angeles will Recycle 100% of City's Wastewater by 2035," (February 21, 2019), https://www.lamayor.org/mayor-garcetti-los-angeles-will-recycle-100-city's-wastewater-2035.

[g] UC Davis Center for Water-Energy Efficiency, *A High-Resolution Assessment of Water Utility Energy Intensity* (LADWP and Los Angeles Sanitation Bureau, 2016).

[h] LADWP, *City of Los Angeles Department of Water and Power 2017 Retail Electric Sales and Demand Forecast* (LADWP, 2017), http://ezweb.ladwp.com/Admin/Uploads/Load%20Forecast/2017/10/2017%20Retails%20Sales%20Forecast_Final.pdf.

B.4 Demand Response

Table 23. Data Sources for Demand Response

Characteristics	Provides	Data Source	Spatial Resolution
Current DR programs and customers; DR goals in terms of MW, services, and degree of automation; current program costs	Guidelines for projecting DR capacity to 2030 (and beyond for CII interruptible load) in terms of program types and sizes; Current value LADWP ascribes to DR resources	LADWP conversations,[a] website,[b] 2017 SLTRP,[c] and DR 2014 SIP[d]	LADWP
Demand eligible to provide DR shed and shift services	Estimate of LADWP DR technical potential in terms of total amount of load that might be possible to shed (MW) or shift (GWh)	LA100 bottom-up load modeling that provides high-resolution characterizations of customer types and end-use load; USC memo on LADWP water system loads[e]	Customer
DR program participation rates as a function of per-participant incentive, marketing efforts, and automation	Estimate of how much load might be economically accessible as a DR resource	California 2025 Demand Response Potential Study[f]	California participation rates by sector
Approximate capacity prices/value under LA100 scenario conditions	Maximum acceptable DR incentive on a per-kW-yr basis, assuming most DR value comes from offsetting firm capacity	LA100 RPM modeling	LADWP
Number of eligible households, buildings, appliances and chargers	Estimate of utility-accessible kW of load reduction per participant; Allows conversion from $/participant-yr to $/kW-yr	LA100 bottom-up load modeling that provides high-resolution characterizations of customer types and end-use load	Customer

[a] Initial conversation held on August 22, 2018, via conference call. Subsequent SME meetings occurred on April 1, 2019, and October 10, 2019.

[b] “Demand Response Program,” LADWP, accessed May 20, 2020: https://www.ladwp.com/ladwp/faces/ladwp/commercial/c-savemoney/c-sm-rebatesandprograms/c-sm-rp-demandresponse.

[c] LADWP, *2017 Power Strategic Long-Term Resource Plan* (2017), https://www.ladwp.com/cs/idcplg?IdcService=GET_FILE&dDocName=OPLADWPCCB655007&RevisionSelectionMethod=LatestReleased.

[d] LADWP and Navigant Consulting. *Demand Response 2014 Strategic Implementation Plan* (2014).

[e] Kelly T. Sanders and Zohrabian Angineh. *Task 4.1: Draft Water Infrastructure Load Characterization Methodology Technical Memorandum* (University of Southern California, 2019).

[f] Peter Alstone, Jennifer Potter, Mary Ann Piette, Peter Schwartz, Michael A. Berger, Laurel N. Dunn, Sarah J. Smith, et al. *2025 California Demand Response Potential Study: Charting California's Demand Response Future, Phase 2 Appendices A-J*. (Berkeley, California: Lawrence Berkeley National Laboratory, 2017). http://www.cpuc.ca.gov/WorkArea/DownloadAsset.aspx?id=6442452699.

Appendix C. Residential and Commercial Building Modeling Details

C.1 Residential Baseline Building Stock

ResStock is a bottom-up, physics-based residential building stock energy modeling tool developed at NREL with support from the U.S. Department of Energy. There is vast diversity in the age, size, construction practices, installed equipment, appliances, and resident behavior in the housing stock. ResStock is a versatile tool that takes a new approach to large-scale residential energy analysis by combining 1) a detailed building stock characteristics database, 2) state-of-the-art physics-based computer modeling, and 3) utilization of high-performance and cloud computing (see Figure 66). ResStock has been used to perform national and regional building stock analysis of single-family homes. The results have been used to identify the top 10 improvements for energy efficiency in each state, as well as quantify potential energy savings, pollution reduction, and utility bill savings (Wilson et al. 2017).

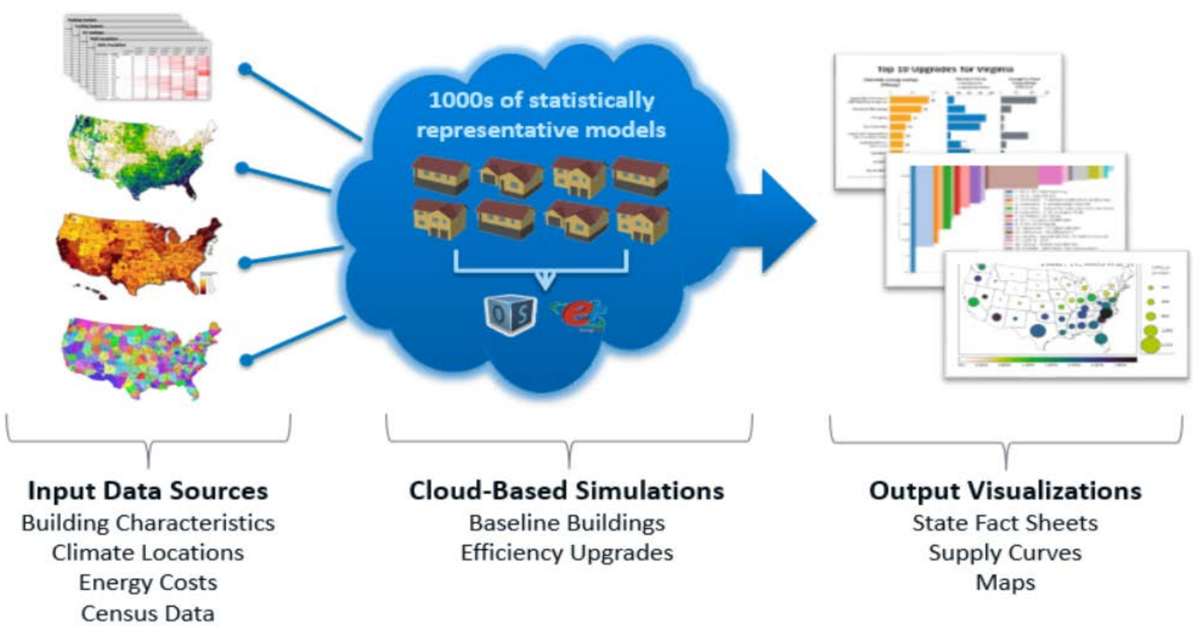

Figure 66. ResStock model diagram

ResStock uses a hierarchical structure of conditional probability tables that define more than 100 building characteristics. For the national implementation of ResStock, the conditional probability distributions for each building component were synthesized from data queried, translated, aggregated, and extrapolated from 11 sources, including the American Community Survey, American Housing Survey, the U.S. Energy Information Administration's Residential Energy Consumption Survey (RECS), historical energy codes, U.S. Energy Information Administration electricity and fuel costs, TMY3 weather data, and other sources from field studies. These data sources are used to create thousands of conditional probability distributions of the 100 building characteristics (e.g., vintage, wall insulation, lighting, cooking range, house size, number of stories, HVAC system cooling, heating fuel, foundation type) that statistically describe the residential building stock. For the LADWP service territory, these distributions describing building characteristics were updated using data sources for the City of Los Angeles and Los

Angeles County. Figure 67 shows the characteristics that were updated to reflect Los Angeles-specific data sources. The most important and heavily used data sources are described below.

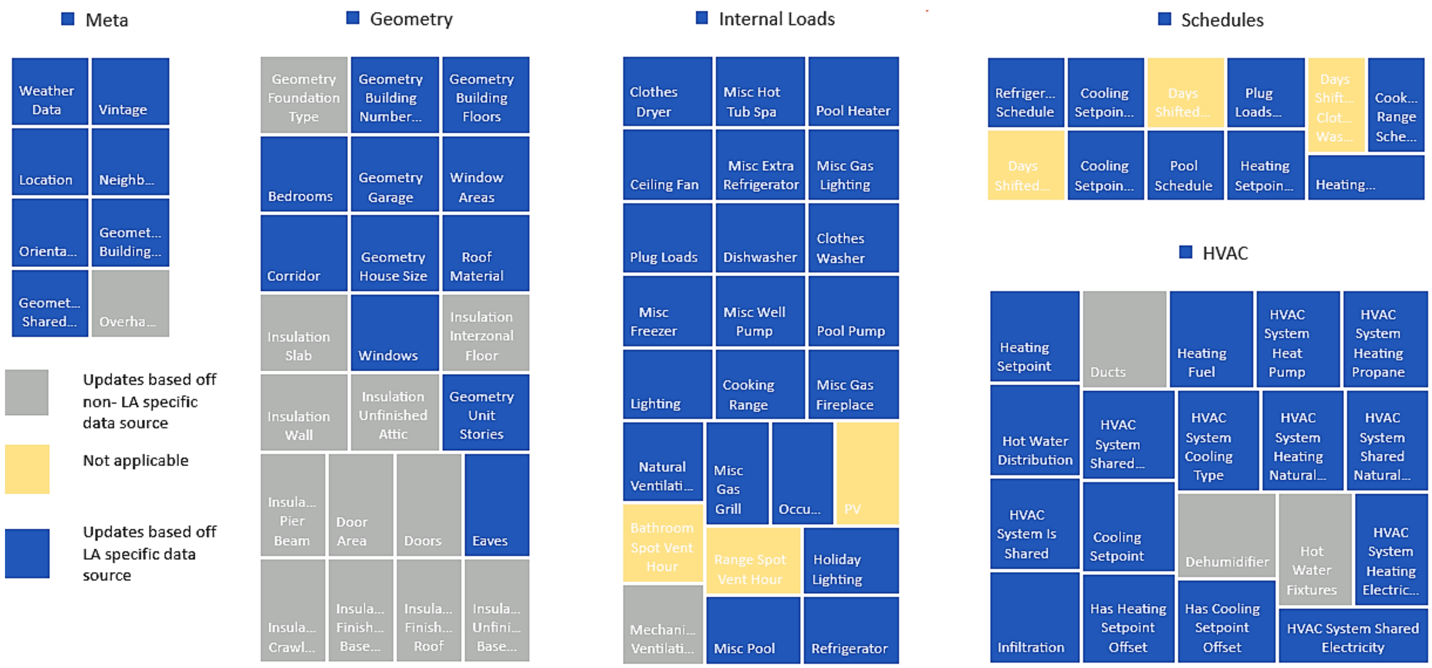

Figure 67. ResStock housing characteristics: Listing and classification by update type

Modeling for most single-family home characteristics was customized to reflect Los Angeles-specific data.

Los Angeles County Assessor Parcels Database

The Los Angeles County Assessor Parcels Database contains data on each parcel in Los Angeles County. Useful information contained in the database includes but is not limited to AIN (i.e., property ID number), property type, property use code, general and specific use details, address, and number of bedrooms and bathrooms. The information contained in the database was used to establish probability distributions for multiple building characteristics including vintage (year of construction), number of units per building, building type, and presence of pools and spas.

Los Angeles County GIS Data Portal

The Los Angeles County GIS Data Portal[53] includes a variety of GIS data resources for Los Angeles County. The Los Angeles Region Imagery Acquisition Consortium (LARIAC) program provides public access to building outlines and other critical geometry building characteristics, including height, roof area, shape length, and footprint area. The data set also connects these outlines to the parcel AIN from the Assessor. This information was used to construct probability distributions for building stories, housing unit stories, footprint aspect ratio, garage geometry, number of housing units per building, and the number of shared walls.

[53] "County of Los Angeles: Enterprise Geographic Information Systems," https://egis-lacounty.hub.arcgis.com.

California Statewide Residential Appliance Saturation Study (RASS)

RASS contains extensive data on residential appliance saturation as a function of various building and demographic parameters. The survey includes the LADWP service area and the corresponding California climate zones. We used the RASS survey data to inform distributions for building stories for single family detached homes, heating and cooling system types and descriptions, heating and cooling setpoints and setback schedules, heating fuel, building type, number of ceiling fans, cooking range, dishwasher, clothes washers and dryers, pools, freezers and refrigerators, and others.

California Lighting and Appliance Saturation Survey (CLASS)

The 2012 CLASS[54] describes the saturation and efficiency characteristics of residential lighting and appliances across California. The lighting information provided includes number of fixtures, fixture wattage and base type, fixture location, control type, number of lamps per fixture, number of installed lamps, and number of in-storage lamps both inside and outside the house. The appliance information includes quantity, fuel type, manufacturer, efficiency levels, and age; for heating and cooling equipment, water heaters, refrigerators, freezers, dishwashers, clothes washers and dryers, ranges and ovens, and other entertainment equipment. From this information, LADWP-specific details were extracted to accurately populate relevant housing characteristics.

CA Dept. of Finance Population Projections for Los Angeles County

The California State Department of Finance provides demographic projections for each county of the state. These projections include the population by county, existing housing stock, and projected new housing permits at 1-year increments starting from 2010 through 2060. We developed a housing stock turnover model specific to the LADWP territory through 2045 based on these trends and demographic projections.

California Building Energy Efficiency Standards – Title 24

Since they were first adopted in 1976, California's Building Energy Efficiency Standards (Title 24, Parts 6 and 11) have been regularly and substantially updated. Each version of the code is in effect for a specific duration. For this project, Title 24 performance requirements were used for HVAC efficiencies for central air conditioners, room air conditioners, furnaces, boilers, and heat pumps. Existing and projected changes in Title 24 were also used to limit technology availability in future projection-years. Envelope properties modeled as conforming to Title 24 include crawlspace insulation, finished basement insulation, interzonal floor insulation, pier and beam insulation, slab insulation, unfinished basement insulation, and wall insulation. Title 24 construction practices also inform infiltration rates.

[54] "CLASS 2012," DNV GL, https://webtools.dnvgl.com/projects62/Default.aspx?tabid=190.

Codes and Standards Enhancement (CASE) Initiative

The CASE initiative recommends updates to the California Building Energy Efficiency Standards (Title 24 Part 6). The Plug Loads and Lighting Modeling[55] and the Pools and Spas[56] CASE reports described below recommend rulesets/algorithms to model the annual energy use of various end uses in newly constructed residential buildings. The reports also compare proposed methodology and algorithms with existing field studies and in-practice algorithms. Based on these algorithms the report provides appliance energy consumption (AEC) equations and load profiles for certain end uses.

Plug Loads and Lighting Modeling (2016)

Plug loads include "white good appliances"—i.e., refrigerators, freezers, dishwashers, clothes washers and dryers, and ovens and ranges—as well as consumer electronics and other miscellaneous electric loads (MELs). The AEC rulesets for each of the white good appliances, combined consumer goods, and MELs were used to develop usage levels and schedules for the ResStock simulations.

Pools and Spas (2013)

ResStock uses the AEC rulesets proposed in this CASE report to develop annual usage levels and schedules for pools, hot tubs, and well pumps. Pool descriptions depend on pool configuration. ResStock only models pools and spas associated with single-family housing units.

OpenStreetMap (OSM) Data

The OpenStreetMap (OSM) data are similar to the data available in the GIS portal mentioned above. Although the OSM data are more recent, it is not always correct. For this reason, OSM data were only used to identify the orientation of the housing units.

Residential Diagnostic Database

The Residential Building Systems (RBS) group at the Lawrence Berkeley National Laboratory (LBNL) collects residential data from diagnostic tests to characterize the energy use and indoor air quality of the California housing stock. They have also used those data to construct algorithms that describe outdoor air infiltration for single-family detached houses in the region. ResStock uses infiltration models based on these algorithms for the LA100 study.

Home Energy Saver – Technical Report (2005)

The Home Energy Saver tool helps residential consumers audit and make decisions about energy use in their homes. This report details the methods and data for estimating energy consumption

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[55] Eric Rubin, Daniel Young, Maxmilian Hietpas, Arshak Zakarian, and Phi Nguyen, *Plug Loads and Lighting Modeling* (2016), 2016-RES-ACM-D. http://www.bwilcox.com/BEES/docs/Rubin%20-%202016%20T24CASE%20Report%20-%20Plug%20Load%20and%20Ltg%20Modeling%20-%20June%202016.pdf.

[56] Chad Worth, Eric Ludovici, Elizabeth Joyce, and Gary Fernstrom, *Pools and Spas: Codes and Standards Enhancement (CASE) Initiative for PY 2013: Title 20 Standards Development: Analysis of Standards Proposal for Residential Swimming Pool and Portable Spa Equipment* (Pacific Gas and Electric Company, Southern California Edison, Southern California Gas, San Diego Gas & Electric, 2013). https://efiling.energy.ca.gov/GetDocument.aspx?tn=71755&DocumentContentId=8324.

of a housing unit. The underlying engineering models estimate energy consumption for six major categories (end uses): heating, cooling, water heating, major appliances, lighting, and miscellaneous equipment.

For this project, Home Energy Saver correlations between HVAC equipment age and efficiency level were used in combination with the equipment age details provided in the RASS survey to estimate efficiency levels for various HVAC systems.

Energy Saving Forecast of Solid-State Lighting in General Illumination Applications, U.S. Department of Energy Report; prepared by Navigant Consulting, Inc. 2016

The U.S. Department of Energy has supported studies forecasting the market penetration of light-emitting diodes (LEDs) in general illumination applications since 2002. These forecasts provide the expected path of LED adoption through 2035 across the United States. For this project, the forecast was extrapolated through 2045, and the market penetration in 2015 through 2045 was used to develop the stock penetration.

C.2 Residential Stock Turnover Model

The residential stock projection model consists of two components: building stock turnover and equipment stock turnover. The building stock turnover model projects the construction of new residential buildings and the demolition rate of existing residential buildings. The equipment stock turnover model projects how the efficiency of the components within that building stock changes over time.

Building Stock Turnover Model

The CA Department of Finance projects substantial population growth in LA County through 2045. Population pressures, along with demolition of existing housing stock, will likely induce the construction of new residential buildings in the LADWP service territory between 2015 and 2045. In order to estimate changes in home count and type distribution out to 2045, it was necessary to understand the historical trends across the LADWP territory. Based on these trends, a Los Angeles-specific building stock growth-decay turnover model (hereafter "the turnover model") was developed to project the construction and demolition of residential units from 2015 through 2045.

The building stock turnover model is based on a previous study that modeled the LA County building stock (Reyna and Chester 2015). This study used historical data regarding the average rate of destruction (decay) and construction (growth) of units built from 1900 through 2010 in 10-year "vintage bins." The construction/destruction rates were based on the American Community Survey and decennial censuses conducted by the U.S. Census Bureau,[57,58,59] which included information about the newly constructed units in each decade as well as the number of

[57] Janet L. Reyna and Mikhail V. Chester, "The Growth of Urban Building Stock: Unintended Lock-in and Embedded Environmental Effects," *Journal of Industrial Ecology* 19 (4): 524–537 (August 2015) https://doi.org/10.1111/jiec.12211.
[58] "About the American Community Survey," U.S. Census Bureau, https://www.census.gov/programs-surveys/acs/about.html.
[59] "Decennial Census," U.S. Census Bureau, https://www.census.gov/history/www/programs/demographic/decennial_census.html.

existing units that were built in earlier decades. Based on these data, a doubly constrained "origin-destination" model was used to develop decay rates for different vintages of the LA housing stock (Reyna and Chester 2015). For each decadal vintage bin, the destruction of those units in the following decades followed an exponential decay curve defined as:

$$S = S_0 e^{-\omega t},$$

where

S = number of units remaining after t decades since construction

S_0 = number of units built in a given vintage bin

$-\omega$ = rate of destruction.

Based on the historical rate of decay for each vintage bin and projections of growth provided by the California Department of Finance (DoF),[60] decay and construction trends were extrapolated to obtain the temporal distribution of the total residential units at the end of each 5-year interval from 2015 through 2045.

These projections of housing units for Los Angeles County were downscaled to LADWP service territory according to the relationship:

$$S_{DWP,i} = S_{County,i} * \bar{\alpha} * \beta,$$

where

- **Population (S):** number of residential units for the vintage (i) and location (DWP/County).
- **Population correction factor ($\bar{\alpha}$):** adjusts the number of LA County housing units per vintage bin based on the fraction of Los Angeles County population that is also located in the City of Los Angeles. The population correction factor is set to a constant 0.36 across all vintage bins.
- **Household density correction factor (β):** adjusts the number of housing units assigned to the city to reflect differences in average household size. Based on the ACS we estimate that there are fewer people per household within the city as compared to the county as a whole, that is:

$$\beta = \frac{h_{county}}{h_{city}} = 1.14,$$

where h is the average number of people per household.

Overall, these correction factors set the number of households in DWP territory to be equal to 41% of the total number of households in LA County. Final LADWP turnover results are shown at the vintage level in Figure 68.

[60] "Demographics," State of California Department of Finance, http://www.dof.ca.gov/Forecasting/Demographics/.

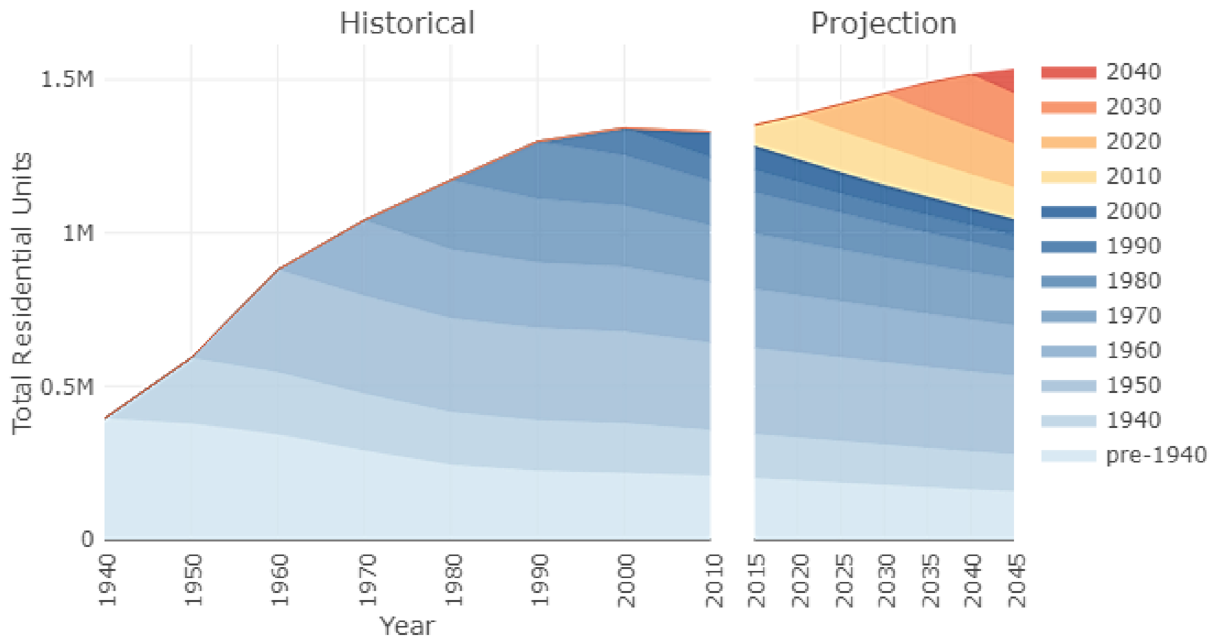

Figure 68. LADWP service territory historical and projected future residential building stock by vintage

The projections for the overall stock turnover are then refined to determine the distribution of building types (as defined in ResStock[61,62]) to apply to the total number of units in the LADWP service territory per vintage bin and modeled year. Normalized distribution factors for each unique combination of building type and vintage bin were calculated based on parcel data for historical vintages. For future vintages, the model assumes that land zoning does not change, so there are increased construction of multifamily high-rise buildings on existing multifamily-zoned land to account for population increases. The stock of multifamily buildings was divided into low-rise (three or fewer floors) and mid- and high-rise buildings (more than three floors) using a correction factor calculated based on the heights of residential multifamily buildings in Los Angeles County. Low-rise buildings are included in the residential building analysis; mid- and high-rise buildings are included in the commercial building analysis. The resulting breakdown of number of housing units per residential building type per projection-year is shown in Figure 69. The same building stock projection (number of units per building type and vintage, by projection-year) is used for all three LA100 load projections: Moderate, High, and Stress.

[61] Eric Wilson, Craig Christensen, Scott Horowitz, Joseph Robertson, and Jeff Maguire, *Energy Efficiency Potential in the U.S. Single-Family Housing Stock* (NREL, 2017) NREL/TP-5500-68670, https://doi.org/10.2172/1414819.
[62] LA100 Internal Deliverable 22 to LADWP. *Technical Memo on Energy Efficiency and Demand Modeling Assumptions*.

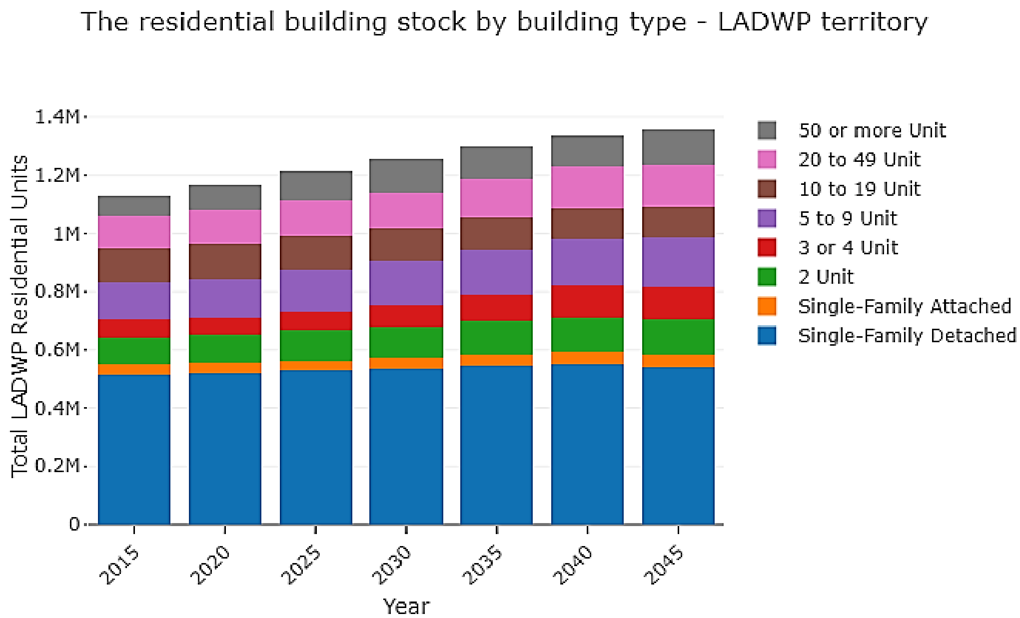

Figure 69. Projected makeup of the residential building stock by building type in the LADWP territory

In Figure 69, the impacts of rising population without substantial increase in household density (i.e., occupants per household) are shown. The amount of 50+ unit buildings built in place of small 5+ unit multifamily buildings shows rapid growth in the large multifamily market in the LADWP territory, which is consistent with current construction trends in and around the city. The number of single-family and smaller multifamily housing units does not increase significantly, in part because the model assumes that zoning of the assessed residential units remains the same.

Equipment Stock Turnover

The equipment stock turnover model incorporates improvements in equipment efficiency and electrification of natural gas burning equipment over time, with assumptions varying by LA100 load projection. Higher efficiency and electric (as opposed to natural gas) equipment is introduced into the stock as either an 1) end-of-life replacement or 2) new equipment due to building stock growth. The model uses average equipment lifetimes to determine the portion of the stock up for replacement in each year, and sales shares to determine the type and efficiency levels of the equipment introduced as replacements or additions. For example, if a given equipment type has a lifetime of 10 years, half of the stock is replaced during each 5-year model interval. The fuel types and performance levels of replacement equipment and equipment that furnishes new housing builds are then defined by sales shares per equipment type, which are specified per projection-year.

Average equipment lifetimes are based on estimates from the EIA (2018) for appliances and lighting, and from National Association of Homebuilders (NAHB) publications and expert judgement (Seiders, 2007; NAHB, n.d.) for windows and roofs. For other opaque envelope components, such as foundation and wall insulation, long lifetimes (i.e., >50 years) were used, given that these components are often never upgraded during the life of a structure. Shorter lifetimes (i.e., 30 years) are applied to walls and roofs that lacked insulation because those homes might be more likely to receive retrofits than homes with some insulation.

For all building components and equipment revised in the turnover model, only currently available technologies are considered, even for the highest-efficiency options. In many cases, the highest-efficiency options correspond to the ENERGY STAR "Most Efficient" specification for each product category. Windows are an exception, as the climate of LADWP service territory does not justify the high cost of ENERGY START "Most Efficient" triple-pane windows. Instead, the highest-efficiency windows are specified as double-pane windows. Speculative technologies or technologies that are currently in development were excluded due to uncertainty about whether or when they might enter the market.

In general, equipment sales shares (i.e., replacement options at end of life) were adjusted for each of the energy efficiency and electrification projections. For energy efficiency only, three levels of ambition are modeled: Stress, Moderate, and High. Electrification is only modeled at two levels: Moderate and High, with the latter being adopted for both the High and the Stress projections.

Stress energy efficiency sales shares were typically derived from existing projections of sales by equipment performance level, where available. For HVAC systems and appliances[63] sales shares were derived from the U.S. Department of Energy's Appliance Standards program's National Impact Analysis spreadsheets, which include projected sales by equipment type, configuration, and efficiency level.[64] Stress projection sales shares for pool pumps were derived from a background report on Title 20 Standards (Worth, 2013). For opaque envelope upgrades, including roof materials, it was assumed that upgrades switched uniformly to the highest performance level available, under the assumption that for the upgrades considered, the additional marginal cost of higher performance was small compared to the minimum required costs to perform any retrofit to that façade element; this assumption was applied for all energy efficiency projections. Window replacements were assumed to move toward primarily double-pane insulated glazing units (IGUs) and primarily non-metal frames.

The Moderate efficiency projection uses sales shares that fall between the Stress projection just described and the High projection; expert judgment was applied to specify the resulting "moderate" level of ambition. The High efficiency projection assumes that equipment sales shares will be dominated by (greater than 90%) or exclusively to (100%) the highest-efficiency unit available.

The electrification projections focus on the four residential equipment categories responsible for the most non-electric energy consumption: space heating, water heating, clothes dryers, and cooking ranges. The Moderate projection was constructed by splitting the difference between the Reference scenario of EFS (Mai et al, 2018), which typically assumes a stagnant electrification levels (i.e., current electrification levels do not increase), and the High projection, in part by favoring electrification of equipment deemed "low-hanging fruit" (i.e., easier from a technical

[63] "Appliances" includes clothes washers, clothes dryers, dishwashers, refrigerators, and water heaters.
[64] U.S. Department of Energy Appliance Standards National Impact Analysis Spreadsheets ("Standards and Test Procedures," DOE, https://www.energy.gov/eere/buildings/standards-and-test-procedures).

and consumer preference perspective to electrify). The Moderate projection has clothes dryers reaching 100% electric sales by 2045 (Figure 70), because any required electrical upgrades would be minor and the consumer experience of electric and natural gas appliances are essentially identical. Water heating is assumed to be the next easiest technology to electrify, reaching 60% of sales by 2045. Cooking is technically a simple swap, but some consumers do have a strong preference for natural gas, so sales shares increase to 50% by 2045 (Figure 71). Space heating is the most technically complex and expensive end use to electrify; we set electric sales to reach 40% by 2045. The High electrification case supports the pLAn's carbon-neutrality targets: all new construction has electric appliances by 2030 and all existing buildings are fully electric by 2050. To achieve the pLAn targets using end of life equipment turnover, all equipment sales must be 100% electric by 2030.

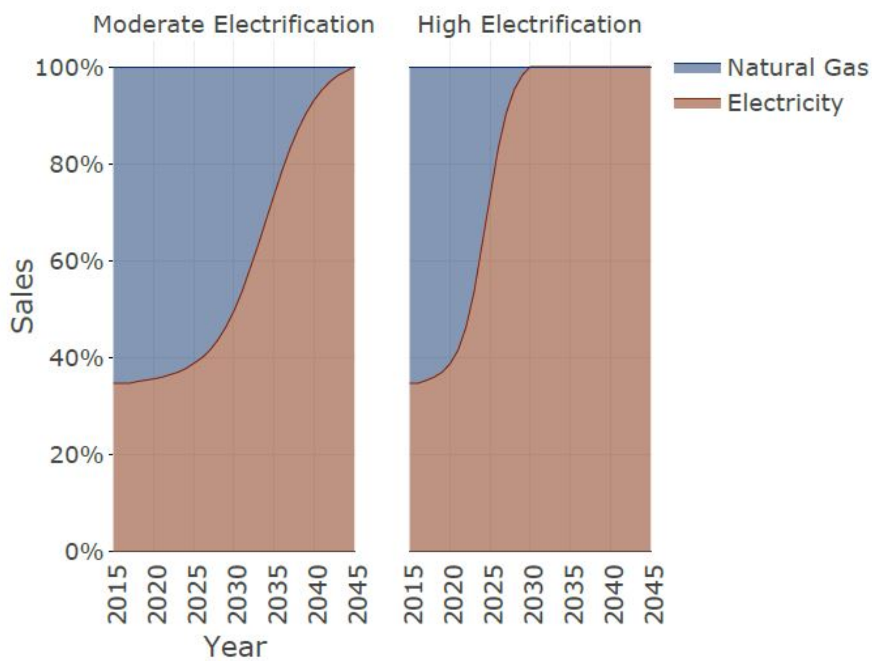

Figure 70. Sales share of clothes drying by fuel type

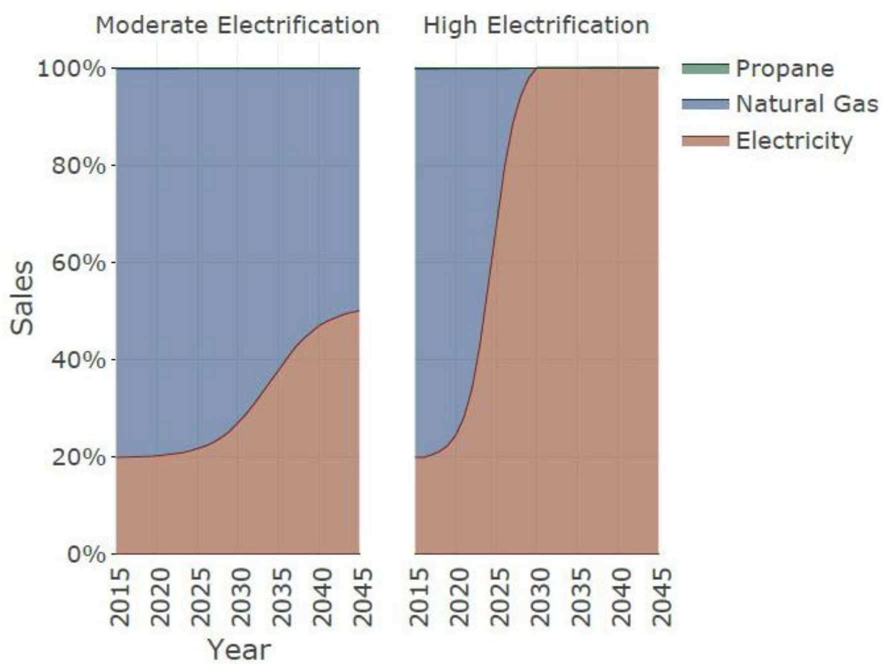

Figure 71. Sales share of cooking ranges by fuel type

Equipment stock is initialized using 2009 RASS survey data.[65] The RASS microdata include approximately 2,700 survey responses for the LADWP service territory. Starting with the RASS survey responses as representative of the initial equipment stock in 2015, the annual changes in equipment are then calculated based on the sales shares for each projection-year per the lifespan and new addition logic described above. Finally, by aggregating equipment of the same type and fuel, the team calculates the stock fuel shares for the LADWP service territory. Fuel shares at 5-year increments (i.e., 2015, 2020, 2025, etc.) are then input as ResStock probability distributions. Efficiency levels are accounted for similarly and are represented as probability distributions that are conditional on fuel type if applicable.

Efficiency Projections

The equipment stock turnover model updates the installed stock shares for each fuel type and performance level, segmented by residential equipment and envelope component category.[66] The effect of the turnover model on equipment stock shares show the same general characteristics for all categories. These overall trends are illustrated here using the examples of dishwashers (Figure 72), space cooling (Figure 73), and water heating (Figure 74).

Figure 72 shows the breakdown of the total stock of dishwashers by efficiency level for each load projection and year in the modeled time horizon. A greater proportion of households are expected to

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[65] CEC, "2019 Residental [sp.] Appliance Saturation Study," California Energy Commission, https://www.energy.ca.gov/appliances/rass/.

[66] Equipment types impacted by the turnover model are clothes dryers, clothes washers, dishwashers, heating and cooling systems, refrigerators and extra refrigerators, pool pumps, and water heaters. Envelope components included foundation insulation in buildings with accessible foundations or underfloor areas (thus excluding slab-on-grade construction and finished basements), insulation in unfinished attics, wall insulation, roof materials/surface coatings, and windows.

have dishwashers in the future, in part because new construction is more likely to have dishwashers than existing stock. Higher-efficiency dishwashers are also adopted over time, with the installed percentage varying by projection. Because all dishwashers are electric, the electrification projections do not affect the market shares of the various dishwasher efficiency levels.

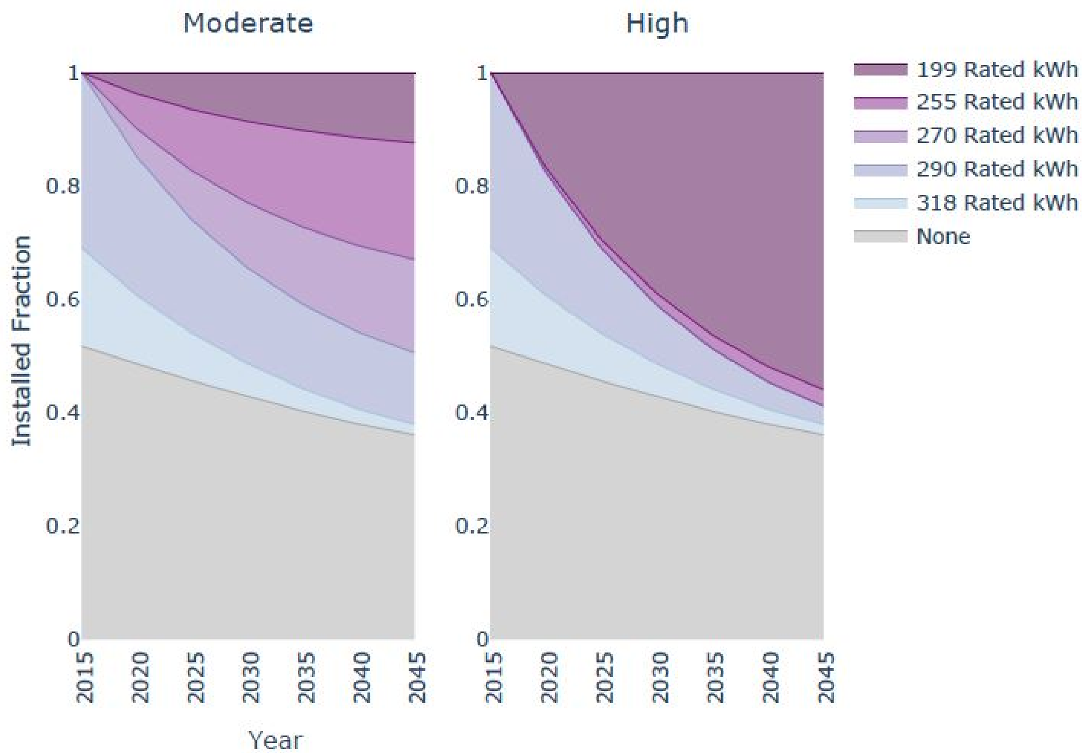

Figure 72. Installed percentage of dishwasher efficiency levels for each projection-year, including "no dishwasher"

Figure 73 shows the stock shares for cooling systems by type, efficiency level, and projection-year. Heat pump systems used for cooling, room and window units, and central AC systems are shown for residences that have standalone cooling systems. Buildings with no cooling system or with shared (central plant) cooling systems are coded as "None." This figure reflects indirect effects from the electrification projections on the resulting equipment efficiency level distributions as space heating systems are converted from natural-gas-based equipment to electric heat pumps. In general, increasingly aggressive efficiency projections lead to increasing adoption of more efficient cooling equipment, both within categories (i.e., among central AC systems) and across categories (e.g., transitioning from room AC systems to mini-split heat pumps).

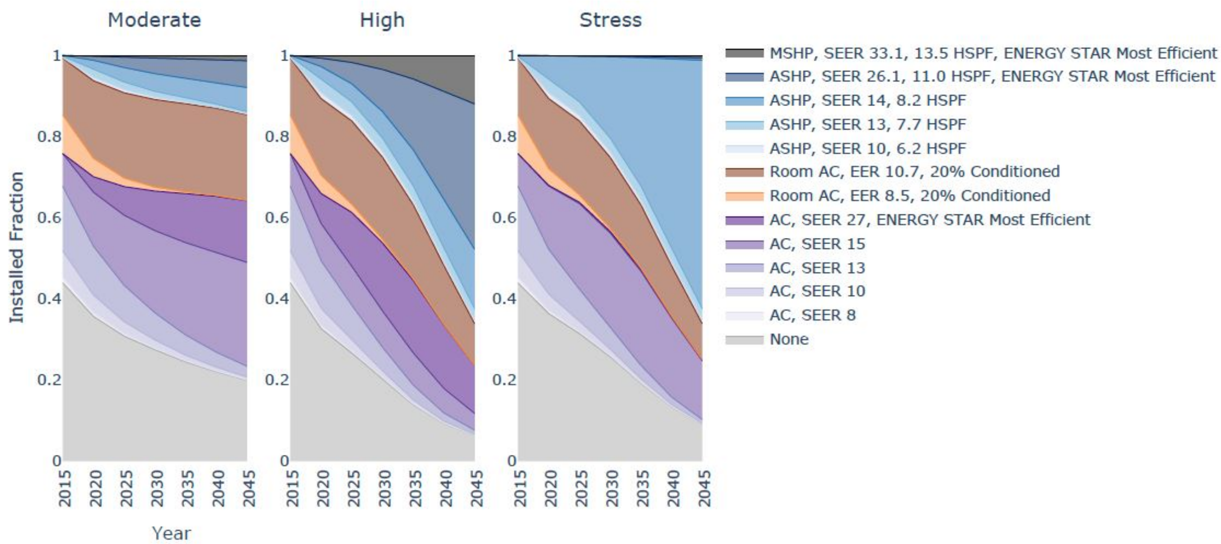

Figure 73. Installed percentage of cooling system types and efficiency levels, by projection-year

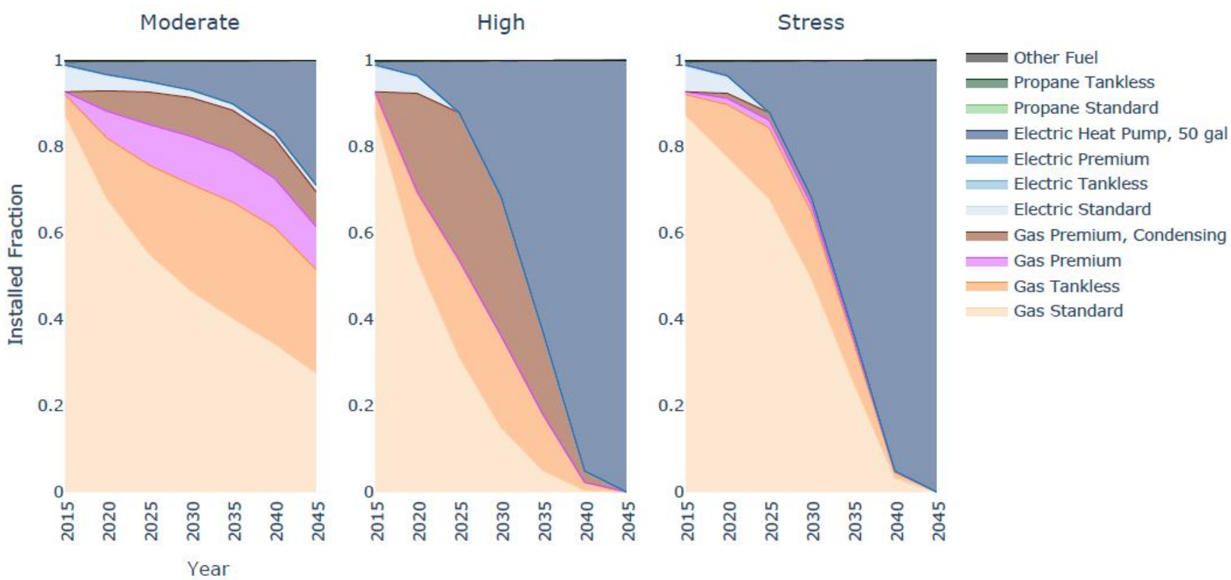

Figure 74. Installed percentage of water heater types and efficiency levels, by projection-year

Figure 74 shows how the water heater stock shares vary by projection-year. In this case, both the efficiency and the electrification dimensions are important. Because nearly the entire stock of residential water heaters in the LADWP service territory today use natural gas, high electrification assumptions are required to get electric water heaters shares above 25% by 2045. Within fuel types, as we also saw in Figure 72 and Figure 73, water heater efficiency levels increase over time, with more rapid increases in the more optimistic efficiency projections; in the Stress projection, the share of water heaters switched to electricity is equivalent to that in the High projection, but standard efficiency units represent 75% of the electric units by 2045, as compared to 8% in the High projection.

Electrification Projections

The High electrification assumption of 100% sales share by 2030, which is the level of ambition required to meet the pLAn goal of all-electric buildings by 2050, produces a dramatic contrast when we compare levels today with Moderate and High results (Figure 75 to Figure 77). We can also see the impact of designating some end uses as easier-to-electrify than others. For example, Figure 75 shows electric clothes dryers comprising about 85% of the stock, as compared to electric stoves only being about 45% of stock in Figure 76, both for the Moderate projection, 2045.

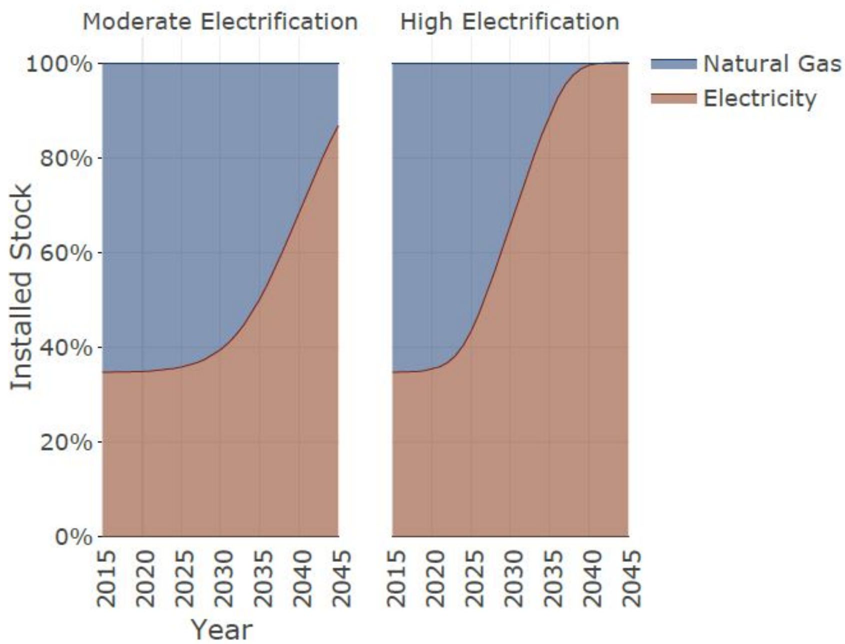

Figure 75. Installed percentage of clothes drying by fuel type

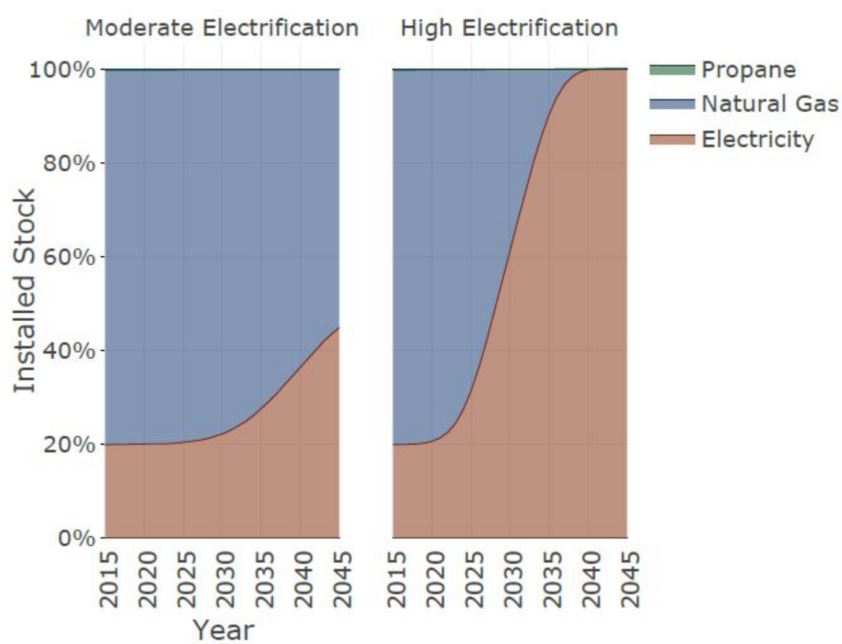

Figure 76. Installed percentage of cooking ranges by fuel type

In response to Title 24 and the guidance of LADWP, additional restrictions around the types of electric equipment installed were put in place for the High and Stress projections to prevent installation of new electric resistance technologies, instead relying solely on heat-pump-based technologies for space and water heating. For example, Figure 77 shows electric baseboard and electric resistance furnaces phased out by 2030 in those high-electrification projections.

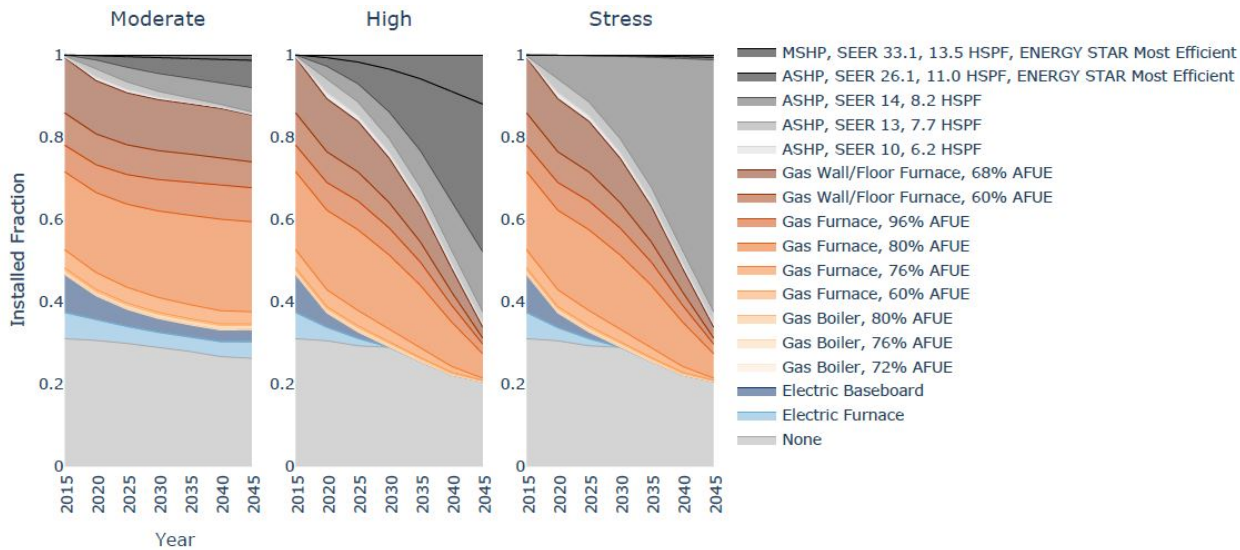

Figure 77. Installed residential heating systems by projection-year

C.3 Commercial Baseline Building Stock

ComStock is a bottom-up, physics-based modeling methodology developed by NREL to represent existing commercial building stock and conduct scenario analysis of how future stock may be impacted by technology adoption trends and policy decisions. ComStock uses the same basic methodological framework as ResStock, but there are some significant differences driven by data availability and the relatively diverse nature of the commercial building stock.

ComStock was originally developed to represent the entire U.S. building stock, and therefore relied on input data that covered the entire country. As might be expected, these data were not particularly detailed or representative of any one part of the country. For this reason, a significant piece of the LA100 project involved finding new data sets that more accurately represent the building characteristics in the LADWP service territory. The following sections give brief descriptions of the key data sets used.

CoStar Buildings Database

The CoStar Group[67] is a publicly traded company that collects and sells information about the commercial building stock around the world. Their data collection methodology employs several thousand people, each a representative of the CoStar Group that covers a specific territory. These agents are responsible for collecting and updating information about the buildings in their market. CoStar claims to have 95% coverage of the building stock, which holds true in urban

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[67] "CoStar Group," https://www.costargroup.com/.

markets like Los Angeles. The company's target market is real estate brokers and developers. Consequently, the database covers only buildings that are typically bought and sold. Notable gaps include schools, municipal buildings, and places of worship. The database contains many characteristics that are of interest to the target market but irrelevant for energy analysis.

For the purposes of the LA100 project, the key pieces of information we use from the CoStar database are building type, year of construction, floor area, and number of stories. These data are used to create probability distributions of building size for a given geography and building type. For LA100, the city was divided to census tract, and in some cases census blocks, to enable the model to accurately represent where buildings of different types are located throughout the city. Because the CoStar database is not publicly available information, the underlying data set cannot be shared, however the sampled results can.

DEER Prototypes

The Database for Energy Efficient Resources (DEER)[68] was developed by the California Public Utility Commission (CPUC) to store information about the energy savings potential of various technologies in different climate zones and building types in California. In order to determine energy savings potential, these technologies were applied to a series of detailed, physics-based whole-building energy models known as the DEER Prototypes. These models were developed to represent the building stock in California and reflect typical construction practices for buildings of different types and vintages in different climate zones. The input characteristics are updated by the CPUC every 1–3 years based on the latest information available from a variety of utility, CPUC, and California Energy Commission (CEC)-funded research projects.

For the LA100 project, these models were a good starting data set for building characteristics in California. The input data from these models were extracted and generalized into a format where they could be recombined to model the specific building stock in Los Angeles. Many of the building characteristics were taken from the DEER Prototype Models, including construction materials, lighting power densities, equipment power densities, occupancy values, ventilation requirements, HVAC system types, HVAC equipment efficiencies, and operational characteristics.

During the process of calibrating the commercial building stock model, changes were made to some of the DEER inputs based on better information specific to Los Angeles. Describing each specific change is not within the scope of this report.

CBECS

The Commercial Buildings Energy Consumption Survey (CBECS)[69] is a national survey of the U.S. commercial building stock that gathers data about building characteristics and energy consumption. This survey is designed to be representative at a national level and is therefore too

[68] CPUC, "Energy Efficiency Resources," California Public Utilities Commission, http://deeresources.com/.
[69] EIA, "2018 Commercial Buildings Energy Consumption Survey Preliminary Results," (U.S. Energy Information Administration, November 18, 2020), https://www.eia.gov/consumption/commercial/.

coarse to capture LA-specific information, but it does contain some useful data fields that are not typically available from other sources.

For the LA100 project, we only use CBECS information on floor-to-ceiling height and building shape, as these attributes vary with building type, because Los Angeles-specific information was unavailable.

Los Angeles Region Imagery Acquisition Consortium (LAR-IAC)

The LAR-IAC data set[70] contains information about building shape, building height, and building location. It was used to calculate two sets of inputs for ComStock. The first was the spacing between buildings. The city was subdivided into census tracts, and for each tract a probability distribution of neighboring building distances in the four cardinal directions was created. These cardinal directions were used because most of the city street grid runs in these directions. The second input was the height of a building relative to neighboring buildings. Again, the city was subdivided, and for each tract a probability distribution was created showing the height differences. For areas with a mix of high and low-rise buildings, this distribution could show a large range, but for much of the city the buildings are similar in height to their neighbors and in those areas the distributions centered around a low height difference.

California End Use Survey (CEUS)

CEUS was a study done by CEC to create end-use load profiles for the California commercial building stock (Itron, Inc. 2006). The study created a model of the whole California commercial building stock by surveying about 500 commercial buildings, making energy models of those buildings, calibrating those buildings to utility data, and then weighting each simulated building based on the amount of the building stock it represented. For the LA100 project, CEUS was primarily used to inform the modification of schedules and to find gross errors in end-use energy modeling assumptions during the calibration process. This is because raw input data about the surveyed buildings is not publicly available.

California Commercial Saturation Survey (CCSS)

CCSS describes the market share of different types of equipment found in commercial buildings (Itron, Inc. 2014). For this project, CCSS was used to determine lighting power densities for the overall building stock, and to create probability distributions for the HVAC system types found in buildings.

CA Dept. of Education Report on Complete Schools and 2015 Student Audit

This data source describes the location of all schools in California along with their enrollment. This number was combined with other information about typical building areas per student to create probability distributions of school size and location. These data were merged in with data from the CoStar database on other building types.

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[70] "Los Angeles Region Imagery Acquisition Consortium," County of Los Angeles, https://lariac-lacounty.hub.arcgis.com.

C.4 Commercial Stock Turnover Model

The commercial forward projection model was divided into three components: stock growth projection, code projection, and adoption assumptions. The stock growth model was used to project the growth of new commercial buildings by building type. Code projection was used to model expected changes in commercial building codes over time, as this was assumed to be a major driver of commercial building efficiency. Finally, adoption assumptions were used to model (a) increased efficiency through early adoption of progressively more-efficient codes and (b) accelerated electrification of key end uses. Of these three components, only adoption assumptions vary depending on the LA100 load projection.

Stock Growth Projection

The time horizon of the study (30 years) requires an accounting of expected commercial building stock growth. At the advice of LADWP these projections were made using the Dodge Data and Analytics Metropolitan Construction Insight (Dodge Data & Analytics, 2nd Quarter, 2018) publication from the second quarter of 2018, one of the data sources used in the 2017 SLTRP. Substantial data are provided in the document; however, of particular note is the total new square footage built in each year by building class and cost of construction for each subclass. Historical data from 2002 to 2017 were provided, and projections through 2022. Given that forecasts are required through 2045, a data-driven model was trained on these data and used to project commercial square footage growth through 2045.

Based on an exploratory time series analysis, we chose to forecast commercial square footage growth by training Autoregressive Integrated Moving Average (ARIMA) models on the part-historical-part-forecasted building square footage data from 2002 to 2022. The models were then exercised to forecast future commercial floor space growth 23 years beyond the provided projections, that is, from 2023 to 2045.

The Dodge Data report categorizes commercial buildings as retail, warehouses, offices, hotels, education, health care, and other. We used an independent ARIMA model for each building type because different building types have different stock growth trends and characteristics. The parameters of each ARIMA model were selected to minimize the validation error. Although Figure 78 only shows the impact of growth, the stock model projection also assumes that existing buildings are demolished and rebuilt (as the same building type) when they reach the end of useful life. Figure 79 shows the growth in commercial square footage by Dodge Data building type.

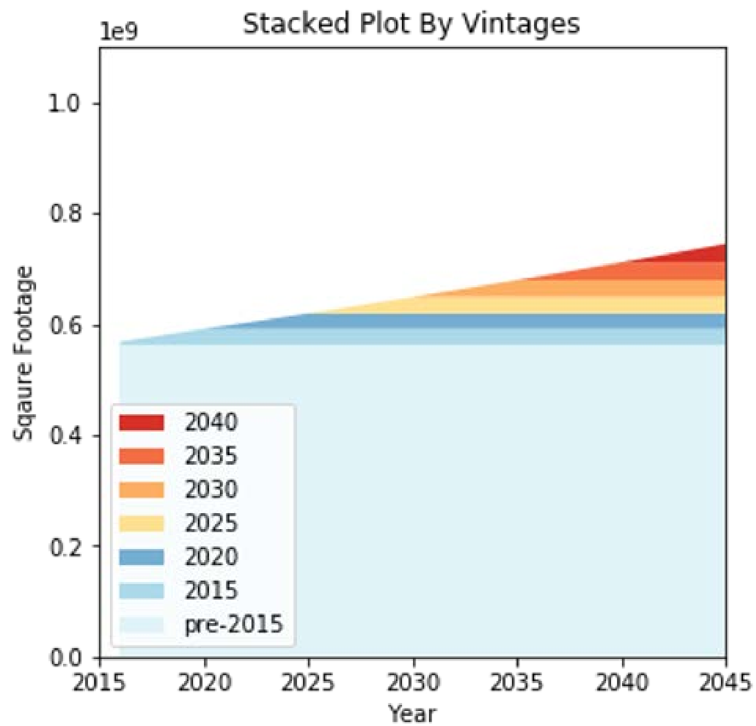

Figure 78. Growth in square footage of commercial buildings by vintage

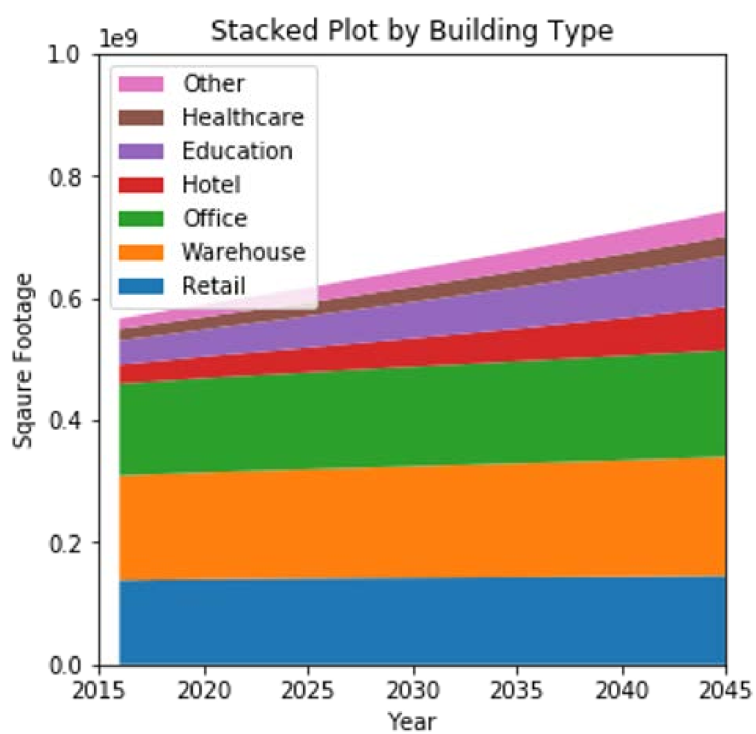

Figure 79. Growth in square footage of commercial buildings by building type

Commercial Building Code Projection

Commercial buildings have a high level of complexity because of the diversity in the size, HVAC system configuration, space usage, etc., across the building stock. To make matters more difficult, the rules governing individual building components also depend on their size and application. For this reason, following the residential buildings approach of specifying the upgrade rate for each individual building component separately would be nearly impossible.

We therefore manage this complexity by placing building components into five major building system categories: envelope, exterior lighting, HVAC, interior lighting, and SWH; and specify upgrades at this coarse level. That is, when each major building system reaches the end of its effective useful life (EUL), the entire system, including all its components, is replaced with either a code-minimum or beyond-code system. This method effectively simplifies the equipment turnover model; however, to implement it we need to specify code-minimum efficiency level for all components starting with today's codes and projecting out to 2075 (to cover aggressive beyond-code assumptions through 2045).

The code projection describes both how codes will improve over time and maximum efficiency levels available on the market today through 2045. A combination of the CPUC DEER efficiency level progressions over time, the projections in EIA (2016b), the 50% Savings Advanced Energy Design Guide for Small to Medium Office Buildings (ASHRAE; AIA; IESNA; USGBC; DOE, 2011), and engineering judgement (minimally used where necessary) were used to develop these projections. Because increasing energy code stringency drives efficiency levels over time, assumptions about code compliance are important. In this study, the Stress projection assumes that 20% of replacements do not meet current energy code, but instead lag by 5 years. This study does not consider that some code mandates such as certain HVAC and lighting controls may have EULs shorter than the building system (HVAC or lighting) to which they pertain, but the relative importance of the persistence of these controls could be studied in future work.

The projections were developed from 2020 to 2075 in 5-year increments (12 total distinct years). Efficiency levels beyond 2045 (the last year of the LA100 study) are meant to represent beyond-code efficiency levels on the market in future years.

The following sections present the methodology and values for the efficiency-level projections for various building components, grouped by major building system. For some components, the number of combinations was prohibitively large, so only a subset is shown.

Envelope

Exterior Doors

DEER provides no efficiency recommendations for exterior doors for any prior years. As such, no efficiency projections were determined for years 2020 through 2075.

Exterior Floors

DEER provides an efficiency recommendation of U-0.73 for unheated exterior ground contact floors for all years. DEER provides no efficiency recommendations for mass exterior floors for any prior years. As such, efficiency projections remained at U-0.73 for unheated exterior ground contact exterior floors, and no efficiency projections were determined for mass exterior floors for years 2020 through 2075.

Roofs

The DEER efficiency levels (defined by assembly U-value) for roofs depend on three characteristics:

1. California climate zone (1 through 16) where the building is located
2. Construction type (insulation entirely above deck [IEAD], mass, and wood-framed)
3. Building category (high-rise residential and nonresidential).

For each of the 16 climate zones, there are three possible construction types and two possible building categories. For the nine DEER years (pre-1975, 1985, 1996, 2003, 2007, 2011, 2014, 2015, and 2017) this results in 864 unique combinations (16 × 3 × 2 × 9 = 864). Many of these combinations have the same efficiency levels. Reviewing the nine DEER vintages, we found five different unique patterns of decreasing U-value. Using the U-value from 2017 to denote each pattern and the roof efficiency data from the 50% Office AEDG, these five patterns were extrapolated out to 2075. Additionally, Title 24 requires cool roofs for nonresidential buildings, and the City of Los Angeles enacted a cool-roof ordinance starting in October 2014[71] that set minimum reflectance for roofing material. DEER vintages 2017 and beyond assume cool roof material.

Exterior Walls

The DEER efficiency levels (defined by assembly U-value) for exterior walls are dependent on three characteristics:

1. California climate zone (1 through 16) where the building is located
2. Construction type (mass, steel-framed, and wood-framed)
3. Building category (high-rise residential and nonresidential).

For each of the 16 climate zones, there are three possible construction types and two possible building categories. For the nine DEER years (pre-1975, 1985, 1996, 2003, 2007, 2011, 2014, 2015, and 2017) this results in 864 unique combinations (16 × 3 × 2 × 9 = 864). Many of these combinations have the same efficiency levels. Reviewing the nine DEER years, it was found that there were six different unique patterns for mass walls, four different unique patterns for steel-framed walls, and four different unique patterns for wood-framed walls. Using the U-value from 2017 to denote each pattern and the exterior wall efficiency data from the 50% Office AEDG, these five patterns were extended into the year 2075.

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[71] LADWP, *Cool Roofs What You Need to Know About LADWP Rebates and Building Code Requirements* (LADWP and LADBS, 2015). https://www.ladbs.org/docs/default-source/publications/ordinances/cool-roof-fact-sheet-and-faq.pdf.

Below-Grade Walls

DEER provides no efficiency recommendations for below-grade walls for any prior years. As such, no efficiency projections were determined for years 2020 through 2075.

Nonresidential Windows

The DEER efficiency levels (defined by assembly U-value and solar heat gain coefficient [SHGC]) for nonresidential windows are dependent on three characteristics:

1. California climate zone (1 through 16) where the building is located
2. Orientation (north facing or non-north facing)
3. Window-to-wall ratio (WWR) (0%–10%, 10%–20%, 20%–30%, and 30%–40%).

For each of the 16 climate zones, there are two possible orientations and four possible WWRs. For three of the nine DEER years (pre-1975, 1985, and 1996) WWR was not included in the efficiency requirements. For the remaining six DEER years (2003, 2007, 2011, 2014, 2015, and 2017) WWR was a criterion for efficiency. This results in 864 unique combinations of efficiency requirements ($16 \times 2 \times 3 + 16 \times 2 \times 4 \times 6 = 96 + 768 = 864$). Many of these combinations have the same efficiency levels. Reviewing the nine DEER years, we found 15 different unique U-value/SHGC patterns. Using the U-value and SHGC from 2017 to denote each pattern and the window efficiency data from the 50% Office AEDG, these 15 patterns were extended into the year 2075.

Exterior Lighting

DEER did not include exterior lighting, so exterior lighting assumptions used ASHRAE 90.1 values for the closest code year. Future vintages used ASHRAE 90.1-2016 values, except for parking lot lighting, which constitutes the majority of buildings-related outdoor lighting energy use (DOE EERE, 2017). Parking lot lighting values assumed evenly spaced light poles with two luminaires per pole (CEC, 2003). Projections of future efficiency for parking lot lighting assumed only luminaire replacement. LEDs will replace metal halide luminaires as the dominate lighting technology by 2030 (CEC 2015), and LED technology will improve over that time, reaching a plateau as luminous efficacy nears its maximum theoretical potential (DOE, 2017). Vintage estimates 2030 and beyond assumed 0.01 W/ft^2 for parking lighting.

Interior Lighting

First-year interior lighting power density assumptions for existing buildings were taken from DEER and were the same as (or more efficient than) the maximum allowable lighting power density values from the most recent version of Title 24 code for that vintage. The 2019 Title 24 version recently approved by the CEC,[72] which takes effect January 1, 2020, includes a substantial step reduction in the allowable lighting power, reflecting a switch to LED technology as the basis for comparison. For this reason, extrapolating future efficiency improvements necessitated a longer time horizon than just recent versions of Title 24.

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[72] CEC, "Building Energy Efficiency Standards: Title 24," California Energy Commission, https://www.energy.ca.gov/title24/.

A comparison of the area-weighted lighting power density (LPD) allowances from 1992 to 2019 Title 24 versions showed an average annual reduction of 2.1% per year. Choosing different versions for comparison gives a low of 1.24% per year reduction between versions 2005 and 2016, and a high of 4.72% between 2013 and 2019. For this analysis, LPD reduction was assumed to be a moderate 2% per year, which is in the middle range of past Title 24 improvements and matches closely with averaged percent per year reductions in the ASHRAE 90.1 space-by-space method. This implies that by 2040 maximum Title 24 values will match the best performance currently available in the 2016 market, and by 2075 the performance will match best-in-market available in 2030, per the U.S. Department of Energy's Building Technologies Office Solid State Lighting performance projections for luminous efficacy.[73]

Projections for LPD followed the same 2% per year improvement, with the LPDs on average slightly lower than the maximum allowed by Title 24. While efficiency projections for some HVAC equipment in the modeling exercise use a linear extrapolation, the percent per year reduction used for lighting prevents the incorrect assumption that LPD efficiency will eventually exceed the currently understood technical potential.

HVAC

Natural Gas-Fired Hot Water Boilers

The DEER gas burner efficiency levels for hot water boilers are separated into three size categories:

1. Less than 300 Btu/h
2. Between 300 Btu/h and 2500 Btu/h
3. Greater than 2500 Btu/h.

For each size category, the efficiency levels are the same for each of the eight DEER years (pre-1975, 1985, 1996, 2003, 2007, 2011, 2014, and 2015). For DEER pre-1975 to DEER 2011, the minimum hot water boiler gas burner efficiency level is 80%, and for DEER 2014 and 2015 the minimum hot water boiler gas burner efficiency level is 82%. EIA (2016) projected typical and high hot water boiler gas burner efficiency levels, respectively, to be 82% and 98% for 2010; 83% and 98% for 2030; and 83% and 98% for 2040. However, condensing (hot water boiler gas burner efficiencies of 90% and higher) are widely available on the market today and have been for some time. It was decided that the minimum gas burner efficiency levels for 2020 would be 92%, increasing 2% every 15 years.

Electric Chillers

The DEER efficiency levels for electric chillers include three types of chillers and several size ranges:

1. Air-cooled rotary screw (less than 150 tons, and greater than 150 tons)

[73] Table 4.2: Present and Future Target Rolled-Up Efficiencies for White Light Package (DOE 2017).

2. Water-cooled rotary screw (less than 75 tons, 75 to 150 tons, 150 to 300 tons, 300 tons to 600 tons, and greater than 600 tons)
3. Water-cooled centrifugal (less than 150 tons, 150 to 300 tons, 300 tons to 400 tons, 400 tons to 600 tons, and greater than 600 tons).

Projected minimum efficiencies are calculated based on prior efficiency levels from Title 24 versions 1995 through 2019. The efficiency levels are converted to a percent of the theoretical Carnot efficiency limit at the rating condition, and then fit with an asymptotic regression to project the minimum efficiency levels through 2075. The values are then converted back into kW/ton.

Heat Pumps – Cooling Mode

The DEER cooling efficiency levels for heat pumps are separated into three categories based on type of heat pump:

1. Packaged terminal heat pump (PTHP)
2. Single package heat pump (supply air fan and indoor coil in same package as heat pump)
3. Split system heat pump (supply air fan and indoor coil in separate package as heat pump).

Using the historical minimum cooling model efficiencies for the eight DEER years (pre-1975, 1985, 1996, 2003, 2007, 2011, 2014, and 2015) linear regressions where created to project the minimum efficiency levels to 2075. For the PTHP, efficiency is only specified in terms of energy efficiency ratio (EER), whereas for the single package and split system heat pump efficiency is specified in both EER and seasonal energy efficiency ratio (SEER).

Heat Pumps – Heating Mode

The DEER heating efficiency levels for heat pumps are separated into three categories based on type of heat pump:

1. Packaged terminal heat pump (PTHP)
2. Single package heat pump (supply air fan and indoor coil in same package as heat pump)
3. Split system heat pump (supply air fan and indoor coil in separate package as heat pump).

Using the historical minimum heating model efficiencies for the eight DEER years (pre-1975, 1985, 1996, 2003, 2007, 2011, 2014, and 2015) linear regressions where created to project the minimum efficiency levels to 2075. For the PTHP, efficiency is only specified in terms of coefficient of performance (COP), whereas for the single package and split system heat pump efficiency is specified in both COP and EER.

Electric Motors for Fans and Pumps

The DEER efficiency levels for electric motors are specified based on four motor characteristics:

1. Number of poles (two, four, six, or eight)
2. Type (open or enclosed)
3. Synchronous speed (900; 1,200; 1,800; or 3,600 revolutions per minute [RPM])

4. Capacity (0–1, 1–1.5, 1.5–2, 2–3, 3–5, 5–7.5, 7.5–10, 10–15, 15–20, 20–25, 25–30, 30–40, 40–50, 50–60, 60–75, 75–100, 100–125, 125–150, 150–200, 200–250, 250–300, 300–350, 350–400, 400–450, 450–500 HP).

For energy modeling purposes, the number of poles, type, and speed are fixed at four poles, enclosed, and 1,800 RPM. Using the historical minimum efficiencies for the nine DEER years, linear regressions were created to project the minimum efficiency levels for different motor capacities from 2020 to 2075, in 5-year increments.

Unitary HVAC system

The DEER efficiency levels for natural gas furnace heating/direct expansion (DX) cooling unitary HVAC systems are separated into two categories based on type of unitary HVAC system:

1. Single package unitary HVAC (supply air fan and indoor coil in same package as DX compressor)
2. Split system unitary HVAC (supply air fan and indoor coil in separate package as DX compressor).

Using the historical minimum heating model efficiencies for the eight DEER years (pre-1975, 1985, 1996, 2003, 2007, 2011, 2014, and 2015) linear regressions were created to project the minimum efficiency levels to 2075 in SEER.

HVAC Controls

Title 24 has long mandated several energy-saving control strategies in large air-based HVAC systems, including air-side economizing and static pressure reset. Historically, small HVAC systems were not required to have these features because the energy savings on these small systems did not justify the expense of added components. In 2019, most HVAC systems of all sizes carry these energy-saving features. For this reason, we assumed that code minimum for 2020 and beyond includes the following for all HVAC systems:

- Air-side economizing if the design airflow volume is greater than the minimum ventilation rate
- Static pressure reset
- Supply air temperature reset based on heating and cooling demand for air-based VAV systems
- Outdoor air temperature for dedicated outdoor air systems.

Additionally, HVAC operation and ventilation schedules were based on the building occupancy schedule and assumed that the system could cycle on without ventilation to maintain thermostat setback temperature setpoints during unoccupied hours.

HVAC System Type Selection

HVAC system type distributions were based on the California Commercial Saturation Survey (CCSS) conducted by Itron for the CPUC, published in August 2014.[74] The CCSS report and appendices describe the prevalence of different heating and cooling technologies by building type and building size over three utility territories: Pacific Gas and Electric (PG&E), Southern

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[74] http://capabilities.itron.com/WO024/Docs/California%20Commercial%20Saturation%20Study_Report_Final.pdf

California Edison (SCE), and San Diego Gas and Electric (SDG&E). These utility territories cover similar climates, building types, and vintages as the LADWP service territory. The prevalence of different kinds of HVAC systems in the LADWP service territory were assumed to be similar. Multifamily system type prevalence comes from the 2009 RASS database for multifamily buildings greater than three stories.[75]

This analysis ignored CCSS data where the heating or cooling system type is unknown, instead repartitioning the remaining data so that the technologies sum to 100%. Buildings with both gas and electric heating systems are modeled as having gas heating, and the small percentage of propane-based heating systems are counted as gas, as these are likely present in only remote areas of PG&E, SCE, and SDG&E service territories and not in the LADWP service territory.

The CCSS data only shows heating system type percentages and cooling system type percentages independently. It does not give percentages for each possible combination of heating system type and cooling system type. For this reason, the distributions in this study assume an equal pairing likelihood for cooling and heating technologies. An exception is for heat pump systems, which are assumed to cover both heating and cooling and are therefore only paired with one another. If there is a heat pump for cooling, a heat pump for heating is also assumed, avoiding combinations like heat pump for cooling but gas furnace for heating.

The CCSS survey data did not list the primary heating technology in a building; rather, it asked whether a given technology was present. Many buildings reported having both boilers and furnaces. This led to an internal inconsistency in the CCSS report data, where buildings with both system types exceeded the number with one type or the other. For this analysis, it was assumed that in buildings with both boilers and furnaces, furnaces were a secondary system type. This may underestimate the percentage of total heating load served by furnaces in the building stock. Additional data on the existing stock would be helpful to better estimate the joint prevalence of heating and cooling technologies and the prevalence of primary and secondary technologies by building size.

Service Water Heating

Natural Gas Service Water Heaters

Service water heating efficiencies are based on the DEER Prototypes, which assume 80% thermal efficiency (for natural-gas-fired water heaters) through 2017. Vintages 2020 and beyond assume condensing gas water heaters with a thermal efficiency of 94%, climbing to 99% in 2050 with progressively lower standby losses (DOE EERE, 2016).

Electric Water Heaters

Commercial buildings with electrified water heating have gas-fired water heaters replaced with heat pump water heaters with a 2.8 annual average COP.

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[75] CEC, "2019 Residental [sp.] Appliance Saturation Study," California Energy Commission, https://www.energy.ca.gov/appliances/rass/.

Technology Adoption Assumptions

The baseline stock estimate generated by the ComStock tool contains the estimated year built of each building sampled, and the fuel types and efficiencies of the building components associated with that year. To bring this baseline stock estimate up to date with the baseline year of 2015, the equipment designated for each sample was replaced with the appropriate newer, more efficient equipment, until each building system was within its lifespan. This initial rollover process ensured that the baseline stock estimates accurately represent the progression of Title 24 code since its inception. Equipment type specifications, including primary fuel, are aligned with the California Commercial Saturation Survey (CCSS) (Itron, Inc. 2014).

Because of the assumption that major building systems are only replaced at the end of their EUL, EUL assumptions are a key driver of the rate of efficiency change and electrification. The EULs of different building components can vary widely. The EULs used for this analysis were based on the CPUC DEER. Table 24 shows the EULs assumed for this analysis.

Table 24. Effective Useful Life of Major Commercial Building Systems

Major Building System	EUL (Years)	Notes
Envelope	70	This applies to both the opaque envelope and fenestration. In future work splitting the opaque envelope from the fenestration should be investigated, as windows are often upgraded at a faster rate than walls and roofs. The 70-year value was based on engineering judgment as the DEER EULs are capped at 20 years per CPUC policy.
Exterior Lighting	15	This closely matches the highest EUL in DEER for outdoor lighting of 16 years.
Interior Lighting	13	This is in line with the EULs in DEER for interior lighting.
HVAC	20	This matches the highest EUL in DEER for HVAC of 20 years.
Service Water Heating (SWH)	15	The highest SWH EUL in DEER is 20 years for a tankless water heater. Most tank-based SWH equipment in DEER has an EUL of 1 year or less.
Plug and Process Loads	15	Plug and process load replacement was not addressed in this study If plug and process loads are addressed in future work, splitting the plug and process loads into subcategories such as personal computing, personal computing displays, printers/scanners, shared displays, point-of-sale terminals, on-site IT equipment, kitchen equipment, medical equipment, etc. will be a necessary part of future projection, both for projecting EULs and for looking at future energy efficiency levels and wholesale technology changes.

Each time a major building system reaches the end of its EUL and is up for replacement, a new system is installed. For each efficiency projection, a different probability distribution is applied to decide the likelihood of adopting either a non-compliant, code-minimum or beyond-code system. Table 25 shows these probability distributions, which were developed to track the narrative descriptions of Stress, Moderate, and High energy efficiency.

Table 25. Commercial Building Energy Efficiency Probabilities by Efficiency Projection

Energy Efficiency Level	Stress	Moderate	High
Non-compliance with code – assuming 5 years behind current code	20%	0%	0%
Current year code minimum	70%	20%	0%
Will be code minimum in 5 years	10%	50%	10%
Will be code minimum in 10 years	0%	20%	20%
Will be code minimum in 15 years	0%	10%	40%
Will be code minimum in 20 years	0%	0%	30%

For example, in the Stress projection, for the simulation year 2030, 20% of the buildings that have major building systems at the end of their EUL in 2030 will replace the old system with a 2025 code-minimum equivalent, 70% will replace the old system with code minimum, and 10% will replace the old system with one that will be code minimum in 5 years (i.e., 2035). The assumption for non-compliance is based on analysis of CASE reports.

Scenarios created for the EFS study are used to construct commercial building electrification assumptions. The LA100 study considers the electrification of space heating and water heating in commercial buildings, and uses the EFS High and Technical Potential scenarios with moderate technology advancement as its basis for constructing market-share probabilities for electric versus gas-fired space and water heating technologies (Mai 2018). Only two electrification projections are constructed for LA100: Moderate and High.

The Moderate LA100 projection uses the High EFS scenario results to construct its market shares by fuel type assumptions because (a) the EFS Moderate scenario shows only slightly more electrification than the EFS Reference scenario and no significant market movement; and (b) Los Angeles presents one of the most attractive climates for electrification because current heat pump technologies can work well year-round. Thus, the High EFS scenario better aligns with the LA100 Moderate narrative description of substantial market change that is nonetheless clearly differentiated from 100% electrification. That said, hospitals, hotels, motels, quick service restaurants, and sit-down restaurants were excluded from water heater electrification in the Moderate projection. This decision was made in consultation with LADWP's subject matter experts, based on the difficulty of electrifying service water heating for these building types.

The High electrification projection represents the modeling team's interpretation of the 100% net carbon neutral by 2050 goal defined by the Los Angeles Mayor's Office. Given the expected component lifetimes of the HVAC and SWH systems, it was necessary to force 100% electrification of replacements starting in the 2035 model year. The 2025 and 2030 model year electrification probabilities were ramped up from the EFS Technology Potential scenario in 2025 by one fifth the difference between the Technology Potential scenario and 100%, and in 2030 by half of this difference. In this projection, all building types experience SWH electrification, and all new buildings are electrified starting in 2030.

Each technology listed in the EFS data set for commercial space heating and water heating uses electricity, gas, or fuel oil as the heating fuel. In the data relevant to California, no fuel oil space heaters are adopted, although a very small percentage of existing water heaters use fuel oil—less than 0.01%. Given how small this contribution is, fuel oil technologies are ignored in the ComStock analysis.

To determine the adoption rate of electrified system types the total sales projected by EFS are summed by year, fuel type, and scenario. Sales in the EFS data set are reported in terms of capacity, not units; however, for the purpose of this analysis the relationship between the two is considered to be linear. The EFS data were then renormalized against the CCSS survey data collected by Itron to align it with ComStock's starting point in terms of space and water heating prevalence and fuels. The adjusted EFS data are then converted into sales shares for each model year. The results of this process are shown in Table 26. These sales shares are applied by interpreting the electric sales share as a probability that a natural gas unit will be replaced with an electric unit when it reaches its EUL; the analysis assumes that once a building end use is electrified it does not fuel-switch back to natural gas.

Table 26. Commercial Electric Technology Sales Shares for Space Heating and Water Heating

	Moderate Electrification (%)		High Electrification (%)	
Year	**Space Heating**	**Water Heating**	**Space Heating**	**Water Heating**
2020	51	62	51	62
2025	52	63	61	70
2030	58	66	79	83
2035	73	72	100	100
2040	88	79	100	100
2045	93	80	100	100

For each analysis year the equipment turnover, including electrification and efficiency adoption assumptions, is conducted for that year and the four years preceding it. For example, in the 2035 analysis year space heating equipment fuel types and efficiency levels are determined for each EUL year 2031, 2032, 2033, 2034, and 2035 and are added together to represent the total change expected between 2030 and 2035.

Efficiency Projections

When applied across the building stock over time, the efficiency assumptions slowly (e.g., Stress projection envelope technologies) or more rapidly (e.g., High projection lighting technologies) increase the overall energy efficiency of the building stock.

Figure 80 shows the energy efficiency adoption rates for building envelope. This figure and the others that follow show the distributions of buildings that have adopted each code efficiency level for each modeled year starting in 2015 and ending in 2045. Because of the long EUL for the building envelope, most of the building envelope remains unchanged from the year of construction. Thus, in the Stress projection (with low efficiency assumptions) about 75% of buildings have envelopes built to 2025 codes or older in 2045. Early adoption of future code-year levels of energy efficiency is able to impact the top quarter of the distribution in the High projection (the 75th percentile of code adoption falls at estimated Title 24 2040 levels), but the average and median levels barely move: the Stress projection achieves 2010 code levels by 2045 using that metric and High only improves on that by a single code cycle (Title 24, 2014).

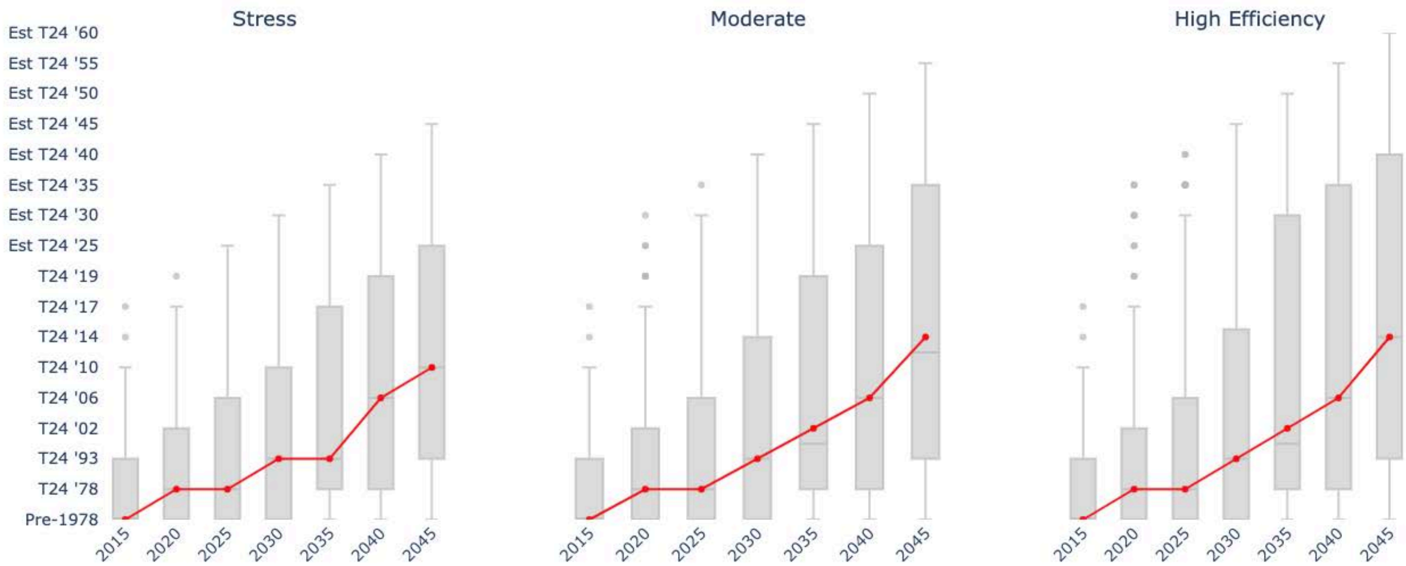

Figure 80. Building envelope energy efficiency adoption rate

The y-axis lists all of the modeled (historical) and projected codes used in ComStock, in order of increasing energy efficiency. The box-and-whisker plots provided for each projection-year demonstrate the distribution of buildings existing in that year in terms of with which code their envelope complies.

There is a stark contrast between the envelope and lighting results. Taking interior lighting as an example, we see in Figure 81 that the lighting EUL of 13 years greatly accelerates efficiency adoption as compared to building envelopes. For example, even before the projection model is applied, ComStock starts with all pre-1993 buildings having had at least one interior lighting upgrade. Then median applied code levels are able to progress to 2035 in the Stress projection and 2050 in the High projection, both by 2045.

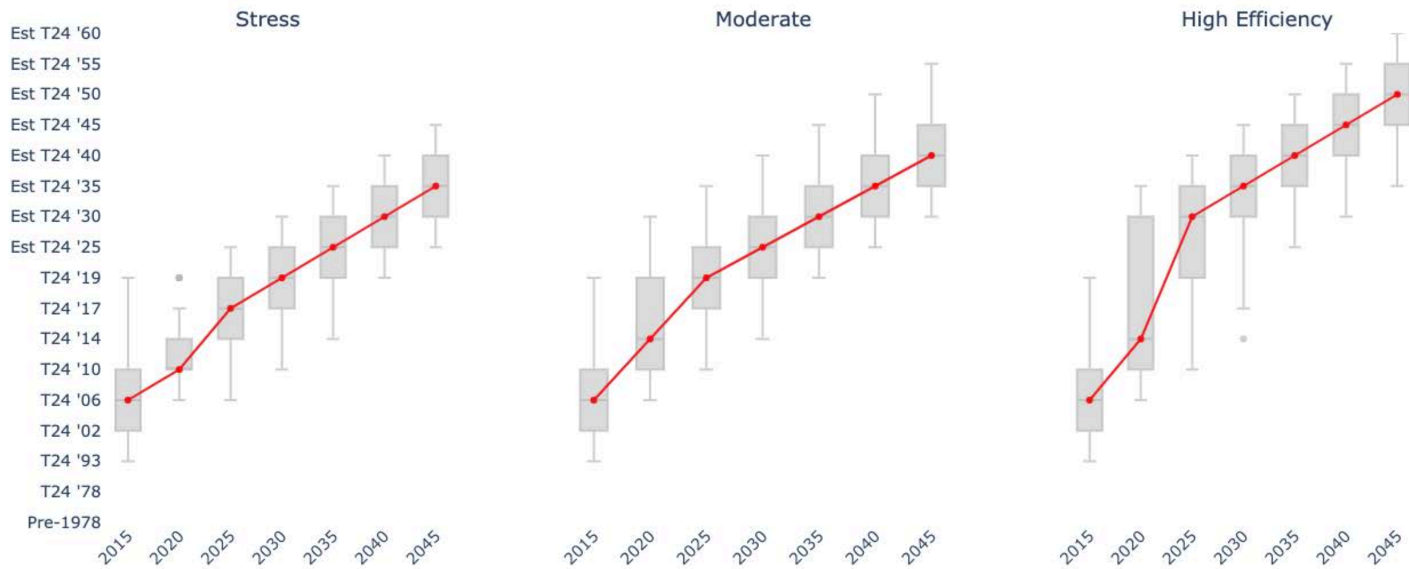

Figure 81. Interior lighting energy efficiency adoption rate

The y-axis lists all of the modeled (historical) and projected codes used in ComStock, in order of increasing energy efficiency. The box-and-whisker plots provided for each projection-year demonstrate the distribution of buildings existing in that year in terms of with which code their interior lighting complies.

Electrification Projections

The results of our service water heating electrification assumptions are shown in Figure 82. Service water heating starts at 62% electrified in the 2015 baseline year, per the California Commercial Saturation Study (Itron, Inc. 2014). Due to the aggressive nature of the assumptions underlying the High electrification projection, the service water heating end use is completely electrified by 2045 in that case. Moderate assumptions attenuate the outcome quite a bit, with service water heating only reaching about 75% electrification in the same time frame.

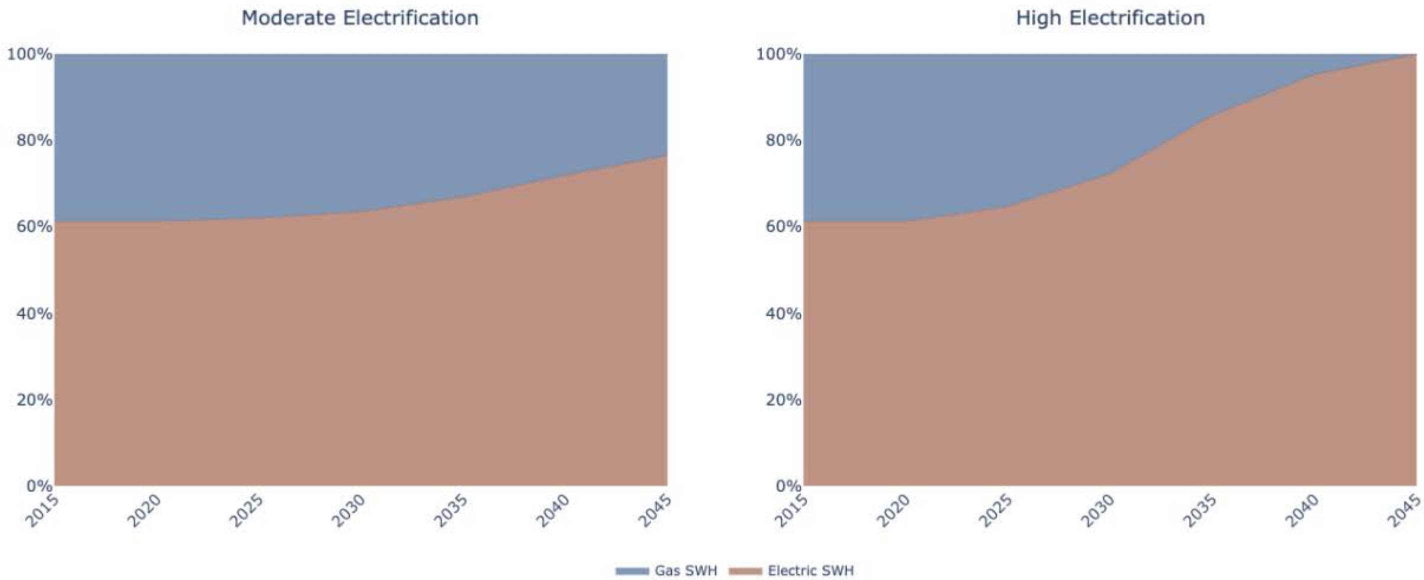

Figure 82. Electrification of commercial building service water heating over for the two electrification projections

The story for HVAC electrification is similar. Starting at 53% electrified in 2015, we estimate that commercial building HVAC would be completely electrified by 2050 in the High projection. The Moderate projection reaches about 80% electrification by 2045.

C.5 Validation of Peak Demand and Load Shape

Validating the modeled energy sales data required defining which criteria are critical within the context of the expected use of the data. For example, the maximum value of the entire retail sales timeseries is critically important as it represents the system peak sales, which in turn drives downstream determination of power system peak capacity needs. Likewise, the time of the peak, as well as the ramp rates around the peak periods help determine what kinds of resources can contribute to system reliability on peak and similar days. This section describes the ResStock and ComStock energy demand validation process and results, focusing on these key metrics that will drive power system decisions in downstream models.

The key metrics are all evaluated for simulations conducted with 2012 weather patterns. The LA100 study uses 2012 weather data throughout the project, to ensure proper spatial and temporal correlations between solar, wind, and load.

The ComStock and ResStock time-series load data results were validated against the 2012 Load Research Data (LRD) used by the LADWP IRP team and LADWP's 2012 SCADA data reported at the Receiving Station (RS) level. The LRD data represent retail sales data for LA and are based on a subset of AMI meters in each sector[76] (commercial, residential, industrial, etc.) and then extrapolated to represent the sector-wide load for LA. The RS SCADA data presents all

[76] The 2012 LRD varied from other LRD versions in that the data were collected by rate type instead of by sector. NREL worked with LADWP SMEs to translate these rate-based data into sector-based data using data provided by LADWP regarding sector rate class participations.

load at a moderate level of geographic resolution—19 aggregate areas across the city. Integrated for a whole year and taken for the whole city, the RS-level data are expected to contain more load than the LRD data, because the LRD data are at the meter level, but the RS level data includes distribution system losses. This loss factor was accounted for with the assistance of LADWP staff, assuming a 4.67% constant distribution loss factor, and the resulting data set is referred to as receiving station minus distribution losses, or RS-DL. The LRD and RS-DL time series have some differences, typically less than 10%. Following further discussions with LADWP,[77] both data sets were included in the validation process for the stock load models.

The validation process led to several changes in the underlying stock models. Issues addressed include equipment schedules that were insufficiently diverse and lacked realistic stochasticity, day-of-week misalignment in the commercial models, and tuning of the residential post-processing algorithm. The result of these changes, discussed below, were presented to LADWP.[78]

The first set of graphs (Figure 83) shows the average weekday (top) and weekend (bottom) load shapes for each of the seasons in Los Angeles. The stacked areas represent the LA100 sectoral load models, while the purple, blue, and dashed lines represent the LRD, RS-DL, and +/-10% bounds, respectively. The bounds are provided to contextualize how close or far the results depicted are from the two LADWP data sources. The models and data sources show relatively good agreement across the combinations presented. Two noticeable imperfections are the models overestimating demand around 3 p.m. in spring, and again at the peak load times in the summer. The latter discrepancy has a magnitude of about 5%. Otherwise, the shapes and magnitudes of the modeled and validation load shapes appear to match quite well when examined at this level of detail.

[77] Internal LA100 Deliverable to LADWP, SME_35: LRD data discussion with Meghan Mooney and Anthony Fontanini (NREL) and Bing Bing Zhang (LADWP).
[78] Internal LA100 Deliverable to LADWP, SME_38: Load Calibration Meeting; SME_40: Climate Adjusted Loads Meeting.

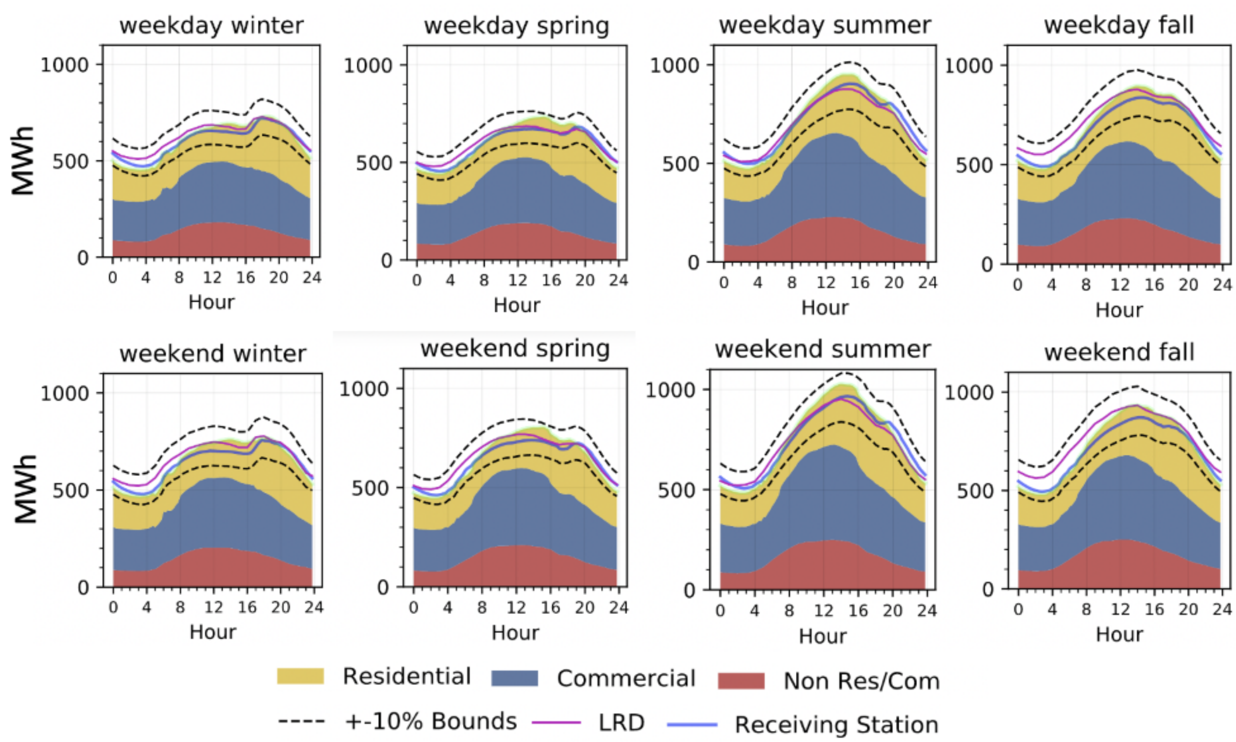

Figure 83. Comparison of model and validation data for average weekday and weekend seasonal profiles

The stacked areas represent modeled results, while the lines represent validation data sources provided by LADWP. Receiving station data exclude distribution losses.

The second set of graphs serves to validate the behavior of the model results during peak periods. Figure 84 presents three separate days: August 29, 2012, September 14, 2012, and August 10, 2012. Each of these days, according to one of the data sources or modeling results, represents the peak day for the system. September 14 is the peak day for the LRD data and the net electric load (NEL) data (not shown). The model results and RS data have their peaks on different days in August.

Several important characteristics of the peak days can be observed and validated with these results. First, the modeled peak (sales) demand, 1,335 MW, falls between the LRD data at 1,364 MW and the RS-DL data at 1,267 MW. This shows that despite some uncertainty in the validation data sources, the load modeling peak matches general expectations. Second, the hour of the peak aligns quite well across the validation data and models. In all three days shown, the modeled peak falls within the RS-DL and LRD peak hours, once again demonstrating that the behavior of the load models aligns with the validation data. This measure is particularly important given outstanding questions regarding capacity factors for solar resources. Third, the ramp rates on and off of the peaks match quite well, a famously important consideration in California given the dispatch challenges that can arise as the sun sets on a peak load day. Collectively, these graphs show strong agreement between the validation data sources and the load models. Why the models differ from the RS-DL and LRD data in predicting August 10 to be the peak day is still unclear; however, what is critical is that the load modes for August 10 match well with the LRD data for September 14 and the RS data for August 29.

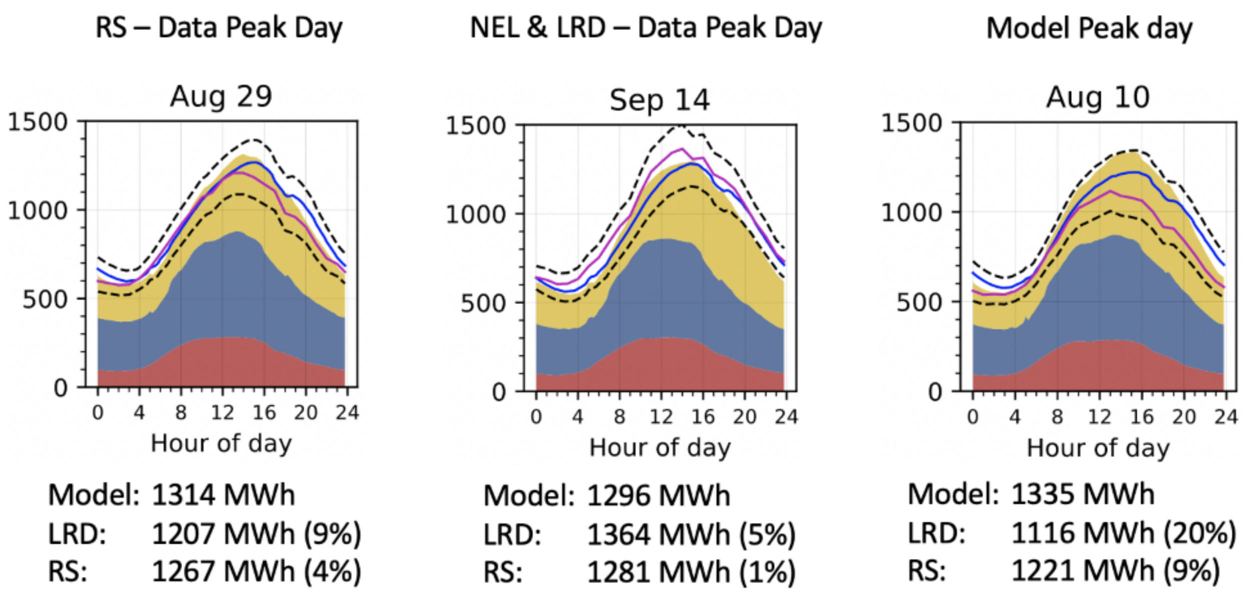

Figure 84. Comparison of load modeling results and validation data sets across the peak days of the RS-DL, LRD, and modeled data sets

The stacked areas represent modeled results, while the lines represent validation data sources provided by LADWP.

Ensuring validation of the load modeling time-series results is a critical requirement for ensuring that future projections, using extensions of the validated baseline load models, are reasonable and representative of potential future projections. By examining the alignment between the load model results and RS-DL and LRD data, key issues were identified and resolved. The ensuing time-series modeling results, when compared seasonally and with respect to peak days, demonstrate significant alignment with the available validation data sources provided by LADWP. Although none of the data sets overlap perfectly, the results presented above demonstrate the validity of the modeling results for their intended usage.

Appendix D. Residential and Commercial Building Supplementary Results

The figures in this appendix provide additional residential and commercial building modeling results without commentary, for reference purposes.

D.1 Commercial Energy Efficiency Projections

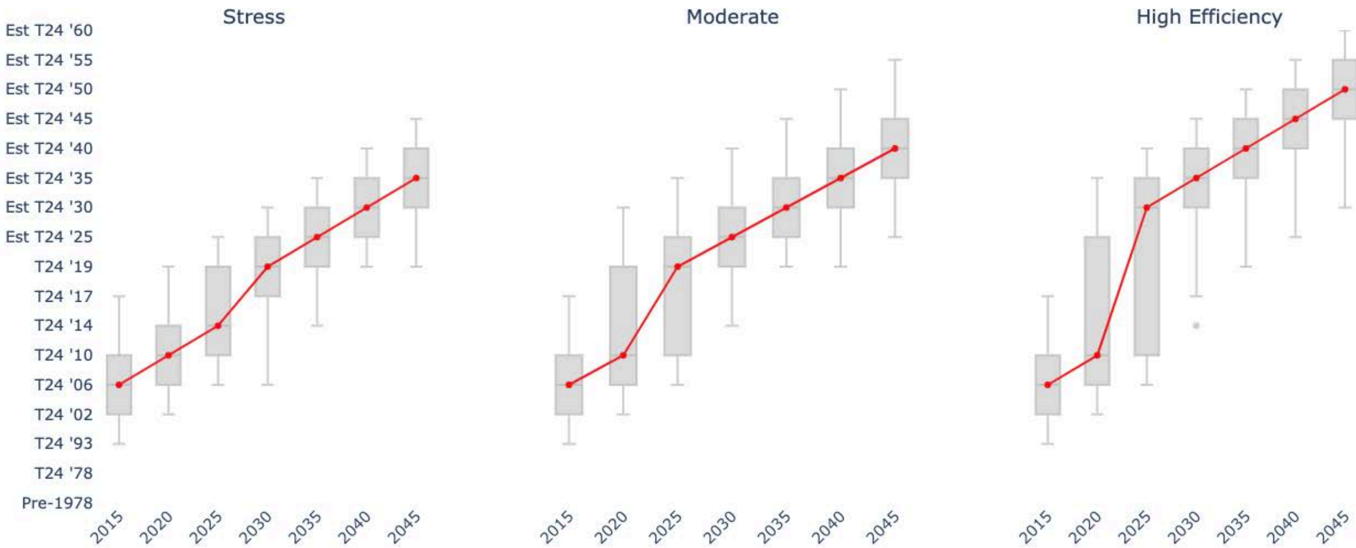

Figure 85. Exterior lighting energy efficiency adoption rate

The y-axis lists all of the modeled (historical) and projected codes used in ComStock, in order of increasing energy efficiency. The box-and-whisker plots provided for each projection-year demonstrate the distribution of buildings existing in that year in terms of with which code their exterior lighting complies.

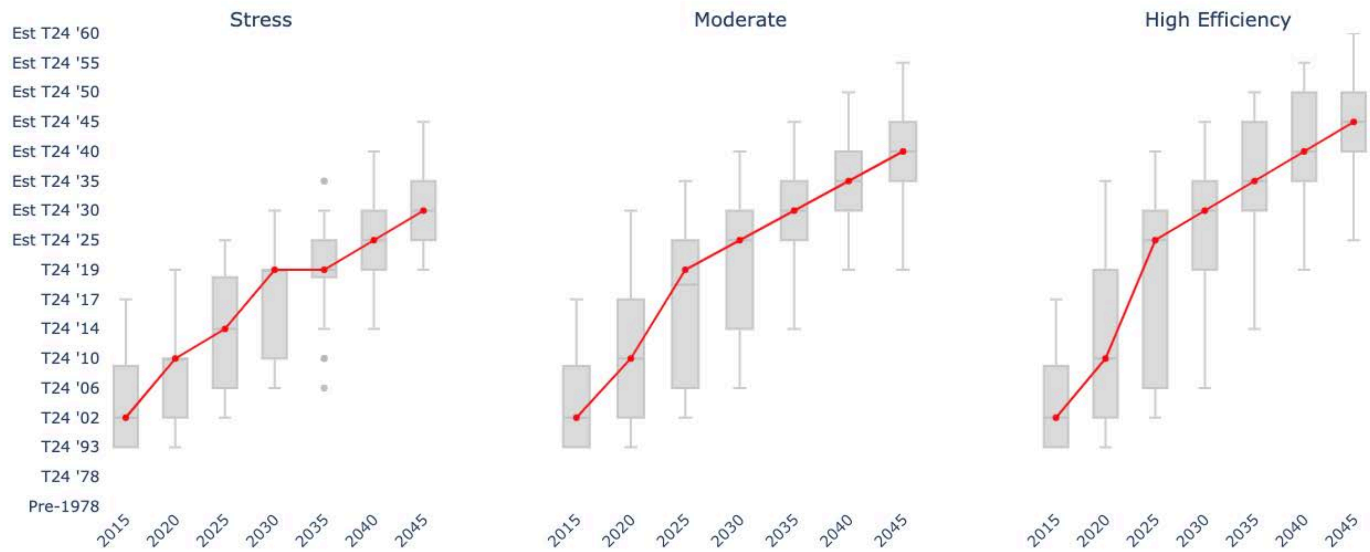

Figure 86. HVAC energy efficiency adoption rate

The y-axis lists all of the modeled (historical) and projected codes used in ComStock, in order of increasing energy efficiency. The box-and-whisker plots provided for each projection-year demonstrate the distribution of buildings existing in that year in terms of with which code their HVAC systems comply. By 2015 all pre-1978 buildings have had at least one HVAC upgrade because the HVAC EUL is 20 years.

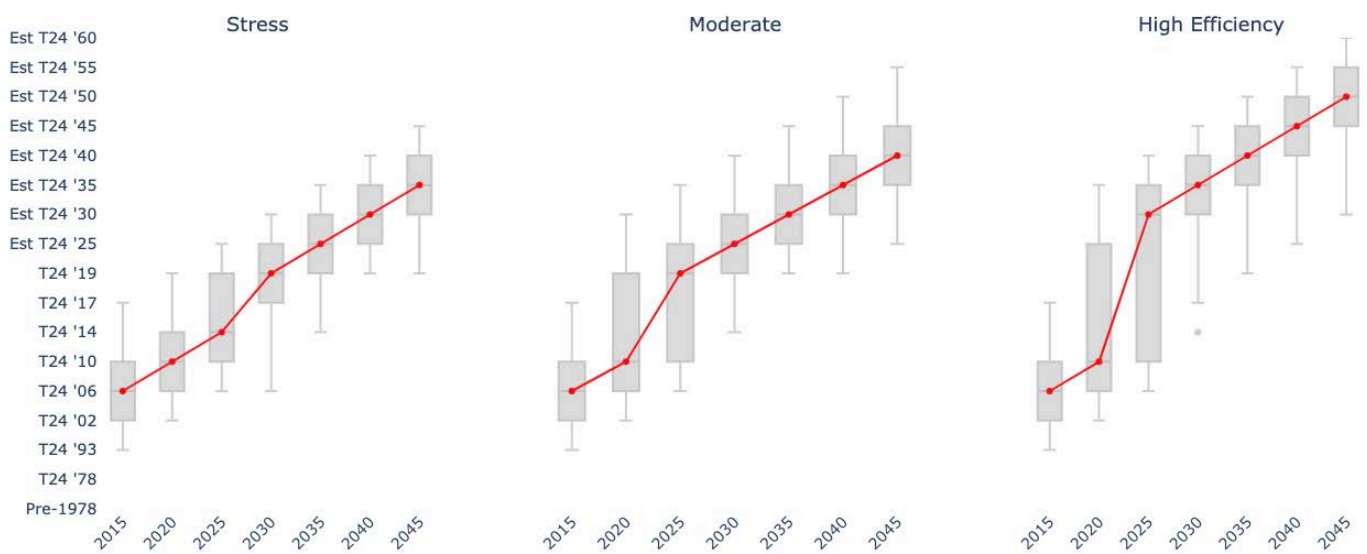

Figure 87. Service water heating energy efficiency adoption rate

The y-axis lists all of the modeled (historical) and projected codes used in ComStock, in order of increasing energy efficiency. The box-and-whisker plots provided for each projection-year demonstrate the distribution of buildings existing in that year in terms of with which code their service water heating complies.

D.2 Commercial Electrification Projections

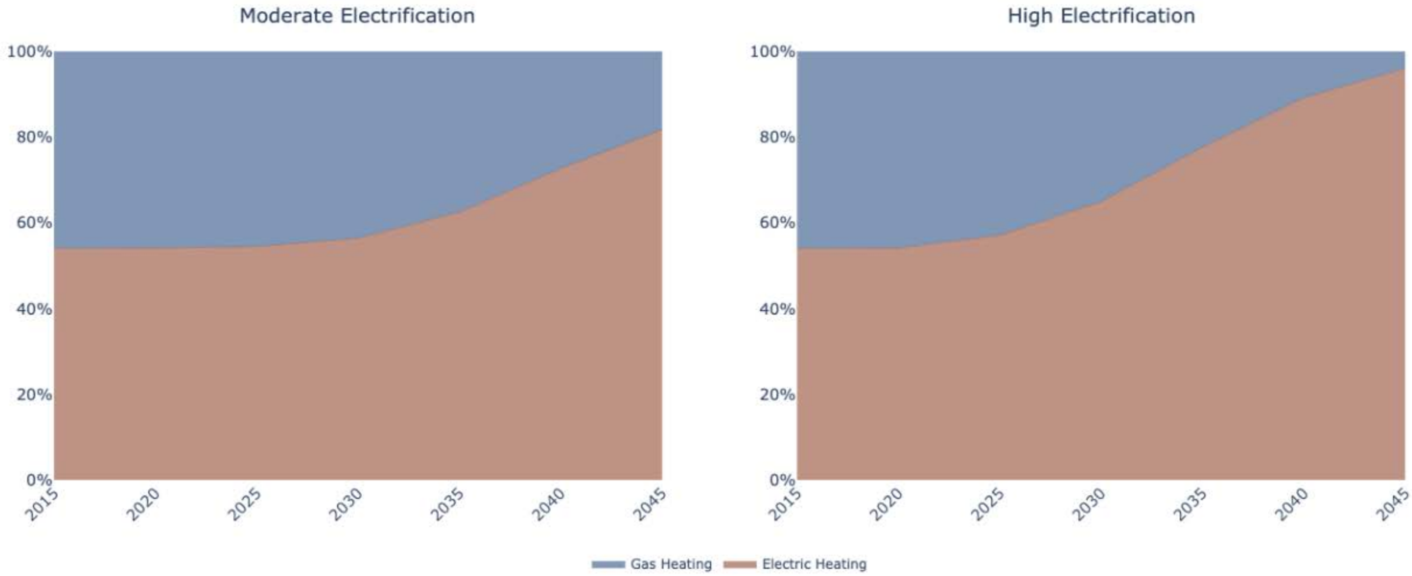

Figure 88. Electrification of commercial building space heating over time for the two electrification projections

Appendix E. Bus Electrification Modeling Details

E.1 Bus Descriptions by Type

School Buses

Based on data from Los Angeles Unified School District (LAUSD) provided by LADWP[79] we consider 1,287 school buses serviced at depots (or yards), as detailed in Table 27. We assume that by 2030 all 1,287 school buses are electrified (fully battery electric vehicles). Bus fleet sizes are considered fixed over time (no additional buses for out years), but these profiles could easily be scaled based on expected population growth or other forecasts. We also assume that each bus will continue to be serviced at the same depot.

Table 27. Summary of School Buses by Depot within LADWP Service Territory

Data from Los Angeles Unified School District (LAUSD) provided by LADWP.

Depot	Address	Number of School Buses
Gardena Yard	18421 S Hoover Street Gardena, CA. 90248	404
Business Division	604 E 15th Street Los Angeles, CA. 90015	400
Sun Valley Yard	11247 Sherman Way Sun Valley, CA. 91352	200
Van Nuys Yard	16200 Roscoe Blvd. Van Nuys, CA. 91406	250
Sepulveda Yard	8920 Sepulveda Blvd. North Hills, CA. 91343	33
	Total	**1,287**

LA Metro Transit Buses

Transit bus information for La Metro was gathered via an ad-hoc JSON Application Programming Interface (API) from the developer.metro.net LA Metro Realtime API.[80] We observe 1,114 transit buses operating during a full weekday, and 579 buses operating during a full weekend day currently serviced at depots within LADWP service territory. Table 28 reports the breakdown of LA Metro buses by depot within LADWP service territory (additional buses are serviced at depot outside LADWP service territory).

- The number of active buses was determined by observation of the entire fleet over multiple days, collecting in real-time data on bus locations.
- Depot locations were determined using information from the LA Transportation Electrification Blueprint and available at Metro.net.[81]
- The number of buses at each depot was determined by minimizing dead heading (distance driven after the last daily stop to reach the depot) for each bus based on its last reported location during the day.

[79] May 15, 2020, communication between LADWP and NREL.
[80] Metro's Realtime API is freely available at http://api.metro.net/ and provides data on the real-time positions of all LA Metro vehicles on their routes.
[81] "Metro Operating Divisions and Other Major Facilities," http://libraryarchives.metro.net/dpgtl/maps/2016-Divisions-Locations.pdf.

Note that the last daily reported location can be the last stop or another location: in some instances buses would continue sending their location up until the point of entering the depot.

Table 28. Summary of LA Metro Transit Buses by Depot within LADWP Service Territory

Depot	Address	Number of Buses
Division 1	1130 E 6th St, Los Angeles, CA 90021	165
Division 2	720 E 15th St, Los Angeles, CA 90021	410
Division 3	630 W Ave 28, Los Angeles, CA 90065	178
Division 5	5425 S Van Ness Ave, Los Angeles, CA 90062	281
Division 8	9201 Canoga Ave, Chatsworth, CA 91311	186
Division 10	742 N Mission Rd, Los Angeles, CA 90033	107
Division 13	920 N Vignes St, Los Angeles, CA 90012	143
Division 15	11801-11927 Branford St, Sun Valley, CA 91352	223
	Total	**1,693**

LADOT Transit Buses

The LA Transportation Electrification Blueprint reports 403 LADOT transit buses in operation, serviced at three depots, all within LADPW service territory. The number of LADOT buses serviced at each depot are reported in Table 29.

Table 29. Summary of LADOT Transit Buses by Depot

Depot	Address	Number of School Buses
Downtown	454-518 E Commercial St, Los Angeles 90012	86
Sylmar	12776 Foothill Blvd, Sylmar 91342	154
Washington	1950 East Washington Blvd, Los Angeles 90021	163
	Total	**403**

E.2 Bus Usage

For each bus, we estimate daily energy requirements based on vehicle miles traveled and hours of operations and assume that buses are charged overnight at their respective depots. Each bus potentially has different start and end charging times based on its current schedule and different energy requirements based on daily vehicle miles traveled (VMT) and fuel economy. We also assume a two-hour service time (e.g., for cleaning) each day for each bus. During this service time the bus is at the depot but cannot be charged. For each bus we assume that charging to completely replenish the vehicle battery happens overnight, during non-operating hours; that is, each bus is assumed to have a dedicated charger that is operated at the minimum power required to fully recharge on-board batteries.

School Buses

Data on 280 school buses (1,232 days) collected by NREL as part of the FleetDNA[82] database is leveraged as a proxy to estimate daily travel behavior of school buses in LA. These data include information on start and end of operating shifts and vehicle speed over time, from which daily VMT can be computed. Figure 89 and Figure 90 illustrate the distributions of school bus operations and daily VMT for weekdays (school buses are assumed to not be operated during weekends). Previous works have suggested that school buses would generally be operated in the mornings and afternoons, primarily to pick children up for school in the morning and drop them back off in the afternoon and their daily VMT distribution has been shown to approximate a Normal distribution.[83] Overall the distributions of when vehicles are being driven, shown in Figure 89, and daily VMT, shown in Figure 90, confirm this assumption.

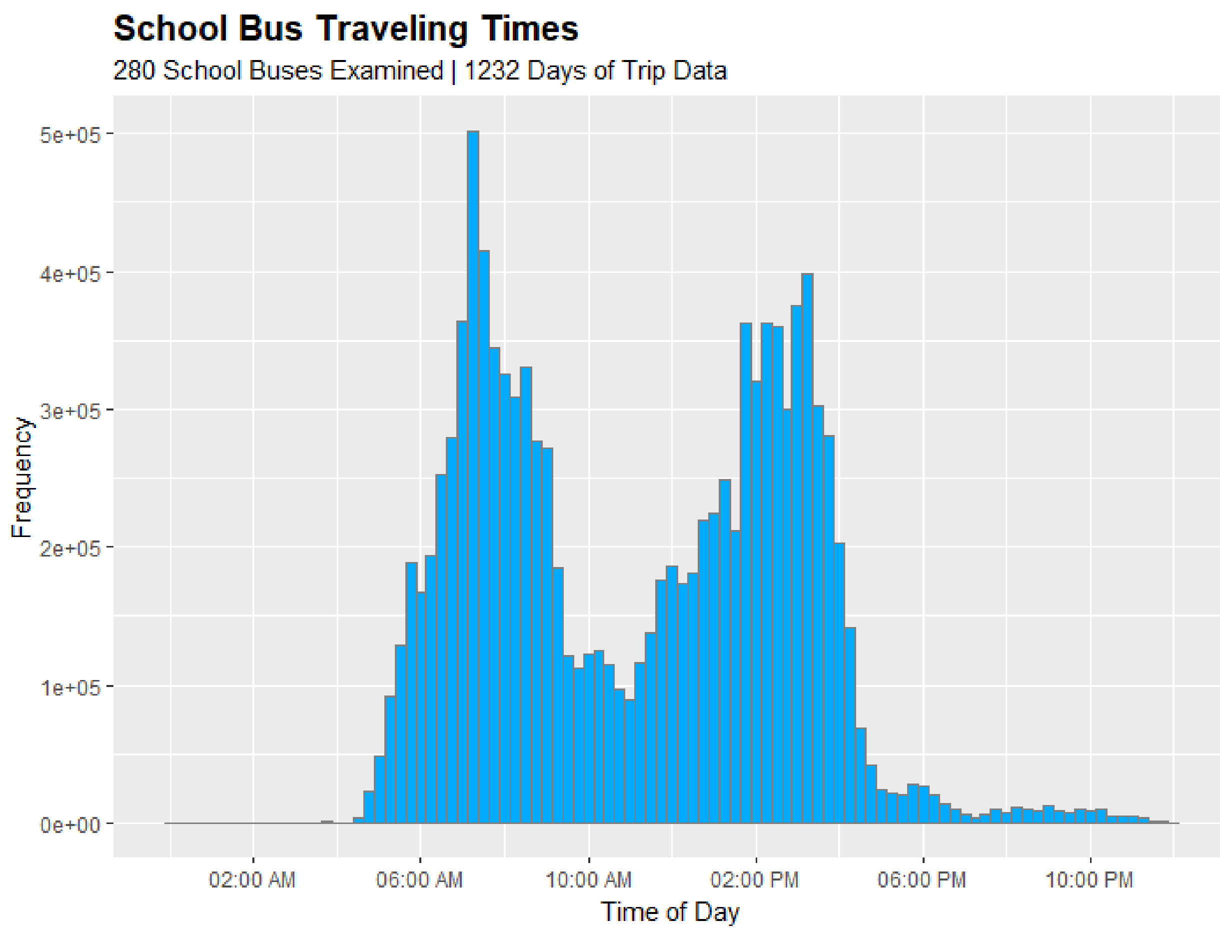

Figure 89. Distribution of school buses daily hours of operations

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[82] "Fleet DNA: Commercial Fleet Vehicle Operating Data," NREL, Accessed January 15, 2019: www.nrel.gov/fleetdna.

[83] Adam Duran and Kevin Walkowicz, "Statistical Characterization of School Bus Drive Cycles Collected via Onboard Logging Systems," *SAE International Journal of Commercial Vehicles* 6 (2): 400–406 (2013), http://dx.doi.org/10.4271/2013-01-2400.

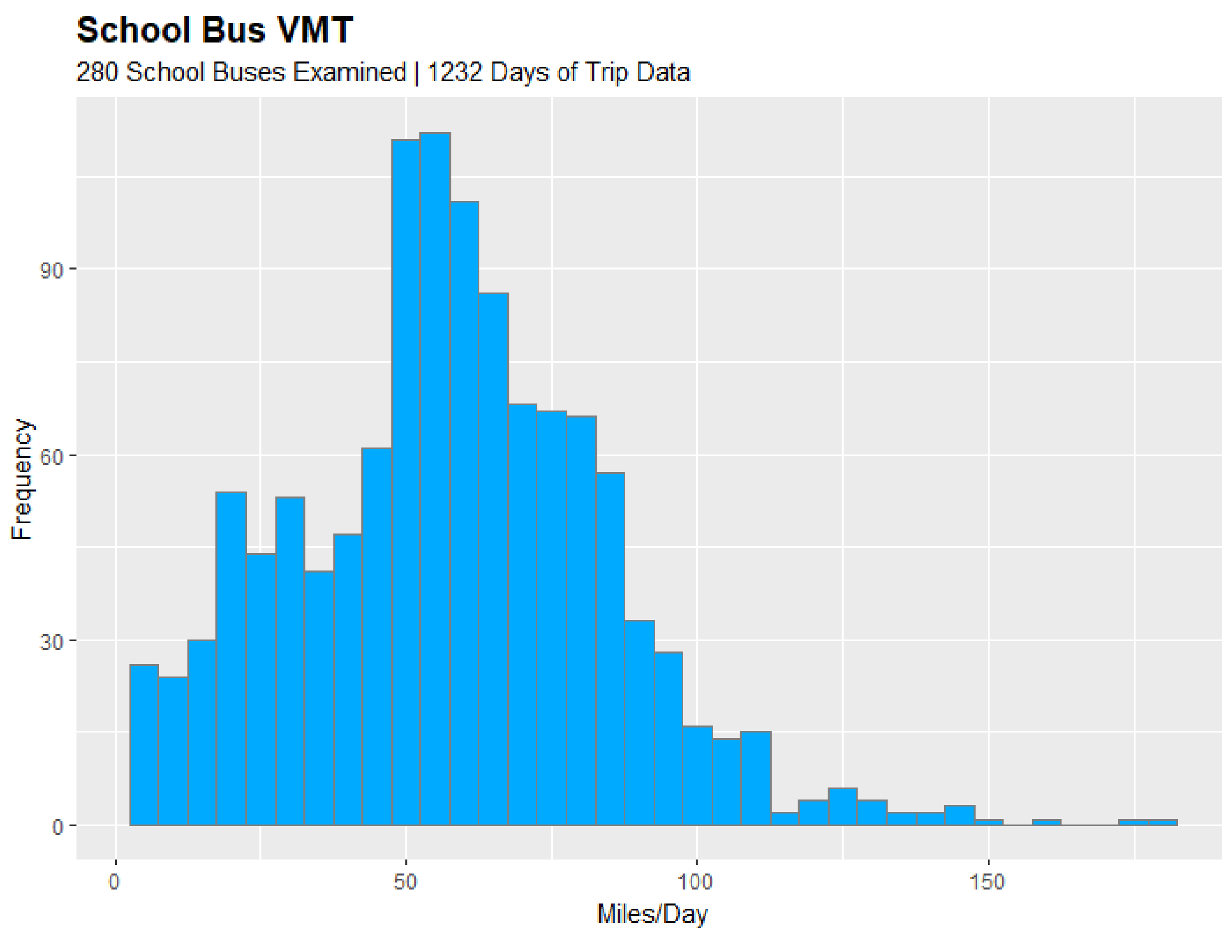


Figure 90. Distribution of school buses daily vehicle miles traveled

For each of the 1,287 school buses in LA considered in this analysis, a daily VMT and corresponding operating hours schedule was randomly sampled (pairwise) from the distributions reported in Figure 89 and Figure 90 to estimate bus usage (no correlations were assumed among buses serviced at the same depot).

LA Metro Transit Buses

The locations of all LA Metro buses were queried via the Metro API every minute for multiple days. These queries generated the following attributes:

- *id* – A unique vehicle identifier.
- *latitude* – The latitude of the vehicle location when queried.
- *longitude* – The longitude of the vehicle location when queried.
- *route_id* – An identification number showing which route the bus is currently running.
- *seconds_since_report* – How many seconds since the vehicle location was updated.

These data are used to estimate daily energy usage on a per-bus basis, as well as dwell location (in which depot each bus is parked while not in operation) and dwell time available for overnight charging. All these data are aggregated at the depot level to produce charging load as seen by the power system.

LADOT Transit Buses

Since detailed data on LADOT bus operation could not be gathered, we assumed that LADOT buses are used with similar duty cycle to the LA Metro buses. For each LADOT bus, a random LA Metro bus was sampled to estimate daily energy use and operating time and was allocated to one of the three LADOT depots, which are assumed to each serve the same number of buses.

E.3 Bus Charging Profiles

Given arrival time, departure time, and energy requirements, we assume that each bus is fully charged while not in operation (typically overnight) while it is parked at the depot. We assume that each bus has access to a dedicated charger. We also assume a two-hour service time at the end of each daily shift (e.g., for cleaning or general servicing) during which the bus cannot be charged. Each electric bus was assumed to consume 2.84 kWh/mi (vehicle fuel consumption, or efficiency) based on previous NREL analysis.[84] We also assume a 90% charging efficiency. For both school and transit buses, we assume that each bus has a dedicated charger and is charged at constant power during the remaining non-operating hours (e.g., if a bus ends service at 10 p.m. and resumes service at 6 a.m., we assume a 6-hour window to fully charge the vehicle battery). The constant charging power for each bus, $P_{charging}$, is then computed as:

$$P_{charging} = \frac{VMT \times FE_{drive}}{(t_{dwell} - t_{overhead}) \times \eta_{chargeEff}}$$

Where VMT is the daily vehicle miles traveled, $FE_{drive}$is the vehicle fuel economy in driving operations (2.84 kWh/mile), t_{dwell} is the total dwell time at the depot, $t_{overhead}$ is the service time during which the bus is assumed to not be available for charging (2 hours), and $\eta_{chargeEff}$ is the charging efficiency (0.9).

Figure 91 and Figure 92 show an example of daily operation for a transit bus during a weekday and a weekend. The red lines indicate the cumulative daily mileage, the green lines represent the speed profile, and the purple lines indicating charging power (starting 2 hours after the end of the daily travel).

[84] Leslie Eudy and Matthew Jeffers, *Zero-Emission Bus Evaluation Results: County Connection Battery Electric Buses* (NREL, 2018), NREL/TP-5400-72864, https://www.nrel.gov/docs/fy19osti/72864.pdf.

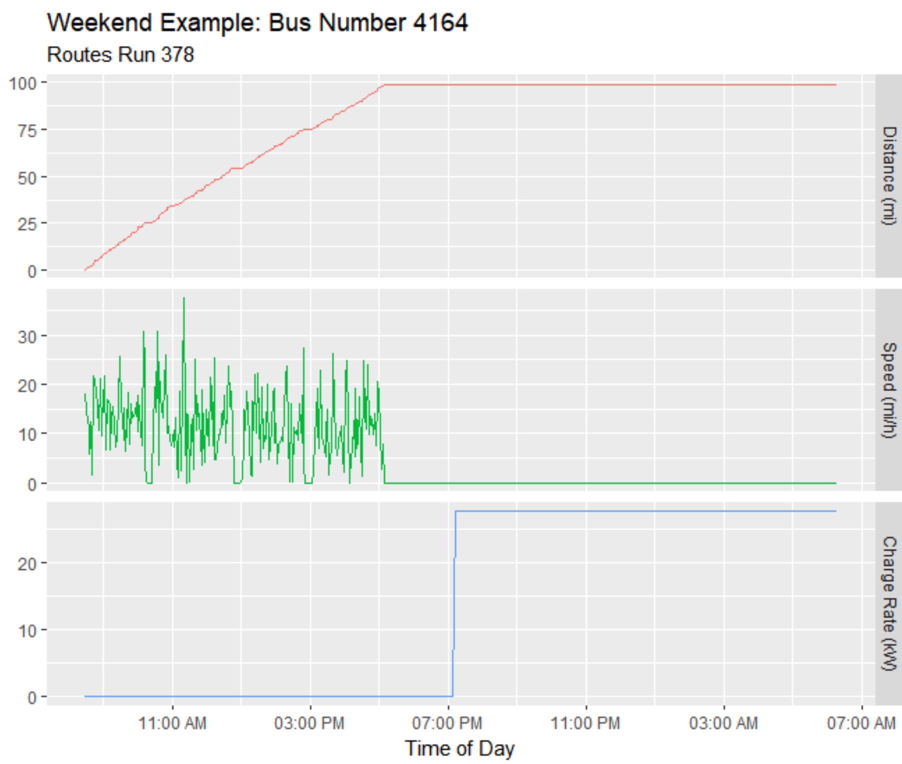


Figure 91. Example of transit bus weekday operations and charging behavior

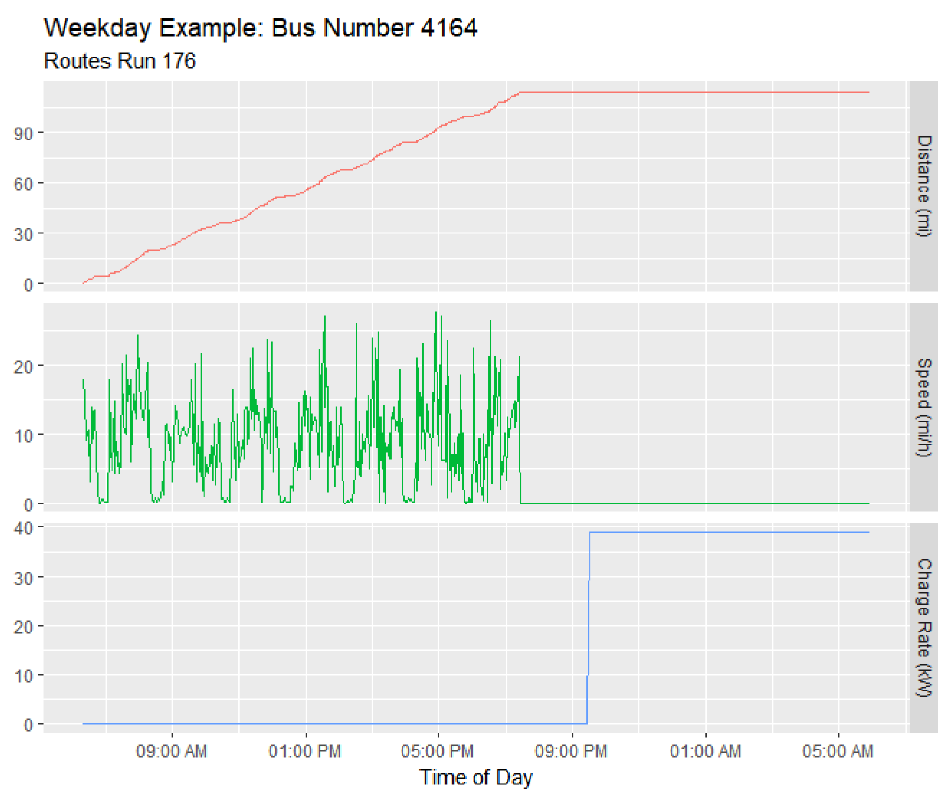


Figure 92. Example of transit bus weekday operations and charging behavior

Figure 93 shows the distributions of charging power required to fully recharge school and transit buses every night (assuming that each bus has access to a dedicated charger and is charged for the entire dwell time, minus two hours of service time, at its depot). Based on this analysis, almost all school buses can be fully charged with a power consumption of less than 50kW; the vast majority of LA Metro transit buses (~90%) can be charged using less than 100kW; and only 1.2% of LA Metro transit buses require more than 150 kW, as shown in Figure 94.

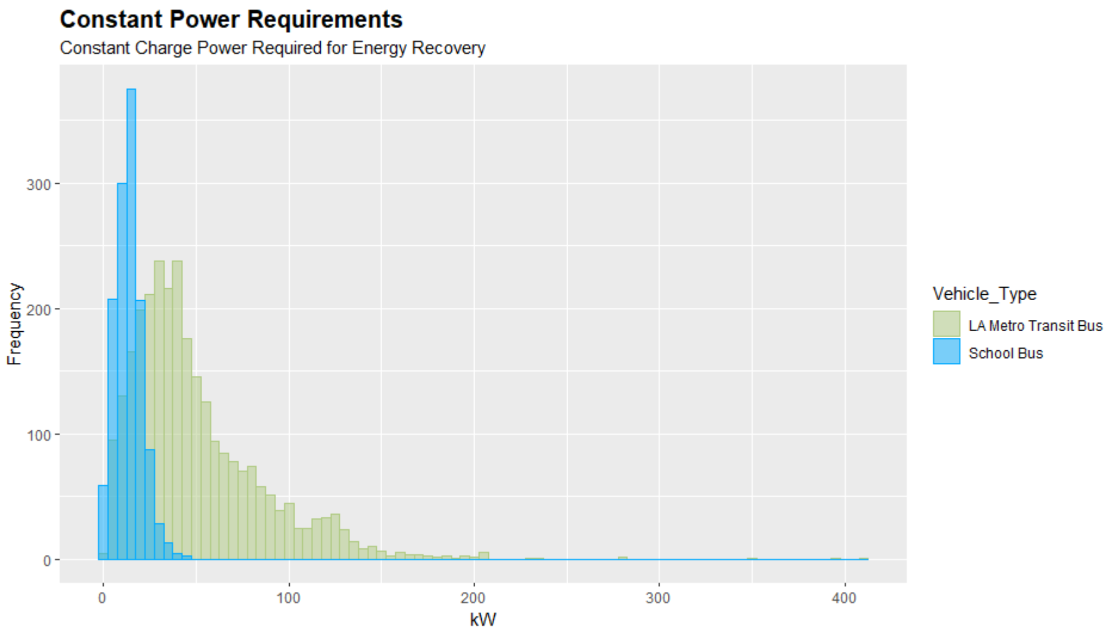


Figure 93. Distribution of bus charging power

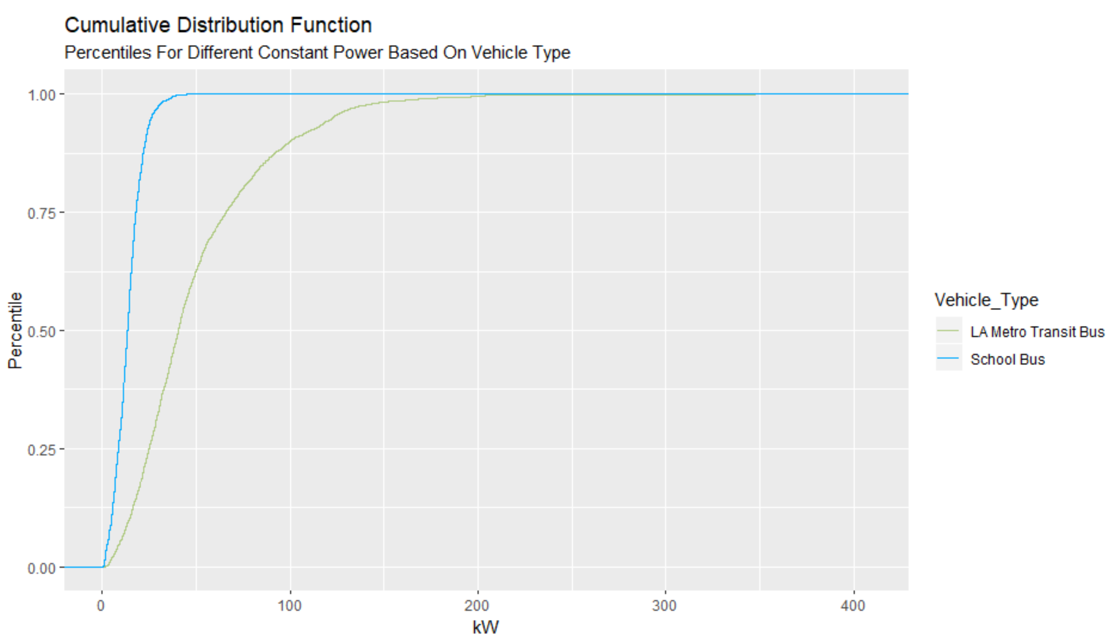


Figure 94. Cumulative distributions of required bus charging power

Charging profiles for all buses are aggregated by depot to generate 15-minute resolution charging loads at each location and for each day type (school buses are only operated on weekdays) that are used for bulk and distribution power system analyses in LA100 and are shown in Figure 95 through Figure 99.

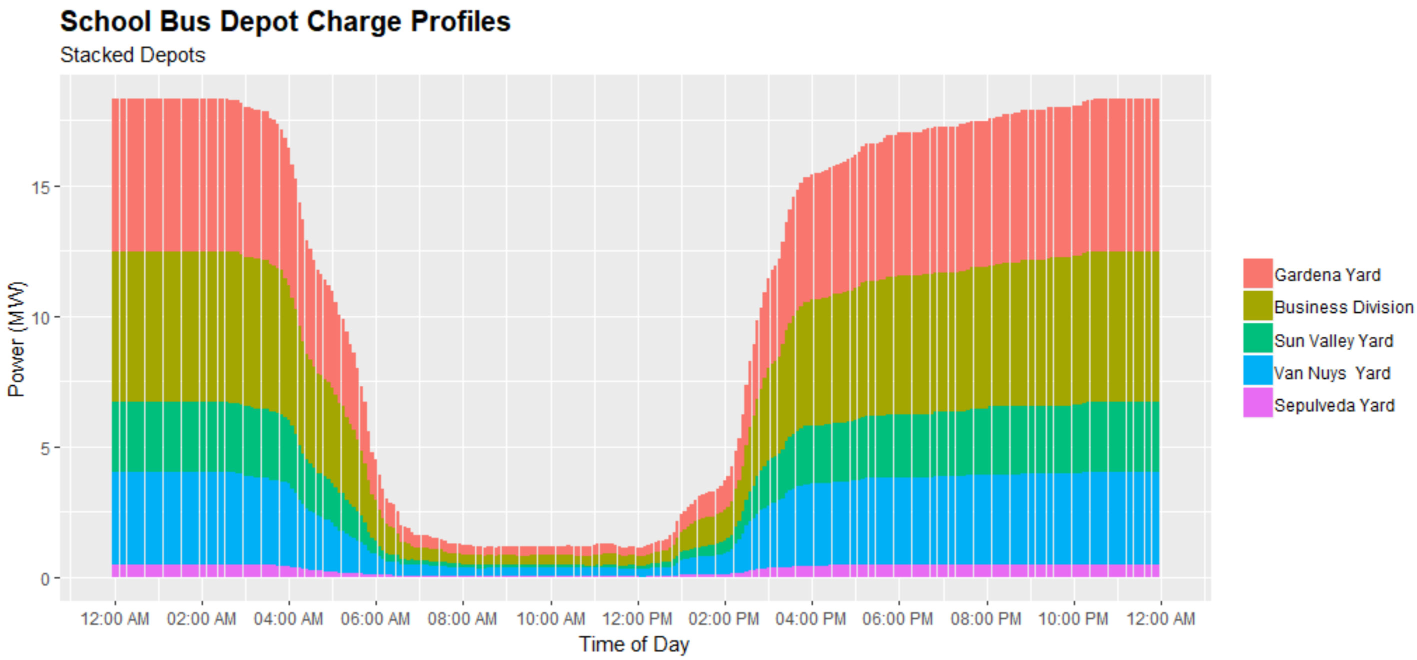


Figure 95. School buses weekday aggregate charging profiles by depot

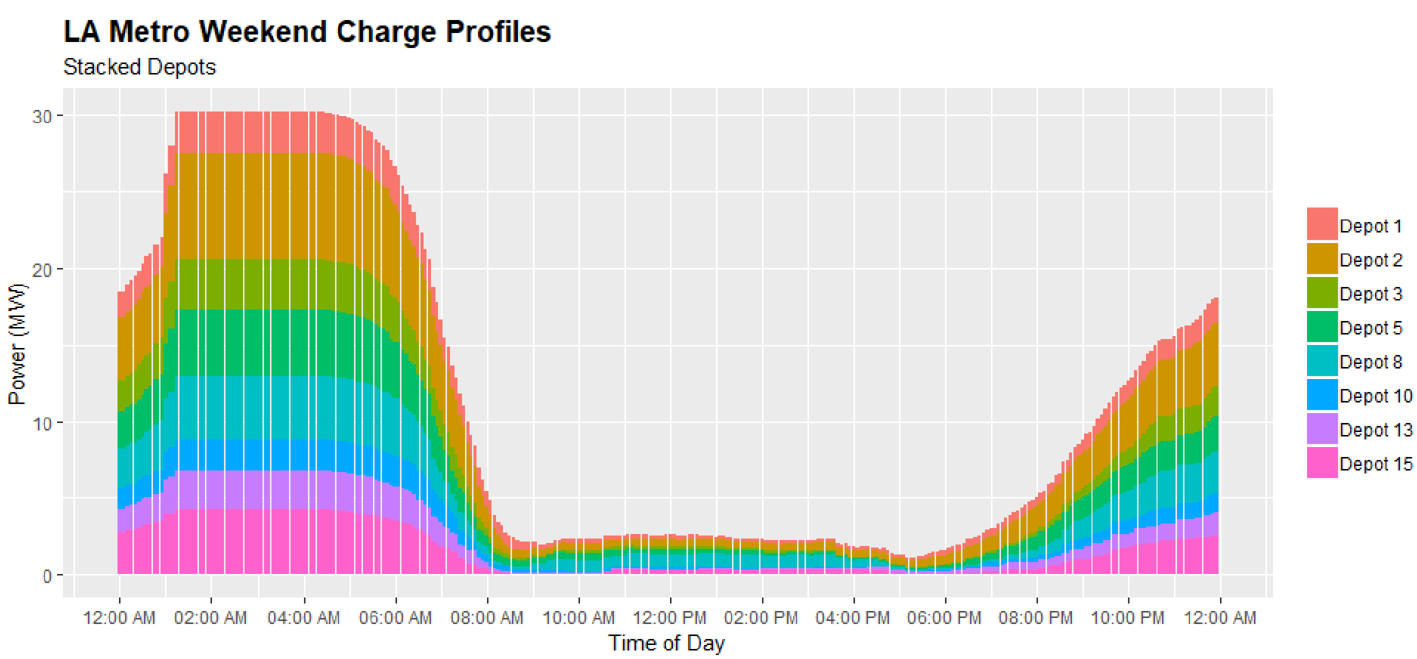


Figure 96. LA Metro transit buses weekend aggregate charging profiles by depot

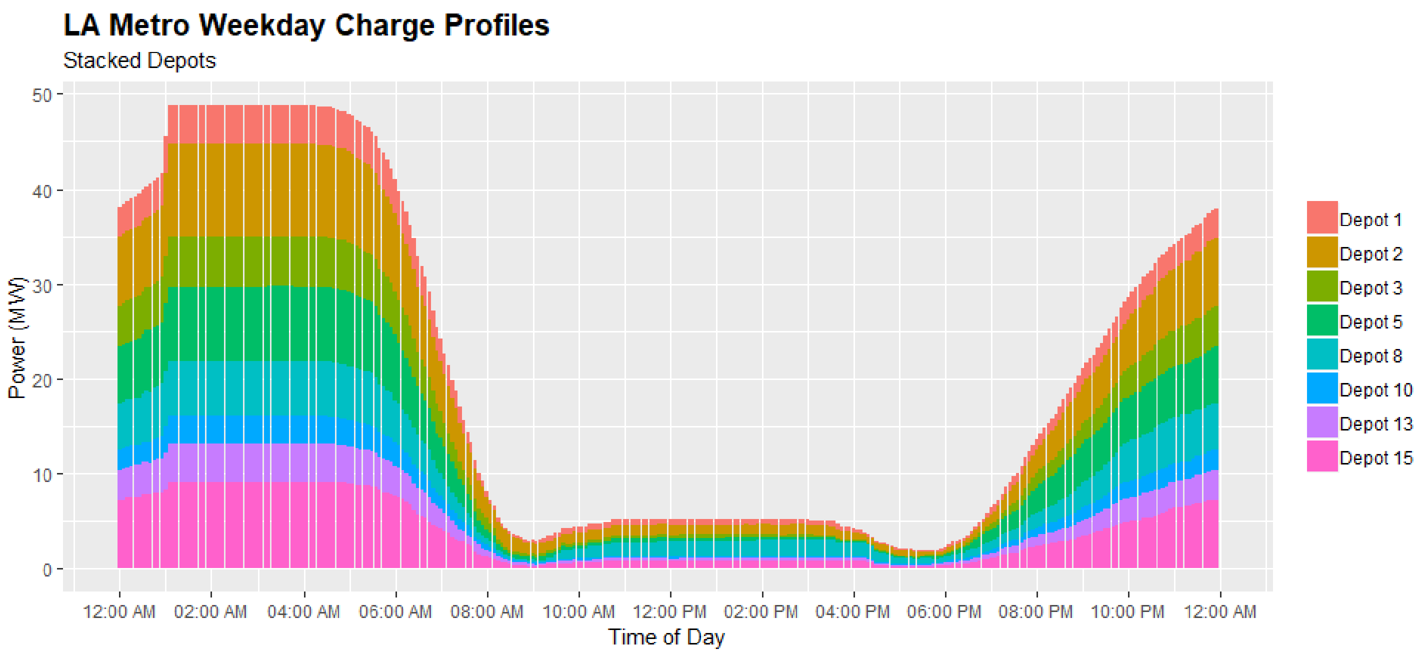


Figure 97. LA Metro transit buses weekday aggregate charging profiles by depot

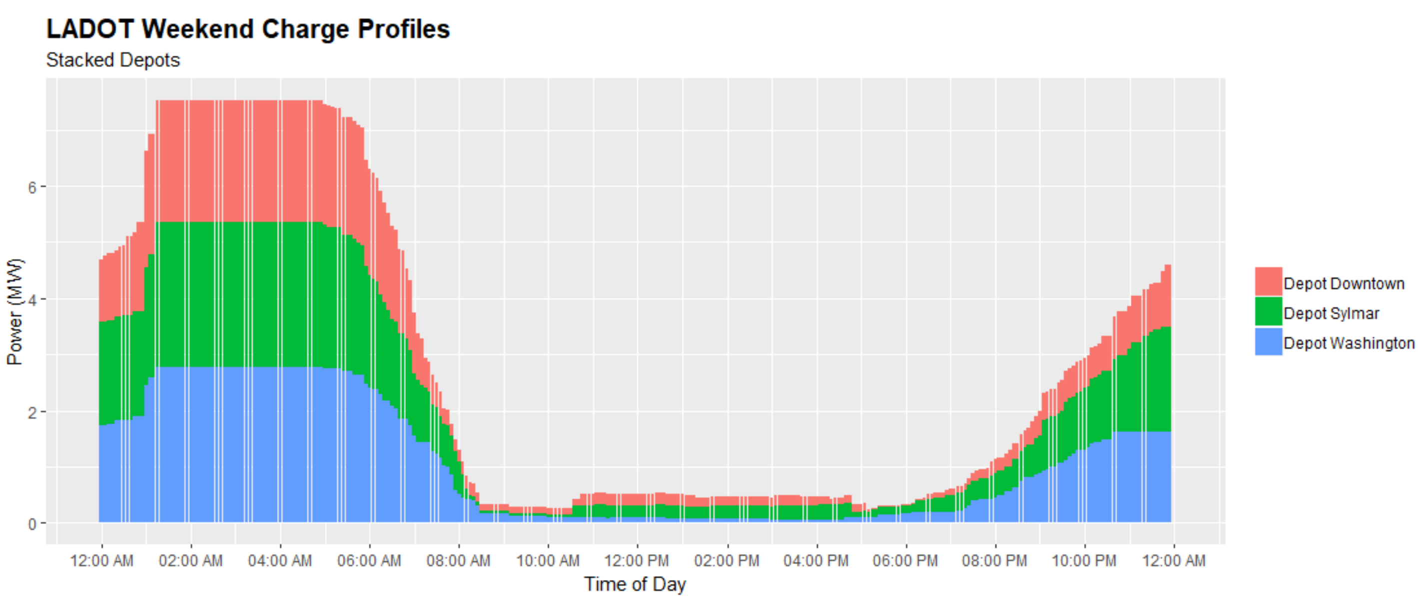


Figure 98. LADOT transit buses weekend aggregate charging profiles by depot

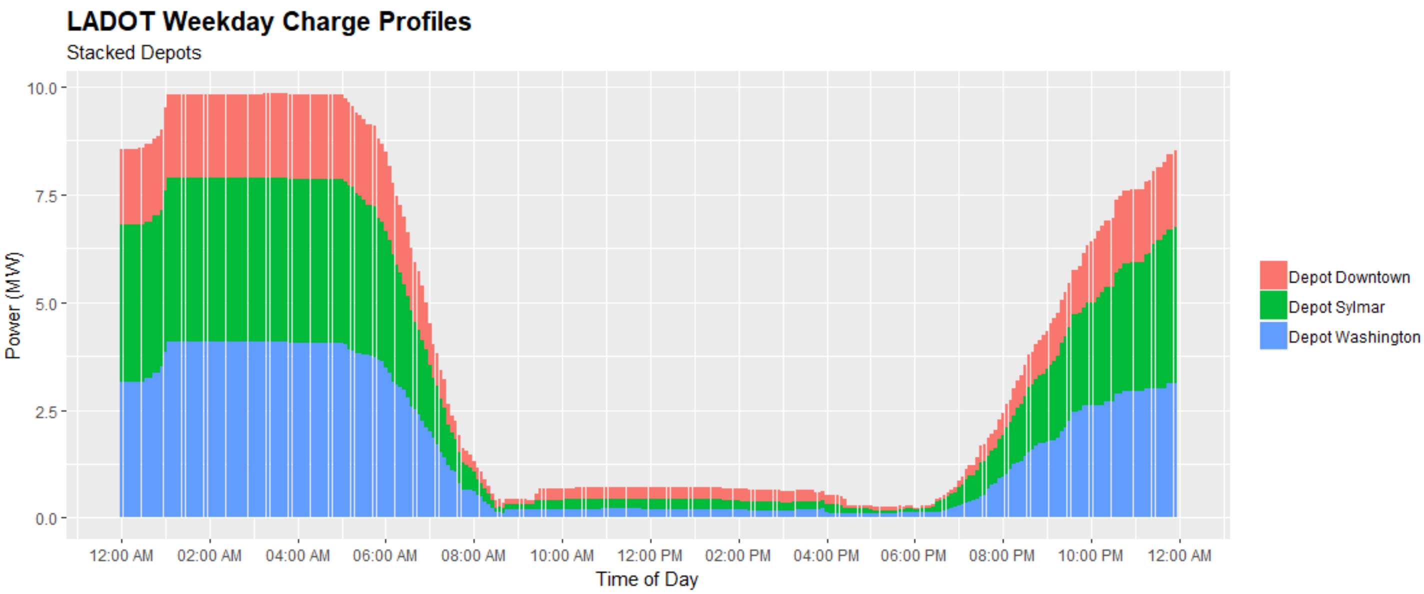


Figure 99. LADOT Transit buses weekday aggregate charging profiles by depot

Appendix F. Gap Agent Loads

Most of the 634,249 agents represented in the LA100 load projections are modeled as commercial buildings, residential buildings, or industrial and other commercial agents described in the main body of this report. The remaining 10,745 are classified as gap agents. For the purposes of LA100 solar adoption modeling, most (7,272) are classified as commercial, a few (648) are classified as industrial, and the remainder (2,825) are simply passed along as “gap.” The commercial gap agents represent commercial buildings that are not modeled in ComStock and are not associated with the airport, port, or movie and video production industry. The industrial gap agents consist mostly of “light industry” sites such as warehouses and other commercially/industrially active buildings not engaged in manufacturing. The “gap” gap agents were simply difficult to classify—the billing, assessor, and other GIS data sometimes conflicted or was otherwise not programmatically interpretable.

Gap agent annual energy use is pulled from the LADWP billing data at the agent level. Altogether, the gap agents account for about 2.78 TWh of annual load in 2015. We then apply the normalized 15-minute load shape that results from aggregating over all other LA100 commercial, industrial, or commercial and industrial loads to approximate each gap agent’s load shape, with the shape selection corresponding to whether the gap agent is classified as commercial, industrial, or “gap,” respectively. The growth seen across all other LA100 commercial, industrial, or commercial and industrial loads is also applied to the gap agents in out years. By doing this and by computing different aggregated load shapes for each projection-year, the gap agent model roughly evolves in a manner similar to the other models. That is, growth, energy efficiency, and electrification are accounted for in a very rough, averaged-over-the-sector way.

Appendix G. Water System Electricity Demand

G.1 Water Supply

The baseline water supply is fixed for each load projection, as it represents a proxy for current water supply. We refrain from defining a specific baseline year (e.g., 2012 versus 2015), as the water system varies significantly from year to year based on shifts in supply sources and demand, most notably due to extreme drought in recent years. Thus, we use “average weather year” assumptions for the baseline year in all three water supply projection cases. Baseline water supply by source is shown in Table 30.

Table 30. Water Supply Portfolio Assumptions for the Base Year

All data in acre-feet per year (AFY)

Water Supply Portfolio Component	Base Year Supply (AFY)
Los Angeles Aqueduct (LAA)	160,461
State Water Project (SWP): West	250,898
SWP: East	14,796
Colorado River Aqueduct (CRA)	48,295
Total Metropolitan Water District (MWD) Imports	313,988
Conservation	—
Local Groundwater	67,135
Indirect Potable Reuse (IPR)	0
Direct Potable Reuse (DPR)	0
Non-potable Reuse (NPR)	10,437
Stormwater Capture	0
Total Water Demand	**552,022**

Supply projections are made for a reference projection, which reduces, but does not eliminate non-LA Aqueduct (LAA) imports over the study horizon, and for the Moderate and High projections, which use the same localized supply portfolio that eliminates non-LAA imports by 2030, and significantly reduces LAA imports starting in 2035. The supply projection used for all three LA100 load projections is shown in Table 31 and Figure 100.

Table 31. Annual Water Supply Portfolio Assumptions for the Moderate and High Projections, in Terms of Absolute Water Volumes to Meet Total Projected Water Demand

All data in acre-feet per year (AFY)

Year	LAA	SWP-West	SWP-East	CAA	Total MWD Imports	Conservation	Local Groundwater	IPR	NPR	Stormwater Capture	Total Water Demand
Base Year	160,461	251,191	15,699	47,098	313,988	—	67,135	0	10,437	0	552,022
2020	275,700	60,344	3,772	11,315	75,430	125,800	112,670	0	19,800	2,400	611,800
2025	293,400	52,744	3,297	9,890	65,930	110,900	110,670	30,000	29,000	4,800	644,700
2030	244,430	0	0	0	0	111,600	106,670	142,000	39,000	9,200	652,900
2035	125,230	0	0	0	0	109,100	114,670	254,000	42,200	16,600	661,800
2040	137,130	0	0	0	0	108,100	114,070	254,000	45,400	17,000	675,700
2045	155,915	0	0	0	0	104,442	114,070	254,000	40,000	17,408	685,836
2050	167,385	0	0	0	0	102,842	114,070	254,000	40,000	17,826	696,123

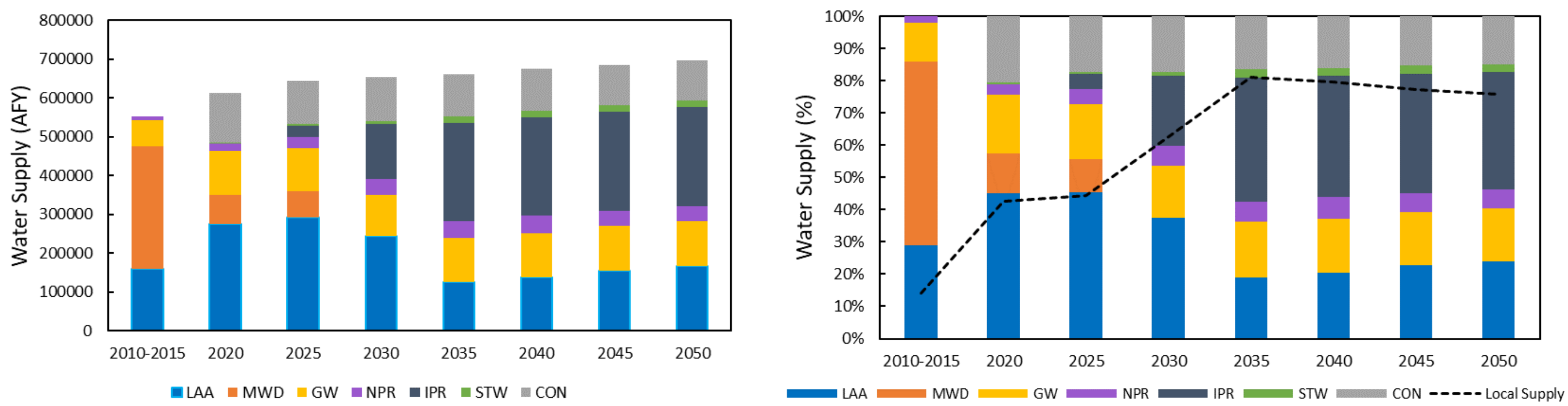


Figure 100. Annual water supply portfolio assumptions for Moderate and High projections, in terms of absolute water volumes to meet total projected water demand (left) and water supply sources as a percentage of total water demand (right)

LAA: Los Angeles Aqueduct, MWD: Metropolitan Water District Imports, CON: Conservation, GW: Local Groundwater, IPR: Indirect Potable Reuse, NPR: Non-potable Reuse Water Recycling, STW: Stormwater

Moderate and High assumptions held constant:

- **Total Water Demand:** Assumes an average weather year demand forecast detailed in "Exhibit ES-S" of LADWP's 2015 UWMP for 2020–2040 (LADWP 2016). For 2045 and 2050, water demand is assumed to grow by 0.3% per year.
- **Local Groundwater (GW):** We prioritized keeping local groundwater estimates consistent with LADWP's to reduce the total need for MWD imports and additional water recycling infrastructure, as local groundwater is presumably a relatively cost-effective source compared to other options. (See "Notable Assumptions" below for more discussion.)
- **Non-Potable Reuse (NPR):** We assume these values to be consistent with the reference projection, as the NPR potential has been extensively studied in Non-Potable Reuse Master Planning (Morrow et al. 2012) and the volumetric values were confirmed based on existing and planned customers.
- **Stormwater Capture (STW):** We assume these values to be consistent with the reference projection as LADWP has already studied stormwater capture potential in the context of Los Angeles-specific hydrology, which would be beyond the scope of possibility in this study.
- **Water Conservation:** Volumetric values reflect the conservation estimates for the reference projection per LADWP's suggestion, as LADWP's 2015 UWMP (LADWP 2016) has already assumed aggressive conservation levels.

Moderate and High assumptions that vary from the reference projection:

- **Los Angeles Aqueduct (LAA):** We assumed these values to be consistent with the reference projection across all three projections, until the point at which MWD imports were eliminated (due to very high water recycling assumptions). At this point, the LAA water supplies were reduced until total water demand was balanced.
- **Metropolitan Water District (MWD) Imports:** MWD imports were determined through reductions from the Reference projection according to increases in water local water supply resources, until they are eventually eliminated. The percentages of water delivered across the two branches of the State Water Project, and the Colorado River Aqueduct were adjusted to reflect the fractional breakdown in the reference year. In this projection, MWD imports are reduced to zero by 2030, mostly due to very aggressive water recycling projects.
- **Indirect Potable Reuse (IPR):** These projections mean to reduce MWD imports as much as possible (thus, maximizing "local" water supplies"), so aggressive water recycling is assumed, even though there are system-wide energy tradeoffs with this decision. These projections consider the recent announcement by the Los Angeles Mayor on February 21, 2019, to recycle 100% of the city's wastewater by 2035 by making a major investment in the Hyperion Water Treatment Plant that will increase the share of water recycling supply to 35% compared to today's 2% (Office of Los Angeles Mayor 2019). Additional assumptions are made to estimate the Hyperion-based advanced water treatment plant capacity. It is assumed that the nominal capacity of the advanced water treatment plant will be 200 MGD (or 224,000 AFY) based on current discharged flow of Hyperion (243,500 AFY in Exhibit 4C in LADWP's 2015 UWMP (LADWP 2016)), which eliminates about 92% of the discharged water and produces the equal amount of advanced level treated water that will be utilized for more groundwater replenishment projects in the Los Angeles Central Basin.

G.2 Annual Load Projections

The pre-efficiency annual load projections for each projection model-year are built up from the supply assumptions just described, the current and future water flows depicted in Figure 101, and the energy intensity estimates provided in Table 32. In addition, future LADWP water-related loads are impacted by on-site power generation plans and energy efficiency assumptions.

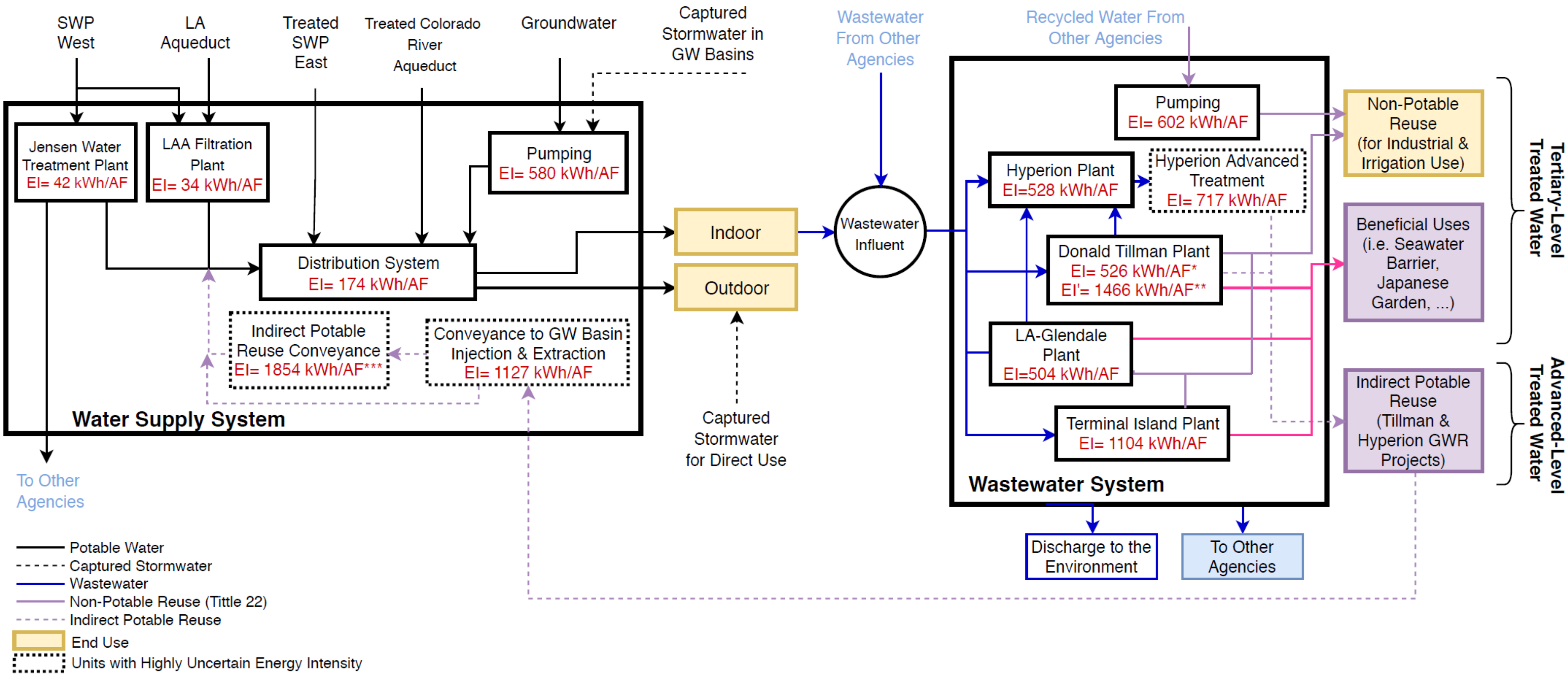
Figure 101 illustrates LADWP's urban water system and facilities. This figure details the water input and output streams across the system boundaries considered in this analysis, which includes the energy consuming facilities included within the "water supply system" and "wastewater system" boundaries. The water supply system includes groundwater pumping, water treatment and distribution of imported and local water supplies prior to consumption in end-use sectors, while the wastewater system includes energy-consuming activities related to wastewater and water recycling treatment and pumping. The figure illustrates advanced treatment processes that are only in the planning stages, in addition to current system components.

Total annual electricity consumption, $E_{y,s}$, of the entire water and wastewater system in year y, for projection, s, was calculated using Equation 1:

$$E_{y,s} = \sum_{n}^{N}(V_{n,y,s} \times EI_{n,y,s}) \qquad \text{(Equation 1)}$$

where $V_{n,y,s}$ represents annual volumetric water supply estimates and $EI_{n,y,s}$ (i.e., electricity per volume of water) refers to the corresponding average treatment and/or pumping energy intensity value(s). Subscripts n, y, and s refer to water portfolio category, year, and projection definition, respectively. The $EI_{n,y,s}$ assigned to each category of the water portfolio reflects the level of treatment and/or pumping required based on each water supply's distinct characteristics (e.g., initial water quality, required level of treatment to desired end-use quality, pumping network characteristics, etc.). $EI_{n,y,s}$, values utilized in Equation 1 are shown in Figure 101 and defined in Table 32.

It is notable that some of the facilities, such as the Jensen treatment plant and the Hyperion wastewater treatment plant, treat water that comes from Los Angeles and other adjacent cities, and therefore the total volume of treated water in these facilities is used as the basis to calculate the electricity demand. In other words, the total electricity consumed for treating the water in Jensen and Hyperion plants is considered in LADWP's load estimates, regardless of the eventual end-use destination of the water. As a result, the 2020–2040 wastewater influent flow projections from Exhibit 4D of LADWP's 2015 UWMP (LADWP 2016) and predicted 2045 and 2050 influent flows are used for calculating projected electricity usage (see Table 33). For Jensen Treatment plant influent flow projections, it is assumed that 17% of the total MWD supply is treated in this plant. Therefore, the average weather year total water supply from Tables 2 and 3 of MWD's 2015 UWMP (MWD 2016b) is used for the period of 2020 to 2040, and an annual growth of 0.5% is assumed for the following years through 2050. We used the same flow projections reported in Table 33 for all three projections.



* Average energy intensity before advanced treatment plant comes online.
** Average energy intensity after advanced treatment plant produces 30,000 AFY recycled water for groundwater replenishment project (i.e. after 2030).
It is calculated as [(74,000 AF*526 (kWh/AF)+30,000 AF*2318 (kWh/AF)]/74,000=1466 kWh/AF.
*** The indirect potable reuse conveyance energy intensity is only applied to Hyperion groundwater replenishment project. No energy intensity is considered for Tillman GWR project.

Figure 101. LADWP's urban water system boundaries and electricity use intensities

Table 32. Energy Intensity Estimates Utilized in Equation 1 for Water-Related Electricity Loads in LADWP's Electricity Service Territory

Water System Component	Supply or Wastewater Component	Energy Intensity, EIn1 (kWh/AF)	Sources and Notes
Treatment at LAA Filtration Plant	Supply	34	2016 UC Davis Study (UC Davis Center for Water-Energy Efficiency 2016)
Treatment at Jensen Plant	Supply	42	2015 UWMP (LADWP 2016)
Groundwater Pumping	Supply	580	2015 UWMP (LADWP 2016)
Tertiary Treatment for Non-Potable Reuse (for Industrial and Irrigation Use)	Supply	1150	2015 UWMP (LADWP 2016); This energy intensity is a weighted average of the energy used for pumping to customers and the incremental energy required to treat water from the tertiary level to advanced and additional treatment levels, as defined in Exhibit 12P of the 2015 UWMP.
Pumping Imported Recycled Water from Other Agencies	Supply	602	2015 UWMP (LADWP 2016); Additional pumping requirements to import recycled water from West Basin Municipal Water District.
Captured Stormwater for Direct Use for Outdoor Demand	Supply	0	No energy requirements for direct use of captured stormwater for irrigation purposes is assumed.
Stormwater Capture and Percolation into the Groundwater Basins (for Groundwater Recharge)	Supply	0	No treatment is assumed for stormwater capture. It is assumed no energy associated with percolation of stormwater into the groundwater basins.
Pumping Recharged Groundwater from Captured Stormwater	Supply	580	It is assumed that stormwater recharges groundwater levels and therefore, pumping this water to the surface is as energy intensive as traditional groundwater pumping.
Potable Water Distribution	Supply	174	2015 UWMP (LADWP 2016)
Hyperion Wastewater Treatment Basin	Wastewater	528	2016 UC Davis Study (UC Davis Center for Water-Energy Efficiency 2016); It includes the energy used to pump the wastewater in Hyperion basin and to treat the wastewater to secondary level.

Water System Component	Supply or Wastewater Component	Energy Intensity, EIn1 (kWh/AF)	Sources and Notes
Advanced Treatment in Hyperion Plant	Supply	717	Per LA Mayor's announcement on Feb 21, 2019, the city is planning to build an advanced water treatment facility to treat Hyperion's effluent flow for groundwater replenishment projects (Office of Los Angeles Mayor 2019). The energy intensity of this project is based on communication with LADWP on March 6, 2019.
Conveying, Injecting, and Extracting Indirect Potable Reuse (Groundwater Replenishment Project)	Supply	1127	This is an aggregate energy intensity for conveyance (81 kWh/AF), injection (523 kWh/AF) and extraction (523 kWh/AF) that is reported by LADWP for Hyperion GWR project in our communication with LADWP on March 6. Note that we used this energy intensity for all GWR supply (i.e., from both Tillman water reclamation plant and Hyperion wastewater treatment plant). This may create uncertainty, but no better estimates of energy intensity were found regarding future projects.
Conveying IPR from Central Basin to LAA Filtration Plant (Hyperion GWP project)	Supply	1854	Energy intensity of Hyperion GWR project is obtained based on our communication with LADWP on March 6.
Conveying IPR from San Fernando Valley to LAA Filtration Plant (Tillman GWP project)	Supply	0	Given the vicinity of San Fernando Valley basin from LAAFP, we assume there is no significant energy intensity associated with this conveyance.
Terminal Island Wastewater Treatment Basin	Wastewater	1104	2016 UC Davis Study (UC Davis Center for Water-Energy Efficiency 2016); It includes energy used to treat and pump the wastewater in Terminal Island basin. This plant has advanced treatment process.
Donald Tillman Wastewater Treatment Basin	Wastewater	526 (before 2030) 1466 (after 2030)	2016 UC Davis Study (UC Davis Center for Water-Energy Efficiency 2016); It includes energy used to pump and treat the wastewater in Donald Tillman basin. The plant is planning to build advanced treatment capabilities; therefore, its EI is predicted to increase. The plant's future EI is calculated by combining its current EI and advanced water treatment EI from Terminal Island plant by influent and advanced treatment flowrates:

Water System Component	Supply or Wastewater Component	Energy Intensity, EIn1 (kWh/AF)	Sources and Notes
			$\frac{74{,}000\ AF*526\left(\frac{kWh}{AF}\right)+30{,}000\ AF*2318\left(\frac{kWh}{AF}\right)}{74{,}000\ AF} = 1466\ kWh/AF$
Advanced Treatment in Donald Tillman Wastewater Treatment Plant	Supply	0 (before 2030) 940 (after 2030)	Because of the lack of information on the energy intensity of the planned advanced water treatment facility in Tillman, it is assumed that advanced water treatment and pumping have a total energy intensity of 940 kWh/AF (1466-526=940 kWh/AF), which is used for 2030 and later years.
LA-Glendale Wastewater Treatment Basin	Wastewater	504	2016 UC Davis Study (UC Davis Center for Water-Energy Efficiency 2016); It includes energy used to treat and pump the wastewater in the LA-Glendale basin. Although LADWP's share is 50% of the treatment capacity of the facility, all electricity consumption in this plant is accounted toward LADWP's power demand.

[1] All projections assume energy efficiency improvements, but these adjustments are made after total annual electricity loads are calculated, as described below. It is understood that there will be variability, as well as uncertainty, across these estimates, but the final projected water-related loads are not very sensitive to fluctuations in these estimates.

The energy intensity of recycled water treatment is highly variable based on the quality of incoming water versus the desired quality of final water products. The incremental electricity consumption to treat the water from tertiary to greater than the tertiary level (i.e., advanced treatment) is allocated to the water supply system when that water is used to offset potable water demand, even if the energy consumption happens at the location of water reclamation plants. In addition, the electricity consumption for pumping recycled water to NPR customers, as well as the energy used for conveying, injecting, and extracting IPR in groundwater replenishment projects, is allocated to water supply energy consumption (see Table 32). As these projects are in the planning stages, there is uncertainty with the energy consumption associated with all stages of groundwater replenishment projects, but our assumptions have been guided by LADWP.

Table 33. Influent Projection for MWD's Jensen Treatment Plant and LASAN's Wastewater Treatment Plants

Year	Hyperion Plant	Terminal Island Plant	Donald Tillman Plant	LA-Glendale Plant	Jensen Plant
2014–2015	294,000	13,700	38,000	13,500	302,549
2020	287,000	10,700	54,000	30,500	312,633
2025	361,000	18,700	74,000	18,500	322,382
2030	377,000	19,700	76,000	18,500	329,274
2035	393,000	19,700	79,000	18,500	337,510
2040	410,000	19,700	81,000	18,500	344,065
2045	410,000	19,700	81,000	18,500	352,666
2050	410,000	19,700	81,000	18,500	361,483

Note that all water at the reclamation plants directly supplying recycled water to LADWP is treated to at least a tertiary level regardless of environmental use or end-use consumption, so the energy cost to treat the water to this level is considered a sunk energy cost because the water would be treated whether it offsets potable use or not. However, the amount of energy used for treating water to a higher quality level than tertiary (i.e., in advanced treatment plants) is allocated to recycled water energy use, and therefore is a water supply-related load (because it offsets potable water use).

Appendix H. "Other" Load Modeling Details

H.1 Outdoor Lighting

The gap model for outdoor lighting describes the electricity used by street lights and parking lot lights that is categorized in the LADWP 2017 Load Forecast as one of the "Other" loads (LADWP, 2017a). This lighting is generally installed by or in cooperation with the city and is unmetered. (In contrast, buildings' and industrial sites' exterior lighting that is metered along with other customer load is captured in the sector models described above.) Based on conversations with LADWP, the load forecast assumes that both outdoor lighting loads and Owens Valley loads have been essentially flat and of approximately the same magnitude for the last few years and will remain so over the coming decade. Thus, a first estimate of outdoor lighting energy use for 2017 would be one half of 255 GWh, or 128 GWh. However, more efficient technologies (e.g., LED fixtures) have been installed in recent years and it is LADWP's understanding that the load forecast has not kept up with those changes (somewhat understandably because the streetlights are unmetered). LADWP internally estimates outdoor lighting energy use to have been 80 GWh and 90 GWh in 2017. We take 85 GWh/year as our central estimate for this end use in model year 2015.

We had two choices for load shape. Hale et al. (2018) estimates an outdoor lighting load shape for Los Angeles County for meteorological year 2012. The LADWP load research data (LRD) also provides an outdoor lighting load shape for 2012. These two options, both scaled to contain 85 GWh of energy over the year, are plotted for a representative week in Figure 102. Overall they show good agreement. We use the 2012 LRD Shape in the LA100 study, to be consistent with LADWP modeling.

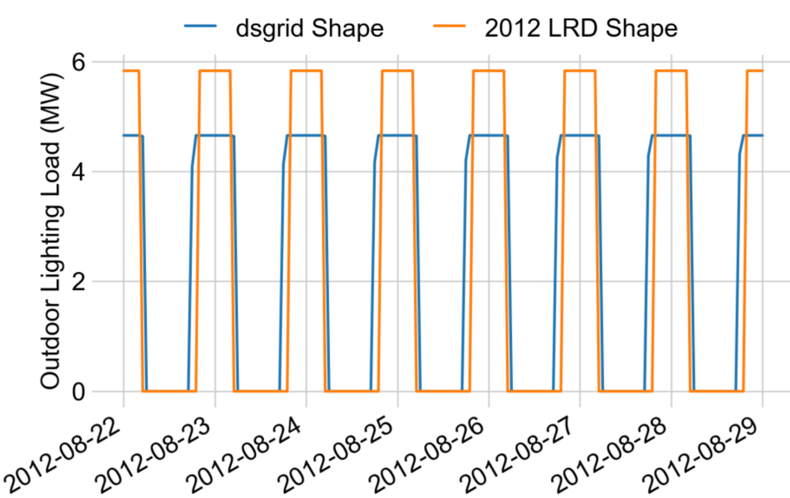


Figure 102. Outdoor Lighting load shapes from the demand-side grid (dsgrid) model (Hale et al. 2018), and LADWP 2012 load research data (2012 LRD)

Based on communication with LADWP, we assume that outdoor lighting is likely to continue to become more energy efficient. We therefore make different efficiency assumptions per load projection. For the Stress projection we assume that outdoor lighting will continue to require 85 GWh/yr of electricity for all study years. In the Moderate and High projections we assume 0.5% and 1% efficiency is achieved year-over-year, respectively. These assumptions result in the annual energy use assumptions shown in Table 34. We retain the load shape used in the baseline year in all cases.

Table 34. Outdoor Lighting Annual Energy Use by Load Projection (GWh)

Model Year	Moderate	High	Stress
2015	85.0	85.0	85.0
2020	82.9	80.8	85.0
2025	80.8	76.9	85.0
2030	78.8	73.1	85.0
2035	76.9	69.5	85.0
2040	75.0	66.1	85.0
2045	73.1	62.9	85.0

H.2 Owen's Valley Loads

In the LADWP 2017 Load Forecast, Owens Valley is one of the "Other" loads (along with outdoor lighting) (LADWP, 2017a). Per conversations with LADWP, Owens Valley load is approximately 135 to 145 GWh/year and holding steady. The 2012 load research data (LRD) contains a timeseries for Owens Valley with about 148 GWh annual load. NREL also submitted a data request, dist_35, which provides more precise timeseries for Owens Valley. The 2015 data contains about 137 GWh in 2015. We therefore use this amount of annual energy for our baseline 2015 year, combined with the dist_35 load shape from 2012 (to align with the study meteorological assumptions). For reference, Figure 103 and Figure 104 show examples of Owens Valley load shapes from the 2012 LRD and data request dist_35, both scaled to contain 137 GWh of energy.

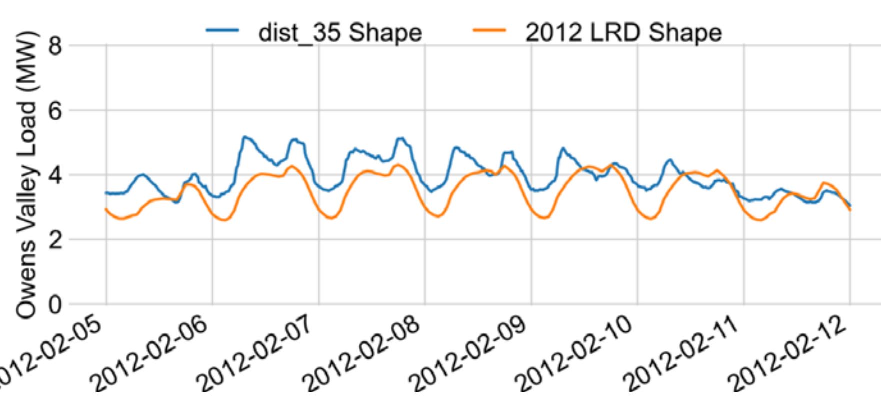


Figure 103. Owens Valley load shapes from the LADWP 2012 load research data (LRD) and the LA100 dist_35 data request, both scaled to match 2015 annual demand (137 GWh): Example of a winter week

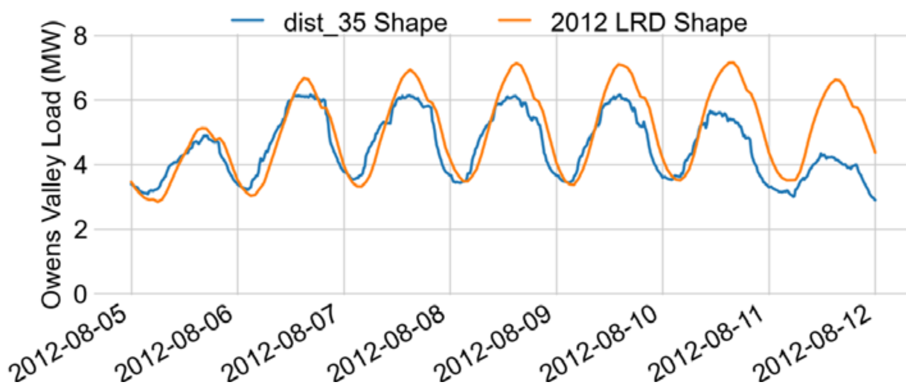


Figure 104. Owens Valley load shapes from the LADWP 2012 load research data (LRD) and the LA100 dist_35 data request, both scaled to match 2015 annual demand (137 GWh): Example of a summer week

Based on communication with LADWP, Owens Valley load is being assumed constant for all projection-years.

Appendix I. Agent Generation

In LA100, we use the agent as our base level of decision making and the smallest geographic resolution in which we represent our loads data. The term “agent” can be understood by the colloquial definition of a property: a single-family dwelling, a multifamily apartment complex, an office park, a school campus, etc. Agents are often called parcels; however, they are not exactly the same thing. The distinction between the two, though subtle and arbitrary for most, should be made. Properties are often made up of one or more parcels, often depending on how land was bought or sold over time. Because buildings straddle multiple parcels and properties are often made up of one or more parcels, we use the agent, a model-specific geographic unit that best represents properties, as our base geographic unit for analysis. A section below describes how agents were generated and classified for dsgrid, dGen, and distribution modeling.

To generate agents, we identify contiguous properties with parking lots or electricity generating buildings (i.e., buildings that have premise IDs in the LADWP Customer Billing Database), that have the same ownership (i.e., the same Assessor’s Parcel Number) and/or the same land parcel (i.e., the same Parcel Identification Number), where no single building or parking lot could belong to more than one agent. To do this, we rely on a NetworkX Graph representation of various data sets (Table 35) which allowed us to generate contiguous land units from shared nodes and edges within the data. The end result is the agent which we use to represent properties in the LA100 study.

Table 35. Agent Generation Data for Graph

Data Layer	Source	Comments
Premises	Geolocated addresses of premises, or customers. Derived from LADWP 2016 Customer Billing Data provided in the OTC study and a premise-to-address lookup table provided in OTC and as part of request bldg_4.	Used to identify electricity generating properties
Parking Lots	Commercial, Industrial, and Government Parking lots as of 2104 from the LA County GIS Portal.	Used in addition to premises to identify agents. Agents with parking lots and without buildings or premises are not modeled in any of the load models; they are strictly used in dGen as “parking_lot_only” agents.
Building Footprints	LARIAC 2014 LiDAR derived data obtained from LA County GIS Portal.	Used to identify properties with building to model in the dsgrid building models.
APN	2016 APN parcel geometries from LA County GIS Portal.	Used to identify properties of the same ownership
Parcels	Official 2018 LA city parcels from LA’s Bureau of Engineering.	Used to identify parcels of land

I.1 Agent Classification

With agent geometries established, we then classify agents by sector for use in the LA100 study. Sectoral classification is performed differently for different models. For the dsgrid load modeling, sectors are classified based on the Title 24 building energy codes,[85] however, for dGen and other standard representations of the data, we classify sectors based on their common definitions. For example, multifamily high-rise buildings taller than 40ft (as identified using the LAR-IAC data set[86]) are modeled in LA100 by the commercial buildings model (ComStock), however, dGen represents these land uses as residential. Table 36 details the agent sectoral classifications for each building or land use type for load modeling compared to grid modeling.

Table 36. Sector Classifications for Load Modeling vs. dGen Modeling

Class	Model	dGen Class	Class	Model	dGen Class
10 to 19 Unit	res	res	Chemical Manufacturing	ind	ind
20 to 49 Unit	res	res	Computer and Electronic Product Manufacturing	ind	ind
2 Unit	res	res	Dairy Product Manufacturing	ind	ind
3 or 4 Unit	res	res	Electrical Equipment, Appliance, and Component Manufacturing	ind	ind
50 or more Unit	res	res	Fabricated Metal Product Manufacturing	ind	ind
5 to 9 Unit	res	res	Flat Glass Manufacturing	ind	ind
Residential Mixed	res	res	Food Manufacturing	ind	ind
Single-Family Attached	res	res	Foundries	ind	ind
Single-Family Detached	res	res	Fruit and Vegetable Preserving and Specialty Food Manufacturing	ind	ind
Assembly	com	com	Furniture and Related Product Manufacturing	ind	ind
Education: Community College	com	com	Glass Container Manufacturing	ind	ind
Education: Primary School	com	com	Glass Product Manufacturing Made of Purchased Glass	ind	ind
Education: Secondary School	com	com	Grain and Oilseed Milling	ind	ind
Education: University	com	com	Gypsum Product Manufacturing	ind	ind
Grocery	com	com	Industrial Gas Manufacturing	ind	ind
Health/Medical: Hospital	com	com	Iron Foundries	ind	ind

[85] Title 24 classifies residential buildings with four or more stories as high-rise and thus commercial, as opposed to residential, buildings.
[86] "Los Angeles Region Imagery Acquisition Consortium," County of Los Angeles, https://lariac-lacounty.hub.arcgis.com.

Class	Model	dGen Class	Class	Model	dGen Class
Health/Medical: Nursing Home	com	com	Leather and Allied Product Manufacturing	ind	ind
Lodging: Hotel	com	com	Light Truck and Utility Vehicle Manufacturing	ind	ind
Lodging: Motel	com	com	Machinery Manufacturing	ind	ind
Manufacturing Light Industrial	com	com	Mineral Wool Manufacturing	ind	ind
Office: Large	com	com	Miscellaneous Manufacturing	ind	ind
Office: Small	com	com	Motion Picture and Video Industries	ind	com
Residential Multifamily	com	res *	Newsprint Mills	ind	ind
Restaurant: Fast-Food	com	com	Nitrogenous Fertilizer Manufacturing	ind	ind
Restaurant: Sit-Down	com	com	Nonferrous Metal (except Aluminum) Production and Processing	ind	ind
Retail: Multistory Large	com	com	Nonmetallic Mineral Product Manufacturing	ind	ind
Retail: Single-Story Large	com	com	Other Pressed and Blown Glass and Glassware Manufacturing	ind	ind
Retail: Small	com	com	Other Wood Product Manufacturing	ind	ind
Storage: Conditioned	com	com	Paperboard Mills	ind	ind
Storage: Unconditioned	com	com	Paper (except Newsprint) Mills	ind	ind
Gap Agents: Commercial	gap	com *	Paper Manufacturing	ind	ind
Gap Agents: Industrial	gap	ind *	Petroleum and Coal Products Manufacturing	ind	ind
Gap Agents: Gap	gap	gap	Petroleum Refineries	ind	ind
Gap Agents: Water Supply Plant	gap	gap	Pharmaceutical and Medicine Manufacturing	ind	ind
Gap Agents: Wastewater Treatment Plant	gap	gap	Plastics Material and Resin Manufacturing	ind	ind
Gap Agents: Pumping Station	gap	gap	Printing and Related Support Activities	ind	ind
Aerospace Product and Parts Manufacturing	ind	ind	Secondary Smelting and Alloying of Aluminum	ind	ind
Aircraft Manufacturing	ind	ind	Semiconductor and Related Device Manufacturing	ind	ind
Air Transportation	ind	com *	Steel Product Manufacturing from Purchased Steel	ind	ind

Class	Model	dGen Class	Class	Model	dGen Class
All Other Basic Organic Chemical Manufacturing	ind	ind	Support Activities for Air Transportation	ind	com *
Aluminum Foundries (except Die-Casting)	ind	ind	Support Activities for Mining	ind	ind
Aluminum Sheet, Plate, and Foil Manufacturing	ind	ind	Support Activities for Water Transportation	ind	com *
Animal Slaughtering and Processing	ind	ind	Textile Mills	ind	ind
Asphalt Paving Mixture and Block Manufacturing	ind	ind	Textile Product Mills	ind	ind
Asphalt Shingle and Coating Materials Manufacturing	ind	ind	Transportation Equipment Manufacturing	ind	ind
Automobile Manufacturing	ind	ind	Veneer, Plywood, and Engineered Wood Product Manufacturing	ind	ind
Beverage Manufacturing	ind	ind	Water Transportation	ind	com *
Cement Manufacturing	ind	ind			

Similar to the sector classification, the LA100 model requirements for agents also vary. Listed below are the different requirements for agents across dsgrid, dGen, and distribution models:

- Has a building: required for building load models (Comstock and Restock) and for L1&L2 EV charging
- Has a premise ID: required by gap agent modeling
- Has a building or a premise ID: required by industrial and large commercial modeling
- Has a parking lot: used for dGen parking lot agents and DCFC charging stations
- Has a building or a parking lot: required by dGen
- Has electric load or a distributed energy resource (EV or DPV): required by distribution models

I.2 Agent Attributes

The final step in the agent generation process is to establish core agent attributes to use in load and grid modeling. Table 37 lists the key agent attributes that were calculated in this study.

Table 37. Core Agent Attributes

Data Theme	Attribute	Source[a]	Comments
Agent Identification	agent_id		Unique ID for agents
Sector Classification	Load Class	Derived from LA County's 2017 Tax Assessor data, LADWP's 2016 Customer Billing data,	
	Load Subclass		
	Load Subclass Detail		
	dGen Class		

Data Theme	**Attribute**	**Source**[a]	**Comments**
	dGen Subclass	and LA100 dsgrid models	
	dGen Agent Parking Lot Type		dGen modeling subtype information used to differentiate parking lot agents versus agents without parking lots
	Single Family or Multifamily Flag		Flag for dGen
Building Information	Building (True/False)	Derived from LARIAC 2014 LiDAR generated building footprints obtained from the LA County GIS Data Portal	Flag for if the premise has a building or not
	Building Count		
	Building Rooftop Area		
Developable Rooftop Information for DPV	Developable (True/False)	Derived from dGen technical potential analysis	Flag for if the agent has a developable building rooftop for DPV or not
	Developable Plane Count		Number of developable roof surfaces; used in dGen rooftop technical potential
	Total Rooftop Developable Area		
	Total Rooftop Developable Capacity		
	Annual Sum Developable Rooftop Generation		
	Annual Developable Rooftop Hourly Capacity Factor Profile (array)		
Parking Lot Information for DPV	Parking Lot (True/False)	Derived from dGen technical potential analysis[b]	
	Parking Lot Developable (True/False)		
	Total Parking Lot Area		
	Total Parking Lot Capacity		
	Annual Sum Parking Lot Generation		
	Annual Parking Lot Hourly Capacity Factor Profile (array)		

Data Theme	Attribute	Source[a]	Comments
Geography	Latitude	GIS	
	Longitude	GIS	
	Block FIPS	2017 American Community Survey	
	Tract FIPS	2017 American Community Survey	
Parcel Tax Information	Property Area	Derived and aggregated to the agent-level from LA County's 2017 Tax Assessor Data	
	Land Value		
	Structure Value		
	Vintage		Used in agent allocation; Used in dGen analysis
	Number of Units		Used in agent allocation
	Assessed Area		
Census Tract Demographics	Tract Median Income	REPLICA[c]	Used for neighborhood demographics in dGen adoption simulations
	Percent of Single-Family Owner Occupied Residential Households in Tract		
	Percent of Single-Family Renter Occupied Residential Households in Tract		
	Percent of Multifamily Owner Occupied Residential Households in Tract		
	Percent of Multifamily Owner Occupied Residential Households in Tract		
Customer Billing	Customer Billing Annual Average Consumption	LADWP 2017 Customer Billing Data	Used in load agent allocation
	Customer Billing Annual Sum Consumption		Used in load agent allocation

Data Theme	Attribute	Source[a]	Comments
Historical DPV	Historical Solar Installed (True/False)	Derived and aggregated to agents from LADWP Historical DPV Installation (data request = dist_2)	Used in training the dGen adoption model
	Historical Solar Date Installed		
	Historical Solar Installed Nameplate Capacity		
	Historical Solar Installed CEC Rating		
Climate	Building Climate Zone	California Energy Commission	Used in load agent allocation
Environmental Justice	CalEnviroScreen Score	California Office of Environmental Health Hazard Assessment	Used for dGen and Environmental Justice analysis
	Environmental Justice Tract (True/False)		

[a] All agent attributes are derived from the source listed in this table.
[b] Parking lot attributes derived from a data set of 2014 commercial, industrial, and government parking lots in LA. Data downloaded from the LA County GIS Data Portal.
[c] Meghan Mooney and Ben Sigrin, "Rooftop Energy Potential of Low Income Communities in America REPLICA," (NREL, 2018), https://dx.doi.org/10.7799/1432837.

Appendix J. Agent Load Allocation

The LA100 agent load allocation is a key aspect of dsgrid coordination. Because dsgrid is a confederation of many individual load models, there are natural differences in geographic resolution of the output load data. But for LA100, we need to have a single geographic unit of analysis for modeling cohesion purposes—therefore we need to converge load modeling efforts at a single geographic scale. That is what the load allocation process does. More specifically, the LA100 agent load allocation is a process whereby we allocate modeled load to our finest LA100 geographic unit—the agent (see Agent Generation for definition). From here, all other load aggregations are performed.

This allocation process is made up of three different methods that rely on different data and assumptions (Figure 105). The residential and commercial building allocation process is the most complex. That process allocates all of the sample weight ascribed to ResStock and ComStock modeled sample buildings to the agent-building level via solving two mixed-integer quadratic programs that seek to match sample building with actual building characteristics (e.g., building type, size, vintage). More details are provided below. The industry and gap modeling is already done at the agent-level. As such, there is no additional work to do in this step (shown in the middle of Figure 105), but it is the case that while some premises are matched to their exact AMI data, others must use average load shapes bootstrapped from the overall LADWP AMI data set. Hand-placement of water system loads (water supply treatment plants, wastewater treatment plants, and pumping stations) was also required. The only industrial and gap loads not explicitly assigned to agents are outdoor lighting and Owens Valley. Their geographic allocation is described below. Finally, the allocation of EV loads is done differently for bus, DCFC and L1/L2 charging. Bus charging is assigned to already-existing depot locations. DCFC station and L1/L2 charging loads are assigned to agents based on filtering, randomization, and sizing processes, details for which are provided below.

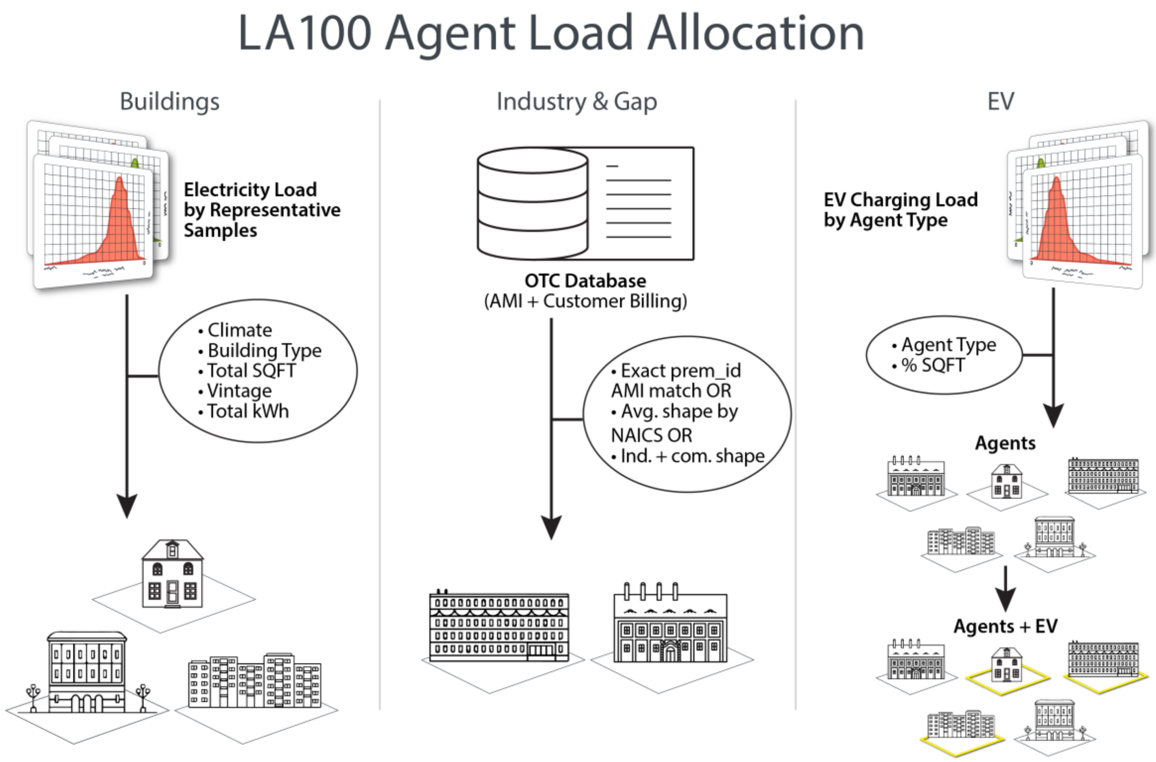


Figure 105. LA100 agent load allocation methods

J.1 Commercial and Residential Building Load Allocation

In the LA100 study, residential and commercial building loads in the aggregate are expressed as sets of ResStock and ComStock *samples* along with their *sample weights*. As described in more detail elsewhere, those samples are constructed to (a) reflect Los Angeles's current building stock and (b) how the stock might evolve under the LA100 load projections. Because ResStock and ComStock employ a sampling methodology, the data they output is not explicitly geolocated, however, some of the input data used to ensure that the models reflect LA's current building stock is geolocated. We are therefore able to construct an allocation process that assigns all of the ResStock and ComStock sample weight to specific geographic locations by minimizing the distance between the current characteristics of those locations (e.g., energy use, number of buildings or housing units, building vintage, building or housing unit size) and the characteristics of the individual model samples.

The allocation process consists of two stages. In the first stage, all of the modeled buildings' sample weight is assigned to specific *subproblems*, where a subproblem is defined as all of the residential or all of the commercial buildings connected to a specific distribution station (DS), or one of the industrial stations (IS) that are connected to the same receiving station (RS). In the second stage, the subproblems are solved by assigning the subproblems' sample weight to specific agent-buildings.

In both stages, we rely upon certain characteristics that we know for both the current, actual building stock and our modeled building samples. The characteristics we use are slightly different for residential and commercial buildings and are of different levels of importance depending on the sector.

The characteristics used for each sector are listed in Table 38. Numeric data are matched based on weighted relative errors computed for each geographic resolution of interest (i.e., agent-building, DS/all IS on the same RS by sector, RS by sector, overall DS [annual_energy only], and overall RS [annual_energy only]). Categorical data are matched based on assumed distances between categories. In Stage 1 the corresponding match distance is computed by comparing the expected distribution of categories against the allocated distribution. A feasible pathway from the expected to the allocated distribution is computed for each subproblem (DS/all IS on the same RS by sector) or aggregate (RS by sector) in terms of the amount of allocated weight that corresponds to (let's say) `category_2` that could be assumed to have been reassigned from an expected `category_1`. Then the match distance attributable to the particular geography and categorical dimension is computed by multiplying the reassigned weight by the assumed distance between `category_1` and `category_2`, summing over all such combinations, and then dividing the result by the total amount of weight expected for the given geography. For Stage 2 the comparison is much more direct—each agent-building has a single category (perhaps "Unknown") assigned for each dimension, and so the distance between the expected and allocated category can be accounted for directly.

Table 38. Data Dimensions Used to Allocate Modeled Building Loads to Specific Locations in the City of Los Angeles

	Residential[b]		**Commercial**	
Dimension Type	**Dimension**	**Weight**	**Dimension**	**Weight**
numeric[a]	annual_energy	1.0	annual_energy	100.0
	num_units[a]	1.0	num_units[c]	0.1
			com_sqft[a]	1.0
categorical[d]	climate_zone	1.0	climate_zone	1.0
	res_building_type	1.0	com_building_type	10.0
	res_vintage	1.0	com_vintage	0.1
	res_unit_sqft	1.0	com_sqft_bin	0.001
	res_kwh_per_unit	1.0	com_kwh_per_sqft	0.1

[a] The numeric dimensions in bold are non-zero for all geo-located agent-buildings. (All characteristics are non-zero for all modeled building samples.) These characteristics are therefore used as weights for determining categorical data distributions, and for weighting the per-subproblem or per-agent-building allocation distances between expected characteristics and what modeled sample loads are assigned.

[b] All numeric characteristics for residential buildings are measured per housing unit.

[c] For commercial buildings, a whole building counts as a unit. Commercial number of buildings/units is de-emphasized in our matching because the ComStock model is normalized on floor area, not number of buildings. The dimensional weights listed for commercial buildings are more complex than those listed for residential buildings because the allocation for commercial buildings had to be re-computed to improve the match between RS-level historical and modeled annual energy.

[d] The weights shown here for the categorical dimensions are, in the Stage 1 problem, divided by the number of categories that describe that dimension squared, because in that case there are that many (number of categories squared) relative distances computed for each dimension, but it is not the case that a dimension with more categories is necessarily any more important to match than a numerical dimension or a different categorial dimension.

J.2 System-Level Gap Loads Allocation

Street lighting and Owen's Valley loads are modeled at the LADWP-level, rather than being assigned to agents. Nonetheless, these loads must be electrically located for those models that need to capture them. To this end, Owen's Valley loads are assigned to the DS-168 Distribution Station for the purpose of bulk-level power system modeling. Street lighting is an unmetered, small load spread throughout LADWP. We therefore assign this to Receiving Stations, proportional to all other RS-level loads and provide these data to both the bulk power system modelers.

J.3 DCFC Load Allocation

DCFC charging station loads are randomly assigned to commercial and industrial parking-lot agents that are within 0.3 miles of an existing 34.5-kV distribution line. This procedure assumes that existing parking lots near the 34.5-kV system are the best candidate locations for DCFC charging infrastructure investments. Charging load is assigned proportionally to parking lot area. We keep selecting acceptable locations until all DCFC charging loads have been allocated.

J.4 L1 and L2 EV Load Allocation

L1 and L2 EV load is allocated to agents based on associated building type, with simulated home charging loads assigned to single-family and multifamily dwelling agents, workplace charging loads assigned to office and industrial agents, and public charging loads assigned to remaining agents. Once an agent has been selected, we assign a number of simulated EVs proportional the assumed share of EVs within the ZIP code and the building's floor area. Eligible agents are randomly chosen until all of the L1 and L2 charging loads have been assigned.

Appendix K. Agent to Grid Allocation

Once we have all loads allocated to agents, we then need to tag these agents to the LADWP electric grid in order for dsgrid to provide various geographic representations of loads for each output grid model. The first step in this process involves tagging agents to secondary transformers. We used LADWP's Customer Address to Transformer System (CAtTs) data (data request = dist_20) to map 95% of the agents to distribution transformers. We then followed the procedure below to check and correct possible erroneous mappings as well as to assign the remaining 5% of the agents to transformers:

1. Re-assign any connections with load to distribution transformer distances > 1,000 feet
2. Re-assigned mapping for some of the extremely overloaded transformers (>3x peak loading):
3. Re-assign top offenders to nearby transformers with capacity, if possible
4. For agents missing connections, use a nearest neighbor method, assigning agents to the nearest transformers within 1,000 feet that have available capacity (accounting for simultaneity).

All assignments used non-coincident agent peak loads and assumed a simultaneity factor of 0.4. We kept multiple agent-to-transformer connections because we had no solid methodology for determining which agents were actually connected to multiple circuits because, in reality, some agents (e.g., a school campus) are made up of multiple premise_ids (i.e., multiple accounts) that are tied to different transformers. In these cases where the data indicated multiple transformer connections, we calculated a "pct_on_transformer" field, weighting the agent load proportionally based on the transformers' kVa, which would later allow us to model the agent's load cross multiple transformers.

With agents allocated to transformers, representing loads across multiple levels of the distribution network (e.g., circuit, distribution station banks, distribution stations, and receiving stations) is performed by dsgrid using a master lookup table derived from a variety of LADWP data sources—specifically, the PGES and FRAMME GIS data (dist_9), the One-Line Diagrams (dist_11, dist_12, dist_13, dist_14), DS-RS and IS-RS lookup tables (dist_22), and circuit to DS Bank lookup tables (dist_27).

In addition to mapping modeled loads to different levels of LADWP's system (i.e., transformer, DS or IS, RS), the description of each agent in terms of sector (and other attributes) and electrical location allows for characterizing different parts of LADWP's system in terms of sectoral composition, CalEnviroScreen score, etc. For example, Table 39 shows the sectoral composition of each RS, estimated on an annual energy basis using the OTC customer billing data for calendar year 2016.

Table 39. Annual Energy and Sectoral Composition of Receiving Stations (RSs) Based on LA100 Agents and OTC Customer Billing Data for 2016

RS	Annual Energy (GWh)	Commercial (%)	Industrial (%)	Residential (%)	Other/Unassigned (%)
A	1,136	81.0	3.6	15.2	0.2
B	1,420	52.4	7.7	39.9	0.0
C	336	36.5	38.2	25.3	0.0
D	1,643	57.8	2.6	39.6	0.0
E	1,324	47.0	4.3	48.7	0.0
F	871	69.5	19.7	10.8	0.0
G	1,177	54.7	2.3	43.1	0.0
H	1,565	61.9	0.8	37.3	0.0
HAL	187	60.1	26.1	13.8	0.0
J	1,563	41.4	13.1	45.5	0.0
K	1,634	49.9	0.5	49.6	0.0
M	806	38.5	14.6	46.9	0.0
N	871	73.0	3.9	23.1	0.0
P	1,854	83.9	1.4	14.8	0.0
Q	1,064	47.9	39.1	12.5	0.5
RIN	776	39.8	11.3	48.9	0.0
S	1,253	44.5	12.1	43.4	0.0
T	938	52.6	3.0	44.5	0.0
U	785	40.2	0.4	59.5	0.0

Appendix L. Demand Response Modeling Details

L.1 LADWP Current Programs and Plans

Three main documents describe LADWP's current approach to DR. The Demand Response 2014 Strategic Implementation Plan (DR 2014 SIP) outlines a path toward achieving 506 MW of DR by 2026 from a combination of commercial, industrial, and institutional (CII) curtailable load (215 MW), residential direct load control (DLC) (145 MW), critical peak pricing (CPP) (68 MW), alternative maritime power (AMP) (41 MW), time-of-use (TOU) tariffs (25 MW), and an electric vehicle (EV) service rider (12 MW) (LADWP and Navigant Consulting 2014). Subsequent long-term planning documents, including the 2017 SLTRP (LADWP 2017b), lean heavily on this implementation plan but modify it in some important ways. The 2017 Distributed Energy Resources Integration Study (DERIS) also describes current and envisions future DR programs, although its perspective is not comprehensive in terms of the types of programs that were examined in detail (URS Corporation et al. 2017).

Based on the language in the 2017 SLTRP, as well as conversations with the LADWP demand response team,[87] DR programs do not appear to be developing as quickly as was originally envisioned in the DR 2014 SIP. Relative to the 2014–2018 period, the current quantity of CII interruptible load is about 38 MW[88] and LADWP no longer anticipates reaching the 200 MW by 2020 benchmark outlined in the DR 2014 SIP. The DR 2014 SIP also emphasizes dispatchability as an important quality of effective DR, specifically recommending automated CII DR dispatch by 2016. However, that has not yet come about; that is, most/all LADWP CII DR participants are still notified of load reduction events via phone, e-mail, or text. With regards to other types of DR programs, LADWP has shelved initial plans for residential air-conditioning and pool-pump DLC (pilot was to be launched summer of 2015), but it is rolling out a residential programmable communicating thermostat (PCT) program in partnership with a third party in 2020. This change of plans is in line with the emerging market preference for PCT- rather than DLC-based residential cooling programs. Automated dispatch of the CII program is still a priority but will follow, rather than precede, the rollout of the residential PCT program.

Relative to the TOU and CPP tariffs envisioned in the DR 2014 SIP, LADWP does not currently anticipate greatly expanding the current TOU program, nor implementing a CPP program in the near term. This is in no small part due to LADWP having slowed its advanced metering infrastructure (AMI) rollout. Another development is that the AMP program is expected to be formally discontinued (it is already informally off the table), because it causes unacceptable levels of point-source air pollution when called upon to reduce LADWP load.[89]

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[87] Initial conversation held on August 22, 2018, via conference call. Elaine Hale (NREL), Hassan Motallebi, Zaw Htin, Alberto Luna, Ashkan Nassiri, Gregory Sarvas, Zahra Heydarzadeh, and Anton Sy (LADWP) were in attendance. Subsequent SME meetings occurred on April 1, 2019, and October 10, 2019.

[88] There are about 25 MW of CII demand response described in the OTC data, which lists current participants and performance. The recent number above was provided on the October 10, 2019, call with the LADWP Demand Response Department.

[89] Under normal conditions, maritime vessels parked in the Los Angeles Port are required to use the provided grid connection and turn off any on-board generators to reduce air pollution. The AMP DR program allowed for that grid connection to be turned off during peak/emergency conditions and compensated the maritime users accordingly.

The 2017 SLTRP captures some of these developments in its walk back of the ambition in the DR 2014 SIP. Where the DR 2014 SIP proposed 200 MW of DR by 2020 and 500 MW by 2026, the 2017 SLTRP states LADWP's current goals as 100–200 MW by 2020 and 200 MW "to a maximum of 500 MW of capacity by 2026." The DR conversation with LADWP further refined that the current goals are 200 MW by 2026 and 500 MW by 2030; that LADWP expects to continue operating an increasingly automated CII interruptible load program that reaches the 215 MW goal by 2030; and that LADWP is rolling out a residential PCT program from which they are expecting to get about 25 MW of response in 2021/22.[90] Our conversations also indicated an openness to expanding the residential PCT program to other communicating end uses, and making up any balance (relative to the goals) with scheduled EV charging and perhaps a CPP program.

Accepting LADWP's current goal as 500 MW by 2030, we see that this corresponds to a DR resource that is 6.9% (Moderate Projection) to 7.6% (Stress Projection) of 2030 peak consumption, as modeled in LA100. By way of comparison, the 2014 DR SIP estimated that meeting the original goal (500 MW in 2026) would correspond to about 8.1% of LADWP's peak load, and also reported that Southern California Edison's 2012 DR capacity of 1,714 MW was about 7.9% of SCE's 2012 peak load. The same report found the 2012 California average (excluding LADWP) DR capacity to be about 5.7% of peak load (LADWP and Navigant Consulting 2014).

The Distributed Energy Resources Integration Study (DERIS) does not add significantly to this conversation, first because the portion of that study concerned with optimal DR program size only looked at HVAC and pool-pump end uses (excluding, for example, flexible EV charging and the current CII program), and second because it did not propose vastly different quantities of HVAC and pool-pump DR as compared to the DR 2014 SIP. The DERIS optimal scenario shows about 146 MW of HVAC and pool-pump DR, which is essentially identical to what the DR 2014 SIP proposes for residential DLC programs.

LADWP currently compensates CII interruptible load at rates of $8/kW-mo. or $12/kW-mo. depending on notification type (day-ahead or 2-hour advanced notice, respectively), plus $0.25/kWh for actual reductions. Given the 4-month demand response season and assuming all twelve 4-hour events that are allowed are called per year, this corresponds to incentive levels of $44/kW-yr to $60/kW-yr.[91] The residential PCT program will be initially incentivized at $60/participant-yr plus a one-time thermostat rebate of $125.[92]

L.2 Water System Demand Response

Today, LADWP's water system contributes 8 MW to the CII interruptible load DR program.[93] Looking forward, our collaborators at the University of Southern California (USC) estimate that up to half of peak water system pumping loads could be shed during peak times (i.e., used as an

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[90] This estimate assumes 750 W/thermostat, and thus corresponds to 33,000 expected participants.
[91] "Demand Response Program," LADWP, accessed May 20, 2020: https://www.ladwp.com/ladwp/faces/ladwp/commercial/c-savemoney/c-sm-rebatesandprograms/c-sm-rp-demandresponse.
[92] Per conversation with the LADWP Demand Response Department on October 10, 2019.
[93] Per conversation with the LADWP Demand Response Department on October 10, 2019.

interruptible load resource) (Sanders and Zohrabian 2019). For this purpose, water system pumping loads are defined as supply distribution pumping, groundwater and groundwater replenishment pumping, and conveyance loads associated with indirect potable reuse (IPR). The peak loads modeled for just these three water system end uses in the LA100 study are summarized in Table 40. These data and the current 8 MW of interruptible load from the water system largely confirm each other, as half of the estimated peak pumping loads for 2015 and 2020 are 9.6 MW and 11.0 MW, respectively. The post-2020 data in Table 40 illustrate our water system modeling assumptions of increasing pumping loads (more IPR and groundwater replenishment) to enable a more local water supply; as well as the energy efficiency differences across the three projections.

Table 40. Water System Peak Pumping Loads (MW) per LA100 Load Projection

Model Year	Moderate	High[a]	Stress[a]
2015	19.3	—	—
2020	21.9	—	—
2025	27.1	27.1	27.6
2030	89.6	88.7	90.6
2035	155.9	154.1	157.7
2045	156.6	154.6	158.4

[a] All three load projections are identical for model years 2015 and 2020.

Looking forward, Sanders and Zohrabian (2019) estimate that up to half of all water system loads could be shifted up to 12 hours. Achieving such a high degree of flexibility is not a given, however, because more of some or all of the following may be required to provide grid responsiveness while fulfilling the fundamental mission of delivering a safe and reliable water supply:

- Detailed understanding of modified operation impacts on water quality, and potential co-benefits of extra capacity to provide DR and avoid sewage system overflows (Olsen et al. 2012)
- Water system infrastructure (e.g., increased pumping and storage capacity [Park and Croyle 2012]; treatment plant modifications suggested by flexibility-oriented studies like Olsen et al. [2012])
- Monitoring and control technology (Olsen et al. 2012)
- Non-standard staff scheduling (Sanders and Zohrabian 2019).

LADWP may also need to work collaboratively across the power and water departments to (a) temporally align water system capital improvements and power system DR needs; and (b) determine how to measure and compensate water system load-shifting DR (Park and Croyle 2012). We therefore reserve this DR option for the High projection, and only for model years 2035 and later, under the assumption that considerable effort (planning and capital improvements) and lead times would be required to unlock this source of demand-side flexibility.

L.3 Demand Response Participation Rates

There is little consolidated information on DR participation rates and how they vary with, for example, incentive level, enrollment efforts of the utility or aggregator, demand response actuation type, or demographic variables. Fortunately, the authors of the recent 2025 California Demand Response Potential Study were able to construct such models, segmented by sector (i.e., residential, commercial and industrial), and calibrated to data from empirical studies conducted in California and actual enrollment rates achieved by mature DR programs operating in California (Alstone et al. 2017). Although not necessarily representative of the participation rates that may be achieved for the types of automated load-shifting programs envisioned in the LA100 study,[94] we use the graphical representations of the models provided in Appendix F of Alstone et al. (2017) as the best available correlations we have between inputs (i.e., incentive level and marketing effort) and outcome (i.e., DR participation rate).

These graphical summaries are reproduced in Figure 106, Figure 107, and Figure 108, which are for residential, small and medium business, and large commercial and industrial customers, respectively. In what follows, DR participation rate assumptions are constructed by assuming an incentive level (the yearly payments made directly to participants to compensate them for their participation), a utility marketing level, and whether "installation is required." We then use the figures to infer a resulting participation level. Utility marketing level and whether "installation is required" is largely determined based on load projection (e.g., the High Projection would assume higher marketing levels and more automation/less installation than the other projections) and study year (e.g., marketing and automation levels stay constant or increase over time). Incentive level can be benchmarked against current utility practice in two cases: interruptible load and residential cooling; in all cases we can compare assumed incentive levels against modeled grid system value conferred by each demand response program and make adjustments to our initial assumptions as needed.

[94] This shortcoming is also recognized by the 2025 California Demand Response Potential Study authors: "The study is designed to include 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."

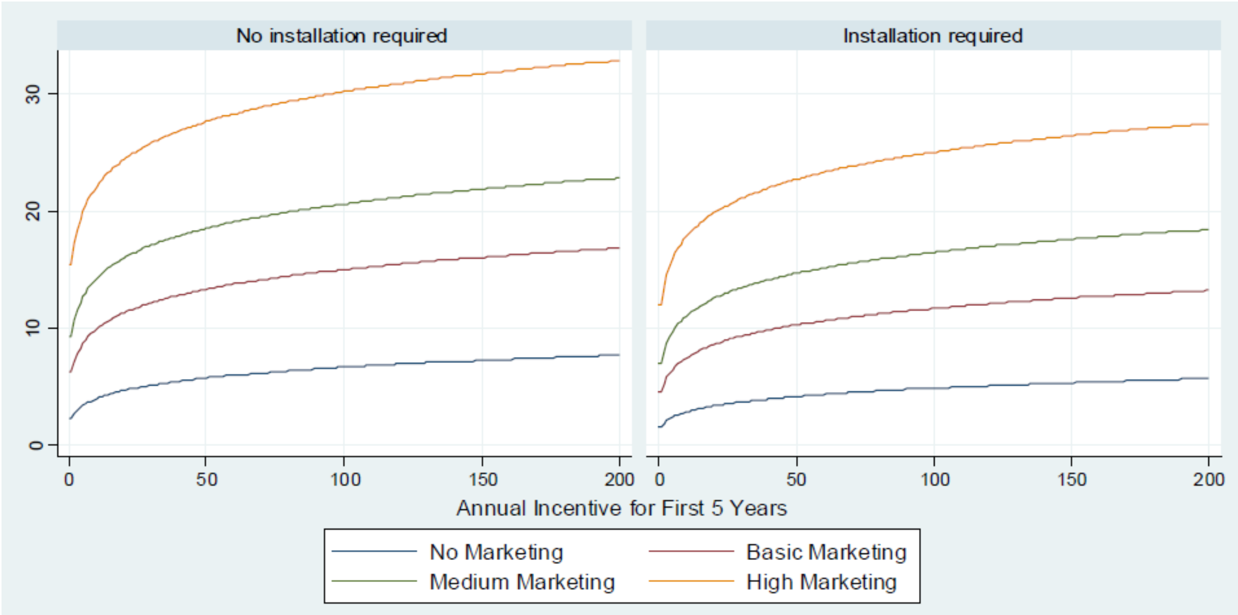

Figure 106. "Achievable Residential Participation Rates by Incentive and Marketing Level" (Alstone et al. 2017, Figure F-5)

X-axis is annual incentive in \$/participant-yr; Y-axis is participation rate (%).

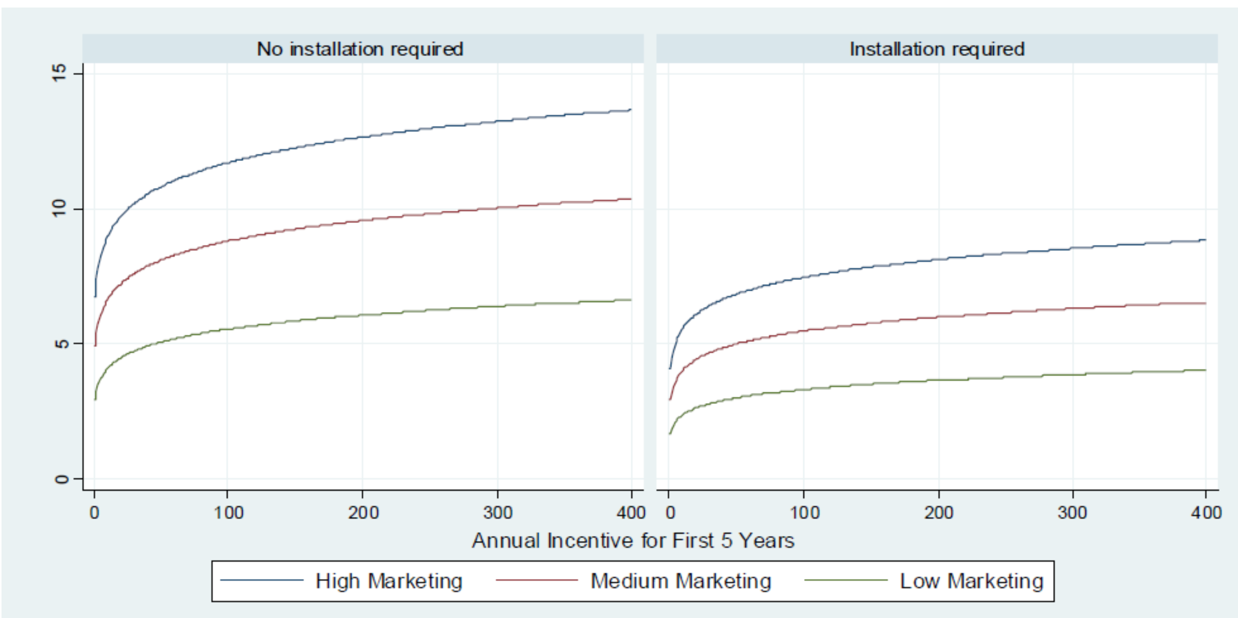

Figure 107. "Achievable Small and Medium Business Participation Rates by Incentive and Marketing Level" (Alstone et al. 2017, Figure F-6)

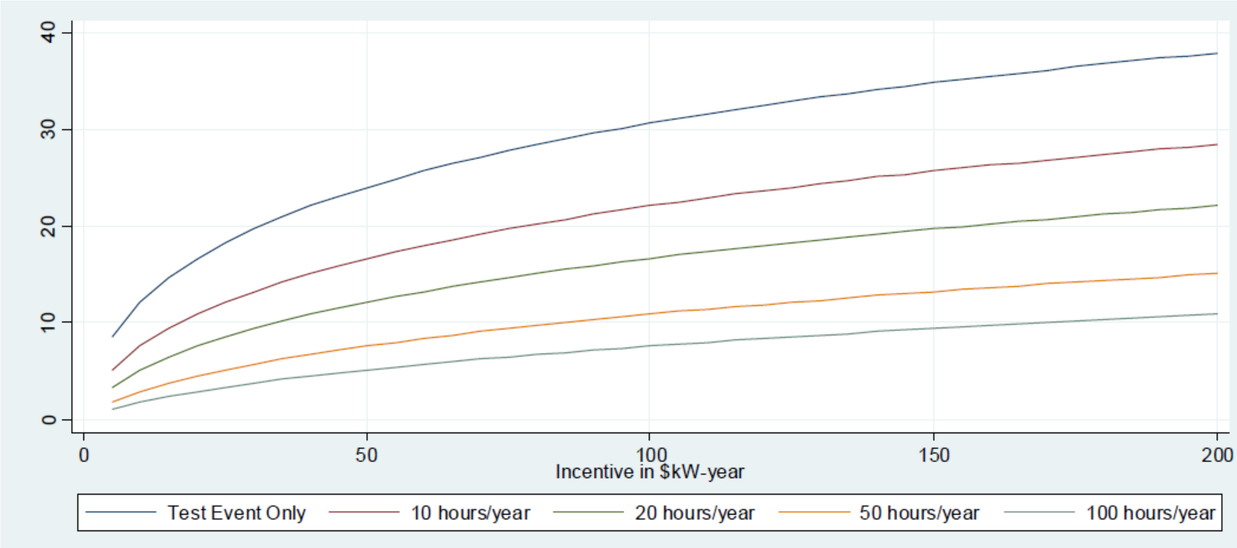

Figure 108. "Achievable Large C&I Participation Rates by Incentive and Average Annual Dispatch Hours" (Alstone et al. 2017, Figure F-8)

L.4 Demand Response Resource Metrics

For the LA100 study, we model demand response from

- Large commercial, industrial, and institutional (CII) customers
- LADWP water system
- Residential end uses: Cooling, Heating, Hot Water, Pool Pumps, Refrigeration, and Schedulable Appliances
- Commercial end uses: Cooling, Heating, Hot Water, and Refrigeration
- Scheduled electric vehicle charging: Home-Level 1 (L1), Home-L2, Work-L1, Work-L2, and Public-L2.

In what follows we refer to the size of these resources in terms of their coincident within-end-use peak demand in megawatts (MW). Figure 109 shows this metric for all eligible demand, grouped by DR program. This metric has the advantages of indicating the maximum response that could be provided by any given end use, and allowing DR from decidedly non-coincident end uses (e.g., cooling and heating) to be summarized in the same plot or table; however, it has the decided disadvantage of not being (necessarily) aligned with system peak.

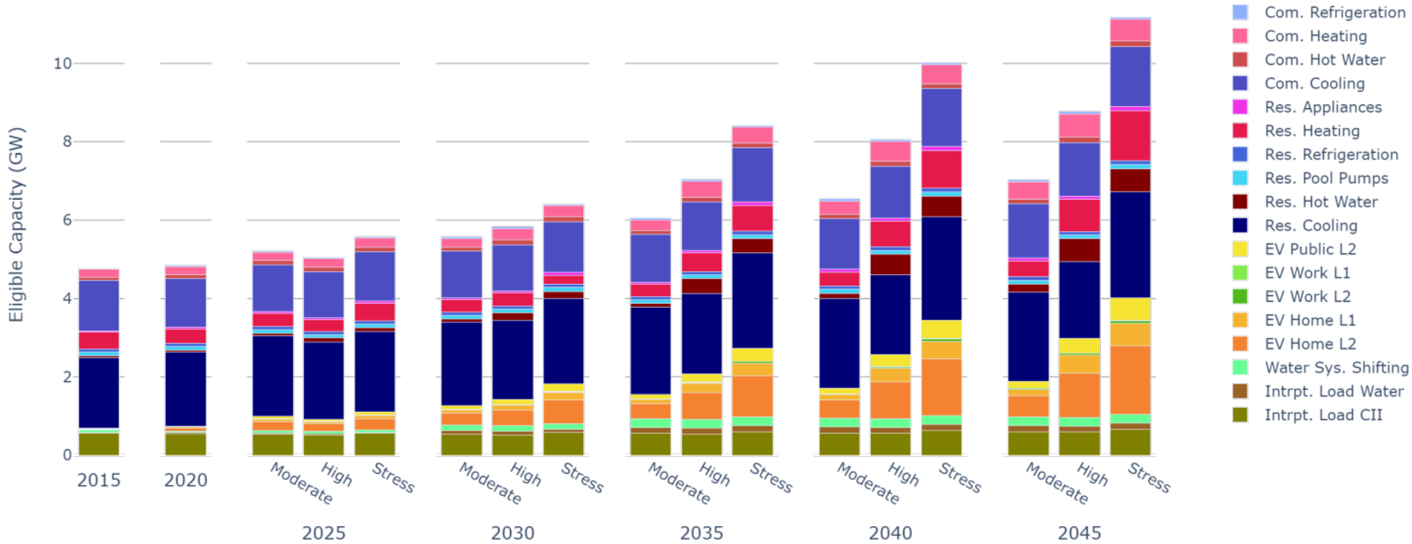

Figure 109. DR-eligible coincident-within-end-use peak demand, by projection-year

All load eligible for a given DR program is aggregated together, then the maximum value (in MW) is taken as the overall resource capacity. These peak values are then plotted together, even though the peaks for different programs mostly happen at different times.

Understanding to what extent a DR resource is aligned with system peak is important because it is a first indicator of whether the resource might be able to provide firm capacity. Therefore, while we mostly report DR capacities coincident within each end use, but non-coincident with each other and with system peak, we also report the amount of each DR resource that is available during system peak. To that end, Figure 110 shows all of the demand at the system peak time that could be eligible to participate in a DR program for each LA100 projection-year.

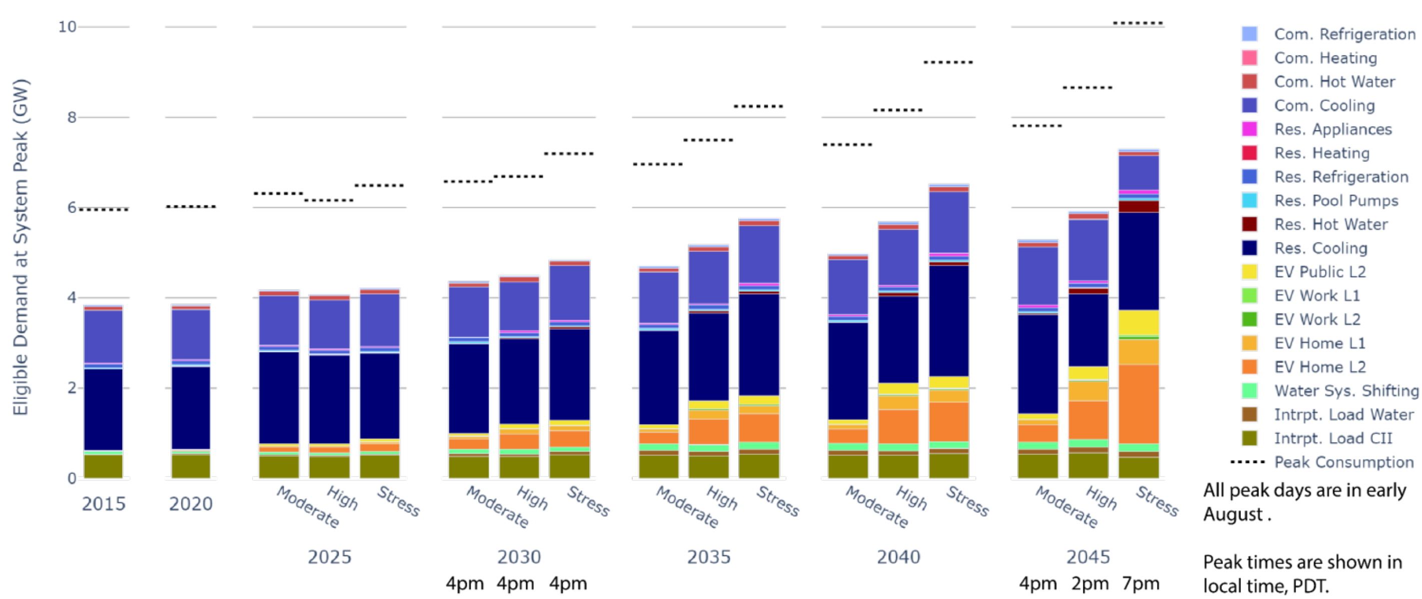

Figure 110. DR-eligible demand at the system peak time, by projection-year

Comparing Figure 109 to Figure 110, we see that while there are some times at which turning off all of the heat pumps or water heaters in LADWP service territory would significantly reduce demand (on the order of 100's of MW), such an action would have almost no impact at the system peak times. We therefore expect those end uses to provide little firm capacity compared to the end uses that do show up in Figure 110—namely, residential and commercial cooling, scheduled electric vehicle charging, large CII interruptible load, and water system DR.

One way the end uses not well-aligned with system peak can provide value is to shift energy use from more- to less-expensive times. We therefore also report the total amount of annual demand that could potentially be shifted. Figure 111 shows this metric for all eligible demand. The eligible resource data summarized in this section, as well as similar and related metrics for participating DR capacity are provided in in tabular form in Table 48 through Table 71.

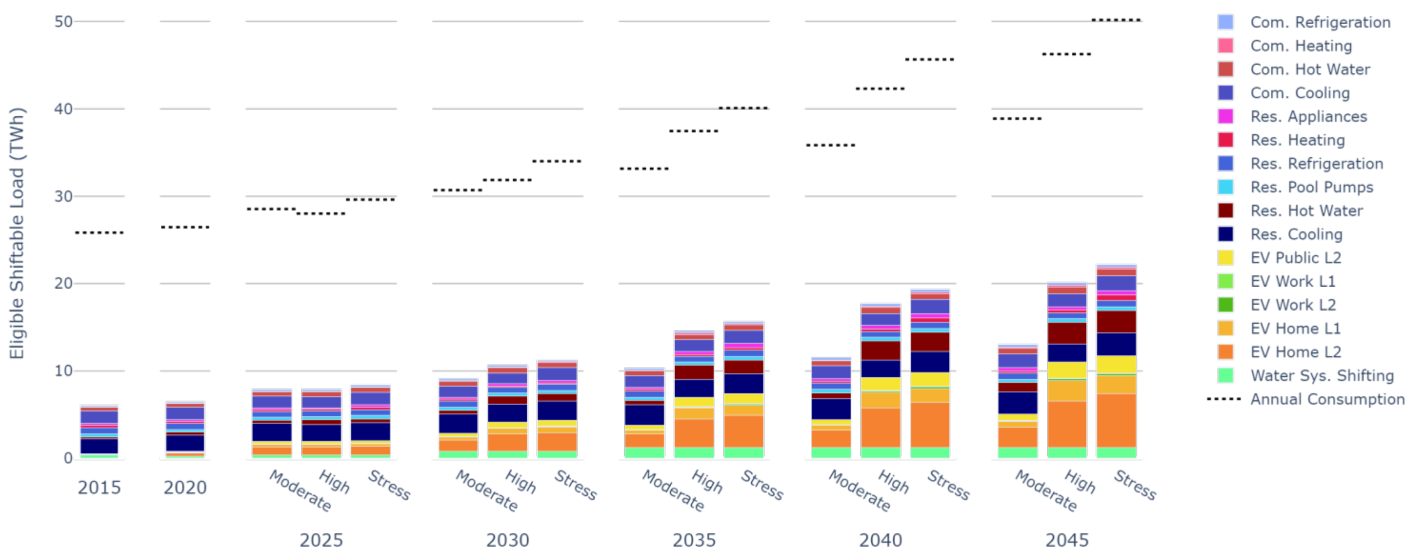

Figure 111. DR-eligible shiftable demand, by projection-year

Finally, the quantities reported here are pre-losses. That is, we report capacities, annual demand, and the like as they would appear from aggregated meter readings. The data in this report do not include distribution or transmission losses. Of course, avoided losses are an important aspect of DR value. While not reported here, losses are accounted for in the grid with models. For example, before passing LA100 load projection data, including the DR resource described here, to the capacity expansion modeling team, we add 8% to represent distribution losses.[95] Transmission losses are then handled endogenously by the capacity expansion model and are reflected in the Receiving Station (RS) nodal prices. Thus, 100 MW of firm DR could offset up to 112 MW of peaking capacity, based on LADWP's current estimate of 12% transmission and distribution losses (LADWP 2017a).

[95] The 12% loss factor reported by LADWP (LADWP 2017a) is roughly split into distribution losses (losses occurring below the receiving station) and transmission losses. We assign distributions losses of 8% based on RPM estimates of transmission losses.

L.5 Sector-Level Demand Response Projections

Overall, the LA100 DR projections are constructed around:

- LADWP's goals for 215 MW of CII interruptible load and 500 MW total DR by 2030
- Shiftable end-use loads enabled by fully automated communication and control technologies, similar to the residential PCT program LADWP is currently rolling out
- Extensive scheduling of water system loads (High Projection only)

with ambition levels informed by the narrative descriptions of the Moderate, High, and Stress Load projections as well as preliminary power system modeling results showing significant capacity and energy needs in many LA100 projection-years. Although we briefly describe our shiftable end-use loads as "similar" to LADWP's new residential PCT program, it should be clarified that in all cases we model shifting from these end uses that could take place any time of day or night (constrained by hourly availability and other requirements detailed below) and that operates to both reduce peak load and take advantage of low-cost energy when it is available. This is in contrast to typical DR programs that are dispatched infrequently to reduce peak loads. We examine such programs for residential cooling, heating, hot water, pool pumps, refrigeration, and major appliances; commercial cooling, hot water, heating, and refrigeration; and L1 and L2 light-duty vehicle charging.

Residential End Uses

The residential DR programs modeled in the LA100 study start with shiftable cooling in 2020. Hot water and heating are added in 2025. Pool pumps, refrigeration, and schedulable appliances follow in 2030. The total amount of load potentially available for shifting comes from the residential end uses modeled by ResStock (all modeled households) and ComStock (only multifamily high-rise buildings). The proportion of each modeled end use considered shiftable for each residential DR program is summarized in Table 41. Pool pumps, refrigeration, and appliances are not reported as distinct end uses in the LA100 ComStock results (to the extent that they are modeled at all, they are lumped an overall "Plug and Process Loads" end use), and so we are not able to represent the potential for multifamily high-rise buildings to participate in such DR programs.

Table 41. Composition of Residential Shiftable DR Programs in Terms of ResStock and ComStock Modeled End Uses

Fraction Shiftable refers to the proportion of end-use demand eligible for DR participation.

	ResStock		**ComStock Multifamily Res.**	
DR Program	**Modeled End Use**	**Fraction Shiftable**	**Modeled End Use**	**Fraction Shiftable**
Res. Cooling	cooling central_system_cooling fans_cooling pumps_cooling central_system_pumps_cooling	1.0 1.0 0.5 1.0 1.0	cooling	1.0
Res. Heating	heating central_system_heating fans_heating pumps_heating central_system_pumps_heating	1.0 1.0 0.5 1.0 1.0	heating	1.0
Res. Hot Water	water_systems	1.0	water_systems	1.0
Res. Pool Pumps	pool_pump hot_tub_pump	1.0 1.0		
Res. Refrigeration	refrigerator extra_refrigerator freezer	1.0 0.5 1.0		
Res. Appliances	clothes_dryer dishwasher	1.0 1.0		

We report the size of each DR program as the peak end-use load multiplied by a participation rate. We determine participation rates for each LA100 projection-year by cross-referencing per projection-year assumptions about marketing, automation, and incentive levels with the curves shown in Figure 106..

To set incentive levels, we convert per-participant incentive levels to per-kW-year incentive levels and qualitatively adjust them (e.g., make higher for the High projection) until the per-kW-year incentive levels are aligned with:

- Capacity prices seen in capacity expansion modeling (RPM) runs (up to about $150/kW-yr)
- Load projection narratives about level of DR ambition (highest incentives for High projection, lowest for Stress projection)
- Initial DR modeling results that showed more value for cooling (aligned with peak) and hot water (year-round availability, more shiftable) as compared to heating (seasonal and not aligned with peak).

Figure 112 illustrates the process used to calculate total DR by end use.

Figure 112. Flow chart of inputs needed to assess total shiftable DR by end use

In choosing between DR capacity metrics, we have two readily available choices:

- Non-coincident end-use peak: Sum of non-coincident peak load/equipment capacity over all eligible resources. For the LA100 study that involves querying the per-household simulation end-use peaks, multiplying by the sample weight and summing over all samples. The result is shown in Figure 113.
- Coincident end-use peak: Peak demand for the aggregated participating end uses. In this case the end-use demand is summed over the entire LADWP service area first, and then we query the peak demand (Figure 114.).

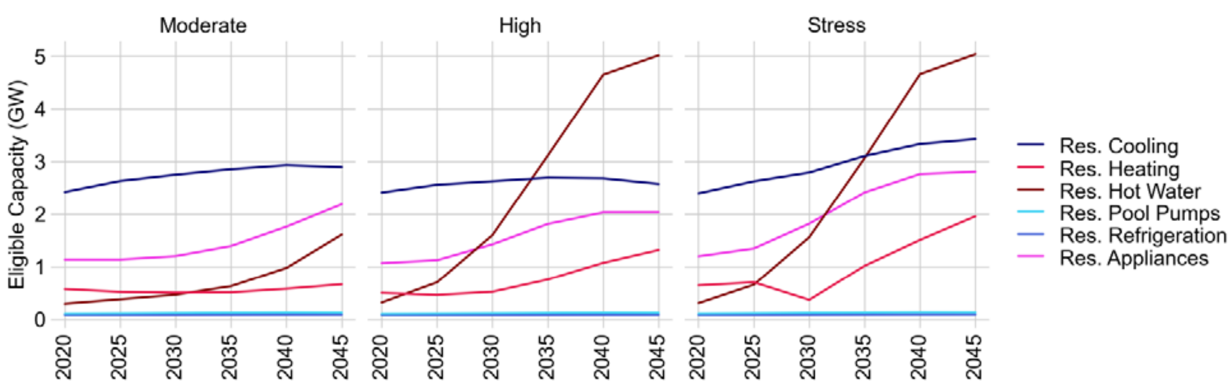

Figure 113. Non-coincident end-use peak demand of all eligible residential appliances

Pool pump and refrigeration equipment capacity is less than 150 MW for all projections and study years.

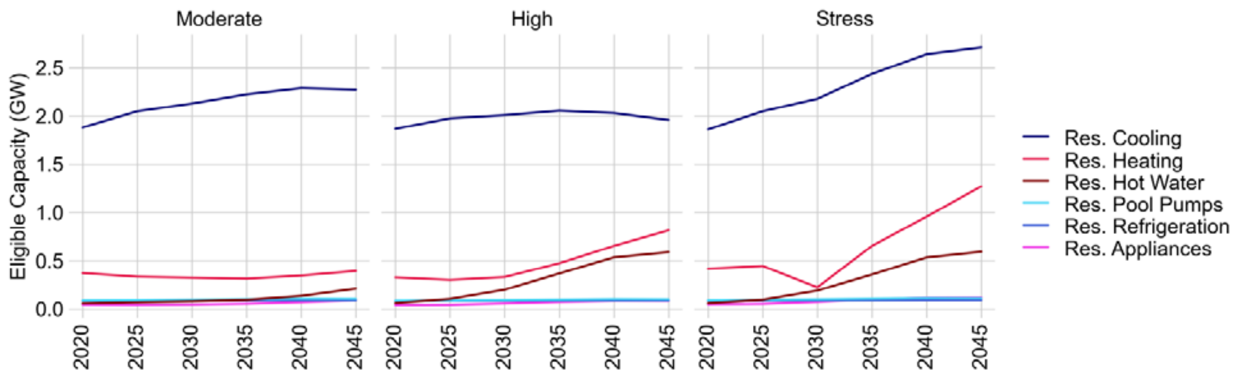

Figure 114. Coincident end-use peak demand of all end uses eligible for each residential program

For all projections and study years, coincident end-use peak demand is less than 125 MW for pool pumps, refrigeration, and schedulable appliances.

Comparing Figure 113 and Figure 114, we see that the non-coincident and coincident measures of program-eligible capacity are significantly different for most end uses. If they were the same, that would mean that all equipment, in every house, reached peak demand at the same time. Of course, that is not what we would expect and is not what we see, but it is the case that some end uses' demand is more temporally aligned across households than others.

For example, many residential air conditioners do run at near-full capacity at the time of their coincident end-use peak, and so we see residential cooling capacity estimates in Figure 114 that are the same order of magnitude of those in Figure 113. In contrast, while about 5 GW of water heating equipment is installed by 2045 in the High projection (Figure 113), at most there is only about 600 MW of coincident demand in the same projection-year (Figure 114). Dividing the values in Figure 114 by those in Figure 113 formalizes this finding, which we report out in Figure 115. Refrigeration, pool pumps, cooling, and heating all have ratios of coincident end-use peak demand to non-coincident end-use peak of 0.6 or above; use of water heaters and appliances are less aligned across households, with ratios of at most 0.2 (and only about 0.04 for clothes dryers and dishwashers).

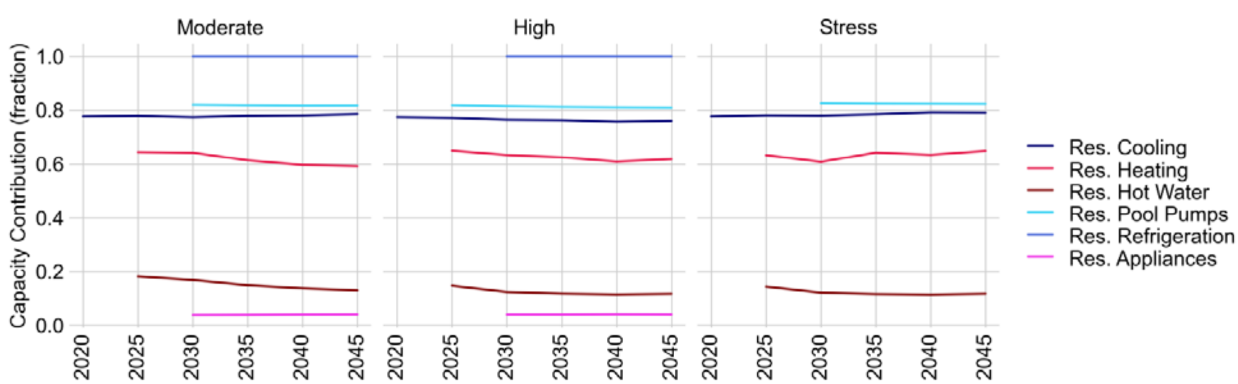

Figure 115. Ratio of coincident end-use peak demand to non-coincident end-use peak demand

Some end-use appliance demand (e.g., refrigeration, cooling) is temporally aligned. Other end-use demand (e.g., schedulable appliances, water heating) is not. The Stress projection assumes no DR from refrigeration or schedulable appliances.

Given these two measures of capacity, which is most useful for describing DR resource? In what follows, we use the coincident end-use peak demand metric (Figure 114), because it corresponds to the maximum possible response the utility could access if they were to ask that end use to reduce load as much as possible over a given time interval. This is analogous to thinking of DR as a variable resource, and the coincident end-use demand peak as the "nameplate capacity" of the aggregate resource, from the utility perspective.

Per-participant incentives are converted to per-kW-year incentives by computing the number of eligible households (cooling, heating, hot water) or appliances (refrigerators, schedulable appliances, pool pumps) per program based on ResStock and ComStock sample data (presence of end-use multiplied by number of households represented by the sample);[96] and then dividing the peak eligible, coincident end-use demand (Figure 114) by those numbers of eligible potential participants. This gives an average kW per participant DR capacity that can be used to convert $/participant to $/kW-year.

Figure 116 depicts the number of eligible appliances/households per modeled residential DR program. The low coincident peak demand, combined with relatively high numbers of schedulable appliances, refrigerators, and freezers, means that residential refrigeration and schedulable appliance capacity per participant is quite low, and thus does not support substantial $/participant incentive levels. On the other hand, kW/participant is much higher for residential cooling, hot water, and heating. These types of considerations and the resulting $/kW-year incentive levels shown in Figure 117 were used to set the per participant-year incentive levels shown in Table 42. Table 42 also shows assumed automation and marketing levels, and the resulting participation rate.

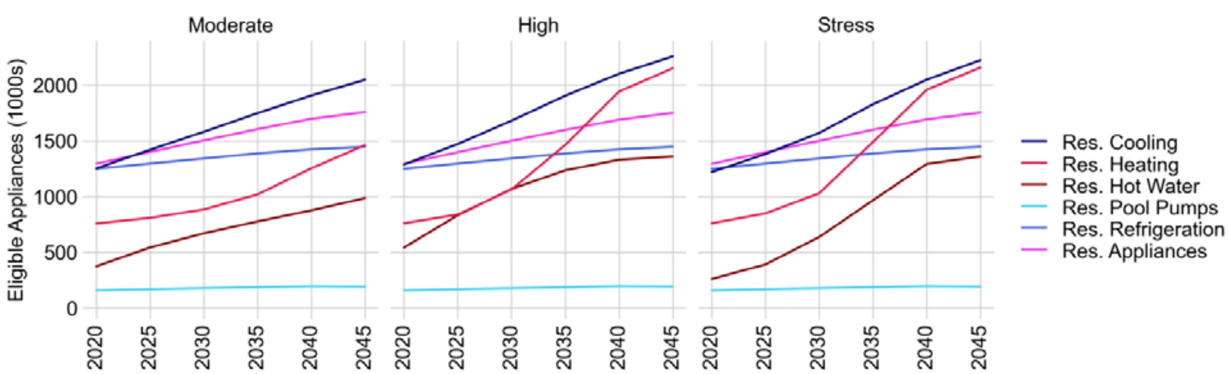

Figure 116. Number of households/appliances eligible to participate in the modeled residential DR programs, by projection-year

Total number of households modeled increases with study year but is constant across projections. Per-projection differences in number of eligible households/appliances are therefore the result of technology adoption rates, which depend on energy efficiency and electrification assumptions.

[96] ResStock samples are per-household. To estimate the number of households represented by each ComStock multifamily building, we divided the ComStock building floor area by the average floor area per multifamily household as represented in the ResStock "Multi-Family with 5+ Units" samples for the same projection-year.

Table 42. Participation Rate Assumptions for Residential Shiftable End Uses by Projection, Developed Using the Participation Rate Model of Alstone et al. (2017) (Figure 106)

DR Program	Projection	RPM Model Year	Assumed Incentive ($/yr)	Installation Required?	Marketing Level	Participation Rate (%)
Res. Cooling	Moderate	2020	60	Y	None	4
		2025	60	Y	Basic	11
		2030	120	Y	Medium	17
		2035–2045	120	N	Medium	21
	High	2020	60	Y	None	4
		2025	120	Y	Medium	17
		2030	150	N	Medium	22
		2035–2045	150	N	High	32
	Stress	2020	60	Y	None	4
		2025–2030	60	Y	Basic	11
		2035–2045	60	N	Basic	13
Res. Heating	Moderate	2020	—	—	—	—
		2025	24	Y	None	3
		2030	24	Y	Basic	8
		2035–2045	24	N	Basic	12
	High	2020	—	—	—	—
		2025	24	Y	None	3
		2030	24	Y	Medium	13
		2035–2045	24	N	Medium	16
	Stress	2020	—	—	—	—
		2025–2030	24	Y	None	3
		2035–2045	24	N	None	5
Res. Hot Water	Moderate	2020	—	—	—	—
		2025	12	Y	None	2
		2030	12	Y	Medium	10

DR Program	Projection	RPM Model Year	Assumed Incentive ($/yr)	Installation Required?	Marketing Level	Participation Rate (%)
		2035–2045	12	N	Medium	13
	High	2020	—	—	—	—
		2025	12	Y	None	2
		2030	24	Y	High	20
		2035	24	N	High	25
		2040–2045	60	N	High	28
	Stress	2020	—	—	—	—
		2025	12	Y	None	2
		2030	12	Y	Basic	7
		2035–2045	12	N	Basic	9
Res. Pool Pumps	Moderate	2020–2025	—	—	—	—
		2030	30	Y	None	3
		2035	30	Y	Medium	13
		2040–2045	30	N	Medium	17
	High	2020	—	—	—	—
		2025	60	Y	None	4
		2030	60	Y	Medium	15
		2035	60	N	Medium	19
		2040–2045	60	N	High	28
	Stress	2020–2025	—	—	—	—
		2030	30	Y	None	3
		2035	30	Y	Basic	10
		2040–2045	30	N	Basic	12
Res. Refrigeration	Moderate	2020–2025	—	—	—	—
		2030	3	Y	None	2
		2035	3	Y	Medium	8
		2040–2045	3	N	Medium	10

DR Program	Projection	RPM Model Year	Assumed Incentive ($/yr)	Installation Required?	Marketing Level	Participation Rate (%)
	High	2020–2025	—	—	—	—
		2030	6	Y	None	2
		2035	6	Y	Medium	9
		2040–2045	6	N	High	17
	Stress	2020–2045	—	—	—	—
Res. Appliances	Moderate	2020–2025	—	—	—	—
		2030	3	Y	None	2
		2035	3	Y	Basic	5
		2040–2045	3	N	Basic	7
	High	2020–2025	—	—	—	—
		2030	6	Y	None	2
		2035	6	Y	Medium	9
		2040–2045	6	N	Medium	12
	Stress	2020–2045	—	—	—	—

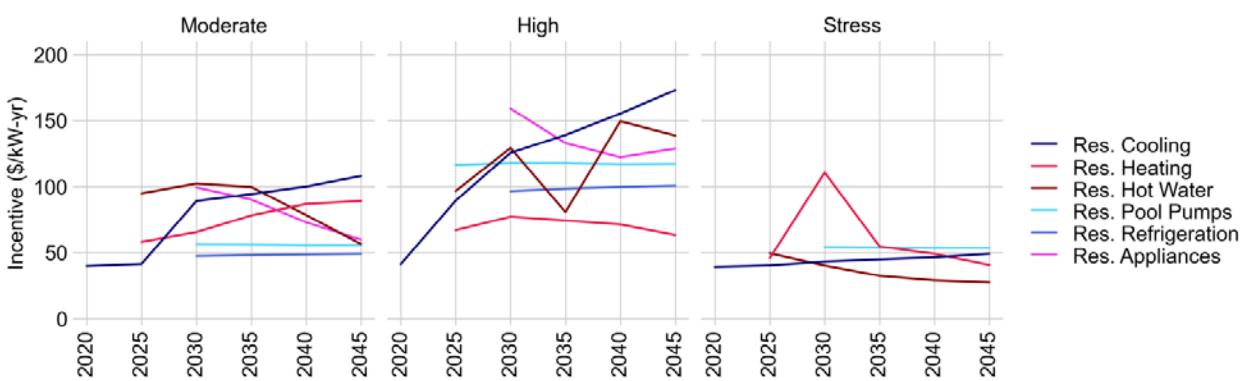

Figure 117. Assumed residential demand response incentives, in $/kW-yr

Incentive levels per participant per year are converted to $/kW-yr based on coincident end-use peak demand per eligible household/appliance.

The resulting residential DR capacity is shown in Figure 118 and Figure 119. Overall, we see that residential cooling is a sizable resource for all projections: even the Stress projection exceeds 300 MW by 2035. The High projection exceeds 600 MW in the same timeframe. Whether that much capacity is actually accessible as a grid resource depends on how well aligned grid needs are with cooling peak consumption, combined with cooling shiftability restrictions. Similar reasoning applies to all other end uses; shiftability restrictions assumed for our modeling are described in the next section.

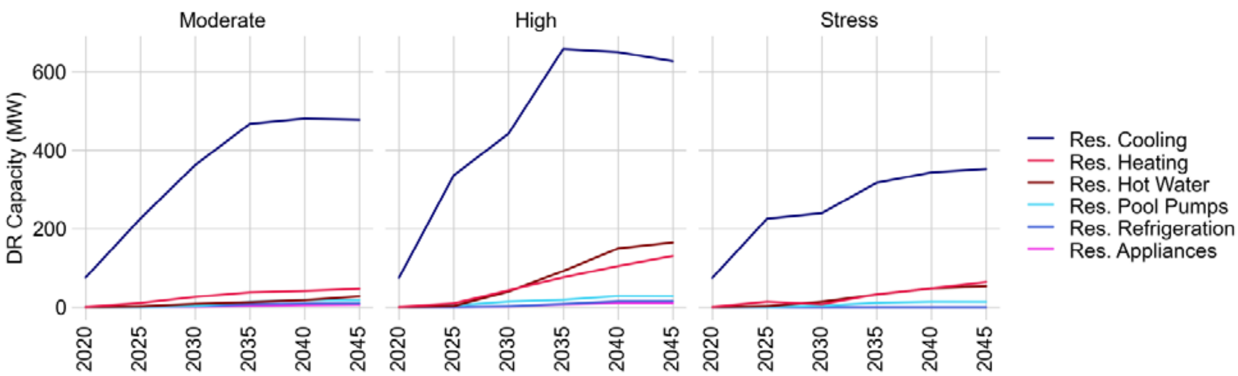

Figure 118. Residential shiftable end uses DR capacity

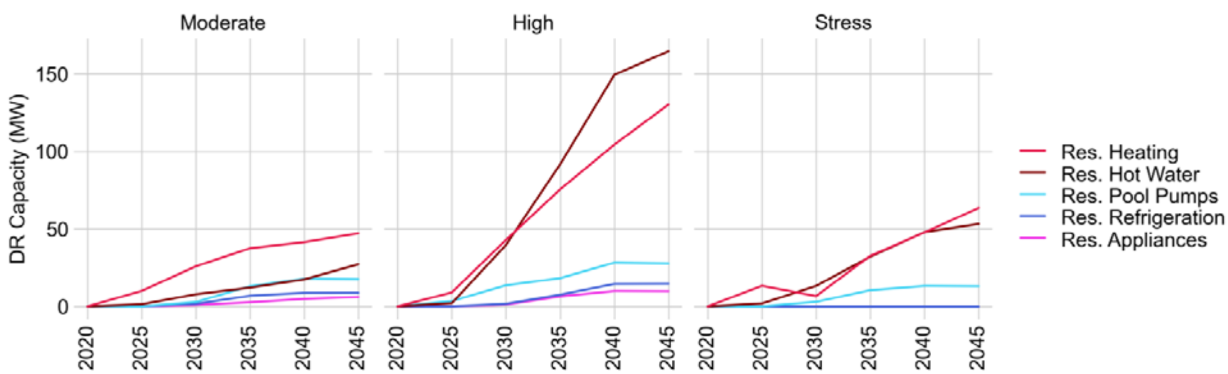

Figure 119. Residential shiftable end uses DR capacity, excluding cooling

Turning to the other residential programs (Figure 119), residential hot water and heating exceed 25 MW and 45 MW, respectively, of demand response capacity by 2045 in all projections. The impact of residential building electrification is apparent in how much more capacity from those end uses is available in both the Stress and the High Projections. All other shiftable end uses (pool pumps, refrigeration, and appliances) yield less than 30 MW demand response capacity each. Their contributions are relatively small in part because these end uses are not captured at the required level of detail in the ComStock multifamily building models. That issue aside, whether it is worth enrolling end uses that make up a fairly small portion of LADWP's load to provide energy shifting depends on how high-value that shifting is in terms of reducing power system capacity and energy costs.

Commercial End Uses

The LA100 commercial demand response programs are shiftable cooling, heating, hot water, and refrigeration, all starting in 2025. The end-use resource for each program corresponds one-to-one with a ComStock modeled end use. The non-coincident (sum of each sample building's peak end-use demand multiplied by the sample weight) and coincident (peak of all eligible end-use demand, first summed together) eligible capacity are shown in Figure 120 and Figure 121.. As with the residential programs, in what follows we define demand response capacity based on coincident demand (Figure 121.), because that metric better corresponds to the utility's perception of a demand response resource as an amount of load that could be reduced for some time period. In contrast with the residential modeling, potential participants are identified one-to-one with sample building models for which the end use in question is present, that is, end-use demand is not further subdivided into per-tenant or per-appliance quantities.

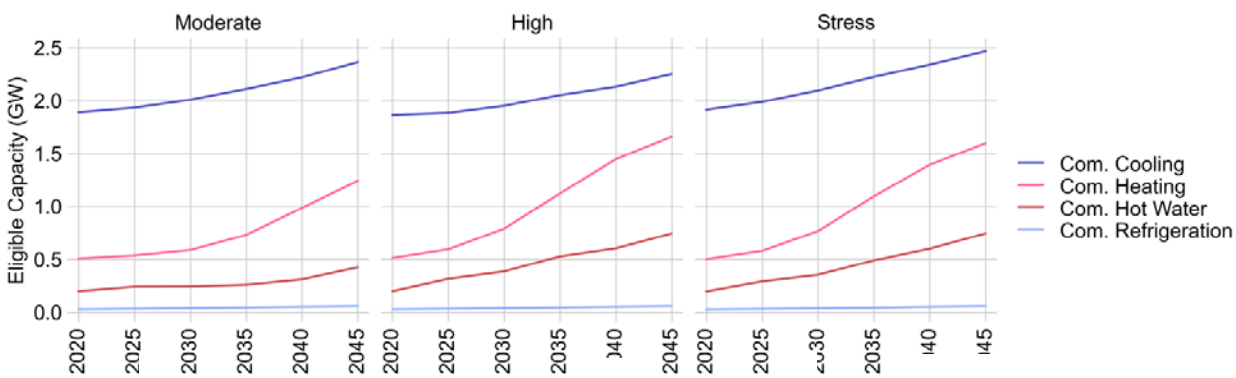

Figure 120. Non-coincident end-use peak demand of all eligible commercial end uses

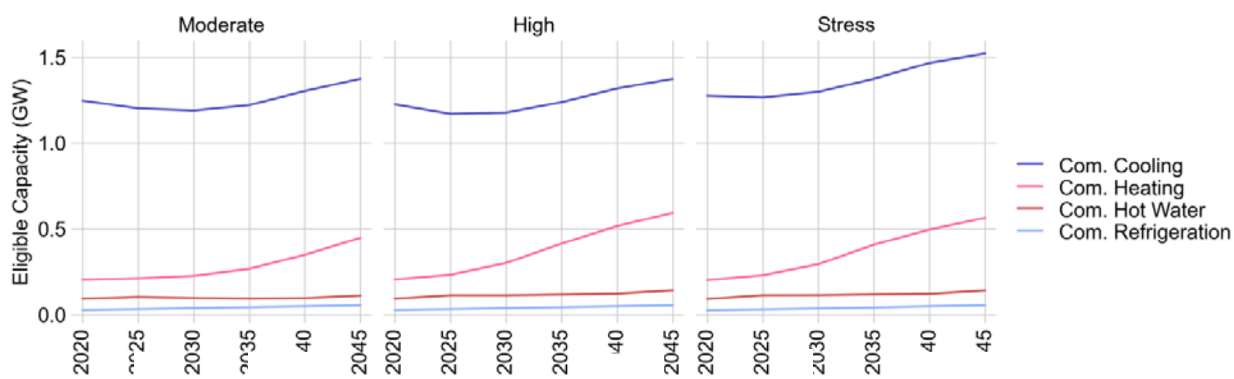

Figure 121. Coincident end-use peak demand of all eligible commercial end uses

As illustrated in Figure 122, the size of each demand response program is the modeled end-use load multiplied by a participation rate. We determine participation rates for each LA100 projection-year by cross-referencing per projection-year assumptions about marketing, automation, and incentive levels with the curves shown in Figure 107. These assumptions and resulting participation levels are documented by demand response program in Table 43.

Table 43. Participation Rate Assumptions for Commercial Shiftable End Uses by Projection, Developed Using the Participation Rate Model of Alstone et al. (2017) (Figure 107.)

End Use	Projection	RPM Model Year	Assumed Incentive ($/yr)	Installation Required?	Marketing Level	Participation Rate (%)
Com. Cooling	Moderate	2020	—	—	—	—
		2025	400	Y	Low	4
		2030	400	Y	Medium	7
		2035–2045	400	N	Medium	10
	High	2020	—	—	—	—
		2025	400	Y	Low	4
		2030	400	Y	High	8
		2035–2045	400	N	High	13
	Stress	2020	—	—	—	—
		2025–2030	200	Y	Low	3
		2035–2045	200	N	Low	6
Com. Heating	Moderate	2020	—	—	—	—
		2025	100	Y	Low	3
		2030	100	Y	Medium	6
		2035–2045	100	N	Medium	8
	High	2020	—	—	—	—
		2025	150	Y	Low	3
		2030	150	Y	High	8
		2035–2045	150	N	High	12
	Stress	2020	—	—	—	—
		2025–2030	50	Y	Low	3
		2035–2045	50	N	Low	5
Com. Hot Water	Moderate	2020	—	—	—	—
		2025	75	Y	Low	3
		2030	75	Y	Medium	5
		2035–2045	75	N	Medium	8
	High	2020	—	—	—	—
		2025	100	Y	Low	3
		2030	100	Y	High	7
		2035–2045	100	N	High	12
	Stress	2020	—	—	—	—
		2025–2030	50	Y	Low	3
		2035–2045	50	N	Low	5

End Use	Projection	RPM Model Year	Assumed Incentive ($/yr)	Installation Required?	Marketing Level	Participation Rate (%)
Com. Refrigeration	Moderate	2020	—	—	—	—
		2025	150	Y	Low	3
		2030	150	Y	Medium	6
		2035–2045	150	N	Medium	9
	High	2020	—	—	—	—
		2025	200	Y	Low	3
		2030	200	Y	High	8
		2035–2045	200	N	High	12
	Stress	2020	—	—	—	—
		2025–2030	100	Y	Low	3
		2035–2045	100	N	Low	6

As for residential demand response, the commercial demand response incentive levels were chosen by converting them to \$/kW-year (based on coincident end-use demand and potential number of participants), and cross-referencing those results against the guidelines:

- Incentive levels should not exceed capacity prices seen in RPM runs (up to about \$150/kW-yr)
- In alignment with the load projection narratives, the High projection should have the highest incentive levels, and the Stress projection should have the lowest
- End uses that showed the most value in our initial demand response modeling results (e.g., cooling) should be incented more than other end uses (e.g., heating)

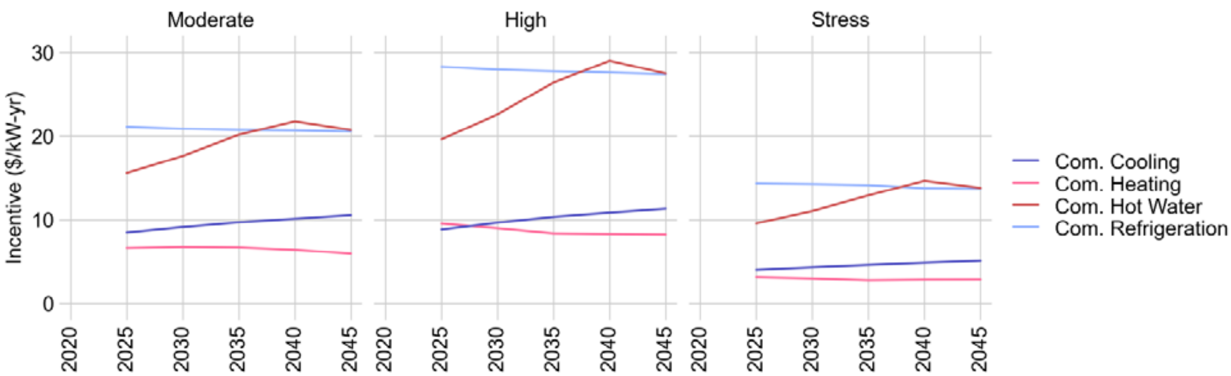

Figure 122. Assumed commercial demand response incentives, in \$/kW-yr

Incentive levels per participant per year are converted to \$/kW-yr based on coincident end-use peak demand per eligible building.

The incentive rates per kW-yr are shown in Figure 122. Comparing to Figure 117, these incentive levels are considerably smaller than what we estimated for the residential programs. This results from the considerably larger size of each commercial resource measured on a per-participant basis (Figure 123.) combined with the limited range of annual incentives (up to \$400) considered in the small and medium business participation model of Alstone et al. (2017) that is summarized in Figure 107. This makes it easy to comply with the first guideline, that incentives should not exceed RPM capacity prices, but also suggests that (a) DR resource might be better represented in a per-tenant commercial building model; and (b) commercial DR programs may sometimes be under-incented.

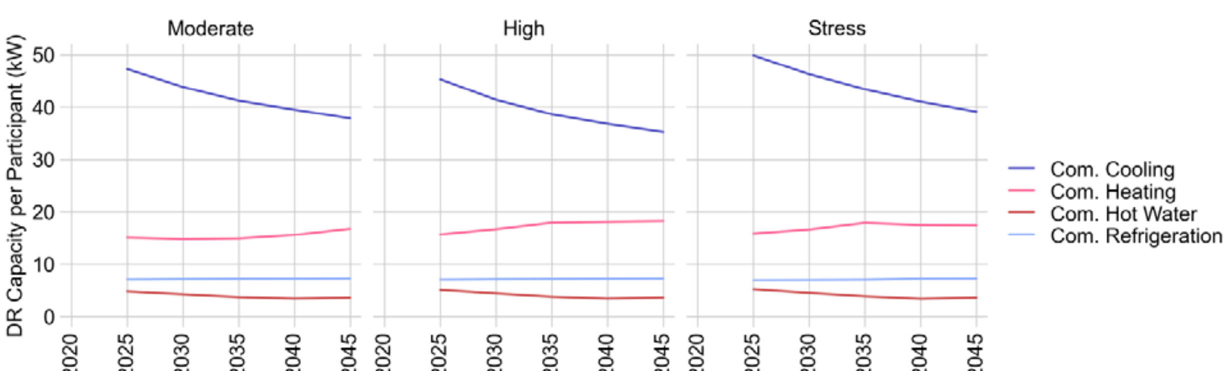

Figure 123. Coincident end-use peak demand per eligible commercial building

We summarize the size of each demand response program by stating the coincident peak consumption of participating end-use load. Figure 124 shows the resulting size of each commercial demand response program in megawatts (MW).

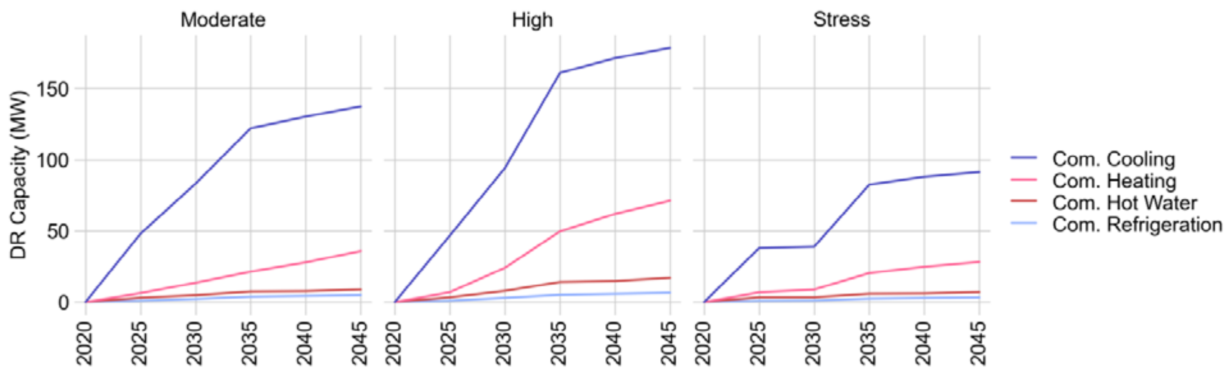

Figure 124. Commercial shiftable end-use demand response capacity

Relative to residential, the sizes of the commercial demand response programs are notably smaller. This mostly reflects Alstone et al.'s (2017) finding that small and medium businesses are more difficult to enroll in demand response programs. The relative size of the end uses we are modeling as shiftable as compared to overall building load and other end uses such as "plug and process" is also at play. On average, commercial buildings tend to be larger than residential buildings, and thus more insulated from outdoor conditions, with conditioning needs more driven by internal heat gains (from occupants and equipment) rather than outdoor conditions. Commercial buildings also serve a diversity of purposes—most commercial buildings will not have sizable refrigeration loads, but others (e.g., grocery stores and refrigerated warehouses) will have very large, potentially shiftable refrigeration loads.

Similar to the residential programs, cooling provides the most commercial demand response capacity under our assumptions. The High projection's electrification and demand response assumptions combine to produce a total of 274 MW commercial demand response in 2045; composed of 179 MW cooling, 71 MW heating, 17 MW hot water, and 7 MW refrigeration.

Electric Vehicle Scheduled Charging

The City of Los Angeles anticipates a transition toward electrified transportation in the coming decades. The LA100 study reflects that by modeling 100% bus electrification by 2030, and 30% or 80% electrification of the light-duty vehicle fleet by 2045 in the Moderate and High projections, respectively. The Stress projection also assumes 80% light-duty vehicle electrification by 2045, but—compared to High—with a greater share of residential charging, which concentrates charging in the evening.

Especially under high electrification assumptions (High and Stress projections), this results in electric vehicle charging becoming a significant fraction of both annual and peak loads. Under the High projection, electric vehicle charging is over 20% of both annual and peak loads by 2045; The Stress projection's assumption of 90% access to residential charging and only 10% access to workplace charging shifts the system peak time from 4:15pm local (PDT) in study year

2040 to 6:45 pm local (PDT) in 2045 and results in electric vehicle charging being about 30% of peak load, similar to cooling (Figure 125).

Furthermore, most of the electric vehicle demand is from L1 and L2 charging. In what follows, DC fast-charging and electric bus charging are assumed to be inflexible demands, essentially operating at full capacity for as long as the vehicles they are serving are plugged in. We are very comfortable with this assumption for DC fast-charging—making such stations more flexible is possible (e.g., by co-locating stationary storage), but not by leveraging the vehicle batteries themselves, because doing so would fundamentally reduce the level of service being provided. Bus charging infrastructure, however, could be designed to provide more flexibility than we are capturing by, for example, not using in-route charging and installing chargers with more power capacity than is strictly needed. We do not model such possibilities in the LA100 study, because bus loads are at most only 0.8% of total LADWP load (Moderate projection, 2030).

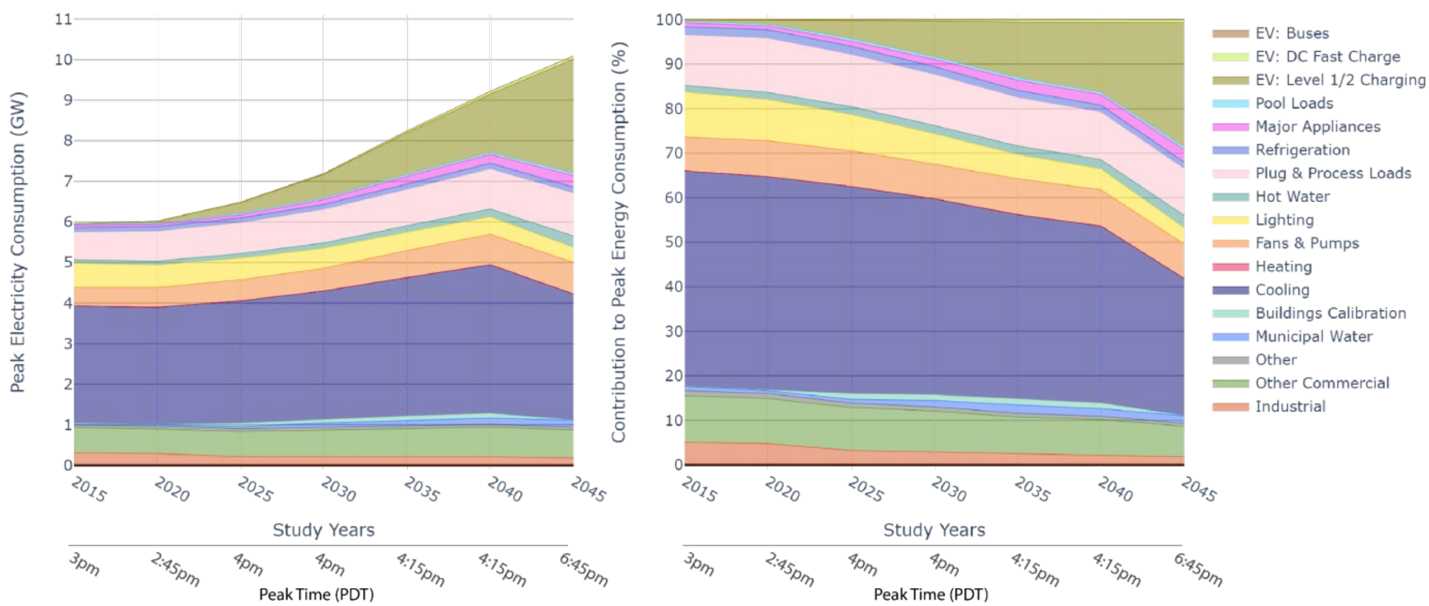

Figure 125. Stress projection peak demand by end use, contributions in GW (left), and share of peak in % (right)

Electric vehicle charging becomes about 30% of peak demand in 2045, in part by shifting the peak system time to 6:45 pm PDT.

(System peak time is 4pm PDT in model year 2040.)

The potential size of L1 and L2 electric vehicle charging loads, combined with the ability to automatically schedule charging, makes this a very important end use to leverage for energy-shifting demand response. Based on this intuition, the large amount of interest in grid-to-vehicle (G2V) and vehicle-to-grid (G2V) technologies, and preliminary demand response modeling results, we (a) assume that demand response participation levels for EV programs will be more in line with what we see for residential, as opposed to commercial, demand response (i.e., participation rates are estimated using Figure 106); and (b) assume relatively high incentive levels, marketing efforts, and levels of automation. Our specific assumptions and the resulting participation rates are summarized in Table 44.

Table 44. Participation Rate Assumptions for Scheduled Electric Vehicle Charging by Projection, Developed Using the Participation Rate Model of Alstone et al. (2017) (Figure 106.)

End Use	Projection	RPM Model Year	Assumed Incentive ($/yr)a	Installation Required?	Marketing Level	Participation Rate (%)
Home L2	Moderate	2020	—	—	—	—
		2025	60	Y	None	4
		2030	60	Y	Medium	14
		2035–2045	72	N	Medium	19
	High	2020	60	Y	None	4
		2025	60	Y	Medium	14
		2030–2045	96	N	High	30
	Stress	2020	—	—	—	—
		2025	48	Y	None	4
		2030	48	Y	Basic	10
		2035–2045	48	Y	Medium	14
Home L1	Moderate	2020	—	—	—	—
		2025	48	Y	None	4
		2030	48	Y	Medium	14
		2035–2045	60	N	Medium	18
	High	2020	48	Y	None	4
		2025	48	Y	Medium	14
		2030–2045	72	N	High	28
	Stress	2020	—	—	—	—
		2025	24	Y	None	3
		2030	24	Y	Basic	8
		2035–2045	24	Y	Medium	13
Work L2	Moderate	2020	—	—	—	—
		2025	48	Y	None	4
		2030	48	Y	Medium	14
		2035–2045	60	N	Medium	18
	High	2020	48	Y	None	4
		2025	48	Y	Medium	14
		2030–2045	72	N	High	28
	Stress	2020	—	—	—	—
		2025	36	Y	None	3
		2030	36	Y	Basic	9
		2035–2045	36	Y	Medium	13

End Use	Projection	RPM Model Year	Assumed Incentive ($/yr)a	Installation Required?	Marketing Level	Participation Rate (%)
Work L1	Moderate	2020	—	—	—	—
		2025	36	Y	None	3
		2030	36	Y	Medium	13
		2035–2045	48	N	Medium	18
	High	2020	36	Y	None	3
		2025	36	Y	Medium	13
		2030–2045	54	N	High	27
	Stress	2020	—	—	—	—
		2025	18	Y	None	2
		2030	18	Y	Basic	8
		2035–2045	18	Y	Medium	12
Public L2	Moderate	2020	—	—	—	—
		2025	18	Y	None	2
		2030	18	Y	Medium	12
		2035–2045	18	N	Medium	15
	High	2020	24	Y	None	3
		2025	24	Y	Medium	13
		2030–2045	24	N	High	25
	Stress	2020	—	—	—	—
		2025	12	Y	None	2
		2030	12	Y	Basic	7
		2035–2045	12	Y	Medium	10

[a] Annual incentives are assumed to be per-vehicle or per-charger.

As indicated in Table 44, we model schedulable electric vehicle charging separately for each combination of charger location and type. Specifically, we model five charger types:

- Home L1
- Home L2
- Work L1
- Work L2
- Public L2

Because L1 chargers are lower-voltage, and thus lower-power, than L2 chargers, they require more charging time to transfer the same amount of energy and will thus tend to be less flexible. We reflect this distinction in our assumptions by setting the incentive levels lower for L1, as opposed to L2 chargers. We also incent Public L2 chargers at this lower level based on the assumption that vehicles are less likely to dwell at public charging stations plugged in, but not charging, as compared to workplace and home charging.

The electric vehicle demand per charger type, and the number of eligible vehicles per charger type, are estimated based on the agent-level partition of charging loads provided by the transportation modeling team. That data set, in addition to providing the demand profiles themselves, can also be used to estimate the number of vehicles per agent, and what kinds of chargers are present. Each agent with charging load is one of Home, Work, or Public. Among the Home and Work agents, some only have L1 chargers, some only have L2 chargers, and some have both. To exactly assign each agent to a charger type and approximately match the originally estimated (at the system level) proportion of L1 versus L2 charging, we assign agents to L2 if the estimated number of vehicles charging at that power level is greater than one half the number of vehicles charging at the L1 level, both evaluated at the agent-level peak charging time.

These final assignments made, we can estimate the size of the demand response resource in terms of coincident end-use demand (Figure 126) as well as the number of eligible vehicles per charger type (Figure 127). Similar to the residential and commercial end uses, this information allows us to convert $/participant incentives into $/kW-yr (Figure 128).

In all projections, home charging is the dominant mode by coincident end-use peak and number of vehicles. The Stress projection has a further preference for Home L2, as compared to Home L1, charging because that exacerbates the evening peak. The High projection has more workplace and public charging than the other projections, but still assumes that most charging happens at home.

Figure 128 demonstrates that our assumed incentive levels follow the guidelines of being less than RPM’s highest capacity prices (i.e., less than $150/kW-yr), higher for more flexible types of charging, highest in the High projection, and lowest in the Stress projection.

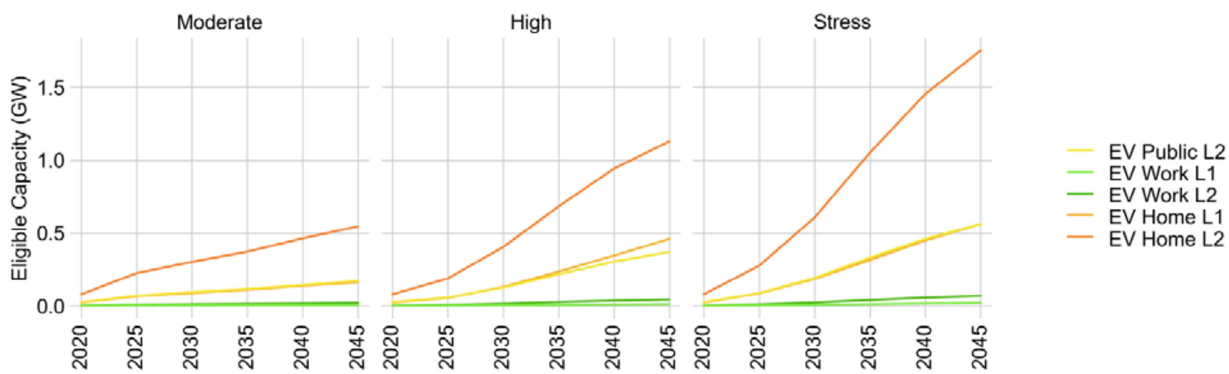

Figure 126. Coincident end-use peak demand of all EV charger types eligible for scheduling

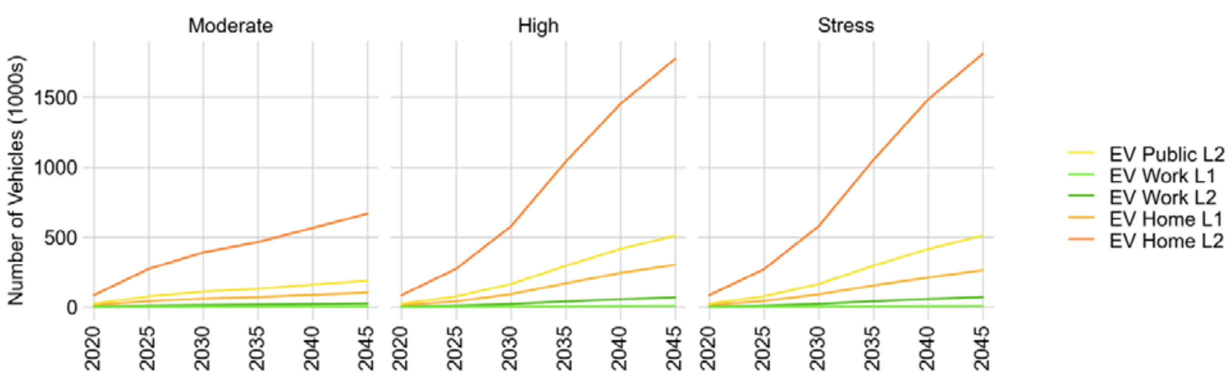

Figure 127. Number of vehicles per charger type that is eligible for scheduling

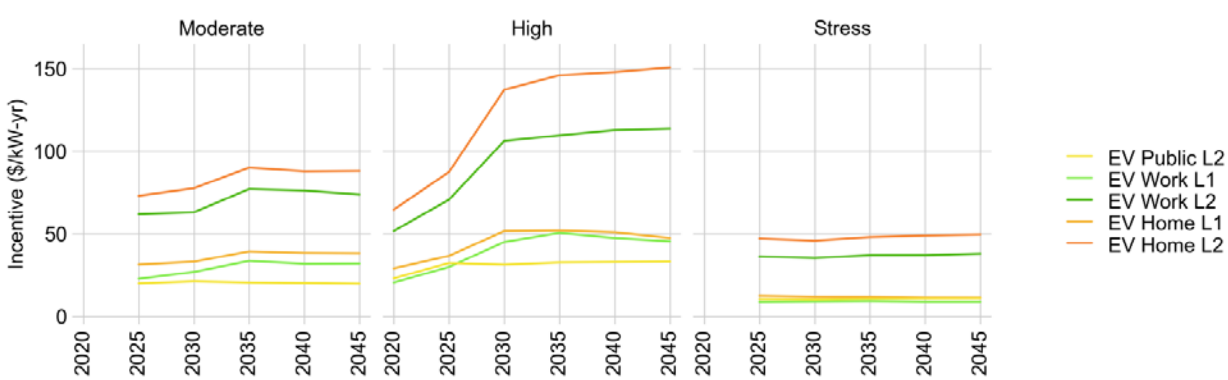

Figure 128. Assumed schedulable EV charging demand response incentives, in $/kW-yr

Incentive levels per vehicle per year are converted to $/kW-yr based on coincident end-use peak demand and number of vehicles per charger type.

The participation rates that result from our incentive, marketing and automation assumptions (

Table 44), multiplied by the non-coincident peak demand per charger type yields demand response capacity per projection as summarized in Figure 129 (all charger types) and Figure 130 (non-Home L2 charger types).

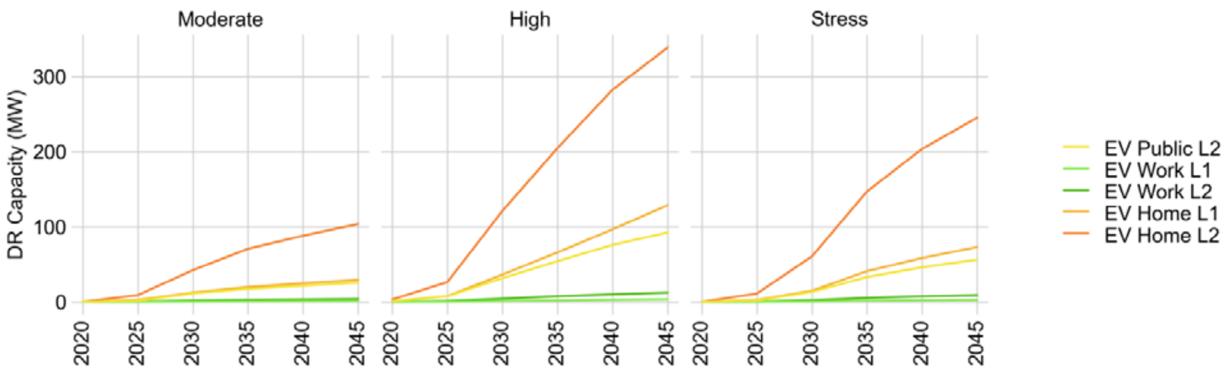

Figure 129. Scheduled electric vehicle charging demand response capacity

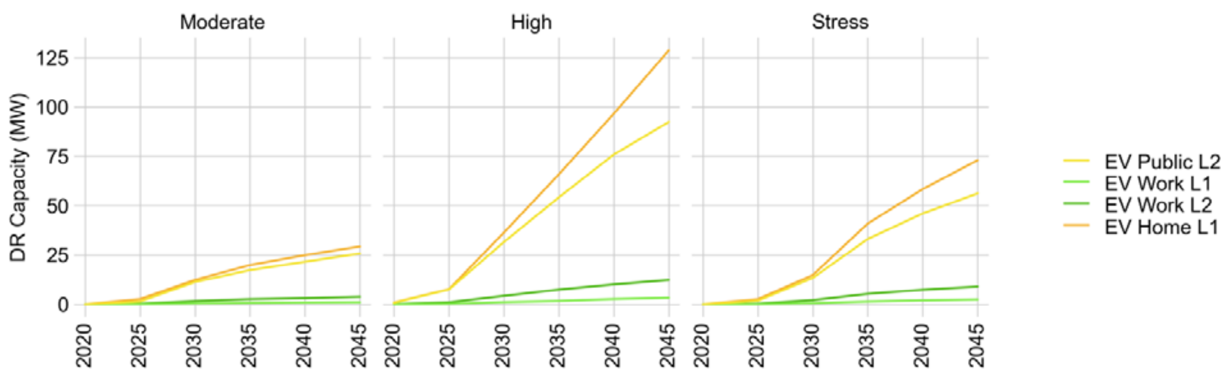

Figure 130. Scheduled electric vehicle charging demand response capacity, excluding Home L2

Figure 129 shows that scheduled electric vehicle charging is a significant source of demand response for all of the LA100 load projections. The program is similar in MW-size to residential cooling, but with the advantages of being less seasonal and potentially more flexible. Schedulable EV charging capacity is also just as sensitive to the amount of vehicle electrification as it is to demand response participation assumptions—although the Moderate projection's more aggressive demand response assumptions results in more residential cooling demand response than the Stress projection, it has less electric vehicle demand response than the Stress projection simply because its pool of potential participants is so much smaller.

Even under the High projection, the LA100 study does not show nearly as much coincident workplace charging as home charging, and the demand response capacities further reflect this. Because workplace charging is often more-aligned with solar generation than home charging, and our understanding of how electric vehicle adoption (e.g., plug-in hybrid versus battery-only, battery sizes) and charging patterns (e.g., where, when, and how often to charge) is still immature, these LA100 study results should be interpreted as initial. In the coming decade it may worth looking for ways to further align EV charging demand and solar generation, beyond what we are going to be able to examine in this study.

Commercial, Industrial, and Institutional (CII)

The LA100 study models demand response from large commercial, industrial, and institutional customers in three forms:

- Interruptible load from non-water system CII customers
- Interruptible load from water system pumping
- Water system demand shifting via scheduled modulation of pumps and treatment processes

Interruptible load is modeled after LADWP's current demand response program, which can be dispatched up to 48 hours over four peak months (June 15 to October 15), no more than one 4-hour event per day. Incentive levels are $8/kW-month for day-ahead notification and $12/kW-month for 2 hour-ahead notification, plus $0.25/kWh for actual dispatch. Thus, the annual incentive levels are $44/kW-year or $60/kW-year, assuming all 48 hours of potential dispatch are called upon.

Total CII Interruptible Load was 15 MW in 2015. We assume there will be 44 MW in 2020, and 215 MW in 2030 (per 2014 DR SIP goals). For all projection-years other than High projection 2035, 2040 and 2045, we assume that half of the peak water pumping demand is available as interruptible load. For model years 2015 through 2030, the amount of CII Interruptible Load from other large commercial and industrial customers is computed as the difference between the assumed total quantity of interruptible load and the amount provided by water system pumping (the 2025 total is assumed to be the average of 2020 and 2030, that is, 130 MW). For years 2035 and beyond we keep the amount of non-water system CII Interruptible Load the same when measured as a fraction of the large commercial and industrial customers' consumption peak. Large commercial and industrial customers are segmented out from the LA100 agent-level load data by filtering for agents with peak load greater than 500 kW. This number was derived by assuming that CII customers can shed up to 20% of their peak load, and then computing the minimum peak load needed to meet LADWP's requirement for at least 100 kW of response per participant. In model year 2030, the amount of non-water system interruptible load corresponds to 6.4% of the Moderate, 6.5% of the High, and 5.9% of the Stress projection's large commercial and industrial agents' peak. These proportions are kept constant for the remainder of the model years.

Finally, we assume only in the High projection that LADWP's water system infrastructure is built out in such a way that its operations are highly schedulable, and able to be co-optimized with the power system, by 2035. In this case, we assume that water system pumping no longer provides interruptible load but is folded into this more flexible water system shifting resource.

The resulting CII demand response capacity is shown in Figure 131.

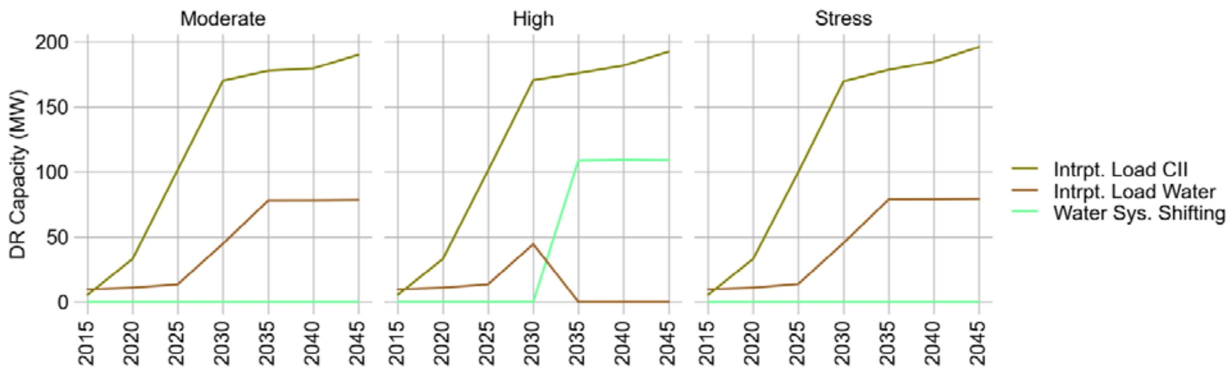

Figure 131. CII demand response capacity, including water system interruptible load and scheduling

The reasonableness of the water system demand response assumptions is discussed in Section L.2 (Water System Demand Response). The level of CII interruptible load can be assessed by comparing current incentive levels, which are $44/kW-yr to $60/kW-yr to the incentive levels that would be required to get the assumed levels of participation. This requires translating the percent of large customers' peak load assumed to participate in the program into a participation rate, which we do by assuming that on average "participation" corresponds to reducing load by 20%. Then we have, for the Moderate projection in 2030:

$$0.064 \cdot (\text{Large Customer Peak}) = (\text{participation rate}) \cdot 0.2 \cdot (\text{Large Customer Peak}),$$

such that the estimated participation rate is 32%. Following this logic for all of the projections 2030 and later, we compute 32% participation for the Moderate and High projections, and 30% participation for Stress. Referring now to Figure 108., we see that, according to Alstone et al. (2017) such participation rates may only be achievable for 10 hours per year (not the 48 hours we assume in our analysis) and with incentive payments of $200/kW-yr or more. This estimate is, however, highly sensitive to the size of the average reduction. If instead participants are able to reduce their load by 50% the corresponding participation rates would be about 12%, which the participation model finds is achievable for 50 hour/year programs given incentive levels above $100/kW-yr.

L.6 Sector-Level Additional Assumptions

In addition to identifying the demand response resource available to provide grid services, it is necessary to specify exactly how those resources may be operated. We specify different operational models for residential and commercial end uses, scheduled electric vehicle charging, interruptible load, and water system shifting.

Residential and Commercial End-Use Shiftability

Better aligning the demand response shiftability assumptions used in bulk system grid models with what is physically realistic, especially for passive thermal storage resources like air conditioning loads, is an active area of research. In lieu of methods able to express all the time-varying aspects of demand shiftability, including non-unity round-trip efficiencies and dissipation, we assume that shifting has an efficiency of 100% and is not subject to dissipation (that is, the same amount of energy is required to fulfill demand at a shifted time or at the original time). Different end uses are modeled as having different levels of shiftability, however, by requiring loads to shift within specified windows, subject to constraints on allowable distance of the shift in both directions, and a capacity constraint (limit on the ability to increase load).

The shiftability assumptions we apply to residential and commercial end uses are shown in Table 45 and Table 46, respectively. The capacity constraint limits the peak of the shifted load (all participating demand allocated to its final timeslot) to be no more than the program capacity (coincident peak of all participating demand in the uncontrolled case) multiplied by the capacity multipliers listed in the tables. The capacity multipliers for the heating and cooling end uses are set to 1.0, because the coincident end-use peak is a reasonable estimate of total available equipment capacity for these loads that vary significantly with outdoor temperature. All other program multipliers are set to 2.0 to capture that additional equipment capacity is generally available to increase load beyond the maximum coincident end-use demand seen in the baseline case. For example, scheduled dishwashing and clothes drying could result in a controlled demand curve with a higher coincident peak than is seen in the uncontrolled case.

Table 45. Energy Shifting Assumptions for Residential End Uses

End Use	Capacity Multiplier	Time Period	Allowable Pre-Shift (h)	Allowable Post-Shift (h)	Demand Fulfilled By
Space Cooling	1.0	7 a.m. – 4 p.m.	2	2	5 p.m.
		4 p.m. – 9 p.m.	2	2	10 p.m.
		9 p.m. – 7 a.m.	2	2	7 a.m.
Space Heating	1.0	7 a.m. – 4 p.m.	2	2	5 p.m.
		4 p.m. – 9 p.m.	2	2	10 p.m.
		9 p.m. – 7 a.m.	2	2	8 a.m.
Water Heating	2.0	All	12	0	N/A
Pool Pumps	2.0	All	6	6	N/A
Refrigeration	2.0	All	2	2	N/A
Appliances	2.0	7 a.m. – 4 p.m.	0	7	4 p.m.
		4 p.m. – 7 a.m.	0	14	7 a.m.

Heating and cooling shiftability is broken up into three windows representing daytime, evening, and overnight. Each window's demand is required to be delivered by the window end-time, or soon thereafter. In commercial buildings we also assume that the demand is differently shiftable over each period, with the daytime demand being most constrained, and overnight demand being least constrained. Except for overnight hours in commercial buildings, we assume that space conditioning can be shifted by at most two hours in either direction.

Residential appliances (clothes dryers and dishwashers) are assumed to be run either during the day (7 a.m. – 4 p.m.) with completion expected by afternoon/early evening, or in the evening/overnight with completion by morning. All other shiftable end uses are assumed not to follow strict diurnal patterns, and demand is generally assumed more movable because it is associated with high thermal capacitance (water heating, refrigeration) or a pumping load (pool pumps).

Table 46. Energy Shifting Assumptions for Commercial End Uses

End Use	Capacity Multiplier	Time Period	Allowable Pre-Shift (h)	Allowable Post-Shift (h)	Demand Fulfilled By
Space Cooling	1.0	8 a.m. – 5 p.m.	2	1	6 p.m.
		5 p.m. – 10 p.m.	2	2	10 p.m.
		10 p.m. – 8 a.m.	4	4	9 a.m.
Space Heating	1.0	8 a.m. – 5 p.m.	2	1	6 p.m.
		5 p.m. – 10 p.m.	2	2	10 p.m.
		10 p.m. – 8 a.m.	4	4	9 a.m.
Water Heating	2.0	All	12	0	N/A
Refrigeration	2.0	All	6	6	N/A

Electric Vehicle Charging Shiftability

In the LA100 Study, electric vehicle charging loads are estimated using EVI-Pro simulations (Wood, Rames, and Muratori 2018). EVI-Pro is a tool that estimates charging infrastructure needs by simulating many trips taken by battery electric and plug-in hybrid electric vehicles. Its main inputs are number and type of vehicles, proportions of vehicles with access to certain types of chargers (e.g., Home - L1, Work - L2, DC Fast Charging), and a database of trip information. EVI-Pro then determines how many chargers are needed to enable all of the required trips. In doing this, it produces charging profiles broken out by charger type.

For LA100, EVI-Pro was used to compute both minimum-delay and maximum-delay profiles. The minimum-delay charging profiles describe what happens if every car starts charging immediately upon being plugged in and continues drawing as much power as possible until the battery is full or the car is unplugged, whichever comes first. On the other hand, the maximum-delay charging profiles assume that charging is put off as long as possible while still reaching the state-of-charge required before the car is unplugged. The minimum-delay profile is the demand curve used in our pre-demand response load projections, that is, we assume people will not delay their vehicle charging absent a signal from the utility.

To understand potential shiftability of electric vehicle charging, we combine the two profiles to define the bounds of a delay-only shifting model of the form:

$$\Delta S(t+\Delta t) = \Delta S(t) + \Delta P(t)\cdot \Delta t$$

$$\underline{\Delta S}(t) \le \Delta S(t) \le 0$$

$$\underline{\Delta P}(t) \le \Delta P(t) \le \overline{\Delta P}(t)$$

where $\Delta P(t)$ is the change in electric vehicle charging power at time *t* in megawatts (MW); $-\Delta S(t)$ is the cumulative amount of charging energy that has been delayed relative to the baseline, minimum-delay charging profile in megawatt-hours (MWh) ($\Delta S(t)$ is always a non-positive quantity); $-\underline{\Delta S}(t)$ is the upper bound on cumulative delayed charging at time *t*; and $\underline{\Delta P}(t)$ and $\overline{\Delta P}(t)$ are the bounds on how much the power profile can deviate from baseline minimum-delay. The model can be produced at either the hour ($\Delta t = 1$ hour) or 15-minute ($\Delta t = 0.25$ hour) resolution, for RPM or PLEXOS, respectively.

To estimate $\underline{\Delta S}(t)$, $\underline{\Delta P}(t)$, and $\overline{\Delta P}(t)$ we start by defining some notation around the minimum-delay and maximum-delay profiles. Namely, we denote

$$P_1(t) = P_{\text{base}}(t) = \text{minimum-delay profile, and}$$

$$P_2(t) = \text{maximum-delay profile.}$$

Then the actual charging profile $P(t)$ is

$$P(t) = P_{\text{base}}(t) + \Delta P(t) = P_1(t) + \Delta P(t).$$

The amount of charging possible at any time *t* is limited by which vehicles are plugged into which chargers. That is, there is a generally unknown quantity of charging capacity available at any particular time, $\overline{P}(t)$. This, together with $P_1(t)$ lets us begin to define $\underline{\Delta P}(t)$ and $\overline{\Delta P}(t)$, as the charging power can be reduced by at most $P_1(t)$ relative to the baseline:

$$0 \le P(t) = P_1(t) + \Delta P(t) \text{ implies that } \underline{\Delta P}(t) = -P_1(t),$$

and the charging power can be increased by at most the difference between $\overline{P}(t)$ and $P_1(t)$:

$$P(t) = P_1(t) + \Delta P(t) \le \overline{P}(t) \text{ implies that } \overline{\Delta P}(t) = \overline{P}(t) - P_1(t).$$

We estimate the maximum available charging capacity $\overline{P}(t)$ by assuming that positive changes in the minimum delay profile $P_1(t)$ approximately corresponds to more cars being plugged into more chargers; and that negative changes in the maximum delay profile $P_2(t)$ approximately corresponds to cars being unplugged from chargers. Thus, given discretized charging profiles with constant timestep Δt we estimate the amount of charging capacity added at time *t* as:

$$\overline{P}_{\text{add}}(t) = \max(P_1(t) - P_1(t - \Delta t), 0)$$

and the amount lost as:

$$\overline{P}_{\text{subtract}}(t) = -\min(P_2(t) - P_2(t - \Delta t), 0).$$

We then note that the total amount of charging capacity at any time *t* must be at least as large as $P_1(t)$ or $P_2(t)$. To estimate how much more capacity than the minimum is available we introduce a heuristic parameter $f_c \ge 0$ that is the minimum surplus charging capacity expected relative to

$$\tilde{P}(t) = \max\big(P_1(t), P_2(t)\big)$$

That is, we define

$$\overline{P}_{\text{base}} = \max_t \tilde{P}(t)(1 + f_c) - \sum_{t'=0}^{t} \left(\overline{P}_{\text{add}}(t') - \overline{P}_{\text{subtract}}(t')\right)$$

and use it to estimate the maximum charging capacity as

$$\overline{P}(t) = \overline{P}_{\text{base}} + \sum_{t'=0}^{t} \left(\overline{P}_{\text{add}}(t') - \overline{P}_{\text{subtract}}(t')\right),$$

which ensures that

$$\overline{P}(t) \geq \tilde{P}(t)(1 + f_c)$$

for all times *t*.

To define $\underline{\Delta S}(t)$ we first observe that baseline charging $P_1(t)\Delta t$ during the t^{th} interval represents charging that could potentially be delayed starting at time *t*. Conversely, maximum-delay charging $P_2(t)\Delta t$ represents charging that must happen by time $t + \Delta t$. As such,

$$\underline{\Delta S}(t) = \underline{\Delta S}(t - \Delta t) + \big(P_2(t) - P_1(t)\big)\Delta t$$

Then if, similar to our development of $\overline{P}(t)$, we introduce a baseline amount of delayable charging $\underline{\Delta S}_{\text{base}}$ and a heuristic minimum delayable time Δt_e applied to the baseline power profile $P_1(t)$ we have

$$\underline{\Delta S}(t) = \underline{\Delta S}_{\text{base}} + \sum_{t'=0}^{t} \big(P_2(t') - P_1(t')\big)\Delta t \leq -P_1(t)\Delta t_e.$$

Finally, defining

$$\underline{\Delta S}_{\text{base}} = \min_t -P_1(t)\Delta t_e - \sum_{t'=0}^{t} \big(P_2(t') - P_1(t')\big)\Delta t$$

completes the heuristic model.

For the LA100 Study we define five such models, one for each charger type. The f_c and Δt_e values we use in each case are listed in Table 47. The values are based on engineering judgement regarding the relative flexibility of the charger types. For example, L2 charging, being higher power but serving similar trips is more flexible than L1; and home overnight charging is more flexible than workday charging, which in turn is more flexible than public charging.

Table 47. Electric Vehicle Charging Shiftability Parameters, by Charging Location and Type

Charging Location	Charging Type	f_c	Δt_e (h)
Home	L1	0.05	2.0
	L2	0.2	6.0
Work	L1	0.05	1.0
	L2	0.2	3.0
Public	L2	0.05	0.5

A visualization of the resulting shiftability model is shown in Figure 132 for the High Projection, 2045 Home L2 chargers. The baseline EV charging load represents the largest load reduction possible for the given hour. Charging load can be increased above baseline up to the dashed black line, which represents our estimate of how much charging capacity is currently accessible by plugged-in vehicles. The purple line summarizes the limit on how many MWh behind baseline the accumulated measure of electric vehicle charging is allowed to be, represented as a number of hours by normalizing that bound against the total connected charger capacity.

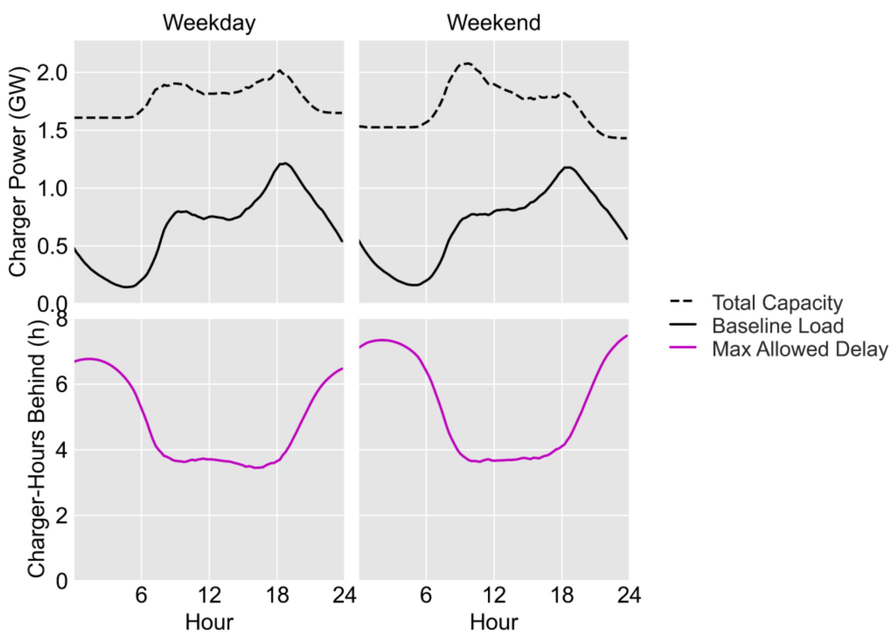

Figure 132. Average shiftability model for weekdays and weekends, Home L2 chargers, High Projection 2045

Interruptible Load

As with LADWP's current program, we assume interruptible load is usable up to 48 hours per year, at most 4 hours per day. We do not, however, restrict this resource to only the summer months of June 15 to October 15.

We also assume that interruptible load can provide spinning, or contingency, reserves. Although LADWP's current interruptible load program relies on email or phone notifications and requires demand response participants to "initiate their own DR curtailment procedure to achieve a predetermined amount of energy reduction,"[97] LADWP intends to transition this program from being semi-automated to fully automated. We assume that this transition happens in the near-term and enables CII Interruptible Load to provide contingency reserves (fast response, with only 10 to 30 minute notification, to respond to times of system stress such as an unexpected generator or transmission outage) by 2025.

LADWP currently describes their program as semi-automated. LADWP initiates an automated process to notify demand response participants of an event via text message, email or telephone. The customer then curtails energy usage during the event through a Building Energy Management System (BEMS), a load control device, or breakers on specific circuits.[98] A fully automated demand response program (Auto DR), in contrast, does not require any manual actions from the customer. The same types of equipment (BEMS, load controllers, breakers on specific circuits) may be used to provide the response, but the actions are triggered directly by a signal sent from LADWP.

Moving toward an Auto DR program was envisioned by LADWP's 2014 DR Strategic Implementation Plan (2014 DR SIP), which suggested initiating a pilot program for this technology in 2016 and using this program for spinning reserves and renewables integration by 2020. A number of power systems already use demand response to provide various operating reserve products. For example, ERCOT consistently has load resources equipped with high-set under-frequency relays providing responsive reserves up to the maximum level allowed by market rules, which was 50% in 2015 and 60% today. The remainder of the Responsive Reserve Service (RRS) providers (and also subject to a 1,150 MW minimum) are required to also provide primary frequency response (ERCOT 2020).

Water System Shiftability

LADWP water system loads are only assumed shiftable in the High projection, starting in model year 2035. The shiftability assumptions are identical to commercial refrigeration, that is, all loads can be moved up to 6 hours in either direction, and the shifted load's peak can be no greater than two times the original peak. These assumptions reflect the idea that significant preparations and some investments would need to be made to improve and verify the flexibility of the water system before allowing half of its demand to be shifted in this manner.

[97] "Demand Response Program," LADWP, accessed April 17, 2020: https://www.ladwp.com/ladwp/faces/ladwp/commercial/c-savemoney/c-sm-rebatesandprograms/c-sm-rp-demandresponse.

[98] LADWP, *Demand Response Commercial and Industrial Program Terms and Conditions* (LADWP, May 15, 2019), accessed April 17, 2020: https://www.ladwp.com/cs/idcplg?IdcService=GET_FILE&dDocName=OPLADWPCCB648615&RevisionSelectionMethod=LatestReleased.

L.7 Grid Modeling Plan

Demand response projections are incorporated into the rest of the LA100 study primarily through bulk power system dispatch modeling. The capacity expansion modeling tool, RPM, and PLEXOS, a commercial production cost modeling software, are used to determine interruptible load and DR shifting profiles at the bulk power nodal level. DR shifting profiles are determined solely by RPM at hourly resolution, but they can be interpolated to 15-minutes as needed. Interruptible load is dispatched directly by both RPM (hourly for 5 representative days) and PLEXOS (15-minute over the entire study year).

The distribution modeling team plans to use the DR dispatch profiles to analyze the effects on specific distribution feeders impacted by EV charging loads. This will require interpolating the DR shifting profiles to 15-minute temporal resolution and then disaggregating them to distribution feeders based on participation factors. Other modeling teams are also welcome to use the DR dispatch profiles if they would like, but at this time we are unaware of any other planned uses.

RPM models the two types of DR, interruptible load and energy shifting, differently. Interruptible load, consisting of CII DR and, in most scenarios, water pumping, is directly dispatched within RPM with an annual program limit of 48 hrs/year, and a daily limit of at most 4 hours per day. The total capacity available for each type of interruptible load in each year is provided by the LA100 DR team to the RPM team and is not a technology RPM is allowed to build or expand in any way. RPM is however allowed to dispatch the resources as needed, to provide both energy and contingency reserve. In that way, by displacing services that other resources would otherwise need to provide, interruptible load influences other build decisions within the model.

Energy shifting DR is incorporated through a price-taker model. The price-taker model uses the marginal values from the energy and capacity constraints in RPM to estimate how DR could be dispatched most optimally for the system. Capacity contribution is estimated by calculating how much DR dispatch reduces net load in the top 100 hours. Energy revenue is adjusted so that DR does not have to pay for increasing load during curtailment hours and cannot get paid for reducing load during curtailment hours, even if the energy price is positive. In addition to maximizing DR program revenues, a regularization term is included in the objective function to encourage final net load profiles (after shifting) with smaller hour-to-hour variability. We do this because the estimated amount of shiftable load is large enough that, without this term, shifting as much load as possible to the lowest price hours creates large swings in demand that would not occur in a real-world, price-making dispatch. After dispatch profiles are calculated in this way for every LA100 scenario-year, the resulting shifted load profiles are included in a final RPM run so they can influence what supply-side resources are ultimately built. These capacity build-outs and the shifted load profiles are then passed along to the production cost modeling team.

Similar to RPM, the production cost model PLEXOS directly optimizes the dispatch of interruptible load but accepts the DR shifting profile as an exogenous input. Unlike RPM, PLEXOS is not directly iterated with the price-taking model—PLEXOS uses fixed demand profiles consisting of the original demand data plus the same shifting profiles used in RPM.

These methods for modeling DR do not maximize the potential value that DR could provide—we are not capturing all of the ancillary service value streams, and by not re-dispatching the shiftable load in PLEXOS we may be underestimating its ability to reduce renewable curtailments and otherwise shift demand to lower-price times. However, we are capturing DR's ability to contribute to the largest and most valuable grid services (Denholm, Sun, and Mai 2019; Neukomm, Nubbe, and Fares 2019); and by not overestimating the responsiveness and flexibility of shiftable demand on an hour-to-hour timescale we are hopefully providing a realistic-enough sense of how some demands may be able to be shifted on a regular basis to better align LA100 demand and supply.

Appendix M. Tabular Summary of Demand Response Results

M.1 Demand Response Capacity

The tables in this section list demand response capacity for each program using the metric of participating end-use peak load, coincident across the end use, but non-coincident with system peak. For all projections, CII interruptible load capacity is 215 MW in 2030, and total capacity exceeds 500 MW by 2030. Blanks in the individual program rows (indicated by plain, not emphasized, text) indicate that a program is assumed not to have started by that year.

Table 48. Moderate Projection Demand Response Capacity

Year	2015	2020	2025	2030	2035	2040	2045
System Peak Demand (MW)	**5,952**	**6,020**	**6,309**	**6,575**	**6,958**	**7,395**	**7,811**
CII Interruptible Load (MW)	*15*	*44*	*115*	*215*	*256*	*258*	*268*
Water System	10	11	14	45	78	78	78
Other CII	5	33	102	170	178	180	190
Water System Shifting (MW)	—	—	—	—	—	—	—
Sched. EV Charging (MW)	—	—	*13*	*68*	*111*	*138*	*164*
Home L1			3	12	20	25	29
Home L2			9	42	71	88	104
Work L1			0	0	1	1	1
Work L2			0	2	3	3	4
Public L2			1	11	17	22	26
Residential Load Shifting (MW)	—	*75*	*237*	*401*	*539*	*571*	*584*
Res. Space Cooling		75	225	362	467	480	477
Res. Space Heating			10	26	38	42	47
Res. Water Heating			1	8	12	17	27
Res. Pool Pumps				3	13	18	18
Res. Refrigeration				2	7	9	9
Res. Appliances				1	3	5	6
Commercial Load Shifting (MW)	—	—	*58*	*104*	*155*	*170*	*187*
Com. Space Cooling			48	83	122	130	138
Com. Space Heating			6	14	21	28	36

Com. Water Heating			3	5	7	8	9
Com. Refrigeration			1	2	4	4	5
Total DR (MW)	**15**	**119**	**424**	**788**	**1,061**	**1,137**	**1,203**
Total DR (% of Peak Demand)	**0.3**	**2.0**	**6.7**	**12.0**	**15.2**	**15.4**	**15.4**

Table 49. High Projection Demand Response Capacity

Year	**2015**	**2020**	**2025**	**2030**	**2035**	**2040**	**2045**
System Peak Demand (MW)	**5,952**	**6,020**	**6,161**	**6,688**	**7,497**	**8,162**	**8,659**
CII Interruptible Load (MW)	*15*	*44*	*115*	*215*	*176*	*182*	*192*
Water System	10	11	14	44	—	—	—
Other CII	5	33	101	171	176	182	192
Water System Shifting (MW)	—	—	—	—	*109*	*109*	*109*
Sched. EV Charging (MW)	—	—	*43*	*194*	*334*	*468*	*575*
Home L1			8	36	66	97	129
Home L2			26	121	205	283	339
Work L1			0	1	2	3	3
Work L2			1	4	7	10	12
Public L2			7	32	54	76	92
Residential Load Shifting(MW)	—	*75*	*350*	*541*	*857*	*956*	*973*
Res. Space Cooling		75	336	442	658	650	626
Res. Space Heating			9	43	76	104	130
Res. Water Heating			2	40	92	149	165
Res. Pool Pumps			3	14	18	28	28
Res. Refrigeration				2	8	15	15
Res. Appliances				1	6	10	10
Commercial Load Shifting (MW)	—	—	*58*	*129*	*230*	*254*	*274*
Com. Space Cooling			47	94	161	171	179
Com. Space Heating			7	24	50	62	71
Com. Water Heating			3	8	14	15	17
Com. Refrigeration			1	3	5	6	7
Total DR (MW)	**15**	**119**	**566**	**1,079**	**1,706**	**1,969**	**2,124**
Total DR (% of Peak Demand)	**0.3**	**2.0**	**9.2**	**16.1**	**22.8**	**24.1**	**24.5**

Table 50. Stress Projection Demand Response Capacity

Year	2015	2020	2025	2030	2035	2040	2045
System Peak Demand (MW)	**5,952**	**6,020**	**6,487**	**7,194**	**8,243**	**9,220**	**10,090**
CII Interruptible Load (MW)	*15*	*44*	*114*	*215*	*257*	*264*	*275*
Water System	10	11	14	45	79	79	79
Other CII	5	33	100	170	179	185	196
Water System Shifting (MW)	—	—	—	—	—	—	—
Sched. EV Charging (MW)	—	—	*16*	*91*	*228*	*317*	*386*
Home L1			3	15	41	58	73
Home L2			11	61	147	204	245
Work L1			0	1	1	2	2
Work L2			0	2	5	7	9
Public L2			2	13	33	46	56
Residential Load Shifting (MW)	—	*75*	*241*	*262*	*392*	*452*	*482*
Res. Space Cooling		75	225	239	317	343	352
Res. Space Heating			13	7	33	48	64
Res. Water Heating			2	13	32	48	53
Res. Pool Pumps			—	3	10	13	13
Res. Refrigeration							
Res. Appliances							
Commercial Load Shifting (MW)	—	—	*49*	*52*	*111*	*122*	*130*
Com. Space Cooling			38	39	83	88	91
Com. Space Heating			7	9	20	25	28
Com. Water Heating			3	3	6	6	7
Com. Refrigeration			1	1	2	3	3
Total DR (MW)	**15**	**119**	**419**	**621**	**988**	**1,155**	**1,273**
Total DR (% of Peak Demand)	**0.3**	**2.0**	**6.5**	**8.6**	**12.0**	**12.5**	**12.6**

M.2 Demand Response Capacity Coincident with System Peak

The tables in this section list demand response capacity for each program using the metric of participating end-use load that is coincident with system peak. All capacity numbers in this section will be less than or equal to what was shown in the previous section. Residential and commercial heating DR capacity is zero in this section because all system peak times are in the summer.

Table 51. Moderate Projection Demand Response Capacity Coincident with System Peak

Year	**2015**	**2020**	**2025**	**2030**	**2035**	**2040**	**2045**
System Peak Demand (MW)	**5,952**	**6,020**	**6,309**	**6,575**	**6,958**	**7,395**	**7,811**
System Peak Demand Time (PST)	**8/6 14:00**	**8/8 13:45**	**8/6 14:00**	**8/10 15:00**	**8/10 15:00**	**8/10 15:00**	**8/10 15:00**
CII Interruptible Load (MW)	*14*	*42*	*108*	*187*	*215*	*216*	*225*
Water System	9	10	12	32	53	53	53
Other CII	5	32	95	155	162	163	172
Water System Shifting (MW)	—	—	—	—	—	—	—
Sched. EV Charging (MW)	—	—	*6*	*47*	*77*	*96*	*114*
Home L1			1	8	13	17	20
Home L2			4	30	50	62	73
Work L1			0	0	0	1	1
Work L2			0	1	2	2	3
Public L2			1	8	12	15	17
Residential Load Shifting (MW)	—	*73*	*225*	*342*	*452*	*471*	*485*
Res. Space Cooling		73	225	337	437	450	462
Res. Space Heating			0	0	0	0	0
Res. Water Heating			0	1	2	3	4
Res. Pool Pumps				1	5	6	6
Res. Refrigeration				2	7	9	9
Res. Appliances				0	1	3	3
Commercial Load Shifting (MW)	—	—	*48*	*84*	*124*	*133*	*142*
Com. Space Cooling			44	77	114	122	129
Com. Space Heating			0	0	0	0	0
Com. Water Heating			3	4	7	7	8
Com. Refrigeration			1	2	4	4	5
Total DR (MW)	**14**	**115**	**387**	**660**	**867**	**915**	**965**
Total DR (% of Peak Demand)	**0.2**	**1.9**	**6.1**	**10.0**	**12.5**	**12.4**	**12.4**

Table 52. High Projection Demand Response Capacity Coincident with System Peak

Year	**2015**	**2020**	**2025**	**2030**	**2035**	**2040**	**2045**
System Peak Demand (MW)	**5,952**	**6,020**	**6,161**	**6,688**	**7,497**	**8,162**	**8,659**
System Peak Demand Time (PST)	**8/6 14:00**	**8/8 13:45**	**8/6 14:00**	**8/10 15:00**	**8/10 15:00**	**8/10 15:00**	**8/10 12:45**
CII Interruptible Load (MW)	*14*	*42*	*107*	*188*	*160*	*164*	*186*
Water System	9	10	12	32	—	—	—
Other CII	5	32	95	156	160	164	186
Water System Shifting (MW)	—	—	—	—	*75*	*75*	*84*
Sched. EV Charging (MW)	—	—	*26*	*160*	*278*	*386*	*463*
Home L1			4	29	58	87	119
Home L2			16	101	169	228	259
Work L1			0	1	1	2	2
Work L2			1	3	6	8	9
Public L2			5	25	44	61	73
Residential Load Shifting (MW)	—	*73*	*335*	*428*	*653*	*669*	*577*
Res. Space Cooling		73	334	414	620	615	516
Res. Space Heating			0	0	0	0	0
Res. Water Heating			0	7	15	24	34
Res. Pool Pumps			1	5	7	10	6
Res. Refrigeration				2	8	15	15
Res. Appliances				1	4	5	7
Commercial Load Shifting (MW)	—	—	*47*	*97*	*168*	*179*	*199*
Com. Space Cooling			43	87	150	161	177
Com. Space Heating			0	0	0	0	0
Com. Water Heating			3	7	13	13	15
Com. Refrigeration			1	3	5	6	6
Total DR (MW)	**14**	**115**	**515**	**874**	**1,333**	**1,474**	**1,508**
Total DR (% of Peak Demand)	**0.2**	**1.9**	**8.4**	**13.1**	**17.8**	**18.1**	**17.4**

Table 53. Stress Projection Demand Response Capacity Coincident with System Peak

Year	**2015**	**2020**	**2025**	**2030**	**2035**	**2040**	**2045**
System Peak Demand (MW)	**5,952**	**6,020**	**6,487**	**7,194**	**8,243**	**9,220**	**10,090**
System Peak Demand Time (PST)	**8/6 14:00**	**8/8 13:45**	**8/10 15:00**	**8/10 15:00**	**8/10 15:15**	**8/10 15:15**	**8/9 17:45**
CII Interruptible Load (MW)	*14*	*42*	*104*	*188*	*212*	*216*	*198*
Water System	9	10	12	33	52	53	57
Other CII	5	32	92	155	159	164	141
Water System Shifting (MW)	—	—	—	—	—	—	—
Sched. EV Charging (MW)	—	—	*9*	*54*	*135*	*189*	*386*
Home L1			2	9	24	35	73
Home L2			7	36	88	122	245
Work L1			0	0	1	1	2
Work L2			0	1	3	4	9
Public L2			1	8	19	27	56
Residential Load Shifting (MW)	—	*73*	*209*	*226*	*303*	*330*	*312*
Res. Space Cooling		73	209	222	294	318	282
Res. Space Heating			0	0	0	0	0
Res. Water Heating			0	2	5	8	23
Res. Pool Pumps				1	4	5	7
Res. Refrigeration	—	—	—	—	—	—	—
Res. Appliances	—	—	—	—	—	—	—
Commercial Load Shifting (MW)	—	—	*39*	*40*	*84*	*90*	*53*
Com. Space Cooling			35	36	77	82	46
Com. Space Heating			0	0	0	0	0
Com. Water Heating			3	3	5	5	4
Com. Refrigeration			1	1	2	3	3
Total DR (MW)	**14**	**115**	**361**	**508**	**734**	**826**	**949**
Total DR (% of Peak Demand)	**0.2**	**1.9**	**5.6**	**7.1**	**8.9**	**9.0**	**9.4**

M.3 Demand Response Annual Shiftable Demand

The tables in this section list the total amount of load assumed shiftable by demand response programs. All participating end-use demand is reported.

Table 54. Moderate Projection Demand Response Shiftable Demand

Year	**2015**	**2020**	**2025**	**2030**	**2035**	**2040**	**2045**
Annual Load (GWh)	**25,832**	**26,457**	**28,536**	**30,697**	**33,152**	**35,840**	**38,880**
Water System Shifting (GWh)	—	—	—	—	—	—	—
Sched. EV Charging (GWh)	—	—	*16*	*143*	*278*	*416*	*553*
Home L1			6	63	128	190	243
Home L2			8	67	130	199	277
Work L1			0	2	3	4	6
Work L2			0	3	5	7	9
Public L2			1	8	12	16	19
Residential Load Shifting (GWh)	—	—	*56*	*285*	*466*	*580*	*686*
Res. Space Cooling			10	49	80	102	121
Res. Space Heating			38	181	300	372	439
Res. Water Heating			0	2	3	3	4
Res. Pool Pumps			1	7	11	13	15
Res. Refrigeration			6	47	72	90	107
Res. Appliances			56	285	466	580	686
Commercial Load Shifting (GWh)	—	—	*76*	*135*	*206*	*225*	*247*
Com. Space Cooling			53	91	135	146	156
Com. Space Heating			2	5	8	10	12
Com. Water Heating			16	26	42	45	52
Com. Refrigeration			5	12	21	24	27
Total Shiftable Demand (GWh)	**—**	**74**	**370**	**878**	**1,364**	**1,577**	**1,806**
Total Shiftable Demand (% of Annual Demand)	**—**	**0.3**	**1.3**	**2.9**	**4.1**	**4.4**	**4.6**

Table 55. High Projection Demand Response Shiftable Demand

Year	**2015**	**2020**	**2025**	**2030**	**2035**	**2040**	**2045**
Annual Load (GWh)	**25,832**	**26,457**	**28,013**	**31,856**	**37,458**	**42,305**	**46,257**
Water System Shifting (GWh)	—	—	—	—	*609*	*613*	*611*
Sched. EV Charging (GWh)	—	—	*212*	*955*	*1,649*	*2,299*	*2,796*
Home L1			36	177	340	507	653
Home L2			132	597	996	1,356	1,611
Work L1			1	5	8	13	16
Work L2			5	20	36	48	58
Public L2			37	156	269	375	458
Residential Load Shifting (GWh)	—	*74*	*366*	*725*	*1,255*	*1,563*	*1,681*
Res. Space Cooling		74	336	447	655	625	655
Res. Space Heating			5	21	35	45	50
Res. Water Heating			11	184	402	618	702
Res. Pool Pumps			14	54	73	113	111
Res. Refrigeration				13	61	116	117
Res. Appliances				5	31	46	46
Commercial Load Shifting (GWh)	—	—	*75*	*166*	*291*	*317*	*348*
Com. Space Cooling			50	99	169	182	193
Com. Space Heating			3	9	18	22	24
Com. Water Heating			17	41	76	81	94
Com. Refrigeration			5	17	29	32	36
Total Shiftable Demand (GWh)	**—**	**74**	**652**	**1,846**	**3,805**	**4,793**	**5,436**
Total Shiftable Demand (% of Annual Demand)	**—**	**0.3**	**2.3**	**5.8**	**10.2**	**11.3**	**11.8**

Table 56. Stress Projection Demand Response Shiftable Demand

Year	**2015**	**2020**	**2025**	**2030**	**2035**	**2040**	**2045**
Annual Load (GWh)	**25,832**	**26,457**	**29,612**	**34,003**	**40,086**	**45,651**	**50,174**
Water System Shifting (GWh)	—	—	—	—	—	—	—
Sched. EV Charging (GWh)	—	—	*55*	*322*	*803*	*1,119*	*1,362*
Home L1			9	51	144	205	260
Home L2			39	215	520	720	866
Work L1			0	2	5	6	8
Work L2			1	7	19	26	31
Public L2			6	47	116	162	197
Residential Load Shifting (GWh)	—	*74*	*242*	*312*	*495*	*582*	*657*
Res. Space Cooling		74	223	237	299	307	349
Res. Space Heating			9	4	17	24	29
Res. Water Heating			9	59	138	199	227
Res. Pool Pumps				12	41	52	51
Res. Refrigeration							
Res. Appliances							
Commercial Load Shifting (GWh)	—	—	*67*	*70*	*143*	*155*	*169*
Com. Space Cooling			43	43	90	97	102
Com. Space Heating			2	3	7	9	9
Com. Water Heating			17	18	32	33	39
Com. Refrigeration			5	6	14	16	18
Total Shiftable Demand (GWh)	**—**	**74**	**365**	**704**	**1,441**	**1,857**	**2,187**
Total Shiftable Demand (% of Annual Demand)	**—**	**0.3**	**1.2**	**2.1**	**3.6**	**4.1**	**4.4**

M.4 Demand Response Resource Capacity

The tables in this section list maximum demand response resource for each program using the metric of eligible end-use peak load, coincident across the end use, but non-coincident with system peak.

Table 57. Moderate Projection Demand Response Resource Capacity

Year	**2015**	**2020**	**2025**	**2030**	**2035**	**2040**	**2045**
System Peak Demand (MW)	**5,952**	**6,020**	**6,309**	**6,575**	**6,958**	**7,395**	**7,811**
CII Interruptible Load (MW)	*579*	*573*	*565*	*625*	*715*	*721*	*754*
Water System	19	22	27	90	156	156	157
Other CII	560	551	538	535	559	565	598
Water System Shifting (MW)	*58*	*41*	*59*	*139*	*220*	*221*	*221*
Sched. EV Charging (MW)	*53*	*131*	*370*	*499*	*616*	*768*	*907*
Home L1	11	23	66	88	110	138	163
Home L2	31	79	224	302	372	464	546
Work L1	0	1	3	3	4	5	6
Work L2	1	3	8	12	14	17	21
Public L2	10	25	69	94	115	143	172
Residential Load Shifting (MW)	*2,489*	*2,521*	*2,668*	*2,756*	*2,870*	*3,030*	*3,154*
Res. Space Cooling	1,801	1,880	2,049	2,128	2,223	2,287	2,272
Res. Space Heating	422	371	334	324	313	346	393
Res. Water Heating	52	57	69	79	93	134	209
Res. Pool Pumps	85	86	90	96	100	105	103
Res. Refrigeration	84	83	84	85	86	88	88
Res. Appliances	45	44	42	45	53	70	88
Commercial Load Shifting (MW)	*1,586*	*1,570*	*1,548*	*1,550*	*1,624*	*1,797*	*1,989*
Com. Space Cooling	1,281	1,248	1,202	1,189	1,221	1,303	1,375
Com. Space Heating	199	203	211	226	267	349	448
Com. Water Heating	85	92	103	97	93	96	112
Com. Refrigeration	21	27	32	37	43	49	55
Total Resource (MW)	**4,766**	**4,836**	**5,210**	**5,568**	**6,045**	**6,536**	**7,025**
Total Resource (% of Peak Demand)	**80**	**80**	**83**	**85**	**87**	**88**	**90**

Table 58. High Projection Demand Response Resource Capacity

Year	**2015**	**2020**	**2025**	**2030**	**2035**	**2040**	**2045**
System Peak Demand (MW)	*5,952*	*6,020*	*6,161*	*6,688*	*7,497*	*8,162*	*8,659*
CII Interruptible Load (MW)	*579*	*573*	*550*	*612*	*694*	*712*	*745*
Water System	19	22	27	89	154	154	155
Other CII	560	551	523	524	540	558	591
Water System Shifting (MW)	*58*	*41*	*59*	*138*	*218*	*219*	*218*
Sched. EV Charging (MW)	*53*	*131*	*309*	*679*	*1,167*	*1,636*	*2,014*
Home L1	11	23	54	130	235	345	460
Home L2	31	79	188	404	682	942	1,129
Work L1	0	1	2	4	6	10	12
Work L2	1	3	7	15	26	36	44
Public L2	10	25	57	126	217	304	370
Residential Load Shifting (MW)	*2,489*	*2,521*	*2,590*	*2,768*	*3,147*	*3,486*	*3,626*
Res. Space Cooling	1,801	1,880	1,974	2,008	2,055	2,030	1,957
Res. Space Heating	422	371	300	330	472	653	814
Res. Water Heating	52	57	103	198	367	534	588
Res. Pool Pumps	85	86	87	91	96	101	99
Res. Refrigeration	84	83	83	83	85	86	86
Res. Appliances	45	44	42	57	72	83	82
Commercial Load Shifting (MW)	*1,586*	*1,570*	*1,547*	*1,628*	*1,813*	*2,006*	*2,165*
Com. Space Cooling	1,281	1,248	1,170	1,177	1,239	1,318	1,374
Com. Space Heating	199	203	232	301	414	516	593
Com. Water Heating	85	92	113	113	117	123	142
Com. Refrigeration	21	27	32	37	43	49	55
Total Resource (MW)	**4,766**	**4,836**	**5,054**	**5,825**	**7,039**	**8,059**	**8,769**
Total Resource (% of Peak Demand)	**80**	**80**	**82**	**87**	**94**	**99**	**101**

Table 59. Stress Projection Demand Response Resource Capacity

Year	**2015**	**2020**	**2025**	**2030**	**2035**	**2040**	**2045**
System Peak Demand (MW)	*5,952*	*6,020*	*6,487*	*7,194*	*8,243*	*9,220*	*10,090*
CII Interruptible Load (MW)	*579*	*573*	*588*	*664*	*761*	*782*	*821*
Water System	19	22	28	91	158	158	158
Other CII	560	551	561	573	603	624	662
Water System Shifting (MW)	*58*	*41*	*60*	*141*	*223*	*224*	*224*
Sched. EV Charging (MW)	*53*	*131*	*464*	*1,011*	*1,748*	*2,437*	*2,964*
Home L1	11	23	86	185	314	449	562
Home L2	31	79	276	605	1,050	1,454	1,752
Work L1	0	1	4	7	12	17	20
Work L2	1	3	11	23	41	56	69
Public L2	10	25	88	191	331	460	562
Residential Load Shifting (MW)	*2,489*	*2,521*	*2,818*	*2,847*	*3,737*	*4,443*	*4,888*
Res. Space Cooling	1,801	1,880	2,049	2,177	2,436	2,639	2,709
Res. Space Heating	422	371	444	223	653	956	1,270
Res. Water Heating	52	57	95	189	356	533	592
Res. Pool Pumps	85	86	93	99	105	110	108
Res. Refrigeration	84	83	85	86	88	90	91
Res. Appliances	45	44	52	73	99	115	117
Commercial Load Shifting (MW)	*1,586*	*1,570*	*1,639*	*1,742*	*1,942*	*2,133*	*2,283*
Com. Space Cooling	1,281	1,248	1,266	1,299	1,375	1,467	1,522
Com. Space Heating	199	203	229	294	408	496	564
Com. Water Heating	85	92	113	114	118	122	142
Com. Refrigeration	21	27	30	36	41	49	55
Total Resource (MW)	**4,766**	**4,836**	**5,569**	**6,405**	**8,410**	**10,019**	**11,180**
Total Resource (% of Peak Demand)	**80**	**80**	**86**	**89**	**102**	**109**	**111**

M.5 Demand Response Resource Capacity Coincident with System Peak

The tables in this section list maximum demand response resource for each program using the metric of eligible end-use load that is coincident with system peak.

Table 60. Moderate Projection Demand Response Resource Capacity Coincident with System Peak

Year	**2015**	**2020**	**2025**	**2030**	**2035**	**2040**	**2045**
System Peak Demand (MW)	**5,952**	**6,020**	**6,309**	**6,575**	**6,958**	**7,395**	**7,811**
System Peak Demand Time (PST)	**8/6 14:00**	**8/8 13:45**	**8/6 14:00**	**8/10 15:00**	**8/10 15:00**	**8/10 15:00**	**8/10 15:00**
CII Interruptible Load (MW)	*545*	*550*	*528*	*552*	*615*	*618*	*646*
Water System	18	20	25	65	106	106	106
Other CII	526	531	503	488	509	512	540
Water System Shifting (MW)	*55*	*37*	*55*	*101*	*151*	*152*	*152*
Sched. EV Charging (MW)	*20*	*62*	*174*	*345*	*424*	*529*	*629*
Home L1	4	10	28	58	72	93	112
Home L2	11	39	108	215	262	324	384
Work L1	0	0	1	2	2	3	3
Work L2	0	1	4	7	9	11	14
Public L2	4	12	32	63	79	98	115
Residential Load Shifting (MW)	*1,943*	*1,977*	*2,192*	*2,136*	*2,246*	*2,329*	*2,405*
Res. Space Cooling	1,798	1,833	2,047	1,983	2,081	2,145	2,200
Res. Space Heating	0	0	0	0	0	0	0
Res. Water Heating	13	12	13	14	16	23	34
Res. Pool Pumps	20	21	23	33	35	37	36
Res. Refrigeration	84	83	84	85	86	88	88
Res. Appliances	27	27	25	22	28	36	46
Commercial Load Shifting (MW)	*1,269*	*1,220*	*1,226*	*1,225*	*1,261*	*1,350*	*1,442*
Com. Space Cooling	1,171	1,110	1,102	1,102	1,137	1,218	1,291
Com. Space Heating	0	0	0	0	0	0	0
Com. Water Heating	78	84	93	87	82	85	99
Com. Refrigeration	20	25	30	36	42	47	53
Total Resource (MW)	**3,831**	**3,847**	**4,174**	**4,361**	**4,696**	**4,978**	**5,274**
Total Resource (% of Peak Demand)	**64**	**64**	**66**	**66**	**67**	**67**	**68**

Table 61. High Projection Demand Response Resource Capacity Coincident with System Peak

Year	**2015**	**2020**	**2025**	**2030**	**2035**	**2040**	**2045**
System Peak Demand (MW)	**5,952**	**6,020**	**6,161**	**6,688**	**7,497**	**8,162**	**8,659**
System Peak Demand Time (PST)	**8/6 14:00**	**8/8 13:45**	**8/6 14:00**	**8/10 15:00**	**8/10 15:00**	**8/10 15:00**	**8/10 12:45**
CII Interruptible Load (MW)	*545*	*550*	*514*	*543*	*596*	*608*	*687*
Water System	18	20	25	64	105	105	115
Other CII	526	531	489	479	492	503	572
Water System Shifting (MW)	*55*	*37*	*55*	*100*	*149*	*150*	*167*
Sched. EV Charging (MW)	*20*	*62*	*189*	*559*	*971*	*1,352*	*1,624*
Home L1	4	10	32	105	206	310	425
Home L2	11	39	117	338	564	761	864
Work L1	0	0	1	3	4	7	8
Work L2	0	1	4	12	21	28	33
Public L2	4	12	35	101	176	245	293
Residential Load Shifting (MW)	*1,943*	*1,977*	*2,114*	*2,061*	*2,155*	*2,175*	*1,897*
Res. Space Cooling	1,798	1,833	1,966	1,883	1,938	1,923	1,611
Res. Space Heating	0	0	0	0	0	0	0
Res. Water Heating	13	12	16	33	59	84	120
Res. Pool Pumps	20	21	22	32	35	37	20
Res. Refrigeration	84	83	83	83	85	86	86
Res. Appliances	27	27	26	29	39	45	59
Commercial Load Shifting (MW)	*1,269*	*1,220*	*1,204*	*1,231*	*1,303*	*1,392*	*1,541*
Com. Space Cooling	1,171	1,110	1,071	1,093	1,156	1,236	1,362
Com. Space Heating	0	0	0	0	0	0	0
Com. Water Heating	78	84	103	101	105	109	125
Com. Refrigeration	20	25	30	36	42	47	54
Total Resource (MW)	**3,831**	**3,847**	**4,076**	**4,494**	**5,174**	**5,677**	**5,917**
Total Resource (% of Peak Demand)	**64**	**64**	**66**	**67**	**69**	**70**	**68**

Table 62. Stress Projection Demand Response Resource Capacity Coincident with System Peak

Year	**2015**	**2020**	**2025**	**2030**	**2035**	**2040**	**2045**
System Peak Demand (MW)	**5,952**	**6,020**	**6,487**	**7,194**	**8,243**	**9,220**	**10,090**
System Peak Demand Time (PST)	**8/6 14:00**	**8/8 13:45**	**8/10 15:00**	**8/10 15:00**	**8/10 15:15**	**8/10 15:15**	**8/9 17:45**
CII Interruptible Load (MW)	*545*	*550*	*538*	*590*	*642*	*658*	*589*
Water System	18	20	24	65	105	105	114
Other CII	526	531	514	525	537	553	475
Water System Shifting (MW)	*55*	*37*	*53*	*103*	*153*	*154*	*174*
Sched. EV Charging (MW)	*20*	*62*	*276*	*600*	*1,037*	*1,449*	*2,964*
Home L1	4	10	50	107	186	268	562
Home L2	11	39	166	363	629	871	1,752
Work L1	0	0	2	4	6	8	20
Work L2	0	1	6	13	24	33	69
Public L2	4	12	51	112	193	270	562
Residential Load Shifting (MW)	*1,943*	*1,977*	*2,053*	*2,211*	*2,494*	*2,721*	*2,658*
Res. Space Cooling	1,798	1,833	1,897	2,022	2,260	2,445	2,166
Res. Space Heating	0	0	0	0	0	0	1
Res. Water Heating	13	12	14	31	57	86	261
Res. Pool Pumps	20	21	31	33	36	38	57
Res. Refrigeration	84	83	85	86	88	90	91
Res. Appliances	27	27	26	38	52	63	83
Commercial Load Shifting (MW)	*1,269*	*1,220*	*1,299*	*1,339*	*1,425*	*1,526*	*898*
Com. Space Cooling	1,171	1,110	1,168	1,202	1,279	1,371	768
Com. Space Heating	0	0	0	0	0	0	1
Com. Water Heating	78	84	102	102	106	108	79
Com. Refrigeration	20	25	29	34	40	47	51
Total Resource (MW)	**3,831**	**3,847**	**4,218**	**4,842**	**5,750**	**6,508**	**7,283**
Total Resource (% of Peak Demand)	**64**	**64**	**65**	**67**	**70**	**71**	**72**

M.6 Demand Response Resource Annual Shiftable Demand

The tables in this section list the amount of eligible end-use demand potentially shiftable by demand response programs. All eligible end-use demand is reported.

Table 63. Moderate Projection Demand Response Resource Eligible Demand

Year	**2015**	**2020**	**2025**	**2030**	**2035**	**2040**	**2045**
Annual Load (GWh)	**25,832**	**26,457**	**28,536**	**30,697**	**33,152**	**35,840**	**38,880**
Water System Shifting (GWh)	*361*	*267*	*386*	*810*	*1,232*	*1,240*	*1,239*
Sched. EV Charging (GWh)	*189*	*551*	*1,551*	*2,096*	*2,581*	*3,213*	*3,803*
Home L1	39	91	261	351	443	565	674
Home L2	108	342	955	1,291	1,581	1,956	2,309
Work L1	2	3	10	13	16	19	22
Work L2	4	12	34	48	59	72	85
Public L2	36	103	290	393	483	600	713
Residential Load Shifting (GWh)	*3,452*	*3,626*	*3,846*	*4,065*	*4,324*	*4,675*	*5,350*
Res. Space Cooling	1,654	1,862	2,039	2,194	2,326	2,378	2,611
Res. Space Heating	315	257	212	198	178	193	209
Res. Water Heating	264	297	365	400	479	661	1,007
Res. Pool Pumps	332	338	355	377	397	416	409
Res. Refrigeration	674	665	670	678	690	700	705
Res. Appliances	212	206	205	218	254	326	409
Commercial Load Shifting (GWh)	*2,045*	*2,077*	*2,101*	*2,119*	*2,212*	*2,416*	*2,659*
Com. Space Cooling	1,436	1,387	1,324	1,307	1,352	1,458	1,559
Com. Space Heating	72	73	78	83	98	125	152
Com. Water Heating	420	466	521	521	523	562	648
Com. Refrigeration	118	151	178	208	238	270	301
Total Shiftable Resource (GWh)	**6,047**	**6,521**	**7,884**	**9,088**	**10,349**	**11,543**	**13,051**
Total Shiftable Resource (% of Annual Demand)	**23**	**25**	**28**	**30**	**31**	**32**	**34**

Table 64. High Projection Demand Response Resource Eligible Demand

Year	**2015**	**2020**	**2025**	**2030**	**2035**	**2040**	**2045**
Annual Load (GWh)	**25,832**	**26,457**	**28,013**	**31,856**	**37,458**	**42,305**	**46,257**
Water System Shifting (GWh)	*361*	*267*	*386*	*802*	*1,218*	*1,226*	*1,222*
Sched. EV Charging (GWh)	*189*	*551*	*1,533*	*3,338*	*5,768*	*8,052*	*9,801*
Home L1	39	91	259	633	1,216	1,812	2,332
Home L2	108	342	945	1,989	3,320	4,519	5,371
Work L1	2	3	9	19	30	49	59
Work L2	4	12	34	73	127	171	209
Public L2	36	103	286	624	1,075	1,501	1,830
Residential Load Shifting (GWh)	*3,452*	*3,626*	*3,890*	*4,407*	*5,268*	*5,911*	*6,335*
Res. Space Cooling	1,654	1,862	1,976	2,033	2,046	1,954	2,047
Res. Space Heating	315	257	171	160	216	281	315
Res. Water Heating	264	297	534	922	1,609	2,207	2,506
Res. Pool Pumps	332	338	345	361	382	402	395
Res. Refrigeration	674	665	661	667	676	684	689
Res. Appliances	212	206	204	263	340	383	383
Commercial Load Shifting (GWh)	*2,045*	*2,077*	*2,079*	*2,143*	*2,320*	*2,529*	*2,776*
Com. Space Cooling	1,436	1,387	1,245	1,236	1,300	1,401	1,488
Com. Space Heating	72	73	85	111	151	183	202
Com. Water Heating	420	466	571	587	630	674	784
Com. Refrigeration	118	151	178	208	239	270	302
Total Shiftable Demand (GWh)	**6,047**	**6,521**	**7,889**	**10,690**	**14,574**	**17,717**	**20,135**
Total Shiftable Demand (% of Annual Demand)	**23**	**25**	**28**	**34**	**39**	**42**	**44**

Table 65. Stress Projection Demand Response Resource Eligible Demand

Year	**2015**	**2020**	**2025**	**2030**	**2035**	**2040**	**2045**
Annual Load (GWh)	**25,832**	**26,457**	**29,612**	**34,003**	**40,086**	**45,651**	**50,174**
Water System Shifting (GWh)	*361*	*267*	*394*	*819*	*1,246*	*1,255*	*1,253*
Sched. EV Charging (GWh)	*189*	*551*	*1,632*	*3,561*	*6,160*	*8,592*	*10,459*
Home L1	39	91	300	639	1,107	1,577	1,997
Home L2	108	342	975	2,147	3,712	5,145	6,188
Work L1	2	3	12	23	39	54	67
Work L2	4	12	36	80	142	198	241
Public L2	36	103	308	672	1,159	1,619	1,967
Residential Load Shifting (GWh)	*3,452*	*3,626*	*4,105*	*4,545*	*5,743*	*6,731*	*7,482*
Res. Space Cooling	1,654	1,862	2,028	2,151	2,297	2,364	2,682
Res. Space Heating	315	257	312	128	336	476	590
Res. Water Heating	264	297	474	848	1,537	2,214	2,526
Res. Pool Pumps	332	338	366	389	413	434	427
Res. Refrigeration	674	665	679	691	705	717	724
Res. Appliances	212	206	246	338	456	526	533
Commercial Load Shifting (GWh)	*2,045*	*2,077*	*2,248*	*2,344*	*2,513*	*2,718*	*2,973*
Com. Space Cooling	1,436	1,387	1,420	1,444	1,499	1,613	1,704
Com. Space Heating	72	73	81	104	144	171	188
Com. Water Heating	420	466	577	597	641	664	780
Com. Refrigeration	118	151	170	199	229	270	302
Total Shiftable Demand (GWh)	**6,047**	**6,521**	**8,379**	**11,270**	**15,662**	**19,297**	**22,168**
Total Shiftable Demand (% of Annual Demand)	**23**	**25**	**28**	**33**	**39**	**42**	**44**

M.7 Demand Response Capacity per Participant

The tables in this section summarize the kW/participant values extracted from the LA100 bottom-up load modeling that were used to convert $/participant-yr incentives to $/kW-yr incentives. In particular, kW/participant was calculated by (a) adding up all demand eligible for a given program in a given projection-year, (b) extracting that demand's peak value (in kW), and (c) dividing the peak kW by the total number of households, buildings, appliances or vehicles eligible to participate.

Table 66. Moderate Projection Demand Response Capacity per Participant

Year	2015	2020	2025	2030	2035	2040	2045
Sched. EV Charging (kW/vehicle)							
Home L1	1.74	1.74	1.53	1.45	1.53	1.56	1.57
Home L2	0.97	0.97	0.82	0.77	0.80	0.82	0.82
Work L1	1.75	1.75	1.58	1.34	1.43	1.51	1.50
Work L2	1.12	1.12	0.78	0.76	0.78	0.79	0.81
Public L2	1.12	1.12	0.90	0.85	0.88	0.89	0.91
Residential Load Shifting (kW/household)							
Res. Space Cooling	1.75	1.75	1.44	1.35	1.27	1.20	1.11
Res. Space Heating	0.59	0.59	0.41	0.37	0.31	0.28	0.27
Res. Water Heating	0.36	0.36	0.13	0.12	0.12	0.15	0.21
Residential Load Shifting (kW/appliance)							
Res. Pool Pumps	0.57	0.57	0.53	0.53	0.53	0.54	0.54
Res. Refrigeration	0.07	0.07	0.06	0.06	0.06	0.06	0.06
Res. Appliances	0.04	0.04	0.03	0.03	0.03	0.04	0.05
Commercial Load Shifting (kW/building)							
Com. Space Cooling	56.73	56.73	47.26	43.83	41.23	39.49	37.86
Com. Space Heating	15.78	15.78	15.07	14.79	14.91	15.59	16.78
Com. Water Heating	4.41	4.41	4.81	4.26	3.72	3.45	3.62
Com. Refrigeration	6.68	6.68	7.11	7.18	7.23	7.25	7.30

Table 67. High Projection Demand Response Capacity per Participant

Year	**2015**	**2020**	**2025**	**2030**	**2035**	**2040**	**2045**
Sched. EV Charging (kW/vehicle)							
Home L1	1.74	1.74	1.31	1.39	1.38	1.41	1.52
Home L2	0.97	0.97	0.69	0.70	0.66	0.65	0.64
Work L1	1.75	1.75	1.20	1.20	1.07	1.14	1.19
Work L2	1.12	1.12	0.68	0.68	0.66	0.64	0.63
Public L2	1.12	1.12	0.74	0.77	0.74	0.73	0.72
Residential Load Shifting (kW/household)							
Res. Space Cooling	1.75	1.75	1.34	1.19	1.08	0.97	0.87
Res. Space Heating	0.59	0.59	0.36	0.31	0.32	0.34	0.38
Res. Water Heating	0.36	0.36	0.12	0.19	0.30	0.40	0.43
Residential Load Shifting (kW/appliance)							
Res. Pool Pumps	0.57	0.57	0.51	0.51	0.51	0.51	0.51
Res. Refrigeration	0.07	0.07	0.06	0.06	0.06	0.06	0.06
Res. Appliances	0.04	0.04	0.03	0.04	0.05	0.05	0.05
Commercial Load Shifting (kW/building)							
Com. Space Cooling	56.73	56.73	45.30	41.40	38.62	36.81	35.27
Com. Space Heating	15.78	15.78	15.69	16.69	17.94	18.10	18.24
Com. Water Heating	4.41	4.41	5.10	4.43	3.79	3.45	3.64
Com. Refrigeration	6.68	6.68	7.07	7.16	7.20	7.25	7.30

Table 68. Stress Projection Demand Response Capacity per Participant

Year	2015	2020	2025	2030	2035	2040	2045
Sched. EV Charging (kW/vehicle)							
Home L1	1.74	1.74	1.93	2.02	2.03	2.12	2.13
Home L2	0.97	0.97	1.02	1.05	1.00	0.98	0.97
Work L1	1.75	1.75	2.02	1.97	1.93	2.01	2.01
Work L2	1.12	1.12	0.99	1.02	0.97	0.97	0.95
Public L2	1.12	1.12	1.14	1.16	1.12	1.11	1.10
Residential Load Shifting (kW/household)							
Res. Space Cooling	1.75	1.75	1.48	1.39	1.33	1.29	1.22
Res. Space Heating	0.59	0.59	0.52	0.22	0.44	0.49	0.59
Res. Water Heating	0.36	0.36	0.24	0.30	0.37	0.41	0.44
Residential Load Shifting (kW/appliance)							
Res. Pool Pumps	0.57	0.57	0.55	0.55	0.56	0.56	0.56
Res. Refrigeration	0.07	0.07	0.07	0.06	0.06	0.06	0.06
Res. Appliances	0.04	0.04	0.04	0.05	0.06	0.07	0.07
Commercial Load Shifting (kW/building)							
Com. Space Cooling	56.73	56.73	49.84	46.28	43.40	41.04	39.10
Com. Space Heating	15.78	15.78	15.85	16.64	17.91	17.48	17.42
Com. Water Heating	4.41	4.41	5.22	4.52	3.87	3.41	3.62
Com. Refrigeration	6.68	6.68	6.97	7.01	7.07	7.27	7.30

M.8 Demand Response Assumed Participation Rates

Here we compile the assumed (shiftable end uses) or computed (CII interruptible load) participation rates across all demand response programs.

Table 69. Moderate Projection Demand Response Participation Rates

Year	2015	2020	2025	2030	2035	2040	2045
CII Interruptible Load (%)							
Water System	50	50	50	50	50	50	50
Other CII							
Relative to Large CII Peak	0.2	1.2	3.8	6.4	6.4	6.4	6.4
Relative to “Curtailable” Portion[a]	1	6	19	32	32	32	32
Water System Shifting (%)	—	—	—	—	—	—	—
Sched. EV Charging (%)							
Home L1			4	14	18	18	18
Home L2			4	14	19	19	19
Work L1			3	13	18	18	18
Work L2			4	14	18	18	18
Public L2			2	12	15	15	15
Residential Load Shifting (%)							
Res. Space Cooling		4	11	17	21	21	21
Res. Space Heating			3	8	12	12	12
Res. Water Heating			2	10	13	13	13
Res. Pool Pumps				3	13	17	17
Res. Refrigeration				2	8	10	10
Res. Appliances				2	5	7	7
Commercial Load Shifting (%)							
Com. Space Cooling			4	7	10	10	10
Com. Space Heating			3	6	8	8	8
Com. Water Heating			3	5	8	8	8

Com. Refrigeration			3	6	9	9	9

[a] We assume that about 20% of CII customers' peak load is potentially curtailable.

Table 70. High Projection Demand Response Participation Rates

Year	2015	2020	2025	2030	2035	2040	2045
CII Interruptible Load (%)							
Water System	50	50	50	50	—	—	—
Other CII							
Relative to Large CII Peak	0.2	1.2	3.9	6.5	6.5	6.5	6.5
Relative to “Curtailable” Portion[a]	1	6	19	33	33	33	33
Water System Shifting (%)	—	—	—	—	50	50	50
Sched. EV Charging (%)							
Home L1			14	28	28	28	28
Home L2			14	30	30	30	30
Work L1			13	27	27	27	27
Work L2			14	28	28	28	28
Public L2			13	25	25	25	25
Residential Load Shifting (%)							
Res. Space Cooling		4	17	22	32	32	32
Res. Space Heating			3	13	16	16	16
Res. Water Heating			2	20	25	28	28
Res. Pool Pumps			4	15	19	28	28
Res. Refrigeration				2	9	17	17
Res. Appliances				2	9	12	12
Commercial Load Shifting (%)							
Com. Space Cooling			4	8	13	13	13
Com. Space Heating			3	8	12	12	12
Com. Water Heating			3	7	12	12	12
Com. Refrigeration			3	8	12	12	12

[a] We assume that about 20% of CII customers’ peak load is potentially curtailable.

Table 71. Stress Projection Demand Response Participation Rates

Year	2015	2020	2025	2030	2035	2040	2045
CII Interruptible Load (%)							
Water System	50	50	50	50	50	50	50
Other CII							
Relative to Large CII Peak	0.2	1.2	3.6	5.9	5.9	5.9	5.9
Relative to “Curtailable” Portion[a]	1	6	18	30	30	30	30
Water System Shifting (%)	—	—	—	—	—	—	—
Sched. EV Charging (%)							
Home L1			3	8	13	13	13
Home L2			4	10	14	14	14
Work L1			2	8	12	12	12
Work L2			3	9	13	13	13
Public L2			2	7	10	10	10
Residential Load Shifting (%)							
Res. Space Cooling		4	11	11	13	13	13
Res. Space Heating			3	3	5	5	5
Res. Water Heating			2	7	9	9	9
Res. Pool Pumps				3	10	12	12
Res. Refrigeration							
Res. Appliances							
Commercial Load Shifting (%)							
Com. Space Cooling			3	3	6	6	6
Com. Space Heating			3	3	5	5	5
Com. Water Heating			3	3	5	5	5
Com. Refrigeration			3	3	6	6	6

[a] We assume that about 20% of CII customers’ peak load is potentially curtailable.

The Los Angeles 100% Renewable Energy Study

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