

Electric Power Infrastructure Vulnerabilities to Heat Waves from Climate Change

by

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ABSTRACT

Electricity infrastructure vulnerabilities were assessed for future heat waves due to climate change. Critical processes and component relationships were identified and characterized with consideration for the terminal event of service outages, including cascading failures in transmission-level components that can result in blackouts. The most critical dependency identified was the increase in peak electricity demand with higher air temperatures. Historical and future air temperatures were characterized within and across Los Angeles County, California (LAC) and Maricopa County (Phoenix), Arizona. LAC was identified as more vulnerable to heat waves than Phoenix due to a wider distribution of historical temperatures. Two approaches were developed to estimate peak demand based on air temperatures, a top-down statistical model and bottom-up spatial building energy model. Both approaches yielded similar results, in that peak demand should increase sub-linearly at temperatures above 40°C (104 °F) due to saturation in the coincidence of air conditioning (AC) duty cycles. Spatial projections for peak demand were developed for LAC to 2060 considering potential changes in population, building type, building efficiency, AC penetration, appliance efficiency, and air temperatures due climate change. These projections were spatially allocated to delivery system components (generation, transmission lines, and substations) to consider their vulnerability in terms of thermal de-rated capacity and weather adjusted load factor (load divided by capacity). Peak hour electricity demand was projected to increase in residential and commercial sectors by 0.2–6.5 GW (2–51%) by 2060. All grid

components, except those near Santa Monica Beach, were projected to experience 2–20% capacity loss due to air temperatures exceeding 40 °C (104 °F). Based on scenario projections, and substation load factors for Southern California Edison (SCE), SCE will require 848—6,724 MW (4-32%) of additional substation capacity or peak shaving in its LAC service territories by 2060 to meet additional demand associated with population growth projections.

DEDICATION

I dedicate this dissertation to my late father Antonio Burillo. His loving efforts to instill in me at a young age an appreciation for science, education, the environment, critical thinking, and community service are the fundamental reasons I completed this PhD dissertation.

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PREFACE

This dissertation, “Electric Power Infrastructure Vulnerabilities to Heat Waves from Climate Change” is the culmination of over a decade’s worth of study and work that I began before my PhD program officially started in January 2014. Electric power infrastructure systems are critical infrastructure systems that are necessary for modern commerce and living. They are vulnerable to outages from heat waves and high demand, and there is significant uncertainty about the future severity of heat waves with climate change and their potential impacts. Moreover, demand for housing is increasing, infrastructure are aging, and mandates exist for new intermittent renewable generation which adds further uncertainty to the systems. Solid analysis, strategic policies, and intelligent implementations are timely and relevant to meet market and regulatory demands without dramatically inflating electricity prices, or worse—exposing infrastructure systems to widespread failures and blackouts. To the best of my knowledge and abilities, this dissertation provides new insight and clarity into all of these issues and is actionable for stakeholders to use immediately.

Daniel Burillo

Tempe, Arizona, July 2018

CHAPTER 1

INTRODUCTION

1.1. A Brief History of Climate Change

Climate change is a naturally occurring phenomenon that humans began contributing to about 10,000 years ago. No one knows what the first climate was, or why it changed, but according to the works of astrophysicists, the climate of the universe was super-hot plasma for the first few seconds (Hawking, 1996). It quickly cooled as space and time expanded. Then, over the course of many billions of years the Milky Way galaxy, our solar system, and planet earth came to be as they are now. Planet earth revolves around a star in an imperfectly circular pattern—sometimes closer, sometimes further. Sometimes getting more energy radiation from the sun, sometimes less. The surface of the earth is mostly covered with water, and as it spins on its wobbly axis, with an orbiting moon, that water splashes, evaporates, condenses, rains, flows, freezes and generally moves all over. On a day-to-day basis, we call this the weather, along with a few other factors too, including air temperature, wind speed, and so on. We label geographic regions of the earth that have particular prevailing weather conditions as having different climates (Design, 2006) (Stewart & Oke, 2012). Over the course of time, earth has gone through several global climate changes, from the asteroid that killed the dinosaurs (Switek, 2016), to the ice ages, to the warm periods such as the one we are in now (Eldredge & Biek, 2010). Earth has also had regional climate changes due to large storms, earthquakes, and volcanic

eruptions that mostly only affect local areas (Crowley, 2000)(Jaramillo et al., 2012). Since human civilizations started intelligently designing ecosystems—by channeling water, doing agriculture, building cities, and so on—we have been changing local climates as well.

Human civilization began to have an impact on the earth's climate at a global scale after the industrial revolution with the burning of fossil fuels into the atmosphere. In the early 1700s, coal-powered steam engines came to market and civilization embarked on a new path (Palermo, 2014). The portable energy transformation device was revolutionary in terms of the way in which physical work could be done, and so as it proliferated throughout the marketplace. The abundance with which humans lived and moved increased dramatically too. In 1896, Swedish chemist Svante Arrhenius concluded that industrial-age coal burning would enhance the natural greenhouse effect, and his general conclusions of the effect of the "man-made greenhouse" were a few degrees Celsius for a doubling of CO₂, which is about the same as modern-day climate models (Shukman, 2018)(Olah, Prakash, & Goeppert, 2011). Since then, oil spills, trash barges, mass pavement, deforestation, various air-born pollutants, and so on have collectively affected the earth's ecosystems and climates as well (IPCC, 2013). For the purposes of this dissertation, the scope of analyses for climate change is on rising air temperatures due to greenhouse gas emissions for electric power infrastructure.

1.2. Infrastructure and Climate Change

Climate change is affecting infrastructure by changing the weather conditions in which infrastructure have to operate. The United States Department of Homeland Security has defined 16 critical infrastructure sectors that are considered vital to the “security, national economic security, and national public health or safety” of the country (DHS, 2015). These critical infrastructure sectors are: chemicals, commercial facilities, communications, critical manufacturing, dams, defense, emergency services, energy, financial services, food and agriculture, government facilities, healthcare and public health, information technology, nuclear, transportation, and water and wastewater systems (DHS, 2015). Across these infrastructure sectors, studies have concluded that climate change will impact physical assets, operations, and use (Field et al., 2014; Melillo, Richmond, & Yohe, 2014) (Sullivan, Colman, & Kalendra, 2015). Hence, climate change vulnerability assessment and adaption planning studies have been rapidly emerging (Warren et al., 2018), (Carter, Handley, Butlin, & Gill, 2017), (Oh, Kim, & Kim, 2018), (Lee & Ellingwood, 2017), .

Infrastructure are generally designed to meet future demand requirements under the constraints of historical weather conditions for their geographic location, but thanks to advancements in global climate modeling researchers are now able to forecast changes in future climate conditions and plan for those as well. Assessments generally rely on climate change scenarios standardized by the Intergovernmental Panel on Climate Change (IPCC) (K. Kim, Ha, & Kim, 2017); however other considerations are made as well for factors such as the

anthropogenic change in urban environments (Hunt et al., 2017), (Prestele et al., 2017). This dissertation uses the Representative Carbon Pathway (RCP) scenarios developed by the IPCC to be standard with other assessments, and considers air temperatures by themselves as individual design constraints. The RCP scenarios are developed with naming conventions equal to the amount of radiative forcing increase from the sun associated with the greenhouse gas effect, e.g. RCP 4.5 and RCP 8.5, which were used throughout this dissertation (van Vuuren et al., 2011), (Arora et al., 2011).

The newest technological advancements in climate change modeling and long-term weather forecasting include high-resolution spatial projections based on “downscaling” techniques. These downscaling techniques aim to improve the geographic and temporal resolution of specific weather projections such as air temperature, wind speed, solar radiation, precipitation, snowpack, and hydrology for specific geographic regions (F. Sun, Walton, & Hall, 2015; Walton, Sun, Hall, & Capps, 2015), (Loikith, Waliser, Kim, & Ferraro, 2018), (Ahmadalipour, Moradkhani, & Svoboda, 2017), (Sanjay, Krishnan, Shrestha, Rajbhandari, & Ren, 2017), (Brekke, Thrasher, Maurer, & Pruitt, 2013), (Tian et al., 2017). However, challenges still exist in incorporating climate change data into practice (Douglas et al., 2017), (Weyant, 2017), (Pindyck, 2017). These challenges range from a lack of understanding as to what parameters to use in complex models, to the methods used in the models, to what to do about the results. Significant literature is emerging to disentangle the contribution of different mechanisms to the response patterns in the very complex climate models, yielding more

transparent models and results (Kröner et al., 2017). Further solutions to these challenges are expected to be met through ongoing collaboration between climate scientists and engineers, which is what is done in this dissertation for electricity infrastructure and heat waves.

1.3. Electric Power Infrastructure and Climate Change

The language in this section was adapted from the content submitted and in review for the chapter “Infrastructure and Climate Change” for the book “Sustainable and Resilient Infrastructure Edited Volume,” by Patrick X. W. Zou and Peter Love, edited by Palolo Gardoni, with: Mikhail Chester, Ph.D., Samuel Markolf, Ph.D., Andrew Fraser, Ph.D., Daniel Burillo, Emily Bondank, Yeowon Kim, and Christopher Hoehne.

Electric power infrastructure broadly consists of three systems: generation, delivery, and demand. In terms of the physical processes, electrical power is created by generators to meet demand via delivery hardware. In terms of functionality however, it is the demand for electric power that drives the development of the other two systems. Reliable electric power is central to city development and economic stability, and is a critical service in modern cities as almost all other major infrastructure and services rely on it: commerce, communication, manufacturing, defense, emergency, finance, agriculture, healthcare, information technology, transportation, and water (Rinaldi, Peerenboom, & Kelly, 2001). Climate change can affect energy trade over time in

ways that are significant to economics and natural resource consumption. For example, more extreme summer and winter temperatures necessarily result in more demand for cooling and heating respectively. Arguably more significant however, is the way that climate change can also affect service reliability. A shortage of electric power generation, or sequence of faults in the delivery network, can result in an interruption in service at any second. This is why generation and delivery systems are built with multiple redundancies, such that individual component outages can occur safely. Unless there are multiple simultaneous outages, the infrastructure system can still deliver power to buildings and other loads without an interruption in service. Table 1 provides a summary of major climate variables and their associated impacts on the power sector Adapted from (ADB, 2012).

Table 1: Summary of Key Climate Drivers and Possible Impacts to Power Systems

Climate Hazard	Key Impacts	Impacted Segment	Adaptation Strategies
Increased Air Temperatures	▪ Lower generation efficiency ▪ Decreased coal-to-gas conversion efficiency ▪ Decreased combined cycle gas turbine efficiency ▪ Decreased solar PV efficiency	Generation	• Implement air chillers or more efficient chillers • Site new generation in cooler locations
	▪ Reduced carrying capacity of lines and transformers ▪ Increased losses in lines and transformers	Delivery - Transmission & Distribution	• Underground hardware • Use more heat-resistant materials • Implement more effective cooling for transformers
	▪ Increased peak demand and total energy demand for cooling	Demand - End Use	• AC energy efficiency • Building thermal efficiency • Peak load shifting
Increase in precipitation	▪ Reduced combustion efficiency due to increased moisture content of coal	Generation	• Protect coal stockpiles • Switch to fuel that is more moisture resistant (e.g. natural gas)
	▪ Damaged power lines from snow and ice ▪ Flooding of underground infrastructure ▪ Damaged towers due to erosion	Delivery - Transmission & Distribution	• Improved flood protection for equipment at ground level • Use covered and/or insulated conductors • Include lightning protection (e.g., earth wires, spark

			gaps) in the distribution network
Decrease in precipitation	▪ Decreased availability of freshwater for thermal cooling	Generation	• Switch to recirculating or dry cooling • Switch to more “water-efficient” fuels (e.g. natural gas, wind, solar) • Increase volume of water treatment system • Restore/reforest land
Sea Level Rise/ Increased storm surge during hurricanes and tropical storms/ Increased nuisance flooding during high tides	▪ Flooding/damage to coastal/low-lying infrastructure	Generation/ Delivery - Transmission & Distribution Demand – End use	• Implement flood control (dams, dikes, reservoirs, polders, etc.) • Improve coastal defenses (seawalls, bulkheads, etc.) • Build in and/or relocate to less exposed locations • Raise structure levels • Improved drainage systems • Protect fuel storage
More frequent/severe extreme events (floods, typhoons, drought, high winds, etc.)	▪ Damaged infrastructure ▪ Disrupted supply chains and offshore activity ▪ Damage to facilities related to soil erosion	Generation Delivery - Transmission & Distribution	• Same as above • Concrete-sided buildings instead of metal • Implement more rigorous structural standards • Implement porous materials for better wind flow • Increased decentralized energy generation • Cite infrastructure away from heavily wooded areas/ rigorously prune trees

Generation is vulnerable to flooding, reduced streamflow, and warmer water and air temperatures which can all cause a shortage of power supply in the system (M. Bartos & Chester, 2015a). There are many ways to physically generate electrical power, but to evaluate the effects of climate change it is helpful to broadly categorize them as those that use water, and those that do not. Conventional hydroelectric and water-cooled turbine generators (e.g. nuclear, coal-fired, and some natural gas) use water, and so are vulnerable to changes in hydrology in three ways. First, flooding can damage physical hardware of above and below ground equipment if that hardware is not sufficiently shielded (Hollnagel & Fujita, 2013). For example, sea level was projected to rise by 1-1.4m by the end of the century, and if that were the case, then 25 coastal plants

in California would be at risk of flooding during 1-in-100 year high-tide events (Sathaye et al., 2013). Second, if the water levels in natural sources are too low (e.g. low river flow during droughts), then production capacity can be dependent upon priority level in access rights or reduced to zero if the water level physically goes below the intake pipe (Wagman, 2013). Third, some once-through generators are vulnerable to increases in water temperature in coastal plants, as a certain amount of temperature rise is necessary to cool the generators, but environmental regulations prevent expelling of water that is too hot to be safe for the ecosystem (EEA, 2008). In August of 2015, the Pilgrim Nuclear Power Station in Massachusetts cut its power because the temperature of sea water used as influent was too high (Abel, 2015). Power generators that do not use water include dry combustion natural gas and solar photovoltaics. These types of “dry” power generators are generally inland, and could be at risk of flooding if they are seated in a basin-like landscape that would collect water from a storm. Dry power generators also operate less efficiently under higher ambient air temperatures, which means they also have lower production capacity to meet peak demand (Daniel Burillo, Chester, Ruddell, & Johnson, 2017). Dry generators are also vulnerable to changes in humidity that can affect their air circulation systems, as well as flooding and storm-gusty winds in general (ADB, 2012).

Delivery systems can be affected by climate change due to higher temperatures causing higher demand, reduced capacity, and congestion; wildfires that can render power lines inoperable due to ionized air; and large

storms that can cause physical damage via flooding and high winds that make trees fall on lines (Campbell, 2012). Delivery systems physically consist of various types of power lines that transport energy, transformers which convert the power to different voltage levels, quality devices for efficiency and reliability, and protection devices that interrupt power flows during hazardous conditions. Climate change can cause failures via physical hardware damage, or create operational conditions that exceed hardware tolerances. Higher temperatures can cause individual components to become inoperable because protection devices will cut them off if power flow is too high for the weather conditions (IEEE, 2012). Additionally, higher temperatures may mean that the amount of power that lines can safely carry may need to be reduced. If too many components are offline or the capacity of the system is significantly reduced, then power may not be available when it is needed causing cascading failures and blackouts as happened in the US in 2003 and 2011 (FERC/NERC, 2012; NERC, 2004). Alternatively, if protection devices are not properly calibrated, then components can overheat. This has happened to hundreds of distribution-level transformers during recent record breaking heat waves in the US southwest (Jerod MacDonald-Evoy, 2016). Moreover, lines can sag to the point that they deformation is irreversible. Not coincidentally, during these record-breaking heat waves, the air is very dry, and the risk of wildfires is high. If wildfires burn under power lines, then those components can fail as well due to air ionization. Like generators, substations are vulnerable to rising sea levels and storm floods near the coast and in basin-like land areas (Sathaye et al., 2013). Flooding can erode

or short the hardware in substations and underground power lines (ADB, 2012). Lastly, severe storms can blow things (such as trees) into power lines and cause outages.

Electric power demand is primarily susceptible to higher air temperatures, which can increase both total energy consumption and the peak demand in regions with significant electric air conditioning (M. Bartos et al., 2016a; Daniel Burillo et al., 2017; Janet L. Reyna, Chester, Wagner, Wagner, & Kainuma, 2017). Demand is typically planned for at city- and state-level geographies based on seasonal weather usage patterns, daily weather usage patterns, and local use patterns. In warm to hot climates, the peak electricity demand is usually in the late afternoon during the summer when businesses are still operating and people are coming home and turning on air conditioners (EIA, 2016c). Historically, preparing for higher peak demand means building additional generation and delivery capacity, but policies aimed at natural resource conservation have targeted building and appliance energy efficiency standards which also offset increases in peak demand (Daniel Burillo et al., 2017). In terms of climate change, higher average temperatures and higher maximum temperatures mean more demand for AC usage, which could mean more energy usage over time, higher power demand for ACs to operate at hotter temperatures, and more installations of ACs total in moderately warm climates. The combined effects could be a significant increase in per capita demand (Daniel Burillo et al., 2017). This may be more than local delivery infrastructure are capable of supporting without systemic or network-wide investments (Willis, Welch, & Schrieber, 2001).

Given the diversity of generation technologies, spread of the transmission network, and fact that electricity demand is directly affected by climate, adaptation strategies take on many forms (Table 1). Robustness is central to many strategies, however, efficiency gains and the decentralization of technologies is often recommended for various aspects.

1.4. Research Objectives

This dissertation answers the broad question of how might more severe heat waves due to climate change affect power systems in the future? It does so by answering five specific sub-questions across four academic papers. The sub-questions are listed below:

- 1) What are the critical processes and components that are at risk of failure from high ambient air temperatures, and or operating temperatures, and why?
- 2) What are the highest air temperature projections to consider in planning processes, and how are those different from historical temperature values generally considered in planning processes?
- 3) What are reasonable ranges of peak demand to plan for, considering Los Angeles County as a case-study region, and potential changes in population, buildings stock, AC penetration, and appliance efficiency?
- 4) How vulnerable are infrastructure systems to low capacity failures?

- a) At a city or county-scale, in terms of “local” reserve margins (LRM),
i.e. aggregate supply-demand balance in a region that has
imports/exports through long-distance transmission from other
regions.
- b) At a sub-city-scale, considering specific power lines & substations
geographically located within the region

5) What demand-side options are available to reduce vulnerabilities?

Moreover, how practical are they to implement?

The remaining chapters are as follows, which answer the research questions and meet the objectives of the dissertation work listed in the proposal as described.

Chapter 2: Preliminary hazard analysis. This chapter is adapted from the conference paper: D. Burillo, M. Chester, and B. Ruddell, “Electric Grid Vulnerabilities to Rising Air Temperatures in Arizona,” in *Procedia Engineering*, 2016, vol. 145. It answers the first research question, and satisfies the first three deliverables detailed in the proposal. (1) Flowchart(s) of component & process dependency from rising air temperatures and service interruption. This chapter contributes a consolidated qualitative understanding of what critical components and physical processes are at risk of failure from rising air temperatures and or operating temperatures, and why. It also provides sample values and methodology for estimating changes in both component and total system outage rates. (2) Software, which was delivered separately. (3) Graphical figures with

failure probabilities as a function of air temperatures. This chapter provides clear estimations of probabilities of power systems failures in terms of objective physical metrics, i.e., percent per 1°C, such that results are intelligible to interdisciplinary audiences. The primary value of this chapter is the qualitative understanding of the hazards or risks of rising air temperatures due to climate change, and sample numerical methods. The specific numerical results are not intended to necessarily be prescriptive.

Chapter 3: Top-down approach for estimating peak demand and resource adequacy. This chapter is published in the journal of Applied Energy. The citation for this article is: D. Burillo, M. V. Chester, B. Ruddell, and N. Johnson, “Electricity demand planning forecasts should consider climate non-stationarity to maintain reserve margins during heat waves,” *Appl. Energy*, vol. 206, 2017. It answers the second research question, provides a base-case comparison to verify the models developed in the following two chapters for the third and fourth research questions, and satisfies the fourth deliverable detailed in the proposal.

(4) Figures comparing historical T_{90} , T_{max} , and projected T_{max} at weather stations for Los Angeles and Maricopa. This chapter provides specific maximum values for historic and future ambient air temperatures that have and will affect power systems across two counties. It provides a consolidated graphical comparison as to how stationarity assumptions can bias the parameter inputs that define reliability tolerances in electric power infrastructure hardware and operational constraints. It also provides comparison as to how significant such biases may be depending upon the region.

Chapter 4: Bottom-up approach for projecting peak demand. This chapter has been submitted to the journal of Applied Energy. The citation for this article is: D. Burillo, M. V. Chester, S. Pincetl, E. Fournier, J. Reyna, "Forecasting Peak Electricity Demand for Los Angeles Considering Heat Waves Heightened by Climate Change.," *Appl. Energy*, (in review), 2018. This chapter answers the second research question from a spatial perspective, as well as the third question and part of the fifth question. It satisfies the fifth through eighth deliverables stated in the proposal. (5) Maps of historical and projected temperatures for Los Angeles County at 2x2 km resolution. (6) Characterization tables & figures for residential and commercial building peak demand performance, Appendix A. This provides clear estimations of the peak demand from AC usage and total building electricity for a range of daily maximum temperatures by building types. It enables clear comparisons of several building energy performance factors effects on peak demand at different daily maximum temperatures. It also enables additional research questions to be asked and answered via software simulation with minimal computational resources. (7) software delivered separately. (8) GIS maps of scenario peak demand projections at the CBG level. These maps provide clear verifiable results that can be used to further refine the software, models, and or methods that comprise our understanding of how climate affects peak demand. Relative to the historical tests, these provide future projections as to what a reasonable range of peak demand is to plan for throughout a region given a range of implementation

scenarios. Enables identification of specific vulnerable “hot spot” areas within region.

Chapter 5: Infrastructure vulnerability assessment. This chapter has been submitted to the journal of Global Environmental Change. The citation is D. Burillo, M. V. Chester, S. Pincetl, E. Fournier, “Electricity infrastructure vulnerabilities due to long-term growth and extreme heat from climate change throughout Los Angeles County.,” *Glob. Environ. Chang.*, (in review), 2018. This chapter answers the fourth and fifth research questions. It satisfies the ninth, tenth, and eleventh deliverables from the proposal. (9) Statistics of component loads, Appendix B. This identifies quantity of components vulnerable to capacity shortages and magnitude of vulnerabilities. (10) GIS heat maps of forecasted component load factors and CBG vulnerability score. This enables identification and prioritization of specific areas within a region that are vulnerable to heat waves, demand increases, and capacity shortages, as well as, regions that could most benefit from aggressive energy efficiency implementations and or implementation of congestion-relieving distributed energy resources, and by how much. (11) Graphs and or updated maps of sensitivity of vulnerabilities to AC efficiency, building types, and distributed energy-resources. This contributes better understanding of effects of implementations of varying quantities of such on peak demand and contingency capacities throughout the region. Overall, it serves as a reasonable climate change impact study that can be used for policymaking.

CHAPTER 2

PRELIMINARY VULNERABILITY ASSESSMENT

This chapter is a published conference proceedings of 2016 International Conference on Sustainable Design, Engineering and Construction (ICSDEC).

The citation for the paper is: D. Burillo, M. Chester, and B. Ruddell, "Electric Grid Vulnerabilities to Rising Air Temperatures in Arizona," in *Procedia Engineering*, 2016, vol. 145.

Abstract

Ambient air temperatures are expected to increase in the US desert southwest by 1-5°C mid-century which will strain the electric power grid through increased loads, reduced power capacities, efficiencies, and material lifespans. To better understand and quantify this risk, a power infrastructure failure model is created to estimate changes in outage rates of components for increases in air temperatures in Arizona. Components analyzed include generation, transmission lines, and substations, because their outages can lead to cascading failures and interruptions of other critical infrastructure systems such as water, transportation, and information/communication technology. Preliminary results indicate that components could require maintenance or replacement up to 3 times more often due to mechanical failures, outages could occur up to 30 times more often due to overcurrent tripping, and the probability of cascading failures could increase 30 times as well for a 1°C increase in ambient air temperature. Preventative measures can include infrastructure upgrades to more thermal resistant parts,

installation of cooling systems, smart grid power flow controls, and expanding programs for demand side management and customer energy efficiency.

Keywords: electric power; energy; infrastructure; reliability; resiliency; failure analysis; climate change; extreme heat

1. Introduction

The electric power grid in the USA, and desert southwest specifically, is of the most reliable in the world (Group, 2011; Nerc, 2015), but like all electrical power systems it is sensitive to heat in terms of its power capacity and component materials' life-span (Denning, 2012). Arizona's power authorities typically plan 10-15 years in advance to manage risk considering increased system burdens due to social, economic, and technological, environmental, and policy factors (APS, 2014; SRP, 2010). These plans do not explicitly consider potential effects of rising ambient air temperatures. Significant increases in ambient air temperatures (1-5°C) are predicted by mid-century (Intergovernmental Panel on Climate Change, 2014; Sathaye et al., 2012), and grid construction projects require as much as 10 years and many millions of dollars each to complete. Therefore, developing a better understanding of the risks of rising air temperatures to the power grid is both timely and necessary to maintain reliable critical infrastructure systems.

Predicting the change in probability of electric power failing is obtained using fault-tree logic in this study (Henley & Kumamoto, 1996). A failure analysis framework is developed inclusive of generation, transmission, and substation component performance using thermophysical equations for power flow and material degradation rate with stochastic inputs for air temperature. The model estimates the probability of failure when supply is insufficient or component outages occur. The effects of increases in air temperature are quantified as changes in power flow capacity (MW) and efficiency (% MWh), as well as the mechanical mean time to failure (MTTF) of component parts. The potential change in multiple simultaneous outages occurring and triggering cascading failures is also quantified. This research estimates the magnitude of the risk of rising air temperatures to critical civil infrastructure systems, and identifies corresponding vulnerabilities within the power grid.

Nomenclature

θ_{μ}	°C	mean of the maximum ambient air temperature during June, July, and August
θ_{σ}	°C	standard deviation of θ_{μ}
θ_{+}	°C	increase in θ_{μ} , input control variable
θ_{PRM}	°C	average temperature at which the PRM is engaged on a day
$\theta_{PRMcrit}$	°C	average temperature at which the PRM reaches its critical value on a day
β_{GC}	%	loss of generation capacity per θ_{+}
β_{TDE}	%	loss of T&D network efficiency per θ_{+}
β_{PKload}	%	increase in peak load per θ_{+}
β_{TC}	%	loss of transmission line current capacity per θ_{+}
β_{SC}	%	loss of substation transformer current capacity per θ_{+}
β_{PK}	%	net peak load adjustment factor per θ_{+}

α	%	probability that two simultaneous component outages lead to a cascading failure in the system
λ	#/day	failure rate
$\Delta P f_b^a$	%	change in probability of failure, or λ , of a system component, where $a = P$ or M , $b = G$ or T or S
$P f_{bk}^a$	%	probability of failure, or λ , of a system component, where $a = P$ or M , $b = G$ or T or S , $k = i$ or f
A_b	years	age of component, where $b = G$ or T or S
IP	%	current in a system component as a percentage of the component's rated ampacity
MTTF	years	mean time to failure
PRM	%	planning reserve margin
PRM_{crit}	%	PRM critical value for potential service interruption and the possibility of cascading failures
S	%	strength loss per year
S_{Teol}	%	strength loss for a transmission line to reach expected lifespan
<i>Commonly used subscripts and superscripts</i>		
P, M		power- or mechanical-based component failure
G, T, S		generation, transmission, substation
i, f		initial (current air temperature scenario with θ_μ and θ_σ), final (higher ambient air temperature scenario θ_+)
μ, σ		mean, standard deviation

2. Methods

This analysis focuses on the thermal performance of the three major current carrying components in the electric power grid: generation, transmission, and substation transformers. This approach is consistent with other recent studies of the impact of rising air temperatures on power infrastructure such as (Sathaye et al., 2013). To estimate how much increasing ambient air temperatures can increase component outages, cascading failures, and ultimately service interruptions, it is necessary to first understand the flow of electric power in the system, as well as the sequence of events that can lead to

interruptions and potentially cascading outages, Figure 1. System operators maintain an n-1 redundancy standard in design at the high-voltage transmission level meaning that the single largest generator, transmission line branch, or substation (of which there are at least hundreds in every region) can fail at any time without any interruption to service (Mistry & Keel, 2013). These n-1 redundancies are represented in Fig. 1b using octagon boxes and logical AND gates. Service interruptions due to major component failures only occur when more than one individual component fails at the same time. Such events can lead to cascading failures including blackouts as in (Ferc & Nerc, 2012).

Service interruption occurs when power does not reach the load, such as a building or street light, and this analysis estimates specifically how much the frequency of service interruptions can increase. Figure 1b shows the two ways that a service interruption can occur that are analyzed in this paper: either there is not enough total generation to meet total demand, or particular power pathways (transmission lines and substations) do not have sufficient capacity to deliver power to the load. The following list explains how increases in ambient air temperatures can trigger failures leading to service interruptions consistent with the lettering in Figure 1b.

- A. High air temperatures can result in reduced peak energy generation capacity and or efficiency losses in the transmission and distribution (T&D) network (M. Bartos & Chester, 2015b; Sathaye et al., 2013). If the system is also in high demand, (B), then load can exceed generation and put the

system in a state of over demand. If there are insufficient generation reserves, then there will be a service interruption.

- B. High air temperatures can result in higher demand, especially during the already hot summer months due to increased burden on building air conditioning systems (M. Bartos & Chester, 2015b).
- C. High air temperatures result in less T&D power flow capacity in lines and transformers (M. Bartos & Chester, 2015b; Sathaye et al., 2013). If a circuit is in high demand, then power flow can exceed safe operating capacity and lines and transformers can exceed their rated ampacities and become in a state of overcurrent (Ferc & Nerc, 2012).
 - i) If protection devices function correctly, then overcurrent will cause tripping of the line or transformer within the T&D network (Ferc & Nerc, 2012). If there is insufficient capacity in parallel branches to provide power to the load, then there will be a service interruption (Ferc & Nerc, 2012).
 - ii) If a protection device fails to trip and a circuit is overcurrent, then a component can exceed its thermal rating. Excess heat accelerates the chemical degradation rate of sensitive materials and can result in mechanical failure (E) (Sen, Pansuwan, Malmedal, Martinoo, & Simoes, 2011; Wan, 1999). Protection devices can fail because they are not accurately designed or calibrated for local climate conditions or other reasons (Nerc, 2015). Depending on the type and location of overcurrent failure, a generator, transmission line,

substation, quality device, or other protection device can fail. If a generator fails, then the system state goes to (A) as the system now has less generation. If a transformer fails, then it goes to (A) and or (C) as the T&D network operates at lower efficiency and or has less power flow capacity. If a power quality device fails, then it goes to (C) again or directly to overcurrent depending on the circumstances. If another redundant protection device fails, then the cycle of potential failures repeats for additional components on connected circuits.

- D. High air temperatures can result in a protection device failing to trip (Nerc, 2015). The device could be calibrated to a certain power rating that should be lower for the actual air temperature. If that occurs during high loading, then a component can go overcurrent and fail as in (ii).
- E. High air temperatures can result in an accelerated physical material degradation rate, which can result in accelerated failures for any electrical devices (Denning, 2012). The same failure scenarios can occur as described above, with the addition of an undesired trip of a protection device. If a protection device fails with an undesired trip, and there is no redundant power flow, then a service interruption occurs.

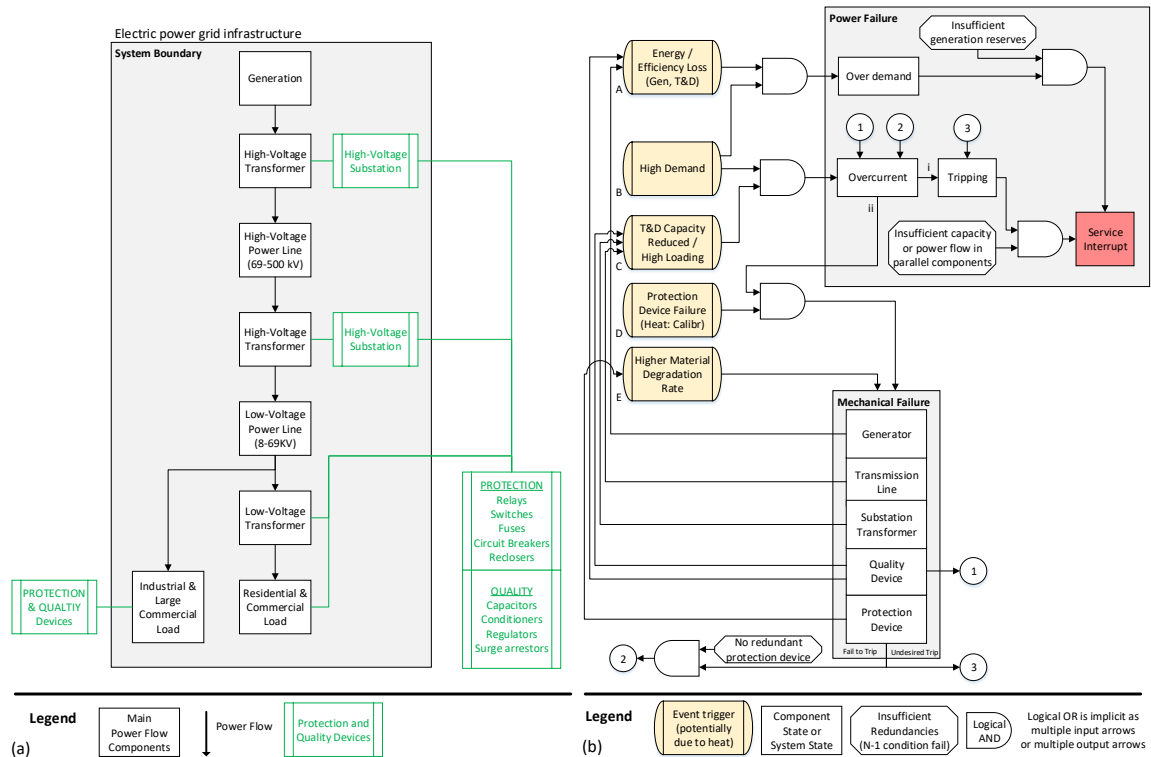


Figure 1 (a) Electricity Infrastructure Analysis System Boundary. (b) Fault Tree to Service Interruption.

(a) Shows the flow of power from generation to load through system components and identifies the analysis system boundary inclusive of major power-flow components including: generation, transmission, substation transformers, and load. Changes in performance of protection and power quality devices are not analysed. (b) Shows the terminal event of a service interruption on the right, and the power- and mechanical-failures that can lead to a service interruption logically preceding from the left. On the far left are the events that can be caused by higher ambient air temperatures and ultimately lead to service interruption in conjunction with other failures as indicated. Mechanical failures feedback into the event triggers as their loss of functionality results in a loss of power-flow that could cause an interruption.

A model is developed to estimate the change in probabilities of component failures (or failure rates) and service interruptions due to increases in ambient air temperatures, shown in equation (1). This is done by quantifying the fault processes in Figure 1 for the primary current-carrying components. The structure of this model is shown in Figure 2 where climate and infrastructure inputs are

used to estimate changes in power-based and mechanical-based failures. These values are used to estimate the change in probability of a cascading event that can be triggered by two or more component failures occurring at the same time.

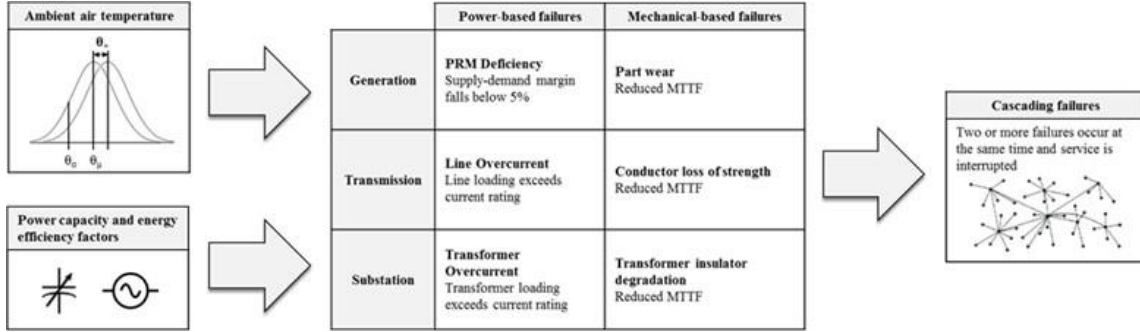


Figure 2. Failure Analysis Model.

The model is structured in five parts: (i) ambient air temperature, the increase of which is the primary control variable, θ_+ ; (ii) power capacity and energy efficiency factors, β 's, which are proportional to ambient air temperature; (iii) probability of power-based failures for each component type, Pf_b^P , for which there could be insufficient capacity to support power demand; (iv) probability of mechanical-based failures for each component type, Pf_c^M , wherein the wear of thermally sensitive parts over time results in a higher failure rate or probability of failure on a given day; (v) cascading failures, that can occur if two or more component failures occur at the same time.

$$\Delta Pf_b^a = \frac{Pf_{bf}^a - Pf_{bi}^a}{Pf_{bi}^a}, \quad a = \begin{cases} M & \text{mechanical-based failure} \\ P & \text{power-based failure} \end{cases}, \quad b = \begin{cases} G & \text{generation} \\ T & \text{transmission} \\ S & \text{substation} \end{cases} \quad \begin{matrix} \% \text{ per} \\ \text{day} \end{matrix} \quad (1)$$

2.1. Ambient Air Temperature

Ambient air temperature is the primary control variable in the model, and is defined as a normal distribution curve with base case mean maximum temperature $\theta_\mu = 42.22^\circ\text{C}$ and standard deviation $\theta_\sigma = 3.04^\circ\text{C}$ from the average maximum temperature at the Phoenix airport for the months of June, July, and August 2009 to 2014 (Weather Underground, 2016). Summertime increases in

air temperature, θ_+ , are modeled as increases in the mean of the maximum temperature θ_μ with no change in standard deviation θ_σ .

2.2. Electric Power Capacity and Energy Efficiency Factors

Electronic components are generally subject to at least two stresses: electrical and thermal (Denning, 2012). Electrical resistance increases as conductor temperature increases, which further increases operating temperature and decreases efficiency (Douglass & Reding, 2006). The model inputs for capacity and efficiency losses are $\beta_{GC} = 0.7\%$, $\beta_{TDE} = 0.5\%$, $\beta_{PKload} = 7.5\%$, $\beta_{TC} = 1.5\%$, and $\beta_{SC} = 0.7\%$ per 1°C increase in ambient air temperature as are the marginal unit linearization of the results in (M. Bartos & Chester, 2015b; Sathaye et al., 2012). The generation factor only considers natural gas plants. These values are for high operating temperatures, which are within the range of this analysis, and are combined into the net adjustment factors $\beta_{PK} = \beta_{PKload} + \beta_{TDE} + \beta_{GC} = 8.7\%$, $\beta_T = \beta_{PKload} + \beta_{TC} = 9\%$, and $\beta_S = \beta_{PKload} + \beta_{SC} = 8.2\%$ per $^\circ\text{C}$.

2.3. Power-Based Failures

Power-based failures are failures where there is insufficient capacity in a circuit to meet demand. These can occur due to insufficient generation, when a transmission line is overcurrent, or a substation is overcurrent.

2.3.1. Generation – PRM Deficiency

PRM is the amount of generation capacity available to meet expected demand, and is calculated as the difference in prospective resources and net internal demand, divided by net internal demand (NERC, 2016). PRM is institutionally managed to maintain reliable grid operations in the event of

unexpected increases in demand and or outages of existing capacity (NERC, 2016). System operators historically issue alerts when PRM falls below 5% and ask customers to curtail their electricity usage (CEC, 1999). Therefore 5% is used as the critical PRM value, PRM_{crit} , where other simultaneous component failures can cause a service interruption and trigger cascading failures.

ΔPf_G^P is estimated in equation (1) assuming PRM is marginally engaged for the top 5% of air temperature values for θ_μ and θ_σ , which is $\geq 47.22^\circ\text{C}$ and represents the expected 4.6 hottest days per year from 2009 to 2014 (Weather Underground, 2016). The temperature that PRM_{crit} occurs at is estimated in equation (2), where $PRM_i = 17\%$ as is WECC's 2024 projected summer PRM (WECC, 2014a). $Pf_{Gi}^P = 1.8\%$ per day is the area under a normal curve of θ_μ and θ_σ above $\theta_{PRM_{crit}}$. Pf_{Gf}^P is estimated by shifting θ_μ by θ_+ .

$$\theta_{PRM_{crit}} = \theta_{PRM} + \frac{(PRM_i - PRM_{crit})}{\beta_{PK}} \quad ^\circ\text{C} \quad (2)$$

2.3.2. Transmission – Line Overcurrent

ΔPf_T^P is estimated in equation (1) assuming that if a line exceeds its rated amperage it will trip. $Pf_{Ti}^P = 0.0032\%$ per day is the area under a normal distribution for the line load as a percentage of the current carrying capacity where $IP_{T\mu} = 60\%$, $IP_{T\sigma} = 10\%$, and rated amperage is equal to 1. Pf_{Tf}^P is estimated by shifting $IP_{T\mu}$ by θ_+ and β_T .

2.3.3. Substation – Transformer Overcurrent

ΔPf_s^P is estimated using the same method as 0 by using equation (1), and assuming that if a transformer exceeds its rated amperage it will trip. $Pf_{Si}^P = 0.0032\%$ per day is the area under a normal distribution for the transformer load as a percentage of the current carrying capacity where $IP_{S\mu} = 60\%$, $IP_{S\sigma} = 10\%$, and rated amperage is equal to 1. Pf_{sf}^P is estimated by shifting $IP_{S\mu}$ by θ_+ and β_s .

2.4. Mechanical-Based Failures

Mechanical failures occur due to physical degradation of thermally-sensitive parts within components such as a conductor, insulator, or contact. A failure rate, λ , is defined as the inverse of the MTTF with units of failures per day. Change in failure rates are estimated as the percent change in the initial and expected λ for increased air temperature conditions as in equation (1).

2.4.1. Generation – Part Wear

A value of 0.001% is assumed for Pf_{Gi}^P , and Pf_{Gf}^P is set to that multiplied by $(1+\theta_+/100)$.

2.4.2. Transmission – Conductor Loss of Strength

There are three primary factors considered in defining the thermal limit of a power line: sag, loss of strength, and the fittings of the conductor (Smolleck & Sims, 1982). Sag is measured as the vertical distance that the line moves closer towards the ground due to thermal expansion, and increases the chance of flashover resulting in a ground fault and outage of the circuit. Such an event typically occurs when a line comes too close to trees, which may occur because

trees have not been trimmed, or the line sags beyond the safety margin (Wan, 1999). While sag is a mechanical process, it is not associated with conductor damage or loss of life (Wan, 1999). Therefore analyzing the physical conductor sag constraints would be redundant with the previous power-based failure analysis for transmission line overcurrent. Loss of conductor strength occurs due to annealing, a gradual process whereby a metal recrystallizes over time, and ACSR conductors anneal at operating temperatures above 100°C (Kopsidas & Rowland, 2011). Significant loss of strength may result in breakages during high mechanical stress events such as gusts of wind (Kopsidas & Rowland, 2011). Properly designed and selected fittings are not a thermal limiting factor for the conductor (Wan, 1999).

$\Delta P_{f_T}^M$ is estimated by equation (1) assuming a $MTTF_{Ti} = 70$ years for ACSR lines based on (Havard et al., 1991) and that it is causally proportional to loss of conductor strength due to annealing. $P_{Ti}^M = \lambda_{Ti} = 0.0039\%$ per day is the inverse of the $MTTF_{Ti}$. P_{Ti}^M is estimated by adjusting MTTF as in equation (3). The strength loss associated with conductor end of life, S_{Teol} , is estimated as the weighted sum of the hours per day over $MTTF_{Ti}$ that a transmission line is expected to exceed nominal current by 10%, 20%, and 30%, and log-linear strength loss factors of 3%, 5%, and 7.5% respectively that are the approximate results of (Bhuiyan, Musilek, Heckenbergerova, & Koval, 2010). This assumes that percentage loss of tensile strength relates 1:1 to reduced lifespan. The initial strength reduction rate, S_{Ti} , is estimated linearly as S_{Teol} per $MTTF_{Ti}$.

Transmission line current is assumed to be normally distributed with initial current loading $IP_{T\mu} = 60\%$ and $IP_{T\sigma} = 10\%$ as in 0. Nominal current is assumed to be 85% of rated capacity. The higher ambient air temperature scenario strength reduction rate S_{Tf} is estimated using the same approach, increasing $IP_{T\mu}$ by β_T and θ_+ accordingly.

$$MTTF_{Tf} = \frac{(S_{Teol} - S_{Ti}A_T)}{S_{Tf}} + A_T \quad \text{years} \quad (3)$$

2.4.3. Substation – Transformer Insulation Degradation

Substations consist of several power quality and protection devices to ensure safe and reliable grid operations, and this analysis focuses on transformers which are current-carrying devices used to change voltage levels for safe and efficient T&D of power throughout the network. The major parts of interest within transformers are the conductor windings and their insulation.

ΔPf_s^M is estimated by equation (1) assuming an initial MTTF of insulation life of 48.9 years as are the results of (Muthanna, Sarkar, Das, & Waldner, 2006) for an oil-based distribution transformer, and is assumed representative of substation transformers. $Pf_{Si}^M = \lambda_{Si} = 0.0056\%$ per day. Pf_{Sf}^M is estimated scaling MTTF by the marginal unit linear adjustment factor from the same study where MTTF decreased from 48.9 to 46 years per 1% increase in ambient air temperature. It is important to note that this method does not explicitly consider the current loading at the substation IP, and that an oil-based distribution transformer may not be representative of transmission-level transformers.

2.5 Cascading Failures

The change in probability of a cascading failure, ΔP_c , is calculated in the same manner as equation (1). $PC_i = 0.0013\%$ per day and PC_i are estimated in equation (4) as one minus the probability that no failure occurs on a random day minus the probability of exactly one failure occurring on a day, times the cascade trigger coefficient $\alpha=10\%$. The probability that two simultaneous outages trigger a cascade are the results of (Song, 2015) wherein a dynamic power flow simulation of a 2,383-bus system was used to assess the probability of cascading failures occurring in the event of two simultaneous outages within 2,896 component branches for n-1 contingency.

$$P_{C_k} = \alpha \left(1 - \left[\prod_{a,b} (1 - P_{bk}^a) \right] - \left[\sum_{a,b} \left(P_{bk}^a \prod_{a,b} (1 - P_{bk}^a) \right) \right] \right), \quad \% \text{ per day} \quad (4)$$

$$\text{where } k = \begin{cases} i & \text{initial} \\ f & \text{final} \end{cases}, \quad \overline{a,b} = \{\text{other } a,b\}$$

3. Results

A 1-5°C increase in ambient air temperatures can significantly increase the rate of mechanical- and power-based failures as well as the cascading outages in the electric grid in Arizona. As listed in Table 2, mechanical failures in transmission lines could increase almost 200% for a 1°C increase. This means that the same strength loss that occurs in an overhead ACSR line over 70 years due to annealing could occur in 25 years, and lines could need to be reconductored or replaced that much more often. Mechanical failures in substations could increase by 16% with the first 1°C θ_+ , and then approximately

double for each 1°C thereafter if conductor insulation oil is not changed with that additional frequency. Power failures due to insufficient generation could be more than twice as likely with a 1°C increase in air temperatures. In that case reserve margins would fall below 5% on very hot days more often with additional load, reduced generation capacity, and reduced distribution efficiency proportional to the distribution of daily max temperatures. Power failure frequency in substations and transformers can increase 22x to 30x respectively for a 1°C θ_+ . Increases in system peak load and decreases in current capacity in those components during peak hours could result in exceedance of rated current and tripping with much higher frequency. The probability of two or more failures triggering a cascading outage can increase by 26x with the first $\theta_+=1^\circ\text{C}$. The change in probability of cascading failures grows exponentially with θ_+ and increases in power-based failures. If the probability of a cascading failure event is currently once every 20-30 years, then that probability could increase to once every 1-2 years with hotter summers if preventative measures are not taken.

Table 2. Increased Probability of Failures per Degree Increase in Ambient Air Temperature.

$\theta_+ (^{\circ}\text{C})$	ΔPf_G^P	ΔPf_T^P	ΔPf_S^P	ΔPf_G^M	ΔPf_T^M	ΔPf_S^M	ΔPc
0	-	-	-	-	-	-	-
1	135	2,955	2,225	1	183	16	2,587
2	400	43,799	28,751	2	409	39	77,788
3	871	305,542	194,967	3	576	73	1,287,827
4	1,620	1,087,885	744,306	4	685	128	10,275,393
5	2,691	2,183,150	1,704,373	5	711	236	35,679,472

4. Conclusion

Specific vulnerabilities in the electric power grid are identified where proactive governance may be able to prevent future outages otherwise resultant from rising ambient air temperatures in Arizona. Preventative measures in operations and maintenance could include more frequent reconductoring and changing of insulators, component derating, upgrades to more thermal resistant parts, forced-air cooling systems, dynamic power-flow routing, and or demand side management programs including energy efficiency, demand response, and peak load shifting (Hedman & Member, 2015; Kopsidas & Rowland, 2011; Wan, 1999). Increased inspections and flexible maintenance schedules around weather patterns could be useful in the interim. Failure to do so may result in outages in other critical interdependent infrastructure systems including water, transportation, telecommunications, and information technology (Rinaldi et al., 2001).

CHAPTER 3

TOP-DOWN APPROACH FOR ESTIMATING PEAK DEMAND AND RESOURCE ADEQUACY CONSIDERING HEAT WAVES FROM CLIMATE CHANGE

This chapter is published in the journal of Applied Energy. The citation for this article is: D. Burillo, M. V. Chester, B. Ruddell, and N. Johnson, "Electricity demand planning forecasts should consider climate non-stationarity to maintain reserve margins during heat waves," *Appl. Energy*, vol. 206, 2017.

Highlights

1. Weather-adjustment methods in electricity infrastructure planning are biased.
2. Climate models project temperatures up to 58°C (136°F) in the US Desert Southwest.
3. Peak demand does not increase linearly with temperature; s-curve more accurate.
4. Los Angeles could experience hazardous power shortages in record-breaking heat.
5. Risk management strategies identified via reductions in peak load & load variance.

Abstract

Climate non-stationarity is a challenge for electric power infrastructure reliability; record breaking heat waves significantly affect peak demand (M. D. Bartos & Chester, 2015), lower contingency capacities, and expose cities to risk of blackouts due to component failures and security threats. The United States' electric grid operates safely for a wide range of load, weather, and power quality conditions. Projected increases in ambient air temperatures could, however, create operating conditions that place the grid outside the boundaries of current reliability tolerances. Advancements in long-term forecasting, including projections of rising air temperatures and more severe heat waves, present opportunities to advance risk management methodologies for long-term infrastructure planning. This is particularly evident in the US Southwest—a relatively hot region expected to experience significant temperature increases that affect electric loads, generation, and transmission. Generation capacity built to meet the 90th percentile (T_{90}) hottest peak demand, plus an additional reserve margin of least 15%, may not be sufficient if air temperature are higher than expected. The problem with this T_{90} planning approach is that T_{90} statistics are based on non-standardized historical (stationary) climate patterns, and forecasts of peak demand and generation capacity are based on stationary methods too.

This study used downscaled global climate models (GCMs) to evaluate the effects of non-stationarity on air temperature forecasts, and simulated the subsequent effects on cooling loads and thermal power generation that impact

local reserve margins (LRMs) useful in long-term grid reliability planning. Air temperature projections in IPCC RCPs 4.5 and 8.5 are that increases could be possible up to 6°C by the end of century, with highs of 58°C and 56°C in Phoenix, Arizona and Los Angeles, California respectively. In the hottest scenarios, we estimate that LRMs for the two metro regions would be on average 30% less than the results from stationary models, which in the case of Los Angeles (a net importer) would require 5 GW of additional local generation to meet electrical demand. We calculated these values by creating a structural equation model (SEM) for peak demand based on the physics of common AC units; physics-based models are necessary to predict demand under unprecedented conditions for which historical data does not exist. We also modeled derating for thermal power plant generation based on the electrical and thermal performance characteristics of different technologies. Lastly, we discussed several strategic actions to reduce the risk of LRM shortages; including implementing technology, market incentives, and urban forms that reduce peak load and load variance per capita as well as their tradeoffs with several other stakeholder objectives.

Keywords: climate non-stationarity; electric power infrastructure; peak demand; risk management; structural equation modeling

1. Introduction: Climate Stationarity Assumptions in Long-term Electricity Infrastructure Planning

Some risk management practices in the electric power sector use “rules of thumb.” One of these rules is to build at least a 15% surplus of power generation to meet peak demand (NERC, 2015a), where contingency capacity or generation “head room” is needed if units go offline. Maintaining a reliable margin is risky business because peak demand changes over time as a result of variations in population, human behavior, technology, and climate (Willis et al., 2001); moreover, infrastructure implementation is a costly and long-term investment. The electric power industry currently considers all of these factors in planning processes; however, they do not plan for climate non-stationarity (Ralff-Douglas, 2016), (APS, 2014), (WECC, 2014b), and (SRP, 2012). Climate non-stationarity affects planning in two ways, wherein changing atmospheric conditions can result in different annual probability distributions of air temperatures (Kysely, Picek, & Beranová, 2010), as well as differences in low, average, and high air temperatures (Hall et al., 2012). The common practice in industry is to plan for future peak demand based on a 90th percentile, also referred to as *T90* or 1-in-10 hottest days, summertime temperature using historical (stationary) probability distributions (WECC, 2014b) and (Miller, Jin, Hayhoe, & Auffhammer, 2007). Peak demand is generally understood to change with temperature during the seasons in many geographic regions, but little knowledge exists in environmental studies to model that relationship beyond historical correlations (Sathaye et al., 2013), (Garcia-cerrutti, Junker, Bender, & Jones, 2012), (M. D. Bartos et al.,

2016), (Santamouris, Cartalis, Synnefa, & Kolokotsa, 2015), (David J. Sailor & Muñoz, 1997), and (David J. Sailor, 2001). With a lack of peer-reviewed literature on the topic, studies can easily, and mistakenly, assume correlation implies causation when assessing the risk of rising air temperatures on infrastructure systems. Accurate scientific knowledge is necessary to maintain reliability in critical electricity infrastructure systems if climate conditions are significantly different in the future.

Failure to properly understand and plan for grid performance at unprecedented high temperatures could result in blackouts. Multiple service interruptions have recently occurred during heat waves due to transformer overloads, transmission line faults, generation shortages, and cascading failures (Barry Fisher, 2014), (Jerod MacDonald-Evoy, 2016), (NERC, 2004), and (Ferc & Nerc, 2012). While grid operators can ramp power generators up or down to respond to sub hourly changes in load (Raineri, Ríos, & Schiele, 2006), those capabilities are physically limited by plant type, total production capacity, and bottlenecks in electrical delivery systems—all of which are determined through long-term planning processes (Willis et al., 2001). If the forecasting methods are not accurate, and engineering tolerances are not sufficient, then contingency capacities could be negatively impacted and component hardware failures could be triggered; systems could be exposed to security threats (R. Smith, 2014), (Salmeron, Wood, & Baldick, 2004), higher probability of blackouts (Daniel Burillo, Chester, & Ruddell, 2016), and unnecessary operations costs (Willis et al., 2001).

Local reserve margin (LRM) is a contingency capacity metric equal to the amount of generation that exceeds the aggregate peak demand within a geographic area. The “local” boundary can be a neighborhood, a substation region, a utility service territory, or several territories, and may or may not include “remote” generation and “long-distance” transmission lines (WECC, 2014b), (WECC, 2014a), (CPUC, 2016), (NERC, 2015c), (SocalEV, 2015), (LADWP, 2016b), (APS, 2016), and (SRP, 2016). Transmission import capabilities are out of the scope of local generation, and are dependent upon generation headroom in other connected local areas. These imports allow for a reduction in LRM regulatory requirements by enabling delivery of non-local resources (Pfeifenberger, 2010). Specific requirements for LRMs vary regionally with consideration for factors such as the reliability of components, likelihood of concurrent peak loads in neighboring regions, and security (WECC, 2014a), (CPUC, 2016), (NERC, 2015c), and (NERC, 2015b).

In this study, we examined assumptions about stationary air temperatures used in infrastructure planning processes, as well as the lack of consideration for future record-breaking heat waves (non-stationarity) that could result in compromised LRMs. We used county lines for Los Angeles and Maricopa (Phoenix) to define local areas for LRMs because these geopolitical boundaries reasonably frame the existing infrastructure, and public data were readily accessible in that format. We used global climate model (GCM) simulations of the Intergovernmental Panel on Climate Change’s Representative Carbon Pathway scenarios RCP 4.5 and RCP 8.5 to define a range of possible future air

temperatures. We considered how existing infrastructure would operate differently if weather conditions were significantly different from historical conditions. We did not attempt to predict physical changes in future supply- or demand-side infrastructure or complete a full planning scenario necessary for legislating local resource adequacy and transfer capacity requirements. Specifically, we studied effects of stationarity assumptions on long-term planning estimates of (1) air temperatures, (2) peak demand, (3) generation capacity, and (4) LRM. We used our quantitative models and results as the premise for a qualitative discussion of options to mitigate the risk of LRM shortages.

2. Methods: Air Temperature Effects on Peak Demand, Generation Capacity, and LRMs

We chose Phoenix and Los Angeles regions to study because they are the two largest cities in the US Southwest Desert area and have growing populations and aging infrastructure that require immediate investments (APS, 2014), (“US Census Bureau 2010 Census Interactive Population Map,” 2017), and (LADWP, 2016c). These regions, already amongst the hottest in the world, are expected to have significant temperature increases in the future (M. D. Bartos & Chester, 2015) and (Sathaye et al., 2013), and were feasible to study because they exist largely within county boundaries for which public data is available. First, we characterized ranges of local temperatures within and across the counties (Los Angeles, CA and Maricopa, AZ) for recent historical, stationary samples for *T90* and non-stationary GCM projections of the daily high

temperature, T_{max} . Second, we created and calibrated a theoretical model to predict peak demand as a function of AC performance at varying T_{max} . We calibrated our model to historical observations of peak demand and T_{max} using county infrastructure data and statistical regression techniques. The nature of our model is that it has multiple levels of equations with terms that fit simultaneously as both predicted and predictor variables; this type of multiple regression analysis is called structural equation modeling (SEM) (Bowen & Guo, 2011). As explained in detail in S1, we chose to focus the majority of our analytical efforts on modeling peak demand because seasonal changes in peak demand are an order of magnitude higher than changes in generation capacity, which are an order of magnitude higher than any delivery system losses. We did not consider losses in any form. Third, we used derating factors from previous studies of power plant operations to estimate decreases in capacity as a function of T_{max} by generator fuel technology. Fourth and finally, we used results of those analyses to calculate LRM, and did a cross-sectional analysis of effects of stationarity assumptions in T_{max} values and peak demand forecasting methods on LRM planning.

2.1. Local Climate Temperatures

We parameterized a range of daily high temperatures (T_{max}) using historical weather station data obtained from (Weather Underground, 2016), and future projections from downscaled Localized Constructed Analogs GCM models through the end of century (Brekke et al., 2013). To quantify a range of stationary

temperature values, we sampled T_{max} from June, July, August, and September during the early-century period (2001-2016) from four weather stations in each county located where coincident power demand data were available in (Sathaye et al., 2013) and (Garcia-cerrutti et al., 2012). Figure 3a shows the weather station locations geographically, and T_{max} for the historical period at 2km x 2km resolution. Data used for the map images were obtained from different sources due to technical reasons, and were used only to produce those map images (“Google Earth Engine: A Planetary-scale Platform for Environmental Data & Analysis,” 2012), (“Google Earth Engine: GRIDMET,” 2012), and (Abatzoglou, 2013). The 90th percentile T_{max} values, $T90s$, shown in Figure 3b, are the range of annual $T90$ from the lowest to highest year in the sample. The early T_{max} values indicate the highest annual T_{max} values for the early-century period. For the non-stationary approach, we used mid-century (2041-2060) and late-century (2060-2099) LOCA T_{max} projections from the 32 GCMs available for RCP 4.5 and 8.5. GCM projections were obtained at $1/8^\circ \times 1/8^\circ$ resolution for the locations indicated in Figure 3a from (Brekke et al., 2013), as these were the most comprehensive spatially detailed future projections publically available at the time. The highest T_{max} in each period for each GCM projection was sampled; the “block maximum” (Zhang, Zwiers, & Li, 2004) range for each of the 32 models was plotted side-by-side to the historical statistics in Figure 3b for each time period and RCP to compare the differences in the range of uncertainties.

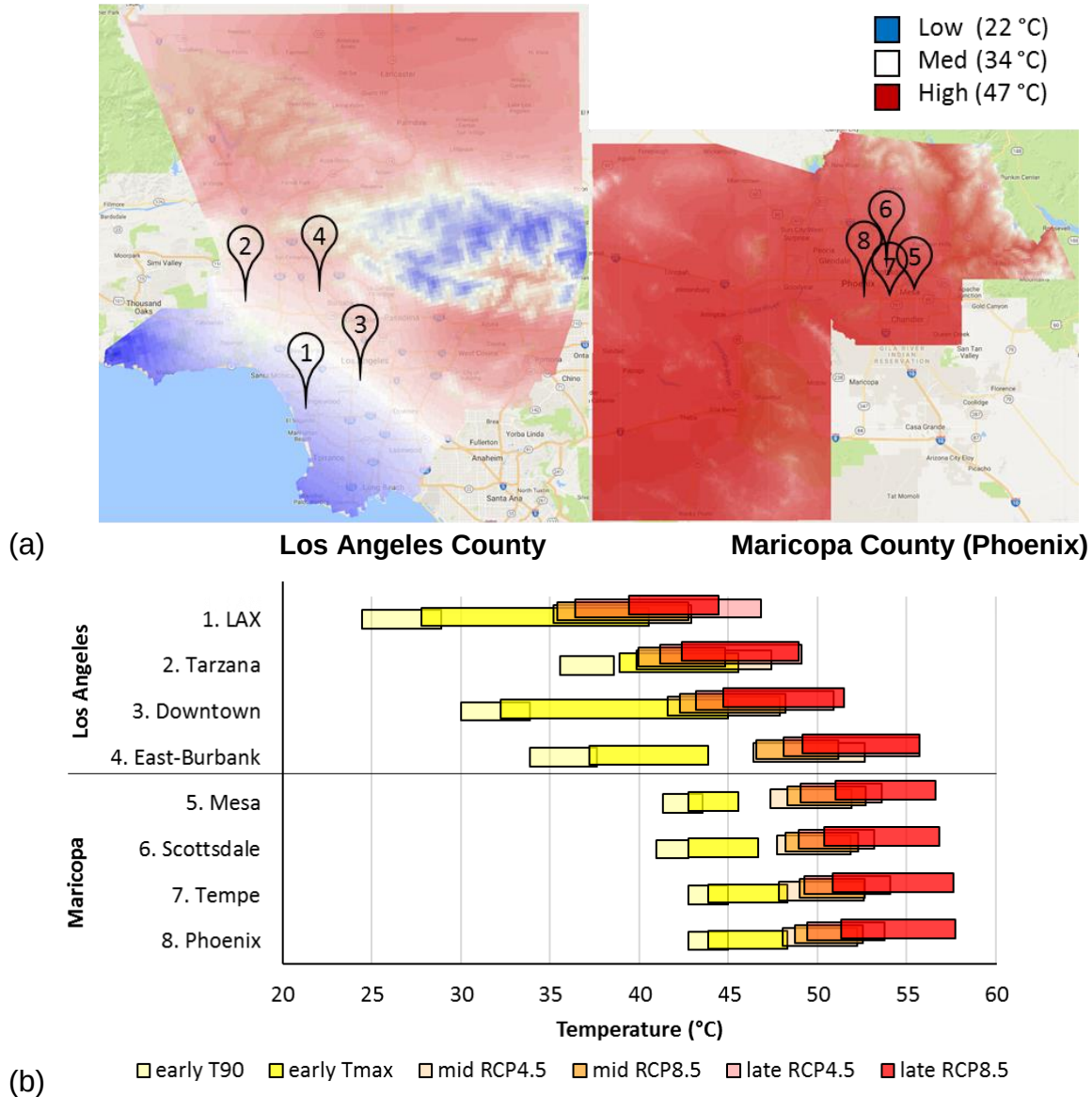


Figure 3. (a) Map of County Weather Stations and Early-century T_{max} . (b) Comparison of Local Temperatures for Early-, Mid-, and Late-century Periods. (a) Shows the Los Angeles locations 1-4 represent coastal, suburban, downtown, and desert landscapes respectively. The Phoenix locations 5-8 represent fringe suburb, two populous neighboring suburbs, and the urban heat island center respectively. (b) Shows early-century (2001-2016) temperature ranges include annual T_{90} and T_{max} . Mid-century (2041-2060) and late-century (2061-2099) ranges include the block maxima of the 32 GCMs sampled for each period and RCP.

2.2. Peak Demand

Electricity Data

The sample of electricity data consisted of the daily maximum demand, which we extracted from the hourly time series values listed in EIA's US Electricity System Operating Data, Form 930 (EIA, 2016c). We collected peak demand data for three representative balancing authorities (LDWP - Los Angeles Department of Water and Power, AZPS - Arizona Public Service Company, and SRP - Salt River Project). The sampling period ranged from July 01, 2015 to September 15, 2016. Hourly load data were also obtained from Southern California Edison (SCE) ("SCE Dynamic Load Profiles," 2016), but were not used in the analysis because we were unable to reconcile differences between SCE's reported hourly (normalization-masked) loads and EIA's total annual demand values. Complete plots of peak demand observations are included in S5 for the best-fit balancing authority to weather station models. The number of observations was approximately 300 for each balancing authority and corresponding weather station at $T_{max} \geq 25^{\circ}\text{C}$ (77°F), which corresponds to most residential air conditioning (AC) thermostat settings in our sample regions (Nahlik et al., 2016) and (CEC, 2009). The top T_{max} observations were 48°C and 46°C (118°F and 115°F) for Phoenix and Los Angeles respectively in the period (Weather Underground, 2016). Because the source data were based on measurements from balancing authority interconnections, they did not explicitly account for distributed energy resources or any delivery system losses. We considered adjusting our methods to account for these factors as described in

S2, and chose not to as we estimated that they have only a ~1% effect on the magnitude of sample values in our study regions, and are therefore not significant for the purposes of this analysis.

Stationary Peak Demand Model

For the stationary model, we used linear regression to relate peak demand in balancing authorities to T_{max} . We used the range $T_{max} = 25^{\circ}\text{C}$ to 40°C (77°F to 104°F) as was common convention in similar studies (Sathaye et al., 2013), (Sathaye et al., 2012), and the nineteen climate studies summarized in (Santamouris et al., 2015). The model was scaled by the fraction of residential and commercial buildings in the balancing authority (EIA, 2014b) to the county (Janet L. Reyna & Chester, 2015) and (A. M. Fraser et al., 2016). Stationary approaches are inherently biased by unavoidable factors, including the observation range and choice in sample range, in our case $T_{max} \geq 25^{\circ}\text{C}$. AC units are generally sized for buildings based on historical weather patterns, so it is coincidental that the aggregate historical performance fits well to a straight line. We excluded all observations less than 25°C to avoid capturing increase in loads at colder temperatures due to the use of electric heating appliances; had we not excluded these observations, peak demand would have visually appeared “U-shaped” when plotted over T_{max} , and an “ x^2 ” type of function could have had a high correlation. Such a function would have produced significantly higher estimates of peak demand at higher air temperatures than a linear function.

Non-Stationary Model

For the non-stationary approach, we created a SEM based on knowledge of the relevant infrastructure and their thermal and electrical performance characteristics and then fit that SEM to the observed data. The most significant temperature-dependent electrical loads in the study regions were AC units, and we chose to model the change in peak demand as characteristic of changes in AC performance only, as explained in S3 and S4. We modeled all AC units as split indoor-outdoor dry air-cooled engineering designs based on previous performance characterization studies in (Faramarzi, Coburn, Sarhadian, Mitchell, & Pierce, 2004) and (Bush & Ruddell, 2015), which showed an increase in active load of 1.33%kW per $1^{\circ}\text{C} \pm 0.35\%$ for seven different AC units. Figure 4, inspired by (Lu, 2012), provides a visual representation of the micro- and macro-scale system dynamics that we considered as the premise for our SEM. As outdoor thermal forces increase, ambient dry-bulb air temperature (T_{dry}) increases, and individual AC loads increase. Duty cycles increase proportional to the ratio of incoming and outgoing building thermal energy ($\dot{Q}_{in}/\dot{Q}_{out}$) at the thermostat set point. At higher T_{max} , the expected number of ACs simultaneously active in a region during the peak period increases up to a theoretical limit of 100%. The mid-section steepness of the s-curve is characteristic of the observed behavior of AC units within a region. We used the corresponding peak demand observations to fit the SEM. Limitations of this stochastic modeling approach can be found in its ability to predict usage patterns of individual AC units at lower temperatures. Our primary objective, however, was to gain insight into the right side of the

aggregate peak demand tail, where—at unprecedented high air temperatures—AC engagement approaches 100%. Therefore, (as discussed in S4) given the large sample size, we did not consider those methodological limitations prohibitive for this study.

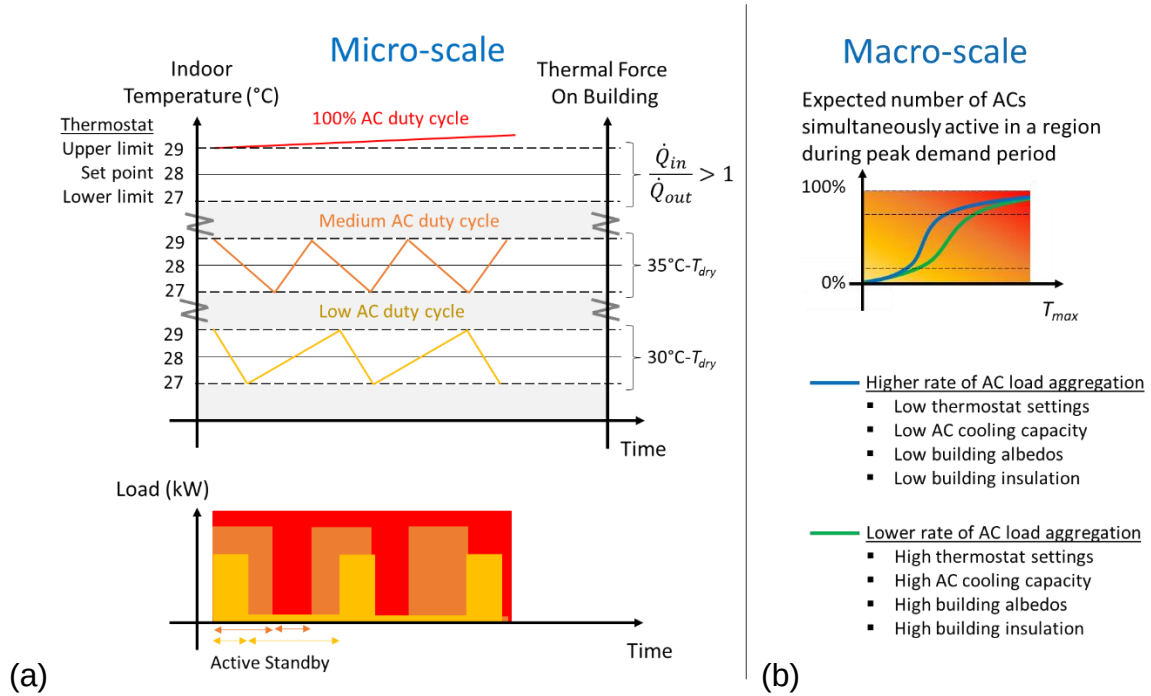


Figure 4. Outdoor Temperature Effects on AC Operations.

(a) Micro-scale. Key performance metrics for a single building, with one standard AC unit, at three different levels of constant thermal force on the building: yellow – low, orange – medium, and red – high. In reality, thermal forces change over time, e.g. hourly, daily, seasonally, and with sunlight, wind, rain, etc.

(b) Macro-scale. Cumulative AC activity as a function of T_{max} , and comparison of relative influencing factors at the building level.

The mathematical form of the SEM is in equation (5), (6), and (7), and the nomenclature in Table 3. Daily peak demand (D_{peak}) is equal to the base peak demand (D_{base}) plus, the product of the macro-scale component, the expected coincident number of ACs in active mode (n), and the micro-scale component,

the average AC load (AC_L). Base peak demand was set equal to average peak demand for days where T_{max} was between 22°C and 24°C (72-75°F) to serve as a sample independent of electric cooling or heating. To estimate the number of ACs simultaneously running at a particular T_{max} , equation (6), we formulated a logistic model (s-curve) to range from one (statistically equal to zero in this case) to the total number of ACs in the system (Q_{AC}) as is an appropriate formulation for such “non-linear chaotic” system behaviors (Strogatz, 2015). The total number of ACs is estimated to be the sum of residential and commercial customers listed for each balancing authority in EIA form 861 (EIA, 2014b), weighted by the average percentage of central ACs installed in residences for Maricopa and Los Angeles (95% and 48%) per county assessor records as reported in (A. M. Fraser et al., 2016). The log-rate of coincident AC duty cycles during peak demand (AC_{CR}) was fit to the data and represents the steepness of the curve. We defined the population average AC load (AC_L) in equation (7), as a geometric function equal to the average nominal load (AC_{NL}) that is also fit to the data, times the compound load factor (AC_{LF}) relative to the nominal load temperature (T_{NL}).

$$D_{peak} = D_{base} + n \cdot AC_L \cdot 10^{-6} \quad \text{GW} \quad (5)$$

$$n = \frac{1}{Q_{AC}^{-1} + e^{-AC_{CR} \cdot T_{max}}} \quad \text{\# ACs} \quad (6)$$

$$AC_L = AC_{NL} \cdot [(1 + AC_{LF})^{(T_{max} - T_{NL})}] \quad \text{kW / 1 AC} \quad (7)$$

Table 3. SEM Nomenclature

Symbol	Units	Description
<i>Dependent/response variable</i>		
D_{peak}	GW	Daily peak demand in region
<i>Structurally interdependent variables</i>		
n	# ACs	Number of ACs coincidently active during peak demand
AC_L	kW	Average load of one AC unit while in active mode
<i>Independent predictor variables</i>		
T_{max}	°C	Daily maximum ambient air temperature (dry bulb temperature)
D_{base}	GW	Base daily peak demand in region, equal to the average demand between $T_{max} = 22\text{--}24^\circ\text{C}$ ($72\text{--}75^\circ\text{F}$)
Q_{AC}	# ACs	Quantity of ACs in region
<i>Constants</i>		
AC_{LF}	%/°C	AC load increase factor ($=1.33\text{ \%kW}/1^\circ\text{C}$)
T_{NL}	°C	Nominal load temperature, T_{max} value for AC_{NL} ($= 29^\circ\text{C}$, 85°F)
e	-	Euler's number ($=2.7182\dots$)
<i>Model fit parameters</i>		
AC_{CR}	$\text{Ln}(\# \text{ ACs}) / 1^\circ\text{C}-T_{max}$	AC coincident rate, log of coincident AC duty cycles during the peak demand period. Represents the steepness of the s-curve.
AC_{NL}	kW	Average AC nominal load while in active mode. Represents average AC size in terms of electrical load at baseline temperature T_{NL} .

To model peak demand for the two counties, we fit and then scaled the SEM as flows. We optimized the AC_{CR} and AC_{NL} parameters to minimize the root mean squared error of the residuals for the balancing authorities' peak demand at $T_{max} \geq 25^\circ\text{C}$. Observations below 25°C were explicitly out of scope of the fitting procedure, as the model's purpose is not to explain the effect of colder weather on peak demand due to electric heating. We defined the best-fit model as the

model with the highest R^2 -value from this approach. Regression results for all balancing authority and weather station combinations are included in S5. County peak demand was estimated by allocating the balancing authority demand to the quantity of residential and commercial customers by annual energy consumption (% Wh) (EIA, 2014b), and scaling up by the total number of residential and commercial buildings in each county per (A. M. Fraser et al., 2016). We assumed the same level of AC penetration in the balancing authorities as the central-AC installation rate in respective counties per (Janet L. Reyna & Chester, 2015) and (A. M. Fraser et al., 2016). We considered model sensitivity to AC penetration, and characterized the effects of additional undocumented non-central ACs (e.g. window ACs or large wet-cooled commercial ACs) in the system on model results in S7. We did not differentiate between residential and commercial buildings for average unit load (AC_L), nominal load (AC_{NL}), or load increase factor (AC_{LF}). The most significant uncertainty factors included in upper- and lower-prediction ranges were $T90$ values, as shown in Figure 3b, unit load increase factor (AC_{LF}) as previously described, and the range of the base peak demand (D_{base}). We parameterized and scaled the range of the base peak demand (D_{base}), as the range of peak demand samples collected for each balancing authority for T_{max} ranging from 22°C to 24°C. We attribute this range to coincident econometric factors and intrinsic heteroscedasticity.

2.3. Generation Capacity

We modeled generation capacity as a constant for the stationary paradigm, and as a linear function of T_{max} for the non-stationary paradigm. The

2014 EIA form 860 lists US power generators by geographic location, and we used the summertime generation capacity values for hydroelectric, natural gas (NG), nuclear, and solar PV generation types in Maricopa and Los Angeles counties respectively (EIA, 2014a). We used those values as-is for the stationary approach, and as values for T_{max} at respective $T90s$ in the non-stationary approach. Generation values listed in these counties did not include energy efficiency, demand response, or distributed energy resources—all of which are considered at some level in resource adequacy planning (Garcia-cerrutti et al., 2012)—nor coal, wind, oil, wood, landfill gas, pumped storage, hydropower, or transmission imports which also provide power within the states of Arizona and California (EIA, 2014a). Likewise, Maricopa and Los Angeles counties did not have any open-loop cooled plants and therefore we did not consider the performance of such plant types. The counties had relatively small amounts of conventional hydropower and solar PV resources within their geographic boundaries; explanation of approaches to their non-stationary parameter values during unprecedented heat waves are in S6. The significant generation resources in the study regions were nuclear and NG plants, both of which rely on thermal processes that are sensitive to temperature.

As explained in S6, nuclear and natural gas power plants are large, complex, and actively managed engineered systems with widely varying technologies and operator practices that affect performance (Hensley, 2011). Since it is not feasible to accurately model each plant’s operational details in this study, we chose to parameterize a range of values for derating factors as a linear

percent per $1^{\circ}\text{C}-T_{max}$ using a range of empirical results from previous studies of plant performance, including dry-cooled plants (0.5-0.65% (Brooks, 2000), 0.83% (M. D. Bartos & Chester, 2015), 0.7-1% (Sathaye et al., 2012)), combined-cycle natural gas (CCNG) (0.2-0.4% (Maulbetsch & DiFilippo, 2006)), and wet-cooled plants (0% plant efficiency as a predictor of capacity in (Henry & Pratson, 2016)). We allocated CCNG plants as 1/3 dry and 2/3 wet, as that was the approximate ratio listed in EIA form 860 per code reporting: CA – combined cycle steam part, CS – combined cycle single shaft, and CT – combustion turbine. We set the base value of NG dry at 0.6% such that the CCNG allocation would be in the observation range; CCNG accounted for 88% and 62% of NG capacity in Maricopa and Los Angeles respectively.

2.4. Local Reserve Margin

To model LRMs for unprecedented high temperatures, and compare stationary and non-stationary paradigms, we combined the output of the respective peak demand and generation capacity models and plotted the resulting LRM curves over a range of daily high temperatures. We calculated LRMs in both absolute (GW) and percentage terms as the amount of generation capacity that exceeds the peak demand for any T_{max} . Planning guidelines for operating reserve margins commonly follow the rule of thumb of $\geq 15\%$, and emergency load curtailment orders are issued when that margin falls to less than 5%, (NERC, 2015a), (NERC, 2015c), (NERC, 2016), and (CEC, 1999). Therefore, we noted T_{max} and LRM at T_{90} peak demand, +10%, and +15% as

potentially hazardous conditions depending on coincident transmission import capabilities. We then compared those values to our modeled margins at historic and projected air temperatures for stationary and non-stationary methods, and considered the additional need for power imports (or other resources) in Los Angeles and reduced capability for power exports from Phoenix.

3. Results

3.1. Air Temperatures

The stationary approaches to parameterize T_{90} resulted in values that were inconsistently lower than historical and projected T_{max} . As shown in Figure 3, only one location had T_{90} s that were lower than T_{max} in all sample periods, all other locations had some years when a T_{90} was higher than another location's T_{max} . The ranges of temperatures across the models varied more within Los Angeles than Maricopa between the lowest year's T_{90} and the highest historical and projected T_{max} (17°C & 24°C vs 6°C & 15°C). The larger range in Los Angeles was due to more variable climate from the coastal areas to inland as shown in Figure 3a. The smaller range for Phoenix was because its normal summertime climate (sunny, hot, dry, flat, low-wind, urban desert) was relatively closer to the most extreme conditions (Weather Underground, 2016) and (Kumar, Mathur, Mathur, Singh, & Loftness, 2016). If the distributions of T_{max} were stationary from year to year, then T_{90} would be a reliable statistic to use as an input for risk management processes; however, we found that T_{max} distributions are significantly inconsistent, as shown in Figure 3b. Using stationary T_{90}

statistics as inputs in planning processes introduces anti-conservative bias to the 15% safety margin.

Non-stationary GCM projections resulted in ranges of projected future T_{max} values that were higher than historical T_{max} values. General trends observed at the various weather station locations within counties were similar, although Tarzana moved in rank from the highest average T_{90} , to the third highest T_{max} . Even a recent sixteen-year historical sample is not sufficient to overcome stationarity bias. Top GCM projections were on average 2°C higher for end-of-century projections than mid-century, and 1°C higher for RCP 8.5 than RCP 4.5. The usefulness of the various daily GCMs projections was not to predict individual daily temperatures or warming trends, but rather to identify the potential magnitude of heat waves for an upper-boundary on temperature inputs for the planning processes. Our non-stationary approach estimated a range for the peak temperatures that regions could experience, and those are possible future conditions that should be explicitly considered in planning.

3.2. Peak Demand

The stationary and non-stationary model projections for peak demand significantly overlapped in the historical range of 25-40°C, and diverged significantly at the highest GCM projected temperatures. As shown in Figure 5a, the stationary model results were that Phoenix and Los Angeles expect peak demands of 12GW and 21GW at their highest block maxima temperatures (28%

and 23% higher than for historical T_{max}). The non-stationary model results were 8-10 GW and 13-19 GW respectively (6% and 7% higher than for historical T_{max}).

Peak demand in Phoenix is more sensitive to average historical seasonal changes in air temperatures than Los Angeles, but results show that *marginal* changes in peak demand are more significant in Los Angeles than in Phoenix at summertime high temperatures. As shown in Figure 5a, in the historical temperature range, from 25°C to respective T_{90} s (33°C and 44°C), peak demand increased in Phoenix and Los Angeles from 3.5 GW to 7.6 GW and 8.2 GW to 11.7 GW (or by 120% and 40% respectively). Peak demand for Phoenix increased more in its historical range because its T_{90} was relatively higher, and Phoenix has higher AC penetration. From historical T_{90} to the highest projected T_{max} however, peak demand increased more in Los Angeles than Phoenix, another 3.9 GW vs 1.2 GW or 34% vs 16%. In this case, the larger increase in peak demand in Los Angeles was due to the larger relative difference between historical T_{90} and non-stationary T_{max} . As shown in Figure 5b, Phoenix's ACs expect to already be running at nearly 100% duty cycle at its T_{90} , whereas Los Angeles's ACs expect to only run at about 60% duty cycle at its T_{90} . Thus, the potential for a record-breaking heat wave to affect peak demand is higher in Los Angeles than Phoenix. See S5 for additional implications of results.

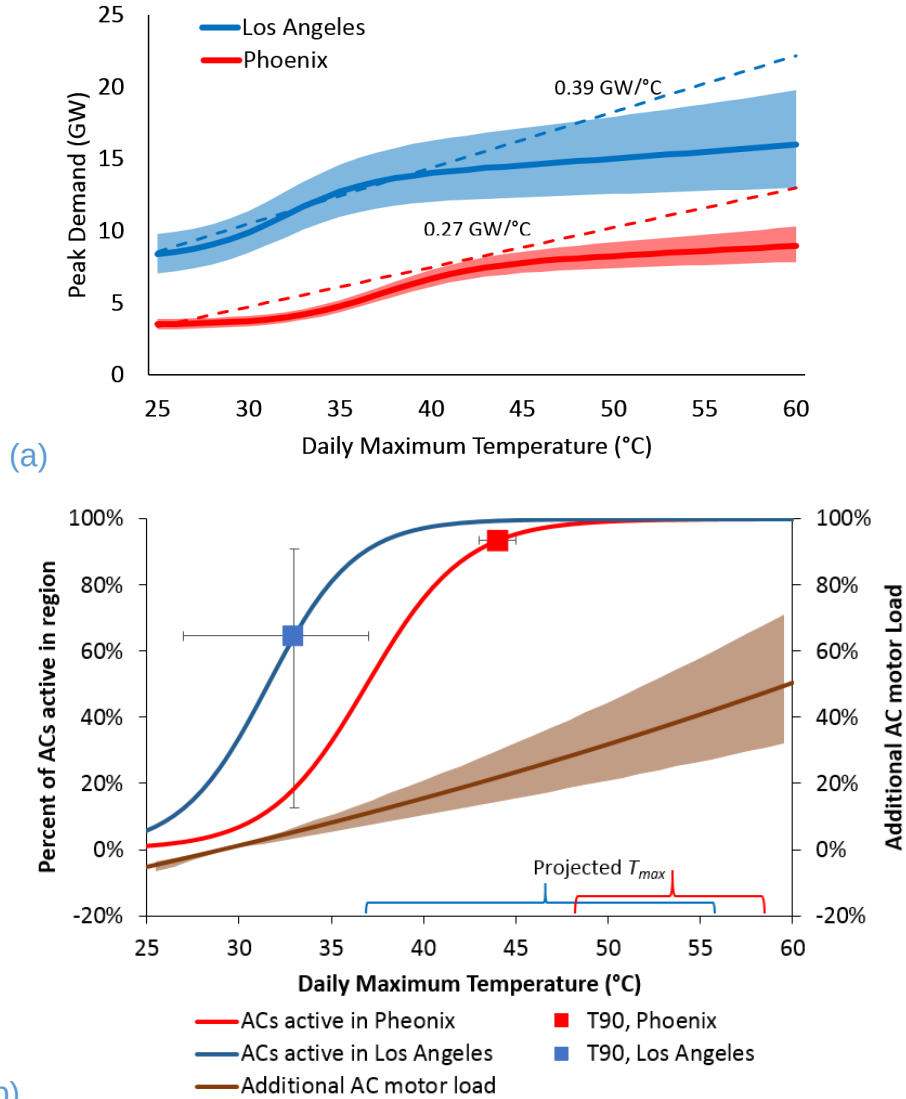


Figure 5 (a) Peak Demand. (b) Peak Demand SEM Factors.

(a) Shows SEM non-stationary approach results shown in solids. Stationary approach shown in dotted lines. (b) Shows the two s-curved lines are expected values, equal to equation (6) divided by Q_{AC} . T90 ranges represent the range of 16-year average values for each of the four locations sampled.

3.3. Generation Capacity

Generation capacities were held constant in the stationary models, and derated up to 7% in the non-stationary models. The stationary and non-stationary

values are listed side-by-side in Table 4 column A under the respective T_{90} and projected block maxima temperature values for each county. The derating factors used are listed in column B. Dry natural gas generators—either entire plants and or the combustion engine portion of CCNGs—were the only significant source of generation capacity loss in the model for the two counties. The expected generation capacity reduction between stationary T_{90} and non-stationary GCM temperatures was 3.3 GW and 3.2 GW in Phoenix and 3.0 GW and 2.7 GW in Los Angeles (potentially another 0.3 GW less in each depending on the cooling technology per S6). This represents a loss of 9% and 16% of dry natural gas plant capacity, or 2.2% and 4.2% loss of total local generation capacity.

Table 4. Summertime Generation Capacities and Derating Factors

Generation type / @ T_{max}	A – Generation capacity (MW)				B – Derating factor (%/1°C- T_{max})		
	Phoenix		Los Angeles		Low	Base	High
	44°	58°C	33°	56°C			
Hydroelectric	95	95	341	341	-	-	-
Natural Gas (dry)	3,292	3,016	3,178	2,739	0.5%	0.6%	1%
Natural Gas (wet)	6,180	6,180	7,251	7,251	-	-	-
Nuclear	3,937	3,937	-	-	-	-	-
Solar PV	446	424	449	412	0.1%	0.35%	0.6%
Total							
Maricopa	13,950	13,652			0.12%	0.15%	0.26%
Los Angeles			11,219	10,743	0.15%	0.18%	0.31%

3.4. Local Reserve Margin

In both the stationary and non-stationary approaches, LRM results indicate Phoenix has sizeable electricity export capabilities, and Los Angeles expects to require imports to meet peak demand when $T_{max} \geq 32^{\circ}\text{C}$ (90°F). As shown in Figure 6, both counties expect to be able to meet local peak demand with local generation capacity up to approximately T_{max} equal to their recent

average T_{90} s. Phoenix expects 70-100%, 6-7 GW, of surplus local generation at its T_{90} , whereas Los Angeles expects to break even 1°C under of its T_{90} , $\pm 15\%$ or $\pm 2\text{GW}$. Both approaches project positive LRM for Phoenix for the highest projected T_{max} (58°C or 136°F) because Phoenix has much more local generation capacity than current demand levels. Potentially hazardous operational conditions (a relative decrease in LRM of 10% to 15% from T_{90} peak demand) are indicated in the linear model for Los Angeles at $34-36^{\circ}\text{C}$ ($93-97^{\circ}\text{F}$), and slightly higher at $36-39^{\circ}\text{C}$ ($97-102^{\circ}\text{F}$) in the SEM model. At the highest projected temperatures for Los Angeles (56°C or 133°F), the linear approach projects potentially hazardous conditions with LRM at -84%, or 9.4GW of demand that current local generators would not be able to meet. The SEM approach projects potentially hazardous conditions with LRM at -31%, or 5GW of demand above generation. If we sum the peak demand and generation capacities of Phoenix and Los Angeles, then the total combined LRM would be negative if T_{max} in Phoenix and Los Angeles simultaneously reached 58°C & 42°C (136°F & 108°F), 45°C & 48°C (113°F & 118°F), or 39°C & 56°C (102°F & 133°F).

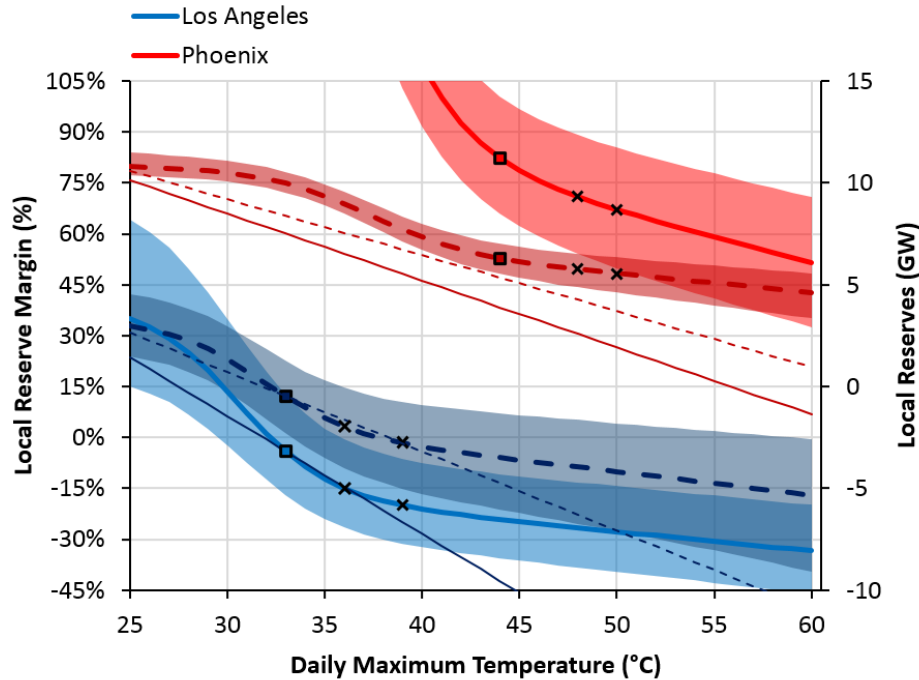


Figure 6. Model Results for Daily Maximum Temperature Effects on Local Bulk Power Reserves.

Thick lines and corresponding shaded areas represent non-stationary models, and thin lines represent stationary model averages. Solid lines represent LRMs as a percentage, and dotted lines as GW. Average T90 values are marked with squares, and relative decreases of 10% and 15% LRM are marked with X's.

4. Uncertainty and Validation

Estimating LRM was a multi-step process, as the sections are titled in this paper, with uncertainty in parameters, methods, and results in each section. The model is not sensitive to marginal errors in AC penetration or AC types. As we explained in S7, Los Angeles likely has on the order of 100,000 undocumented window AC units (~10% of customers), which we can infer through differences in the model fit parameters AC_{NL} and AC_{CR} , and which do not significantly affect results. The most significant uncertainties in results stemmed from the range of the temperature-independent peak demand, which we attribute to econometric factors and inherent randomness. Uncertainty ranges were larger in Los Angeles

than Phoenix due to higher variability of air temperatures throughout the region. Finer spatial allocation of demand and T_{max} data could significantly reduce this uncertainty as in (Garcia-cerrutti et al., 2012). The worst-case scenario results for LRM for Los Angeles were at $T_{max} = 56^{\circ}\text{C}$ (133°F) where an additional 9.4 GW (84%) or 4.9 GW (31%) capacity was expected to meet demand in the linear and SEM approaches respectively. The combined effects of uncertainty for the SEM approach at $T_{max} = 56^{\circ}\text{C}$ and 58°C were low, expected, and high estimates of LRM of -2.3 GW, -4.9 GW, and -8.2 GW ($-31\% \pm 12\%$) for Los Angeles and 3.6 GW, 4.8 GW, and 5.7 GW ($55\% \pm 19\%$) for Phoenix. The SEM results suggested that T_{max} would be potentially hazardous at temperatures $36\text{-}39^{\circ}\text{C}$ ($97\text{-}102^{\circ}\text{F}$) or higher, and during the 2014 extreme heat event where T_{max} reached 38°C (100°F) in downtown Los Angeles, the Los Angeles Department of Water and Power alerted customers to curtail power (Barry Fisher, 2014) and (LADWP, 2014). The recent study in (Sathaye et al., 2012), used straight-line methods for peak demand and generation capacity to estimate a need for up to 38.5% additional generation capacity for the entire state of California under end-of-century A2 and B1 climate change emissions scenarios. See S7 for further details of uncertainty and validation.

5. Discussion: Long-term Strategic Planning for Climate Non-Stationarity

Stationarity had a significant effect on forecasts of daily high temperatures, peak demand, generation capacity, and local reserve margins. Updating long-term forecasting processes to consider climate non-stationarity

explicitly would enable better evaluation of risks. Without a clear understanding of both climatological and power grid uncertainties, decisions can significantly lack certainty as to whether operational margins are sufficient to ensure reliability and security. While our findings indicate value in creating new knowledge of climate non-stationarity effects on power systems, creating new knowledge “on paper” is a very different proposition than creating new infrastructure implementations in practice.

There are many ways to maintain reserve margins and reliable power services in grid systems, all of which have various tradeoffs. As shown in Figure 7, we systematically considered several technology alternatives, market incentives, and urban form options that affect LRMs. We included load variance explicitly because less variance means more consistent load, more capacity for contingencies, and lower operations and maintenance costs (Willis et al., 2001). We also identified effects of those options on several other complex interdependent factors that are priorities for stakeholders. The remainder of this discussion section follows the structure of the options identified in Figure 7 that may mitigate the risk of LRM shortages in the event of unprecedented heat waves. We do not intend for this discussion to be exhaustive nor advocate any particular option; our intention is to advance the discourse of this complex topic in a clear and structured manner.

Options / Effects		Resource adequacy				Other factors			
		Climate-independent peak load	Climate-dependent peak load	Bulk gen. & transmission capacity	Load variance	Total energy consumption	Power quality	Power congestion	Water use
Technology implementation									
Resources	Distributed solar PV without VAR control	↓	↓	-	↓	-	↓	-	-
	Distributed solar PV with smart-inverter & energy storage	↓	↓	-	↓	-	↑	↓	-
	Combined cycle natural gas plant	-	-	↑	-	-	↑	↑	↑
	Nuclear power plant	-	-	↑	-	-	↑	↑	-
Loads	General appliances: higher energy efficiency standards	↓	↓	-	↓	↓	-	↓	↓
	ACs: variable speed motors for refrigerant systems	-	-	-	-	-	↑	-	-
	ACs: dual-systems with ice thermal storage	-	↓	-	↓	-	-	↓	↑
	ACs: water-based evaporative systems	-	↓	-	↓	↓	↑	↓	↓
Market incentives									
Util.	Utility profits dependent on energy sales	↑	↑	-	↑	↑	-	↑	↑
	Utility profits dependent on load consistency	↓	↓	-	↓	↓	-	↓	↓
Ratepayer	Time-of-use rates with summertime super-peak	↓	↓	-	↓	-	↓	-	-
	Demand response incentives	↓	↓	-	↓	-	↓	-	↑
	Economically viable pro-sumer options	↓	↓	-	↓	-	↓	-	↓
	Energy efficiency rebates	↓	↓	-	↓	↓	-	↓	↓
Urban form									
	High-density transit oriented development	↓	↓	-	↓	↓	-	↓	↓
	High building albedo and shading	↓	↓	-	↓	↓	-	↓	↓
	High building thermal insulation	↓	↓	-	↓	↓	-	↓	↓

Figure 7. Climate Risk Mitigation Options and Effects.
Arrows indicate an increase or decrease in the factor. Green indicates higher efficiencies and or conservation of limited natural resources. Red indicates the opposite.

Technology Implementation – Electricity Supply Resources

Additional electricity supply resources will be required to meet demand as population growth and urban development continues. New resources will likely include distributed energy resources (DERs), natural gas generation, and nuclear technologies (APS, 2014) and (LADWP, 2016c). Most solar PV, storage and demand response systems in the US Southwest are installed “behind-the-meter” (Andersen, 2016). Solar PV provides an average decrease in net load (Poullikkas, 2013), but does not necessarily effect peak loads or peak reserve margins (Janko, Arnold, & Johnson, 2016). Yet, if solar PV is combined with storage, demand response, and advanced controls, the combined set of assets

can yield higher load factors and offer ancillary services desirable to electric utilities (Beach, Kozinda, & Rao, 2013) , (Armendáriz et al., 2017) , and (Heydarian-Forushani, Golshan, & Siano, 2017). Because of this, DERs may one day offset the need for some portion of additional centralized generation systems and delivery infrastructure in the US. CCNG plants are a bulk generation solution expected to meet a large portion of future peak loads (APS, 2014). They are relatively low-cost and agile resources capable of short turn-on times with fast ramping rates to meet demand spikes, but have no effect on load variance, require transmission systems, use water resources, and emit greenhouse gases (Adibhatla & Kaushik, 2017). Nuclear plants produce energy at a very low price, but that energy is used to meet baseload demand only (APS, 2014). Nuclear technology also currently consumes significant quantities of fresh water or grey water for cooling operations (Macknick, Newmark, Heath, & Hallett, 2012). While nuclear plants operate without greenhouse gas emissions, non-stationarity climate events have resulted in radioactive containment failures such as the incident at Fukushima (Asian Development Bank, 2012).

Technology Implementation – Building Cooling Load

More efficient appliances provide the same functionality with less energy consumption. If appliances are more efficient, then the climate-independent peak load decreases, therefore the climate-dependent load decreases as well, and the system is less vulnerable to inaccurate estimations of demand. Likewise, total energy consumption decreases, and greenhouse gas emissions per appliance

decrease. For AC units, variable speed motors can improve power quality by reducing AC cycling, but whether or not they have a significant effect on peak load depends on application ((NEMA) National Electrical Manufacturers Association, 2001). AC systems with thermal storage can significantly offset peak load, but add cost (Ruddell, Salamanca, & Mahalov, 2014). Water-based evaporative systems use much less power, but require water to operate, and are often not accepted by users as the sole-source of air conditioning due to insufficient comfort levels when the weather is both hot and humid (Kumar et al., 2016) and (Parsons, 2003). AC units in the US are currently rated for efficiency and sold primarily on the basis of SEER metrics that emphasize performance in a range of moderately warm to hot temperatures, but during heat wave conditions the unit's EER rating is a better indicator of efficiency (SCE, 2003). It is possible to design AC units that are more efficient under the hottest conditions or that utilize thermal storage to achieve "flat" efficiency curves that do not degrade at the hottest temperatures (Bush & Ruddell, 2015).

Market Incentives – Supply Side & Utilities

Some studies suggest that the traditional utility business model, that couples energy sales to profits, is not compatible with certain energy efficiency goals or large amounts of DER (Gabel, 2016). The former issue is because utility revenues are primarily dependent on total energy sales, but the costs of providing reliable infrastructure are primarily dependent on capital expenditures, operations, and maintenance (Gabel, 2016). Profits increase with volumetric

energy sales, and costs are relatively flat. Therefore, financial incentives must exist to be relatively inefficient in some processes. Hence, public regulatory commissions exist to oversee the prices set for ratepayers. The alternative business model is referred to as a “decoupled” market, where “excess” profits are carried forward and accounted for in adjusting the following years’ prices ((CPUC), 2016) and (PG&E, 2016). When utility profits are decoupled from energy sales, load serving entities can implement effective conservation programs without violating fiduciary responsibility to shareholders (Bhatti, 1993). This structure has been implemented in several states with positive effects on energy efficiency. For example, California’s per-capita annual energy consumption has remained relatively flat since decoupling was implemented in the 1980s, whereas many other states’ has steadily risen (D. Wang, 2013). Market design determines rules by which participants must play (Brijs, De Jonghe, Hobbs, & Belmans, 2017). If utilities’ profits were a function of key reliability precursors, such as smaller load variance, then utilities would have a direct incentive to reduce peak load (including shifting it to off-peak hours), resulting in less congestion, higher utilization of lower-cost base-load bulk generation resources, and more contingency capacity for non-stationary extreme heat events.

Market Incentives – Demand Side & Ratepayers

One philosophy for evaluating public policy is to consider whether the rules are equitable, efficient, transparent, administratively simple, and support

achieving greater policy goals (Lave, 1985). Current retail electricity rate schedules in Los Angeles and Phoenix generally meet these criteria via monthly energy billing with tiered and time of use rates (APS, 2017), (SRP, 2017), (LADWP, 2016a), and (SCE, 2017). Charging residential ratepayers monthly based on total energy use is simple, transparent, equitable, and promotes energy efficiency. Higher electricity prices during peak hours helps to reduce peak load by incentivizing ratepayers to take action to shift flexible or non-critical usage to off-peak hours when electricity can be generated at lower cost (Albadi & El-Saadany, 2008). Incentivizing ratepayers to turn off loads in the form of demand response relieves congestion on the grid; however, the majority of that relief comes from industrial customers who often switch to onsite diesel power or natural gas combined heat and power units (Aghaei & Alizadeh, 2013). Rebates are available in some localities for ratepayers to obtain solar PV, storage, or demand management technologies (NC Clean Energy Technology Center, 2017). One-time rebates for building energy efficiency enhancements have also been found to reduce demand and peak load (Greening, Greene, & Difiglio, 2000). Overall, these incentives generally reflect the philosophy that electricity is both a critical infrastructure necessity and a non-critical commodity. Electricity is critical for powering infrastructure systems such as water, transportation, food, fuel, communications, and finance (Rinaldi et al., 2001). It is also critical in residential buildings for lighting, cooking, cleaning, and climate control.

Urban Form

Per capita power demand and energy consumption are both significantly lower in high density, multi-unit housing structures than in lower-density, single-dwelling unit buildings (Chester, Nahlik, Fraser, Kimball, & Garikapati, 2013). Multi-unit buildings can also take advantage of centralized industrial air conditioning systems that are more efficient and less sensitive to weather (Bush & Ruddell, 2015). Regardless of building type, high albedo (e.g. white roofs), shade (e.g. trees on the west side), and better thermal insulation in general, significantly improves building energy efficiencies (C. Smith & Levermore, 2008) and reduces peak load and load variance.

Summary

Actions that can reduce peak load and load variance per capita can mitigate the hazard potential of climate non-stationarity for record-breaking heat waves. Sound application of risk management principles and free-market incentives are generally effective. However, with limited options in the market, including services that are not monetized, some level of governance is valuable to provide minimum standards where there otherwise might not be any. Because electric power infrastructure systems are so large, complex, and interdependent within themselves and across other systems, myopic “one-size fits all” technocentric solutions to climate hazards are unlikely to have significant impact. Climate hazards can be reasonably mitigated by considering multiple options

from multiple stakeholders' perspectives and accordingly investing in a portfolio of options.

6. Conclusions

Planning and operating power infrastructure based on stationary climate assumptions exposes the system to measurable and avoidable risks. Insufficient acknowledgement of non-stationary climate trends will result in low reserve margins during record-breaking heat waves, higher probability of infrastructure failures, and system vulnerability to multiple outages or security threats disabling entire cities' critical infrastructure. Linear correlation methods result in overestimation of the effects on LRM, and could result in wasteful expenditures to maintain safety margins if used in investment planning processes. Our SEM approach is a more reasonable estimation method. As new knowledge enables better understanding of the climate, new methods for managing risks of low-probability, high-impact events are valuable to maintaining reliable electricity infrastructure systems. Future work should consider additional climate non-stationarity factors, including probability of simultaneous heat waves across nearby geographies (WECC, 2014a), (CPUC, 2016), (NERC, 2015c), wildfire potential (FERC, 2003), (Sathaye et al., 2012), drought (M. D. Bartos & Chester, 2015), (Mann & Gleick, 2015), and transmission import capabilities from neighboring regions as well as relevant changing physical, network, and sociotechnical attributes of aging delivery systems and building loads (M. D. Bartos et al., 2016), (Sathaye et al., 2012), and (Janet Lorel Reyna, 2016).

Strategic actions can be taken to reduce the risk of LRM shortages from non-stationary heat events without compromising other stakeholder objectives, including implementing technology, market incentives, and urban forms that reduce peak load and load variance per capita.

Acknowledgments

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Supplementary Information

S1. System Boundary

Electric power grid systems and earth climate systems are both complex and complicated. The literature has not converged on a single correct approach to use to answer our research questions related to the two, so we chose to define our own approach in this study. To do so, we focused the scope of the modeling tasks such that we could calculate the most significant factors needed to answer our research questions with available data and resources. We made three major decisions in this study to include or exclude factors in terms of infrastructure, climate, and geography as follows.

Decision 1: We exclusively considered peak power demand and generation capacity. We chose to focus our efforts on modeling the relationship between peak summer demand, generation capacity, and the daily maximum temperature, T_{max} , and to not consider changes in peak delivery losses. We made this decision by considering the order of magnitude differences in reported seasonal factors. Daily peak demand was reported 70-130% higher in the summer than the winter in our analysis regions (EIA, 2016c), cumulative seasonal generator capacity was reported up to 7% less in the summer than in the winter [12], and seasonal differences in delivery system losses were reported less than 1% (Wong, 2011). Power lines and transformers were therefore

excluded from this study because their effect on study conclusions was negligible relative to other factors.

Decision 2: We used daily maximum air temperature, T_{max} , as our only climate variable. Technically, the daily 2-meter near surface air temperature. We chose this factor as our predictor variable because it is influenced by relevant thermal forcing factors on peak demand including: air temperature during the peak power demand period (4-6pm), humidity, wind speed, barometric pressure, solar radiative energy, and various site-specific urban heat island factors (Daniel Burillo, Chester, Chang, & Thau, 2015; Garcia-cerrutti et al., 2012; Gui & Phelan, 2007; Hensley, 2011). We explicitly chose to not consider hourly climate data or the several other factors listed because they are multicollinear (i.e. interdependent), our research questions were not about hourly demand, and our intention for this work was to answer research questions about unprecedented heat in as simple and accessible manner as possible.

Decision 3: We used county lines as geographic boundaries. We did this because they were compatible with publically available data needed for this analysis. While county boundaries are not be exactly the same local boundaries that a utility would use to calculate LRM or resource adequacy requirements, they do contain the vast majority of supply and demand nodes, and are therefore suitable for our purposes to evaluate potential unintended consequences of stationary methods. Moreover, we chose Maricopa and Los Angeles specifically because these counties are large established regions, with growing populations, and immediate need for investments in new and retrofitted infrastructure. They

also have significantly contrasting characteristics in terms of average infrastructure age, weather pattern diversity, and electric power imports/exports that enabled insightful comparison.

S2. Electricity Demand Data

The sample consisted of the daily maximum of the hourly demand values for balancing authorities listed in the EIA's U.S. Electricity System Operating Data, Form 930 (EIA, 2016c). These data do not capture potentially higher peaks that occur on a sub-hourly scale (Miller et al., 2007); however, weather-adjusted load factors have decreased attributable to the increased use of ACs (M. Bartos & Chester, 2014; Miller et al., 2007). Therefore, as our primary objective was to predict peak demand during periods of high AC usage, we considered hourly demand data sufficient.

EIA's peak demand data embedded demand response capacity, behind-the-meter distributed generation capacity, and delivery system losses (EIA, 2016a). Demand response and distributed generation were listed as approximately 1% of peak capacity (EIA, 2014b) and 1% of annual energy sales (EIA, 2014a), respectively, for the sample sets used in this study, so they do not significantly affect the types of conclusions sought in this study. Transmission and distribution system losses typically range from 5-10%. Such differences are attributed due to physical line length and line voltage level (Wong, 2011). Industry practice is to embed losses within peak demand values, and to use an adjustment factor for delivery systems avoided when quantifying the value of

distributed resources (Wong, 2011). We chose to do the same, and assumed no differences in loss rates within or across the two counties.

S3. Temperature Dependent Electrical Loads

Temperature-dependent electrical loads include those used for cooling, such as ACs, fans, refrigerators, and chillers (EIA, 2013b) and (EIA, 2003). Given that approximately 30-70% of commercial and residential summertime building peak electricity consumption is attributable to space heating or cooling (EIA, 2013a), Phoenix is on the high end of that range (Ruddell et al., 2014), residential and commercial buildings account for over 90% of energy consumption in the sampled balancing authorities, and the range of difference in seasonal peak demand for the ~1 million customers in each of the balancing authorities is 70%-130%, we chose to model the temperature sensitivity of peak demand as characteristic of changes in AC operations.

S4. AC Load Characterization

We chose to characterize the AC load as a simple geometric function because doing so effectively characterizes the net effects of the relevant physical phenomenon, and fits the observations. ACs use electricity to power three induction motors: a compressor, an indoor evaporator/ blower fan, and an outdoor condenser/exhaust fan. The compressor typically uses about 80% of the power in the system (S. K. Wang, 2000), (Faramarzi et al., 2004), and (Bush & Ruddell, 2015). As outdoor thermal forces increase, the compressor has to do

more work to compress the recirculating refrigerant, and the induction motor draws more power to do that work at a higher slip ratio. The mechanical, thermal, and electrical forces at work, detailed below, behave as linear, exponential, and arc-curve functions, which when acting together in this context can be succinctly formulated as a compound growth function. The characteristic behavior occurred in an SCE lab experiment in (Faramarzi et al., 2004) at a compound rate of 0.92 and 1.68%kW per $1^{\circ}\text{C}-T_{\text{air}} \pm 0.07\%$ for two reciprocating- and four scroll-compressor-units respectively. Our geometric characterization range fits the EPRI-ASU-SRP field data in (Bush & Ruddell, 2015) for a 5-ton rooftop AC as well, that operated in uncontrolled field conditions with incident solar radiation, wind speed, humidity, and UHI. We chose to use the midpoint value of 1.33%kW per 1°C to characterize the system behavior for T_{max} for an unknown distribution of ACs in the system, inclusive of the other multicollinear thermal forcing factors. We could have further parameterized the SEM (7) for all three motors, but chose not to unnecessarily parameterize the model as the simpler-version fit SCE's lab results within the stated range of uncertainty of the test measurement devices. Average AC load can increase (in terms of current) up to about three times the nominal load until the fuse blows, the circuit breaker switches, or other hardware breaks before that (Faramarzi et al., 2004), (Lennox, 2016), and (ART Plumbing & AC, 2016).

AC power load increases with higher air temperature due to the additional work that the compressor motor does to mechanically compress and heat the recirculating refrigerant (Faramarzi et al., 2004). This is because higher heat

removal rates are required, and the compressor works at a lesser efficiency across a higher thermal gradient. The process is a complex function of the density of the refrigerant, head pressure, and suction pressure for each unique hardware configuration (Faramarzi et al., 2004). As quoted from the same report:

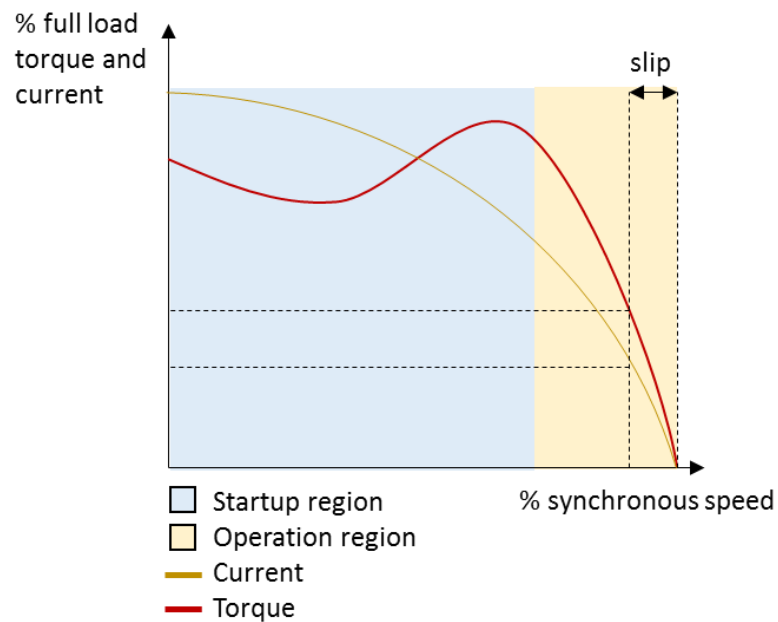
“The increase in power usage as ambient temperature increased is attributed to the increase in compressor work, which is a function of the compression ratio and mass of circulating refrigerant. At high ambient temperatures, the heat rejection ability of the RTU [rooftop air conditioning unit] degrades, which results in high head pressures [due to warmer refrigerant vapor at the compressor intake]. Therefore, the compressor must work against a greater pressure difference between the evaporating and condensing pressures. The high head pressure also causes a slight rise in suction pressure. At higher suction pressures, refrigerant becomes denser and the compressor has to compress a larger mass of vapor. Figure 7 demonstrates that, of the six units tested, only those from manufacturer A did not experience an increase in mass flow rate at high ambient conditions. It is not clear why these units behaved differently and this observation is being investigated.”

The four physical principles relevant to parameterize the relationship between average air temperature and average AC power load are the ideal gas law, thermal convection, electrical resistance, and electromotive force via

induction. Per the ideal gas law, gas pressure, density, and temperature are all linearly related. Convection has an energy transfer rate that is linearly proportional to the difference in temperature of a solid surface and a fluid media (air) per Fourier's Law (Daniel Burillo et al., 2015). Absolute temperature change through convection is a function of the integral of the energy transfer rate over time. The energy transfer rate is assumed constant at each time step of the quasi-steady state model. Thus, compressor motor workload due to pressure change is increased by a cumulative sum of forces. The absolute temperature of the compressor motor is a function of the temperature of the incoming gas, outgoing gas, mechanical friction of its moving parts, electrical load, and ambient heating sources including air temperature. The electrical resistance in the compressor motor wiring is not significant as the temperature coefficient of copper is 4.29×10^{-3} per 1°C ("Resistivity, Conductivity and Temperature Coefficients for Common Materials," 2016). In an induction motor, the difference between the mechanical rotating speed and synchronous alternating current speed is known as "slip." In steady state operations, the slip is approximately 3% for common motor sizes such as those in common AC units (EngineeringToolBox, 2016). An increase in compressor motor workload due to changing gas pressures means an increase in mechanical resistance; which forces a decrease in rotational speed, an increase in slip, and therefore an increase in inductance and an increase in amps. This in turn forces an increase in motor torque, resulting in a higher kW load, and incidentally a slower rate of

recirculation of refrigerant and cooling capacity. Percent slip and percent current are inversely related from 0 to 100% as shown in

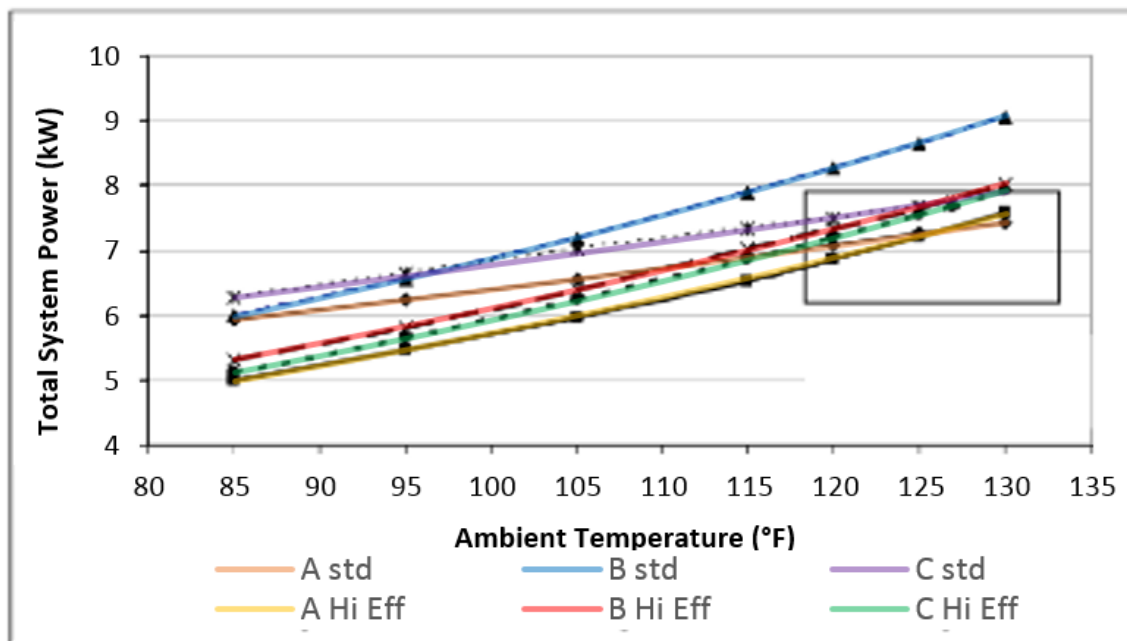
S Figure 1 (based on (EngineeringToolBox, 2016)). The system power load is characteristic of a linear cumulative function acting upon the rightmost 3~10% an arc function. Modeling arc-length and slip percentage for individual ACs would be an over-parameterization.



S Figure 1. Slip in Electrical Induction Motors.

The relationship that we want to model has a form that resembles a compound growth function in the study range, therefore we chose to model it as such in equation (3). AC unit load and compound growth factors were deduced from SCE's study as shown in S Figure 2 and listed in S Table 1, which fit the data as accurately as the reported uncertainty of the measurement equipment. The high and low ranges calculated are 0.90% and 1.75%kW per 1°C. We

attribute the difference in the percent change ranges as primarily due to the type of compressor motor in each AC unit. According to the manufacturer specifications in the SCE report, the A std. and B. std. units used reciprocating compressors and the other four used scroll compressors. The difference in model results is $\sim 0.9\% \text{ kW}/1^\circ\text{C}$ vs. $\sim 1.7\% \text{ kW}/1^\circ\text{C}$ for reciprocating and scroll compressors respectively.

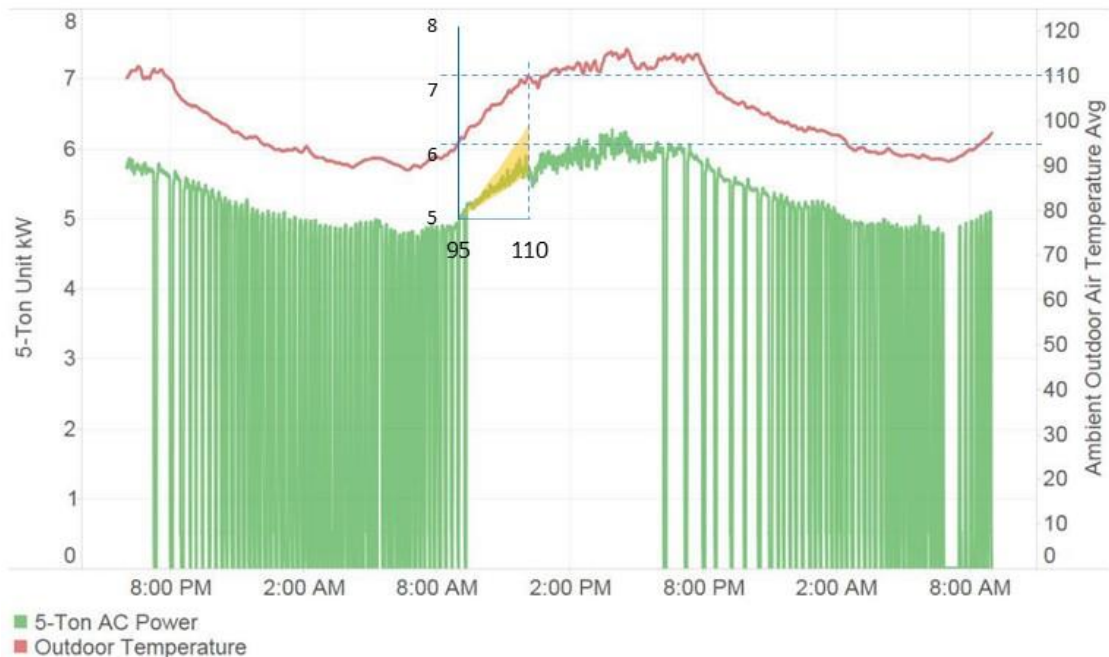


S Figure 2. AC Load Factor Characterization. Colored lines represent the compound growth model as parameterized in the SEM. They are overlaid on top of Figure 5 from (Faramarzi et al., 2004) "Total System Power Consumption Based on RTTC Test Data for All Six Standard and High Efficiency Units Subject to Various Ambient Temperatures."

S Table 1. Parameterization of AC Unit Load Behavior.

Manuf. Unit	Nominal Load (kW @85°F)	Load Factor %kW/1°C	Motor Type	Nominal Tonnage	SEER/EER (Btu/hr/W)
A Std.	5.95	0.90	Reciprocating	5	10.0 / 8.8
A Hi Eff.	5.00	1.68	Scroll	5	13.0 / 11.0
B Std.	6.00	1.68	Scroll	5	10.2 / 8.9
B Hi Eff.	5.35	1.65	Scroll	5	12.0 / 10.7
C Std.	6.30	0.92	Reciprocating	5	10.0 / 8.0
C Hi Eff.	5.15	1.75	Scroll	5	13.0 / 11.0

We chose to use the midpoint value of 1.33% in our base-case model fit in equation (3) rather than speculate on the distribution of the types of compressor motors installed in AC units in the region. We also chose to create equation (3) in the form of a nominal power value times a compound growth factor, as opposed to disaggregating the load contributions from the compressor and the two fan motors – which have much less reason to vary in load at higher temperatures. We did this because the compressor motor accounts for about 80% of nominal power, so the methodological difference are not significant to results, and the simplified form is more accessible. Thus our methods are as simple as possible, but not oversimplified. S Figure 3 shows our parameterization range for AC performance consistent with the field data collected in (Bush & Ruddell, 2015).



S Figure 3. AC Load Factor Characterization Field Validation.

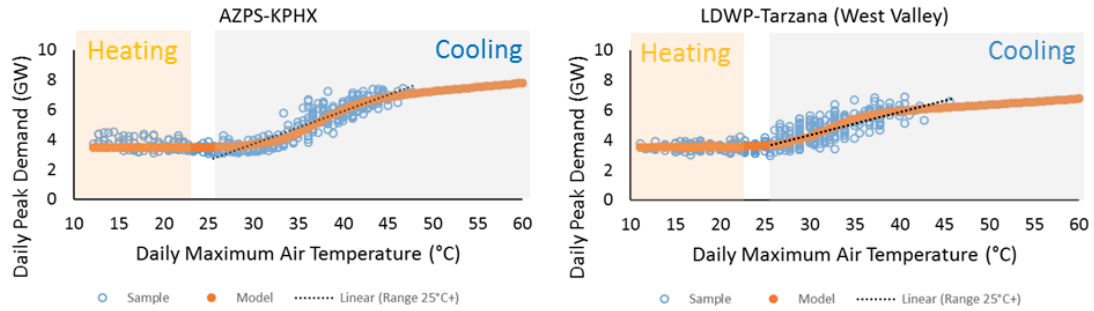
The yellow shaded overlay shows the compound growth model fit from S Figure 2 consistent with the observational data from (Bush & Ruddell, 2015) "Power consumption of a 5-ton A/C unit for a baseline day." Note, the x-axis of the overlay is in units of °F, whereas the main figure x-axis represents time, so the overlay is shown for the segment of 100% duty cycle load with the closest to linear segment of natural ambient temperature rise.

We used a SEM based on a sigmoid function to aggregate individual AC unit performance to represent the entire population for a region. We modeled AC units as having some average nominal base load and relatively low duty cycle when the outdoor temperature is just above the thermostat setting. When the outdoor temperature is significantly higher than the thermostat setting the AC unit has to run longer and under more stress to cool the indoor air to the same degree. The indoor air then reheats at a faster rate. If the thermal force on the building is more than the AC's cooling capacity at the thermostat setting, then the

AC will run uninterrupted at 100% duty cycle. Of course, the system never actually operates at 100% AC engagement, as in practical terms, someone will always be traveling with their AC off, hardware will be broken somewhere in the system, and there will always be a few people who simply choose not to use their ACs. Likewise, the sigmoid only approaches 100% as the independent variable approaches infinity. Similarly, the “expected number” of ACs active is an average statistic equal to a probability times a quantity. With large quantities (i.e. over 1,000,000 ACs in each county) the probability that the actual coincident amount is significantly different than the expected amount is very small, and the volatility of the difference decreases the closer to 100% – which is what we are interested in in this study. Since our objective was to model the aggregate performance of the entire AC-population-system in a county, and not to model the performance of individual AC-human-actors, we do not consider this material.

S5. Balancing Authority Weather Station Model Fits

The model best fit balancing authority to weather station combinations that were used in this study are shown in S Figure 4, along with the actual source data from EIA. Complete SEM results are listed in S Table 2.



S Figure 4. Daily Peak Demand SEM Fit.

Maximum hourly demand (GW) is plotted by balancing authority for each day from 2015-07-01 to 2016-09-15 as a proxy for peak demand (GW). Increases in peak demand at temperatures above 25°C are attributable to electric cooling for indoor climate control.

S Table 2. Model Best Fit Results for Balancing Authority to Weather Station Combinations.

Balancing authority - weather station	D _{base} (GW)	D _{base} range (GW)	Q _{AC} (# AC _S)	AC _{CR} (Ln(#ACUs) / 1°C-Tmax)	AC _{NL} (kW)	R ²
AZPS						
AZPS-KPHX	3.45	0.63	1.1E+06	0.3771	2.58	0.89
AZPS-Scottsdale	3.39	0.78	1.1E+06	0.4019	2.62	0.88
AZPS-Mesa	3.67	1.04	1.1E+06	0.4263	2.03	0.72
AZPS-Tempe	3.45	0.63	1.1E+06	0.3771	2.58	0.89
SRP						
SRP-KPHX	3.38	2.72	9.4E+05	0.3742	2.87	0.73
SRP-Scottsdale	3.34	2.74	9.4E+05	0.3971	2.93	0.73
SRP-Mesa	4.34	6.12	9.4E+05	0.3930	1.76	0.44
SRP-Tempe	3.38	2.72	9.4E+05	0.3741	2.87	0.73
LDWP						
LDWP-KQCT (Downtown LA)	3.63	1.88	6.7E+05	0.4627	3.66	0.25
LDWP-LAX (West LA)	4.49	2.49	6.7E+05	0.4627	2.31	0.01
LDWP-Tazana (West Valley)	3.51	1.09	6.7E+05	0.4248	3.21	0.59
LDWP-KBUR (East Valley/LA)	3.54	1.21	6.7E+05	0.4497	3.23	0.50
LADWP-Lancaster	3.69	1.54	6.7E+05	0.3958	2.81	0.44
SCE						
SCE-KBUR	0.36	0.17	2.4E+06	0.4939	3.49	0.40
SCE-Tazana (West Valley)	0.38	0.15	2.4E+06	0.4674	3.59	0.55

The stationary and non-stationary approaches produced models that correlated to the data similarly at temperatures $\geq 25^{\circ}\text{C}$. As shown in S Table 3, the coefficients of correlation (R^2) were within 0.02 for models from the two approaches, and reasonable overall (~ 0.9 MC and ~ 0.6 LAC) given the inherent heteroscedasticity of peak demand, and econometric factors that we did not account for. Correlating T_{max} records from a single weather station location to peak demand resulted in better fits for Phoenix than Los Angeles, which we

attribute to the greater heterogeneity of the weather (Figure 1a) across Los Angeles compared with Phoenix.

S Table 3. Comparison of stationary and non-stationary models.

	D_{base} (GW)	D_{base} range (GW)	Q_{AC} (# ACs)	AC_{CR} (Ln(#ACs) / 1°C-<i>T_{max}</i>)	AC_{NL} (kW)	Slope (GW/ 1°C)	R²	D_{peak} @ <i>T_{max}</i>=45°C (GW)
Stationary straight-line models								
AZPS-Phoenix*	-	-	-	-	-	0.22	0.87	6.96
LDWP-Tazana (West Valley)**	-	-	-	-	-	0.16	0.6	6.17
Non-stationary SEMs								
AZPS-Phoenix	3.45	0.63	1.1E+06	0.3771	2.58	-	0.89	6.96
LDWP-Tazana (West Valley)	3.51	1.09	6.7E+05	0.4248	3.21	-	0.59	6.17

* $Q_R = 10^6$, $Q_C = 1.2 \times 10^5$

** $Q_R = 6.3 \times 10^5$, $Q_C = 4.3 \times 10^4$

AC penetration assumptions do not significantly affect the SEM fit or prediction values for peak demand at any T_{max} . Because of the way the SEM works, when the AC penetration parameter is increased, the fitting procedure compensates with a smaller average AC unit size. As shown in S Table 4, if the average AC unit size is actually smaller in Los Angeles than in Phoenix, then Los Angeles must have $O \sim 10^5$ undocumented (non-central) AC units installed, which does not significantly affect results. If we were to replot S Figure 4 with these different parameters, the resulting figures would not be visibly distinguishable from each other.

S Table 4. Sensitivity of AC Penetration and Size.

	D_{base} (GW)	D_{base} range (GW)	Q_{AC} (# ACs)	AC_{CR} (Ln(#ACs) / 1°C-<i>T_{max}</i>)	AC_{NL} (kW)	Slope (GW/ 1°C)	R²	D_{peak} @ <i>T_{max}</i>=45°C (GW)
Sensitivity of SEM LDWP-Tarzana to AC penetration in residential and commercial (R & C) sectors								
Scen. A: P _R = 48%, P _C = 48%	3.51	1.09	6.7E+05	0.4248	3.21	-	0.59	6.17
Scen. B: P _R = 48%, P _C = 90%	3.51	1.09	7.1E+05	0.4262	3.04	-	0.59	6.16
Scen. C: P _R = 60%, P _C = 48%	3.51	1.09	8.3E+05	0.4323	2.59	-	0.59	6.14
Scen. D: P _R = 60%, P _C = 90%	3.51	1.09	8.7E+05	0.4337	2.47	-	0.59	6.14
Scen. E: P _R = 80%, P _C = 90%	3.51	1.09	1.1E+06	0.4429	1.89	-	0.59	6.13

In Figure 3 we saw Los Angeles's AC coincidence rate curve to the left of Maricopa's and slightly steeper. The county's sample temperatures were also generally cooler. These observations imply lower temperature thresholds for AC engagement in Los Angeles than Maricopa, and a higher rate of AC duty cycling for any T_{max} . The lower temperature threshold can be attributed to lower human thermal comfort levels at higher humidity, cultural differences in clothing choices (Arizonans wear even less than Californians), econometric factors, and or less effective building insulation. The higher duty-cycling rate, measured as 0.42-0.44 versus 0.38 (Ln(#ACs)/ 1°C- T_{max}), infers that the AC units in Maricopa must generally have higher cooling capacities and or the average building must be more thermally well insulated. These implications are supported in S7 where results are found similar to those of previous quantitative studies of the specific topics.

S6. Generation Technologies and Fuel Types

Several power generation technologies and fuel types were considered. This section includes explanation for conventional hydroelectric and solar PV, which were not significant to findings, as well as detailed explanation of cooling mechanisms within wet thermal electric (natural gas and nuclear) plants. Hydro power was considered because Los Angeles and Maricopa Counties have about 200 MW of combined capacity, the greater states of Arizona and California have almost 13 GW, heat wave conditions are also draught conditions, and draught is a significant risk to reliable Hydro power operations (M. D. Bartos & Chester, 2015) and (EIA, 2014a). Research and development of comprehensive models of the effects of climate on critical infrastructure systems requires definition of computationally distinct factors and influences (Henry & Pratson, 2016), so we chose to consider air temperature as one factor. We considered solar PV as well because implementations are being primarily driven by government policies as a means of offsetting greenhouse gas emissions and avoiding realization of higher RCP scenarios.

Conventional Hydroelectric

Conventional hydroelectric power output is a product of the force of the reservoir water passing through the turbines and the turbine efficiency. This power can be expressed formulaically as the multiple of the turbine efficiency, density of water, flow rate through the turbine, acceleration due to gravity, and net hydraulic head acting on the turbine (M. Bartos & Chester, 2015b). Turbine

efficiency is a function of its mechanical design which is independent of ambient air temperature. The density of water is subject to change from pressure and water temperature. That change is order 0.01% per 1°C of the water temperature (“Water - Thermal Properties,” 2016). Surface water temperature changes less than 1:1 with air temperature, and the temperature of the intake water deep below the surface is even less affected by air temperature. Streamflow rate and hydraulic head may be susceptible to drought (M. D. Bartos & Chester, 2015), however estimation of drought or the impacts of air temperature on drought is beyond the scope of this study. Otherwise, flow rate and hydraulic head are generally controlled by the plant operator and are therefore not affected by air temperature (M. Bartos & Chester, 2015b). Change in hydroelectric power output with increase in ambient air temperature is therefore parameterized as zero in the model for this study.

Solar PV

Power output of solar PV is mostly dependent upon the engineering of the cell and the angle of incidence of the sunlight. The maximum theoretical efficiency of a solar cell using a single p-n junction to create power is known as the Shockley-Queisser limit, and is 30% for the most common material, silicon, with bandgap of 1.1 eV (Shockley & Queisser, 1961). This means that if the sun is shining with 1,000 W/m² of radiative force, the most perfectly designed single silicon solar cell would be able to produce 300 W/m² of generation capacity under optimal conditions. Solar PV performance can exceed the Shockley–

Queisser limit by implementing solar cells with multiple p-n junction layers. The maximum solar PV generation capacity, with an infinite number of layers is 68% for standard sunlight, and 86.8% for concentrated sunlight (Vos, 1980).

For any engineered solar PV system, power output increases with radiative forcing input, and can decrease with air temperature due to internal carrier recombination from thermal excitation (Dubey, Sarvaiya, & Seshadri, 2013). A formula for this relationship is expressed in (Dubey et al., 2013) where solar power generation is equal to the product of the generation under peak radiative conditions, the fraction of sunlight incident on the cell, and one minus the product of the ambient dry bulb temperature above a reference temperature (typically 25°C) times a power-temperature coefficient. Average power-temperature coefficients are listed for 6 different common PV technologies with a range from 0.001 to 0.006. We used the EIA summertime capacity values listed as is, and did not attempt any disambiguation between solar PV implementations that may or may not be paired with battery storage, configured within micro grids, or adjusted for solar irradiance by time of day. Parameter values for decrease in solar PV generation capacity per 1°C increase in ambient air temperature used are 0.1-0.6% with a median base value of 0.35%.

Thermal Electric

Nuclear and natural gas plants produce power using thermal electric generation processes. In steam-turbine plants, purified water is recirculated in a closed-loop to spin the turbine of a synchronous motor and create spinning

reserve power. High pressure water is heated by the plant's fuel combustion process, converted into a high pressure steam to spin the turbine (at $\sim 500^{\circ}\text{C}$), then condensed into "cool" water (at $\sim 300^{\circ}\text{C}$) into a small reservoir for pumping and recirculation (Arrieta & Lora, 2005). Condensation is managed through plant design and operations which control the pressure in the condenser chamber, and the heat removal rate from the condenser, similar to AC systems. In the water-cooled-nuclear- and wet-NG-plants, a second water loop system pumps cooling water through the condenser coils and then to an evaporative cooling tower to remove heat from the condenser. If the evaporative cooling tower is properly designed, then the recirculating water temperature will enter the condenser just above the theoretical limit of the wet bulb temperature (T_{wet}) on hot days. T_{wet} is by definition less than or equal to the dry bulb temperature, T_{dry} , and T_{max} that is our predictor variable in this study (Hensley, 2011). For a constant absolute humidity (kg water vapor / kg air), as T_{dry} increases, T_{wet} increases; the vapor carrying capacity of the air increases, therefore the relative humidity decreases; and a cooling tower will evaporate more water to cool the recirculating water to the new equilibrium T_{wet} (Hensley, 2011). In dry-cooled NG plants the process is the same, except the condenser uses a fan to force ambient or chilled air over a heat-sync and cool/condense the generator steam back into a liquid with a theoretical limit of T_{dry} or the chiller design. Hybrid cooling systems have been created to realize the cooling performance of the wet system on the hottest days of the year and the water conservation of the dry system during the remainder of the year (Bushart, 2014).

NG combustion-turbine plants produce power very similarly, using an open-loop pressurized air system to spin the generator turbine instead of a closed-loop water system. Typically, more than half of the power produced by the turbine is used to power the air intake compressor (Brooks, 2000). Simple-cycle efficiency is improved at higher pressure ratios and higher combustion temperatures. Thus, while specific generation capacity varies by physical properties of the inlet air and the motors, the power output of a single-shaft MS7001, for example, decreases linearly by 0.65% per 1°C rise in inlet air temperature as measured from the ISO standard reference temperature of 15 °C to 50°C according to lab test results by the manufacturer (Brooks, 2000). Using an evaporative cooling system to lower the intake air temperature can offset those losses and increase power output by 4-12% at $T_{dry} > 40^{\circ}\text{C}$ depending on the relative humidity (T_{wet}) (Brooks, 2000). A combined cycle natural gas (CCNG) system improves overall electrical efficiency by adding a steam-turbine generator to recover waste heat from the combustion gases in the outgoing air stream.

S7. Uncertainty and Validation

Estimating LRM was a 4-part process, with uncertainty in parameters, methods, and results in each section. We mentioned the most significant in the primary narrative. This SI section describes some of the other uncertainty in our methods and validation of our results.

Allocation of Base Peak Demand

Our source data for electricity demand was aggregated by balancing authority, and we scaled those values up to the county-level by building allocations. If we weighted allocations of peak demand strictly by population, then Los Angeles's would have been 2.6 times higher than Maricopa's. Our building allocation method produced slightly lower results because Los Angeles has only 2.3 times as many residential buildings as Maricopa, and about half the central AC penetration in those buildings. Furthermore, the annual residential and commercial building energy consumption in AZPS is about even at 45% and 44%, but in LDWP is weighted more heavily on commercial at 35% and 57% (EIA, 2014b), so the net effect is only slightly less peak demand than a strict population allocation method.

AC Penetration and Average Unit Size

The range of SEM results for average residential AC_{NL} sizes was reasonable (1~5 kW) per (Faramarzi et al., 2004) and (Ruddell et al., 2014); however, we find it unlikely that the average AC_{NL} size is larger in Los Angeles than Phoenix given the differences in historical climates. More reasonable is that Los Angeles has at on the order of 100,000 (10% of the customers in the LDWP balancing authority) undocumented non-central ACs in operation (e.g. window ACs). Model sensitivity to AC penetration is listed in S Table 4, and has less than 1% effect on peak demand projections. Increasing the AC penetration

assumption input significantly reduces the AC_{NL} nominal load parameter, in the fitting procedure, and slightly increases AC_{CR} coincident rate, for a negligible combined effect on overall model fit and predictions. The higher coincidence rate, $AC_{CR} = 0.44$ vs 0.42 , is attributable to higher duty cycle rates from lesser AC cooling capacity, i.e. smaller average unit size, AC_{NL} . Therefore, we figure the reality of AC penetration and average unit size is somewhere between scenarios “C” through “E” in S Table 4.

Another consideration is the amount of (large) water-cooled AC units in the system. Water-cooled AC units are more energy efficient than air-cooled and are often designed to operate using cooling towers completely analogous to wet-cooled thermal power generation systems (S. K. Wang, 2000). Due to economics of scale, water-cooled AC units are generally recommended only for large commercial and industrial applications where >300 tons of cooling capacity is required (Kline, 2016). If we assume this is true in implementation, then there are 2-4 orders of magnitude more of the smaller air-cooled ACs than water-cooled. So, for less than 1% of the building stock, the $1.33\%/1^{\circ}C-T_{max}$ compound growth factor for AC compressor motor workload is not applicable. The AC_{NL} average unit size per building in these cases is also at least 10 times larger than the rest of the building stock, or mathematically there would be 10 times the units per building. Either way, the sensitivity analysis already described for AC penetration not accounted for the assessors' databases is inclusive of this uncertainty, and it is not significant to results.

Building Thermal Efficiency and Indoor Temperature Preferences

Results indicate that buildings are less thermally efficient in Los Angeles than Maricopa, and that the population generally prefers lower thermostat settings as well. Building thermal performance was estimated for the two counties in (Nahlik et al., 2016), using time-based units, equal to a weighted average of 52 and 45 hours in Los Angeles and Maricopa. Those time values were defined as the modeled time for the indoor temperature to rise from 25°C to 32°C (77 to 90°F) in the absence of air conditioning for local outdoor temperatures of 37°C and 44°C (respective $T_{97.5}$ s in the study), with 9% and 2% relative humidity. The local-weather-weighted statistics in that study modeled Maricopa's buildings' indoor temperature rising to 32°C in 16% less hours than Los Angeles's buildings when 42% more indoor-outdoor temperature gradient was applied (17°C vs 12°C). Los Angeles county has a lower inflection temperature for rise in peak demand in our sample data, (25°C vs 28°C or 77°F vs 82°F) S5. This pattern is historically consistent in Los Angeles to at least 1986 (Santamouris et al., 2015). The Los Angeles value of 25°C is consistent with previous studies by the California Energy Commission that identify average indoor thermostat settings at 25°C (CEC, 2009). Arizona is well known for its “dry heat” – where low humidity results in more efficacious evaporative cooling processes (e.g. human sweat) – and normative “casual” attire. These factors have been shown to correlate to preferences for slightly warmer indoor

temperatures (Buratti, Ricciardi, & Vergoni, 2013), (Yang, Yan, & Lam, 2014), and (Taleghani, Tenpierik, Kurvers, & Van Den Dobbelsteen, 2013).

Weather-Adjusted Peak Demand

Our SEM approach for peak demand resulted in an s-curve, which resulted in marginal increases in peak demand that are an order of magnitude less per $1^{\circ}\text{C}-T_{max}$ at high temperatures than in the mid-range of the curve. Prior to this work, all peer-reviewed literature identified on power infrastructure vulnerability to climate change speculated that peak demand will continue to increase at either the same rate or a steeper rate at high temperatures $>40^{\circ}\text{C}$ (Garcia-cerrutti et al., 2012), (Santamouris et al., 2015), (Sathaye et al., 2013), and (M. D. Bartos et al., 2016). This is the first study that concludes that peak demand *must* increase at a relatively slower rate at very high temperatures, due to aggregate coincidence of AC duty cycles, and is the only study that considers this factor.

Modeling D_{peak} as a univariable, multivariate function of T_{max} using our SEM approach produced models that fit the data as well as the climate zone factors would allow. SEM R^2 values are slightly ($<10\%$) higher than R^2 values using uni-variable ordinary least squares regression in the observation period $T_{max} \geq 25^{\circ}\text{C}$. For the Maricopa balancing authorities with relatively homogeneous weather patterns, our R^2 values were comparable to the models used by the CAISO in making weather-adjustment recommendations to resource adequacy requirements (0.9 ± 0.04) (Garcia-cerrutti et al., 2012). CAISO's models are the

most robust that we were able to find in the literature. Those models are multi-variable multi-variate for peak load, consider 3-day categorically weighted sums of daily maximum and minimum temperature (as proxy for UHI-factors), as well as, demand response, distributed energy resources, and other power infrastructure performance factors that are beyond the scope of this study. Our model for Los Angeles could similarly be divided into several smaller models to fit the observed data, and have tighter uncertainty bands for each if we had done a categorical allocation of D_{peak} for building stock in smaller more homogeneous climate zones such as the CEC climate zones. This would have required access to higher spatial resolution demand data or further assumptions for allocating demand by building quantity. Such an analysis would be useful to answer different research questions as it would beg for consideration of T_{max} coincidence across the geographies, which we accounted for in our $T90$ uncertainty ranges.

Local Reserve Margin

Definition and verification of LRMs was limited by the geography that we chose to consider. However, records for net imports and exports by balancing authority demonstrate that our county-based estimates were not unreasonable. LDWP imports (not including SCE activity) ranged from 0.3 to 1 GW from Aug 1-7, 2016, with T_{max} at Tarzana station from 31-34°C (EIA, 2014a) and (Weather Underground, 2016). Similarly, AZPS had daily peak outflow of 2.7-3.1GW from June 22-29, 2016 with T_{max} at KPHX ranging from 41-45°C. While the AZPS statistic was more indicative of wholesale power demand in connected service

areas, it is sufficient to conclude that Maricopa had a sizeable LRM surplus at the time (EIA, 2014a) and (Weather Underground, 2016).

Generation Derating Factors

Generation derating factors were consistent with generator data reported by the EIA for seasonal capacities. EIA form 860 summer and winter generator capacities for every generator in the USA. Sparse data exists to validate our derating factors, so we chose to average the difference of summer and winter capacities over a 30°C temperature difference as rough test for reasonableness. Using this approach, the most seasonally sensitive plants were Maricopa's Ocotillo natural gas combustion turbine generator and Los Angeles's Grayson CCNG with levelized de-rating factors of 0.65% and 0.44% per 1°C- T_{max} respectively. These values were within the range of the non-stationary approach derating factors used as listed in Table 2. All generation factors matched within 0.05% using this approach (including 0% values), except for solar PV which was not significant in the model.

CHAPTER 4

BOTTOM-UP APPROACH FOR PROJECTING PEAK DEMAND

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Highlights

1. Peak hour electricity demand projected to increase by 0.2–6.5 GW (2–51%) by 2060.
2. Rising air temperatures projected to increase peak demand by 4–8% by 2060.
3. Maximum temperatures in inland regions are projected to reach 54 °C (129 °F).
4. Shared wall housing can reduce peak demand by up to 50% per building.
5. Air conditioner SEER ratings effective for annual demand, but not peak demand.

Abstract

Los Angeles County (LAC) is a large urbanized region with 9.7 million residents (as of 2010) and aging infrastructure. Population forecasts indicate that

LAC will become home to an additional 1.2–3.1 million residents through 2060. Additionally, climate forecasting based upon representative concentration pathway (RCP) scenarios 4.5 and 8.5 indicate that air temperatures will increase by 1–4°C (2–7 °F) in the region. Both of these factors are expected to result in higher summertime peak electricity demand from growth in the number of buildings, the percentage of installed air conditioners (ACs), and the additional cooling load on those air conditioners. In order to understand potential electricity infrastructure reliability issues due to excessive electricity demand, a long-term peak demand forecast was developed with consideration for those factors using hourly residential and commercial (R&C) building energy models at census block group resolution. Peak hour electricity demand was estimated to increase from 9.5–12.8 GW for R&C sectors in LAC, to 13.0–17.3 GW (2–36%) and 14.7–19.2 GW (16–51%) by 2060 for the various efficiency scenario ranges of the population projections by the California Department of Finance and the Southern California Association of Governments respectively. While marginal increases in ambient air temperature due to climate change accounted for only 4–8% of future increases in peak demand, inter-annual variations in maximum temperatures affected results by 40%–66% over the 20-year periods. Population growth of at least 1 million persons is anticipated to occur mostly in the peripheral cities of Palmdale, Lancaster, and Santa Clarita, bringing an additional 0.4–1 GW of peak demand in those regions. Building and AC efficiency are anticipated to improve as national and state efficiency standards increase and as older, less efficient units are replaced; this could offset some of the projected increases in

peak demand. Additionally, future development of shared wall, multi-family dwelling units could further support population increases of 2.5 to 3 million people without corresponding increases in peak demand.

Keywords: building energy modeling; peak demand; demand forecasting; spatial analysis; heat waves; climate change

Introduction

Demand for electricity increases significantly as air temperatures rises in developed urban environments with high levels of air conditioning (AC) penetration (M. D. Bartos et al., 2016; D. Burillo, Chester, Ruddell, & Johnson, 2017; Garcia-cerrutti et al., 2012; Ralff-Douglas, 2016; David J. Sailor, 2001; David J. Sailor & Muñoz, 1997; Santamouris et al., 2015; Sathaye et al., 2013). Despite a general understanding of this phenomenon, little knowledge exists as to how increases in air temperatures due to climate change can affect peak demand within cities (Dirks et al., 2015). Previous studies have observed that rising air temperatures can result in both direct effects of increased electricity use due to increased AC use, as well as compound effects from increased implementation of AC over long periods of time (Isaac & van Vuuren, 2009; D. J. Sailor & Pavlova, 2003). Moreover, extreme heat waves may result in outages within regions due to high demand, capacity shortages, and cascading failures (Eaton, 2013; FERC, 2003; Ferc & Nerc, 2012; Hines, Balasubramaniam, &

Sanchez, 2009; Nerc, 2015). Several incidents have occurred in Los Angeles County (LAC) which has high levels of AC penetration (Barry Fisher, 2014; Ferc & Nerc, 2012; Jerod MacDonald-Evoy, 2016; van Vuuren et al., 2011). Because outages can happen at the transmission-, circuit- or neighborhood-level (Willis et al., 2001), it is valuable to be able to predict peak demand with the same level of detail. While electric service providers may have historically planned for annual peak demands during the winter, or 90th percentile summer peak demands (e.g. California Energy Commission, Western Electricity Coordinating Council, North American Reliability Corporation (Garcia-cerrutti et al., 2012), (Miller et al., 2007; NERC, 2015a; WECC, 2014b)), in a warmer future, peak demand may occur in the summer instead, or be so much higher during extreme heat events that safety margins are exceeded as in the record breaking cases in (Jerod MacDonald-Evoy, 2016; LADWP, 2014; The Associated Press, 2018) Hence, developing a better understanding of the relationship between climate change and peak demand is critically important for maintaining reliable electric power service and reliable critical infrastructure in general (Rinaldi et al., 2001).

Prior studies have considered effects of rising air temperatures on annual energy consumption and peak demand, including growth within LAC specifically (LADWP, 2016d)(CAISO, 2015). No study to date has considered the combined effects of population growth, changing building technology, energy appliance technology, and climate, each at a high-spatial resolution, throughout a region on peak demand. Top-down statistical models, and bottom-up building energy models have become the methods of choice to analyze various aspects of the

problem. Burillo *et al* 2017 (D. Burillo, Chester, & Ruddell, 2017), includes a review of top-down approaches, and advanced those further by developing a structural equation model, based on non-linear stochastic performance of AC units, which demonstrates how peak electricity demand could be forecast more accurately for heat waves at a regional-scale using fewer predictor variables than other models. The US DOE's EnergyPlus physics-based building energy simulation software has become a popular tool for researchers to develop detailed "bottom-up" models of individual buildings specifically calibrated for various building standards, climates, and occupant usage patterns around the world, including (Chaudhary et al., 2016; Y. S. Kim, Heidarinejad, Dahlhausen, & Srebric, 2017; Royapoor & Roskilly, 2015; K. Sun, Hong, Taylor-lange, & Piette, 2016). Huang and Hwang 2015 (Huang & Hwang, 2016) used such models to consider effects of rising temperatures on annual energy demand for representative future years' (aka time slices) in Taiwan, and Dirks *et al* 2015 (Dirks et al., 2015) did the same for both annual and peak electricity demand for cities throughout the eastern US. Similarly, Reyna and Chester 2017 (Janet L. Reyna et al., 2017) developed calibrated residential building archetypes for LAC, which were subsequently used in this study, by considering annual electricity consumption, spatially, throughout the region, including various sub-categories of building types, the five different California building climate zones, and various building and appliance energy efficiency scenarios. All of those studies relied on weather station data and/or representative year time slicing; no study considered maximum temperature forecasts in a spatially explicit manner at a regional scale.

Doing so would enable consideration of the most stressful potential conditions at any location throughout a region.

LAC is a valuable location to develop new insights because it is a complex and fast-growing region where, in addition to rising air temperatures, AC penetration is rising, population is growing, infrastructure is changing, and there are a range of different climate zones (California Energy Commission, 2014; CEC, 2017; LADWP, 2016d; SCAG, 2016a). As electricity infrastructure hardware ages, and growth continues, there will be need for both new and retrofitted infrastructure (Willis et al., 2001). LAC's coastal, inland, and desert climates capture a range of conditions where AC use would be required (Barry Fisher, 2014; D. Burillo, Chester, & Ruddell, 2017). First, the region could experience 1-4 °C or 2-7 °F warmer temperatures, on average, by mid-century. Additionally, while historical 90th percentile hottest temperatures have been 33°C (91°F) in LAC (Miller et al., 2007), maximum air temperatures could reach up to 54 °C (129 °F) by 2060 in certain parts of the County (Hall et al., 2012),(M. Bartos & Chester, 2014). Approximately 45% of residential buildings in LAC currently have air conditioning (Andrew M. Fraser et al., 2017; Janet L. Reyna et al., 2017), and with its current stock of 2.3 million buildings, peak demand increases at a rate of 300-400 MW, or 2-5%, per 1 °C (1.8°F) over the range of 25-40 °C (77-104 °F) (Sathaye et al., 2013),(D. Burillo, Chester, & Ruddell, 2017). New development favors installation of central AC units , so those rates will increase in the future, especially in neighborhoods which currently have low AC penetration (Andrew M. Fraser et al., 2017),(D. J. Sailor & Pavlova, 2003).

Population is expected to increase, from 9.7 million in 2010, by 1.2-3.1 million people (12-32%) by 2060; thus, residential and commercial buildings energy use could increase proportionally (Janet L. Reyna & Chester, 2015; SCAG, 2016a; Sleeter, 2017). New buildings in LAC will be constructed to meet Title 24 building energy standards—with significant improvements beyond the existing stock in attics, walls, water heating, and lighting efficiency—but percent reductions in peak demand from those standards are not nearly as large as in annual energy consumption (CEC, 2016). Moreover, there is a requirement for solar PV to be installed on all new homes, which figures to further contribute to the “duck curve” issue of a faster load ramping rate, and slightly lower peak later in the day at or near sunset (California ISO, 2016). While high-density multi-family housing is generally more energy efficient than single-family housing, a net increase in population can still result in a net increase in annual energy consumption and peak demand. Consequently, our case-study specific research goal is to understand what ranges of peak demands are reasonable to expect in LAC through 2060, considering potential changes in population, building stock, AC penetration, appliance efficiency, and higher air temperatures due to climate change.

Projecting peak demand spatially into the future allows us to consider the efficacy of various strategies that utilities could use to manage peak demand amidst rising air temperatures. Moreover, by considering the most stressful conditions in any geography, in any period, we can support infrastructure planning processes with a single image that accounts for all the potential heat

wave scenarios that could affect different areas in the county at different times. In the discussion section we consider how utilities and regulators may better plan for resource adequacy requirements, neighborhood specific infrastructure capacity requirements, appliance energy standards, and building zoning requirements. This type of detailed peak demand forecast can be used in siting and sizing new infrastructure investments to prevent outages and improve reliability. Whether new capital investments be in traditional bulk systems components or distributed renewable energy resources, effective grid modernization will mitigate harmful environmental emissions, improve public health through better air quality, and reduce hazardous emergency response incidents that have resulted in numerous auto collisions and deaths (Winn, 2017).

Methods

To project peak electricity demand throughout Los Angeles County, we adopted and refined the bottom-up building energy modeling approach developed by Reyna and Chester (Janet L. Reyna et al., 2017), incorporating aspects of the T_{max} approach developed by Burillo *et al* in (D. Burillo, Chester, & Ruddell, 2017). We used EnergyPlus hourly residential (Janet L. Reyna et al., 2017) and commercial (Deru et al., 2011) (R&C) building models calibrated for LAC specifically. We projected peak demand for the two sectors at census block group (CBG) resolution based on prior classification and allocation of building types from the County Assessor Database and Residential Appliance Saturation

Survey in (Janet L. Reyna & Chester, 2015). We did not consider demand from the industrial sector (10-30% of total annual electricity consumption per (Pincetl & LA Energy Atlas Development Team, 2017) and (EIA, 2014b)) , e.g. transit, streetlights, heavy manufacturing etc., as the factors that influence that sector's demand do not necessarily scale with population or climate. The residential building models were originally calibrated for annual electricity consumption, whereas the original commercial building models were not specifically calibrated for electricity consumption (Deru et al., 2011). Hence, the analysis was much more rigorous for residential buildings, and the commercial building results should be considered conservative per the performance characterization detailed in (Daniel Burillo et al., 2018) Appendix B. Peak demand values were estimated as the average of hourly consumption from noon-6pm, per residential peak time of use pricing periods in the area (LADWP, 2016a; SCE, 2017), and results verified as reasonable using historical data as explained in the Verification and Uncertainty section. We did not attempt to account for peak load shifting due to rooftop solar PV from the perspective of the grid. Demand and load are two distinct phenomenon, see discussion section for further consideration of this topic. The effects of rising air temperatures were simulated in terms of T_{max} as in (D. Burillo, Chester, & Ruddell, 2017), by modifying sample historical data for LAC in the "EPW" weather input files as detailed in (Daniel Burillo et al., 2018) Appendix A, and creating performance characterization tables of all combinations of buildings for any daily T_{max} . Peak demand projections were developed with low and high demand scenarios for each of the following six factors, of which four

are positive effects (rising air temperatures, population growth, building stock turnover and AC penetration), and two which are negative (housing densification and AC efficiency). Sensitivity analysis was conducted to test how significant each factor contributed to changes in peak demand and what opportunities may be most promising in terms of bolstering the region's capacity to adapt to future record-breaking heat waves.

Rising air temperatures were considered in the context of the daily maximum air temperature, T_{max} . Base period values of T_{max} were obtained at 2 km² grid cell resolution for 1981-2000, and future values were obtained from the same source of downscaled projections in (M. Bartos & Chester, 2014; Hall et al., 2012) for RCP4.5 and RCP8.5 to 2021-2040 and 2041-2060 representative of low and high temperatures. Two sets of projection images were created to inform two distinct issues. First, **composite** images of the highest projected T_{max} in each 2 km² grid cell for each time period and RCP were created to project the highest peak demand in any CBG at any time, which could stress any component at any time. The composite images are comprised of T_{max} values from many different days. Second, **hottest day** images were created of the highest T_{max} throughout all of LAC on any day. These images inform the resource adequacy requirements for the region during a possible record-breaking heat wave. Because LAC covers approximately 12,000 km² (5,000 mi²), and has five climate zones, the definition as to what the hottest day means for the county is debatable. We tested three definitions: number of days with the highest average T_{max} , highest single-cell T_{max} , and most grid cells over 35°C (95°F). Results indicated that the first

definition consistently produced the highest peak demand projections, consequently this was chosen to be the working definition of the hottest day. The spatially explicit temperatures used are shown in Figure 8.

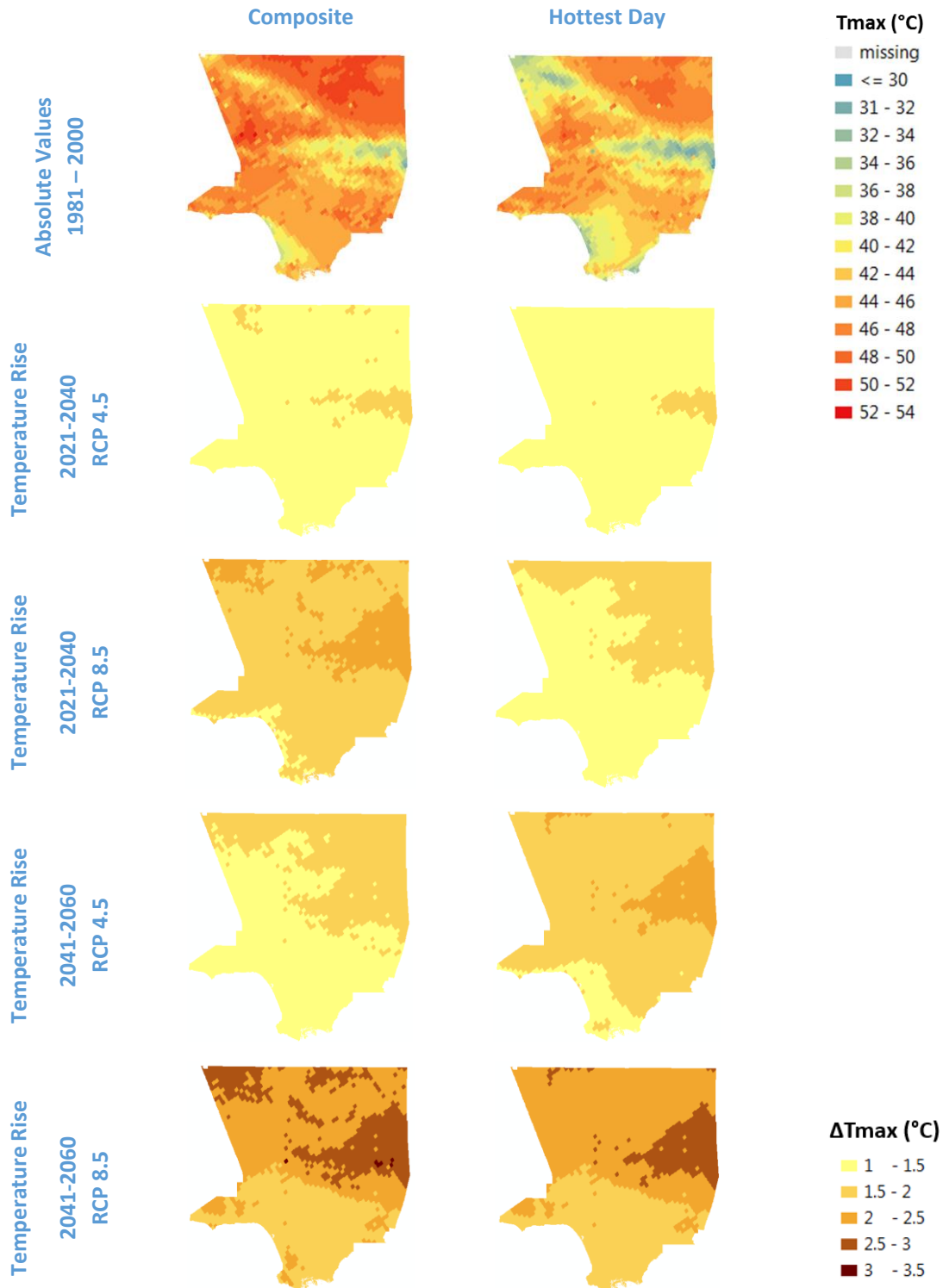


Figure 8. Historical and Future Maximum Temperature Projection Images. Top images are the baseline period, the bottom images are future changes from the baseline period. The actual values of temperature increases range from 0.9 to 3.2 °C.

Population growth is a direct driver of peak demand because the number of buildings consuming electricity are directly proportional to the population.

Growth was modeled for two scenarios which differed primarily with respect to the influence of land use zoning on density/sprawl (Whittemore, 2012). The low growth scenario was based on the California Department of Finance (DoF) and U.S. Geological Survey's projections, which started at 9.7 million in 2010, and then increased to 10.3 million in 2040, and 10.9 million in 2060 primarily on the fringe and in the northern (and hotter) region of LAC (Sleeter, 2017). The high growth scenario was based on the Southern California Association of Governments (SCAG) projections, which additionally included significant infill of already developed areas, resulting in total projected population values of 11.4 million in 2040 and 12.8 million in 2060, (SCAG, 2016a),(SCAG, 2016c),(SCAG, 2016b). Both population projections were spatially explicit, although based on different methodologies, and required different allocation approaches to generate CBG level results, as detailed in (Daniel Burillo et al., 2018) Appendix C.

Following the work of Reyna and Chester 2015 (Janet L. Reyna & Chester, 2015), population growth (Figure 9) was modeled as a function of proportionally increasing residential and commercial building stock in CBGs, using EnergyPlus archetypes specifically calibrated for LAC . In short, initial building stock was defined as a total of 2.3 million buildings in 2010, spatially located as in (Janet L. Reyna et al., 2017) and (Janet L. Reyna & Chester, 2015) based on the County Assessor Database, with 4 main types of residential buildings (single-family and multi-family, detached, attached, small, and large, SFD, SFA, MFS, MFL) with up

to 12 dwelling units (DU) per building structure, and 15 types of commercial buildings. Residential building stock was increased at the rate of 3 persons per DU per current statistics from the US Census (“US Census Bureau 2010 Census Interactive Population Map,” 2017) and SCAG projections (SCAG, 2016c). Commercial building stock was increased proportionally in each CBG with population, with the same proportion of building types as existed in the sample in 2010.

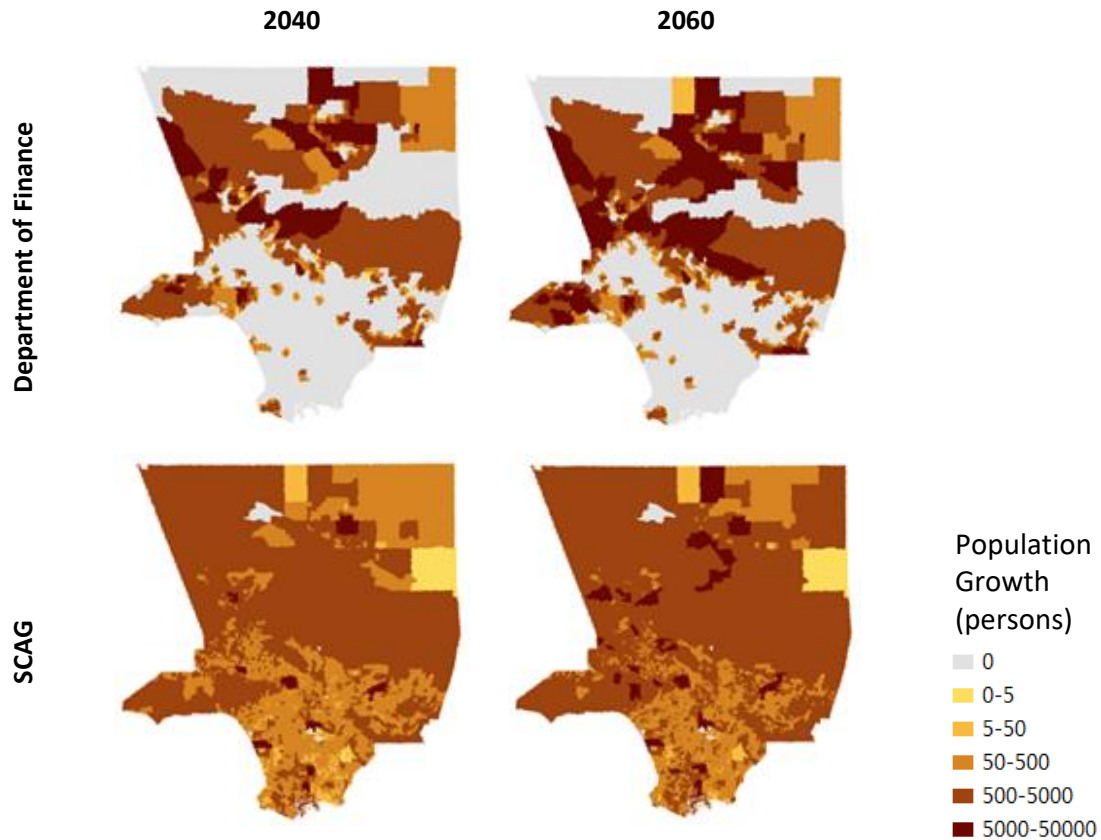


Figure 9. Projected Increases in Population (Persons) From 2010 to 2040 and 2060 From CA Department of Finance/USGS and SCAG by Census Block Group.

Building stock turnover included replacement of older vintage buildings with new buildings for the residential sector only. Newer vintage buildings were designed in (Janet L. Reyna et al., 2017) to meet the most recent iteration of Title 24 building energy standards (minus rooftop solar) (CEC, 2016) with more thermally efficient shell constructions and energy efficient appliances. Those residential buildings were developed for the five California Energy Commission Climate Zones in LAC and for seven vintages from pre-1940 to 2008. Turnover rates were modeled by replacing older buildings with the newest of the same type per the housing density scenarios. Low, medium, and high turnover rates of

0.03%, 0.3%, and 3% of DUs per year, per CBG were used, based on the range identified for LAC in (Janet L. Reyna & Chester, 2015). It was assumed that all new buildings would have central AC and replace older buildings without central AC first. Thus, a higher turnover rate results in a larger peak demand, as AC accounts for 60-70% of electricity consumption while in use (D. Burillo, Chester, Ruddell, et al., 2017). While newer buildings are more energy efficient per square foot, they were also coded to have larger floorplans (Janet L. Reyna et al., 2017), so the net correlation between building vintage alone and energy consumption is not consistent in the models.

Housing densification was primarily considered to accommodate population growth. Single family detached buildings require more land area per capita and are generally less energy efficient per area than multifamily attached buildings (Janet L. Reyna & Chester, 2015). Zoning policy can affect what types of buildings can be built in different neighborhoods (Whittemore, 2012). The 2010 initial allocation for LAC was SFD=47%, SFA=8%, MFS=24%, and MFL=21% per Reyna and Chester in (Janet L. Reyna et al., 2017), and consistent with SCAG in (SCAG, 2016c). According to SCAG, “66 percent of the 1.5 million new homes expected to be built in the SCAG region will be multifamily units, reflecting demographic shifts and anticipated market demand.” (SCAG, 2016c). Therefore, we used the recent historical allocation for the high demand scenario, the SCAG allocation for medium demand, and a ratio of 90% MF to 10% SF for new buildings for the low demand scenario.

Air conditioning penetration was increased in the model as new buildings were added to meet population growth and through building turnover by replacing older buildings without AC first. AC penetration was considered explicitly because a significant portion of homes in LAC do not currently have central AC. The initial AC penetration values in each climate analysis zone (CZ) were obtained from (Janet L. Reyna et al., 2017), allocated by building type and CBG at 45% for LAC at large, where CZ6=39% (coast), CZ8=42% (central-basin), CZ9=39% (urban), CZ14=78% (Mojave desert), CZ16=61% (forests) (CEC, 2017).

Air conditioning efficiency was adjusted for all residential buildings in the model to project the effects of higher standards on peak demand. Current standards require SEER 13 for new residential sized ACs in California (CEC, 2016). The original building energy models developed in (Janet L. Reyna et al., 2017) were coded with 20 different types of ACs to represent the current building stock implementations based on the California Residential Appliance Saturation Survey (RASS) (CEC, 2009). For practical computational purposes, we further clustered residential AC in to three categories as listed in Table 5 per the characterization in (Daniel Burillo et al., 2018) Appendix B. Room air conditioners (RACs) were allocated to half SEER 8 and half SEER 16 per the individual building model characterizations. It is the California Energy Commission staff's projection that these standards will rise to at least SEER 16 by 2040 (Stoms, 2017). Therefore, we set all residential buildings to use SEER 16 in the low-

efficiency (high demand) scenario, and SEER 21 ACs in the high efficiency (low demand) scenario.

Table 5. AC Technology Classification.

AC type	Definition	Clustering of (Reyna & Chester) (Janet L. Reyna et al., 2017)	Base allocation
No AC	No AC	No AC	44%
Low efficiency	SEER 8	All SEER 10 or less + ½ of all RACs	26%
Medium efficiency	SEER 16	All SEER >10 + ½ of all RACs	30%
High efficiency	SEER 21	n/a	0%

Results

Peak demand was projected to increase in LAC for residential and commercial sectors from 9.5-12.8 GW to 12.3-16.7 GW (~30%) in 2040 and 13.1-19.2 GW (~45%) in 2060. Additional demand was projected primarily in the Lancaster, Palmdale, and San Fernando Valley regions if the DoF's low population projections are realized (CZ 14 and 16), and primarily in the area from West Valley to Pomona (CZ 9) if the high SCAG population projections are realized,

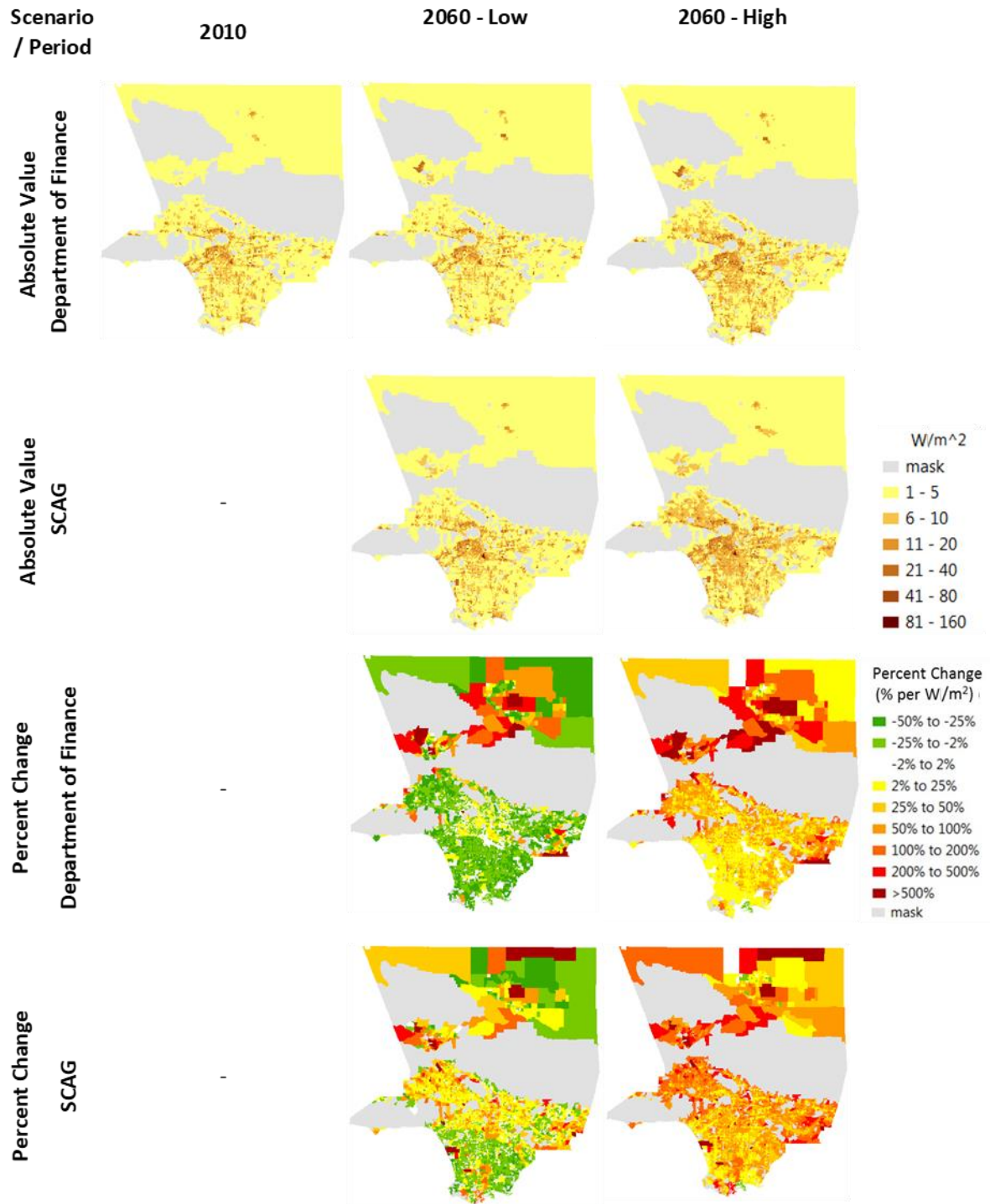


Figure 10. The lower values depend upon high implementation of multi-family dwelling units with high efficiency AC and appliances, all of which would likely require proactive regulation based on historical precedent (Whittemore,

2012),(Mideksa & Kallbekken, 2010),(Vine, 2012). The initial allocation of peak demand was estimated as 37-44% residential and 56-63% commercial, which increased over time faster for the residential sector. The total values are listed in Table 8, and further R&C sector details in (Daniel Burillo et al., 2018) Appendix B. The residential sector contributed more to increases in peak demand due to the higher AC penetration rates over time and the flat performance curves of many commercial building models. (i.e., commercial buildings' peak demands did not increase with higher T_{max} .) Results for the commercial sector should be considered conservative, and future work should include further research and development of the commercial building models, as again, the NREL manual explicitly states that this type of energy demand forecasting is beyond the scope of use at this iteration of the models (Deru et al., 2011).

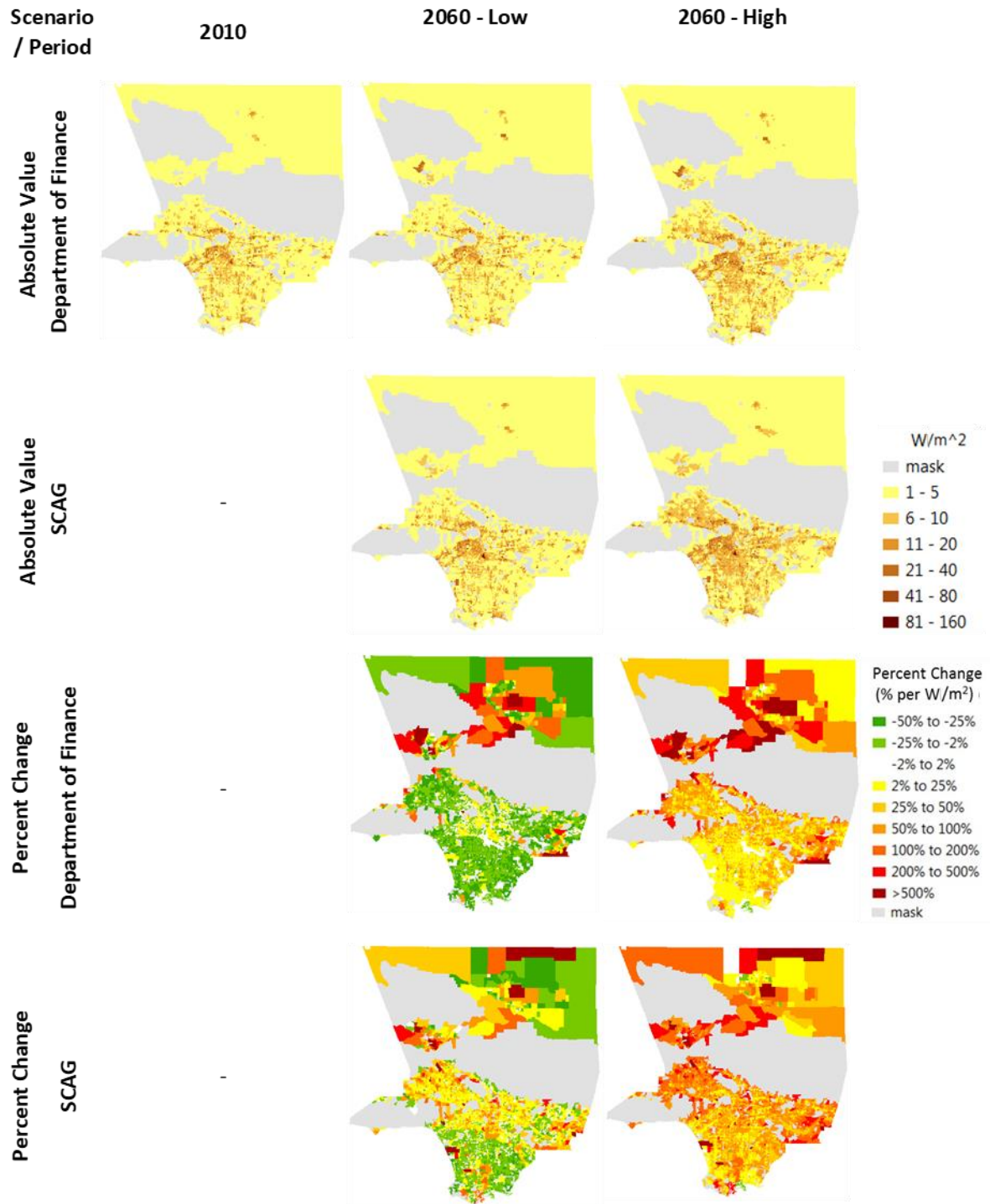


Figure 10. Composite Peak Demand Projections and Percent Change for Base and Future Period Low and High Scenarios.

Table 6. Range of Peak Demand Projections for LAC for Residential and Commercial Sectors Only

	LAC Total Peak Demand (GW)			
Time Period	Finance - Low	Finance - High	SCAG - Low	SCAG - High
<i>Hottest Day</i>				
2010	9.5	12.8	-	-
2040	12.3	15.8	13.1	16.7
2060	13.0	17.3	14.7	19.2
<i>Composite</i>				
2010	-	13.5	-	-
2040	12.9	17.3	13.8	18.4
2060	13.6	18.8	15.4	20.9

Differences in peak demand were observed across areas within LAC due to differences in population, building type, building density, and climate. The composite image projections were cumulatively about 10% higher than in the hottest day projections. In all 2060 scenarios, the major increases in peak demand were in areas with both high population growth and high air temperatures: Santa Clarita (0.33 to 0.62-1.26 GW) and Palmdale plus Lancaster (0.63 to 0.65-1.3 GW). The remainder of the demand increases were spread around the already developed areas, consistent with the population projections. The highest demand increase scenario, with 19.2 GW peak, was based on approximately 1 million new lower-efficiency SFDs in CZ 9 from West Valley to Pomona and 100% AC penetration, which may not be feasible due to space limitations. Those values should be considered a high estimate. Several CBGs appear green in the northern region due to AC efficiency gains being larger than the effects of population growth. In both low demand high efficiency scenarios, the in-basin area has significant green on the map. In the DoF case this was

because peak demand decreased from 4 GW to 3.33 GW, and in the SCAG case peak demand stayed the same overall with small pockets of increases around Manhattan Beach, Torrance and Long Beach. In the SCAG high efficiency scenario, the central CZ 9 region from West Valley to Pomona's peak demand was projected to increase from 7.5 GW in the base period to 9 GW. In all figures, CBGs with >50% area classified as protected lands are masked per the 2017 California Protected Areas Database (GreenInfo Network, 2018).

Rising air temperatures resulted in increases in peak demand of 4.8-8.3% on future hottest days. The difference in LAC's peak demand across the range of historical hottest days was more significant than the potential increase due to climate change. Historically, annual hottest day average T_{max} ranged from 34-43 °C (93-110 °F), for peak demand of 9.5-12.8 GW, or a 34% difference in R&C sectors. The effects of RCPs 4.5 and 8.5 were average increases in average T_{max} from 42.7 °C (108.9 °F), allocated in the CBGs in the base period, to 44.2 °C (111.6 °F) and 44.6 °C (112.3 °F) by 2060 respectively. The resulting difference in peak demand forecasts were 12.54 and 13.14 GW in the 2060 low growth case, and 17.71 GW and 19.18 GW in the 2060 high growth case. The range of future sensitivity to air temperature is due to the range of possible technology implementations that may occur with population growth. The major difference was attributable to increase in AC penetration rates associated with building stock turnover, which had a 27-30% effect across the scenarios. New DUs with shared walls had 25-50% lower peak demand than single-family detached units at temperatures over 35 °C (95 °F). Therefore, the range of new DU types

implemented with increasing population had a 1-4% effect on peak demand across the range of allocations. Raising the AC rating from SEER 16 to SEER 21 increased peak demand by up to 2% as engineering optimization appeared to be counter effective at temperatures above 45 °C (113 °F) per the characterization in (Daniel Burillo et al., 2018) Appendix B. The effects of increases in AC penetration are generalizable to approximately 0.65% peak demand per percent AC penetration.

Verification and Uncertainty

In order to consider the reasonableness of our work, the results of the individual building models and total projections were each compared to prior studies for the base period as written below. Regarding future scenarios, a straight-line increase in peak demand with population growth would be 12% or 32% by 2060 for the Department of Finance and SCAG projections respectively. Therefore, given the range of building efficiency scenarios considered, and allocation of population to mostly warmer climate regions which already have higher AC penetration and demand, we consider both the projected increase of 2-36% in the Department of Finance case, or 16-51% in the in SCAG case to be reasonable.

Countywide peak demand was verified as being reasonably modeled in the base period. If R&C sectors account for 70-90% of total annual electricity consumption per EIA records and UCLA's Energy Atlas (Pincetl & LA Energy Atlas Development Team, 2017),(EIA, 2014b), and if the same proportion is true

for peak demand, then extrapolating our estimates of 9.5–12.8 GW yields 11-18 GW, which mostly overlaps the following three estimates ranging from 12.8–17.3 GW. First, according to EIA hourly records, peak hourly demand for LADWP was 6,870 MW in 2016, and was 2.0 times the average in that year (EIA, 2016c). Scaling LADWP’s peak demand by number of residential customers (1.3 million) by population (3 persons per household) (EIA, 2016b) to the current population of LAC (9.8 million) yields a peak demand of 17.3 GW. Second, according to the UCLA Energy Atlas, LAC’s annual electricity consumption was approximately 20 billion kWh for residential buildings, 16 billion kWh for commercial buildings, and 20 billion kWh for industrial and other in 2010, or 56 TWh total (Pincetl & LA Energy Atlas Development Team, 2017). The average of the annual median electricity consumption for LAC in 2010 over a one year hourly period was 2.3, 1.8, and 2.3 GW respectively, or 6.4 GW total (Pincetl & LA Energy Atlas Development Team, 2017). If peak demand were two times the annual average measure, then it would be 12.8 GW. Third, according to the California Energy Commission, peak demand for the entire state of California was 57—64 GW each year from 2005 to 2016 (California Energy Commission, 2014). The population of LAC is approximately $\frac{1}{4}$ the state’s population (37.3 million in 2010) (“US Census Bureau 2010 Census Interactive Population Map,” 2017), so a straight population allocation results in a peak demand estimate of 14-17 GW.

CBG specific results were limited in their precision by data processing as explained in (Daniel Burillo et al., 2018) Appendix C. Land in certain CBGs may not actually be feasible to build on due to forests, lakes, or other constraints that

were not captured. These details do not affect the overall insights of this study but should be considered in any neighborhood-specific land development studies before any specific urban development plans are implemented.

Individual building peak demand, modeled as the average of noon-6pm hourly results, were estimated within a reasonable range of historical values. According the UCLA Energy Atlas (Pincetl & LA Energy Atlas Development Team, 2017), the 2010 median annual electricity consumption for buildings was: 6,726 kWh (0.5 Wh/ft²) or 0.77 kWh per hour for single family units, 9,612 kWh (0.43 Wh/ft²) or 1.1 kW per hour for multi-family units, and 38,599 kWh (0.96 Wh/ft²) or 4.4 kW per hour for commercial buildings (Pincetl & LA Energy Atlas Development Team, 2017). The low-end of peak demand per DU across LAC in the base period was modeled at 1.5, 1.0, 0.7, and 0.7 kW for the SFD, SFA, MFS, and MFL types which were approximately twice the median values. Commercial buildings were modeled as 108 kW per building using the lowest value from the three vintages published. Those values overlapped the range of median values when considered over the range of building floor spaces listed in (Daniel Burillo et al., 2018) Appendix B. As quoted there, the use of the commercial building models exceeded their intended use in this report as they were not specifically calibrated for electricity consumption. Again, the high T_{max} commercial peak demand values are likely underestimates for, as shown in that same Appendix, they did not significantly increase with air temperature in the model.

Temperature effects on peak demand was approximately 300 MW per 1°C, or 3-4% per 1°C for the current infrastructure, which is consistent with historical observations found in (D. Burillo, Chester, Ruddell, et al., 2017), (Sathaye et al., 2013), and (D. J. Sailor & Pavlova, 2003). Increases in peak demand did not appear to decline until $T_{max} = 53^{\circ}\text{C}$, approximately 10°C higher than estimated in (D. Burillo, Chester, Ruddell, et al., 2017), attributable to the method of averaging noon-6pm building consumption for LAC's peak demand as opposed to using individual buildings' maximum hourly consumption which occurs later in the day.

AC efficiency clustering (grouping AC types into as few as possible for practical computational purposes) may have resulted in high estimates of peak demand at maximum temperatures due to the method of allocating room air conditioners into half SEER 8 and half SEER 16. Consequently, the percent demand reductions from upgrading ACs in high efficiency scenarios should be considered an upper estimate. Moreover, using only SEER ratings does not account for additional AC specifications that are known to affect performance, including compressor motor type (Faramarzi et al., 2004). Furthermore, SEER ratings are based on performance over a weighted range of outdoor temperatures from 18-40°C (65-104°F) (SCE, 2003), whereas the range of outdoor temperatures in this study are up to 54°C (129°F). Thus, model results which indicated that some SEER 21 rated ACs performed less efficiently than SEER 16 at temperatures above 40°C are not implausible as manufacturing companies have a direct financial incentive to optimize hardware to a

specification that affects average annual energy consumption as opposed to worst-case peak demand.

AC penetration initial values were obtained from (Janet L. Reyna et al., 2017) based on the RASS (CEC, 2009), equal to 0.39, 0.42, 0.39, 0.78, and 0.61 for CZ 6, 8, 9, 14, and 16 respectively. These values were different than the values estimated in the Energy Commission's Residential Energy Demand Model, which were also based the RASS at 0.908, 0.514, 0.595, 0.730, and 0.742 for CZ 6, 8, 9, 14, and 16 respectively. Values from (Janet L. Reyna et al., 2017) were used because it is more reasonable that the coolest climate zone, CZ6 would have the lowest AC penetration value, not the highest. Increase in AC penetration was computed only with building turnover and the addition of new buildings, which may be conservative, as people may purchase AC units for the first time in existing buildings during a heat wave.

Other factors. We did not consider electrification of other technologies such as natural gas ovens, stoves, water heaters, nor petroleum-based vehicles. Efficiency improvement of home appliances was projected in (Janet L. Reyna et al., 2017) to reduce annual electricity consumption by 13-15% for water heaters, refrigerators, and television/computers each. If that consumption were spread evenly throughout the day, then it would have a 1-2% effect on peak demand. Electric vehicles could have positive or negative effects on peak demand depending upon their charging schedules and whether or not battery discharging is realized.

Discussion

Our results show that wide ranges of increases in peak demand are possible for LAC relative to both total resource adequacy requirements and geographic location. This could pose significant problems or opportunities depending upon the constraints on existing infrastructure capacity. For example, because LAC is already a net importer of electricity (D. Burillo, Chester, & Ruddell, 2017), if peak demand increases more than current transmission capacity can support, then either new long-distance transmission will need to be built, at \$1-3 million per mile (Mason, Curry, & Wilson, 2012), or new local generation. If growth occurs disproportionately along the outskirts of the network, and land is readily available, then either option may be practical to meet demand. However, if demand increases are concentrated downstream within the delivery network, then options could be severely limited. Even if transmission capacity is available in the future, central generation systems may not be viable sources of energy production as local lines and substations may not have the capacity to support the additional power flow. This could be especially true in the already well-developed central urban areas. Conversely, growth in such congestion-limited regions could be prime locations to pilot “smart city” grid modernization projects with distributed solar PV and storage that could offset peak load on delivery infrastructure and meet California state renewable generation goals such as SB 350 (California Energy Commission, 2018).

As grid modernization efforts are being directed towards reducing emissions from the electricity sector with clean local renewable sources, future

research can use the same bottom-up tools as developed in this study to aid in siting and sizing capital investment projects. California is already experiencing significant issues with the phenomenon called the “duck curve,” in which rooftop solar PV is offsetting demand from the perspective of the grid during the day and shifting peak load later towards sunset (California ISO, 2016). The surplus generation is so significant during the day, that California has paid Arizona to take the excess (Toll, 2016). Thus, energy storage (e.g. batteries) are becoming higher priority in balancing load on distribution circuits as solar PV penetration is increasing (CA ISO, 2017). However, the levelized cost of battery energy is still two orders of magnitude higher per kilowatt-hour than for other fuel sources (Zakeri & Syri, 2015). Hence, identification of critically congested circuits is valuable, as upgrading distribution lines and substations may be even more costly in certain areas (e.g. \$10-130 million USD per substation and \$1-3 million USD per mile of line length (Mason et al., 2012)), especially considering parallel power flows. To address this, the residential and commercial building energy models used in this study could be further calibrated throughout each hour of the day to characterize the difference between the demand profile and the shifting load profile that is occurring with the implementation of distributed solar PV. Combined with local infrastructure capacity data, the difference in the performance curves would provide critical insight into the amount of peak load that would need to be shifted to maintain safe operating contingency capacities on the components. Moreover, such tools would support developing specifications for batteries to meet demand during near-peak hours after sunset.

Improvements in building and appliance energy efficiency can also play a significant role in maintaining peak demand at current levels, and thus safeguarding contingency capacities on infrastructure components. The major opportunity identified in the results was that dwelling units with shared wall spaces had as much as 50% less peak demand per capita in the models than single-family detached units. Because 60—70% of peak demand within residential buildings was attributable to AC, the increase in peak demand associated with increased AC penetration can be roughly cancelled if old single-family detached dwelling units are replaced with new high efficiency multifamily units. Moreover, replacement of older ACs with newer units resulted in decreases in peak demand that created room for about 10% population growth in the central basin area.

Beyond the next update to improve AC efficiency standards to SEER 16, different, or differently optimized AC, additional technologies will be necessary to reduce peak demand within the residential sector. Peak demand will be more sensitive to air temperature in the future, as AC penetration increases, and therefore future work should consider tradeoffs between AC standards that result in designs which are optimized to minimize annual energy use as opposed to peak demand. While improvements in AC SEER ratings are significant for total annual electricity consumption, their effects on peak demand saturate and become counter effective after SEER 16. A different metric is necessary to optimize for performance under extreme heat conditions. A new “peak performance rating” for ACs could be useful to adapt to extreme heat conditions

as there would then be incentive for ACs to be engineered for more efficient performance at over 45°C (113°F).

CHAPTER 5

INFRASTRUCTURE VULNERABILITY ASSESSMENT

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Highlights

1. Components vulnerable to rising air temperatures by 2-20% of rated capacity.
2. Only infrastructure at Santa Monica Bay not vulnerable to temperatures above 40°C (104°F).
3. Population growth and technology affects peak demand more than climate change.
4. Santa Clarita, Lancaster, Palmdale and West Valley to Pomona at highest risk.
5. Need for 848—6,724 MVA (4-32%) of new substation capacity, DER, or load shifting.

Abstract

Heat waves have posed serious challenges to electricity infrastructure, including a major blackout in Southern California in 2011 and emergency curtailment in 2014. Understanding how future temperature change might impact future electric power systems is critically important to ensure the future operational reliability. Using existing spatial projections of peak hour electricity demand for Los Angeles County (LAC)—with consideration for rising air temperatures under RCP 4.5 and RCP 8.5 at 2 km² grid cell resolution, two population growth scenarios, new residential and commercial buildings, higher air conditioner (AC) penetration, and improved AC efficiency—we estimated vulnerabilities in the LAC’s electricity infrastructure to 2060. Results were that generators, substations, and transmission lines, except those near the Santa Monica Beach, could lose 2—20% of safe operating capacity due to air temperatures above 40 °C (104 °F). We further allocated spatial forecasts of peak demand to substations—using a Voronoi polygon method and the components’ de-rated capacities during heat waves—and identified where and by how much substations could exceed thermal limits and be automatically tripped by protection gear. Based on recent historical load factors for substations in the Southern California Edison service territory, an additional 848—6,724 MW (4-32%) of delivery system capacity will be needed by 2060 to maintain reliable operations, not including the Los Angeles Department of Water and Power (~1/3 of the county). Some of that system capacity may be met more cost-effectively by investment in distributed energy resources than in new central generation plants

and/or substations and/or transmission lines. If increases in peak load cannot be mitigated and/or additional infrastructure capacity cannot be added in the corresponding locations, then LAC's electricity infrastructure will be vulnerable to outages and cascading failures during heat waves.

Keywords: electricity infrastructure; vulnerability assessment; capacity shortages; climate change; extreme heat; peak demand

Introduction

Research into the effects of climate change on electric power infrastructure systems is still in its nascent stages, and has so far largely focused on national and regional scales (Asian Development Bank, 2012; Forzieri et al., 2018; IPCC, 2013; Panteli & Mancarella, 2015; Ralff-Douglas, 2016; US Department of Energy, 2016). Dozens of studies have considered how power generation capacity could be reduced (M. D. Bartos & Chester, 2015; Bonjean Stanton, Dessai, & Paavola, 2016; D. Burillo, Chester, Ruddell, et al., 2017; Miara et al., 2017; van Vliet, Wiberg, Leduc, & Riahi, 2016). Likewise, many studies have considered how electricity demand can increase with extreme temperatures, i.e., more air conditioning (AC) load during higher highs and heating load during lower lows (Auffhammer, Baylis, & Hausman, 2017; M. D. Bartos et al., 2016; D. Burillo, Chester, Ruddell, et al., 2017; Garcia-cerrutti et al., 2012; Janet L. Reyna et al., 2017; David J. Sailor, 2001; David J. Sailor & Muñoz, 1997; Santamouris et al., 2015; Sathaye et al., 2013). Most of the studies

of climate change effects on electricity demand were either based on high-level statistical methods or focused on total annual energy demand, and only a few have considered peak demand, which causes the most stress in other components (Dirks et al., 2015). Moreover, while it is generally understood that too much heat stress on materials can cause physical damage, evidenced by the existence of circuit breakers and protection relays (IEEE - PES, 2013; IEEE, 2012; IEEE Standards Association, 2012), only a few studies have attempted to quantify how delivery components will be affected by rising air temperatures (M. Bartos et al., 2016b; Sathaye et al., 2012). No single study has been identified that has considered all of these factors together at sub-city scales including their dependencies to delivery power from generators to loads. Synthesizing understanding of the effects of climate change on components and processes has enabled us to consider infrastructure vulnerabilities inclusive of the multiple conditions necessary for service interruptions to occur. The concept of vulnerability is particularly useful for describing states of susceptibility of systems to harm, and for guiding actions to enhance well-being through reduction of risk (Adger, 2006), which in this case is shortages in electricity supply and/or delivery capacity that results in unmet demand.

We defined our system boundary in this study for delivery infrastructure to include components at the transmission level, because multiple simultaneous outages during heatwave can and have resulted in blackouts affecting millions of people (FERC, 2003; Ferc & Nerc, 2012). While the majority of service interruptions occur at the distribution level, where there is little or no redundancy,

there is also very little potential for cascade and so the results tend to affect fewer customers (Hines et al., 2009). Excessively high temperatures can result in service interruptions at the transmission level via a combination of high demand, and (i) insufficient cumulative generation resources, or (ii) insufficient capacity in delivery components, or (iii) widespread cascading failures due to a combination of multiple instances of either of the former (Bie, Lin, Li, & Li, 2017; Hines et al., 2009; Panteli & Mancarella, 2015). Of the North American power outages and blackouts that have resulted from failures at the transmission level, 25—50% can historically be related to causes that can be influenced by rising air temperatures, including operation failures, fires, over demand, and supply shortages—which are standard reporting “cause codes” used by NERC and Eaton (Eaton, 2013; Nerc, 2015; Vaiman et al., 2012).

Electricity infrastructure can be affected by rising air temperatures in two ways that are relevant to this study’s methodologies for the quantification of vulnerabilities. First, there can be a direct reduction in the components’ (generator, transmission line, or substation) safe operating capacities. Since electric power flow creates heat, and components can only tolerate so much before protection gear trips or internal parts physically break (IEEE, 2012), their capacity to support power flow can decrease as ambient air temperatures rise. Second, there can be an increase in the load on those components due to increased AC use as previously cited. Hence, we use the term thermally *de-rated component capacity* to refer specifically to the reduction in wattage that electricity generators can safely supply, or that transmission lines and substations can

safely deliver to loads. We also use the term *de-rated load factor* to refer to the percent loading of peak hour electricity on the component for its thermally de-rated capacity.

Developing a spatially explicit quantitative understanding of electricity infrastructure vulnerabilities to climate change is critical for long-term capital investment planning (Ge, Wang, Lu, & Liu, 2015; Zhu et al., 2016). Doing so supports identification of locations and magnitudes of potential future hazards, as well as tactical maps for siting future adaptation projects. Because Los Angeles County, California (LAC) has both expansive existing infrastructure in moderate climate zones, and significant demand for new infrastructure in the same and developing areas with warmer climate zones, studying LAC provides an interesting case study, which will likely yield transferrable lessons for other cities around the world. The combination of reliable electricity and affordable AC technologies has resulted in cities in LAC growing and expanding into regions with air temperatures that are otherwise considered uncomfortable and often pose public health risks, including the northern San Fernando and Antelope Valley areas (Association, 2016; Taleghani et al., 2013; Yang et al., 2014), which have historically reached temperatures of up to 52 °C (126 °F) (F. Sun et al., 2015). We used forecasts of how peak demand could increase in LAC at a census block group (CBG) or neighborhood-scale, considering similarly high-resolution forecasts of air temperature, population growth, building density, and appliance efficiency (Daniel Burillo et al., 2018). LAC already imports over 1 GW of peak demand during the summer, and has the capacity to import significantly

more power (CPUC, 2016; EIA, 2016c). But, if there is insufficient capacity in the delivery network on path to the load locations, then either new generation plants will need to be sited closer to loads, or distribution capacity expanded, or demand somehow shifted from peak to off-peak hours, or demand met via some form of distributed energy resources (DER) such as onsite solar PV and batteries (Willis et al., 2001). With a better understanding of electricity infrastructure vulnerabilities in LAC, we can better evaluate how public policy can develop adaptation measures to meet the risks of extreme heat events from climate change.

Long-term investments are inherently a matter of public policy because electric power is a critical infrastructure system (Rinaldi et al., 2001). California and Los Angeles specifically, have been leaders in developing environmental policies that affect the electric power sector, including reducing greenhouse gas emissions and conserving limited natural resources, such as the Zero Net Energy plan (“California’s Zero Net Energy Action Plan | Latest on ZNE,” 2018), building energy standards (CEC, 2016), renewable portfolio standards (“Community GHG Inventories For Cities In LA County,” 2017), climate action plans (Los Angeles County Department of Regional Planning, 2017), and more (Vine, 2012). Furthermore, according to Senate Bill X1-2 (Simitian, Chapter 1, Statutes of 2011), all retail sellers of electricity shall serve 33% of their load with renewable energy by 2020, and according to SB 350, 50% by 2030 (California Energy Commission, 2018), California has made significant progress on those goals achieving 30% renewable energy as of November 2017, with 57% originating

from solar PV (California Energy Commission, 2017), and more planned (LADWP, 2016c; SCE, 2015). But not all of that energy has the same value in the system; California has produced so much surplus generation for solar PV during mid-day off-peak hours that it has paid Arizona to take some of it (Penn, 2017; Toll, 2016). Because of these time-of-day capacity and usage issues, a mix of solar PV in conjunction with some form of complementary storage (e.g., batteries), fast-ramping central generation (e.g., natural gas), and or power imports will have to be implemented to meet future demand as regulated by California policies.

Using the results from a recent LAC-specific climate study with spatial projections for air temperature and peak demand (Daniel Burillo et al., 2018), recently released spatial data on infrastructure from the US Department of Homeland Security (Homeland Infrastructure Foundation-Level Data, 2017a, 2017b), and substation load data from Southern California Edison (SCE) (Southern California Edison, 2016a), we asked and answered several questions. First, how much capacity would be reduced at individual generator plants, transmission lines, and substations with higher air temperatures? Second, considering both increase in peak demand for future scenarios and decrease in capacity, what would the de-rated load factors be for components throughout the county in the future? Third, what neighborhoods or cities have the highest risk of delivery infrastructure capacity shortages, and should therefore be prioritized for capital investments and/or demand-side-management programs?

Methods

In order to understand where and how new infrastructure should be effectively built in LAC to meet future demand and avoid outages from climate change induced heat waves, we conducted a vulnerability analysis of the major components to rising air temperatures and peak demand through 2060. Electricity infrastructure sensitivities to extreme heat were estimated for generation, substation, and transmission line components individually, and then evaluated together as vulnerabilities for outages. First, sensitivities were considered in terms of potential de-rating due to high air temperatures only, i.e., decreases in percent loadability or reduced MW capacity at generators, MVA capacity at substations, and ampacity in transmission lines. Second, vulnerabilities were assessed for components in terms of potential future de-rated load factors by considering both decrease in loadability (de-rating) due to higher air temperatures, and increases in peak hour loading due to combined population growth and technology change under higher air temperatures from prior forecasts (Daniel Burillo et al., 2018). Due to data constraints, future de-rated load factors were estimated for total generation and individual substations, but not transmission lines. Estimating load factors at individual generator plants would not be particularly valuable in this analysis, as they work collectively to provide power in conjunction with transmission imports to supply power to the region. Therefore, generation capacity was considered in aggregate in terms of local reserve margin, with results indicative of either increased need for additional local generation capacity, peak reduction, and/or imports.

Extreme heat effects were evaluated using 2 km² grid cell resolution projections for the daily maximum air temperature (T_{max}) from (F. Sun et al., 2015; Walton et al., 2015), for a base period of 1981-2000, and two future periods, 2021-2040 and 2041-2060. Future projections were based on the standardized climate change scenarios from the Intergovernmental Panel on Climate Change (IPCC) Representative Carbon Pathway (RCP) scenarios: RCP 4.5 and RCP 8.5 for low and high scenarios respectively. Rising air temperatures were considered spatially in terms of (i) relative increase throughout the county, at approximately 1.5 °C (2.7 °F) by 2040 and 2 °C (3.6 °F) by 2060 on average, and (ii) degrees above 40 °C (104 °F). The approach of considering degrees above 40 °C (104 °F) was used because that is the value listed in the ANSI/IEEE standards cited in SCE's Interconnection Handbook (Southern California Edison, 2016b), and may be problematic if that is the rating that all hardware are designed for. Some locations in LAC reached as high as 50°C (122 °F) in the base period from 1981-2000, and some in the future in RCP 8.5 could reach as high as 54 °C (129 °F) by 2060. Two sets of air temperature projection images were used as previously developed in (Daniel Burillo et al., 2018), **composite** images and **hottest day** images. First, composite images were of the highest projected T_{max} in each 2 km² grid cell for each time period and RCP scenario. Second, hottest day images were of the T_{max} in each grid cell on the day that the highest average T_{max} occurs across the county for each period and RCP. These two definitions respectively inform capacity derating factors for individual

components and the total resource adequacy requirements for the region as a whole during a possible record-breaking heat wave.

Two sets of peak demand forecasts were used based on low and high projections of change in air temperature, population, buildings, and appliance efficiencies. The low case based on the California Department of Finance's (DoF) projections of population growth, which was mostly in the northern San Fernando and Antelope Valley region, and the other based on the Southern California Association of Government (SCAG) which included about double the population growth with infill in the basin area. It is important to note that the demand forecasts were for residential (Janet L. Reyna et al., 2017) and commercial (Deru et al., 2011) (R&C) buildings only, and did not consider industrial or other sectors. A summary of all the urban infrastructure scenarios considered is listed in Table 7, and results in Table 8. See (Daniel Burillo et al., 2018) for high-level sector comparison analysis, as well as additional analysis differences within R&C sectors including in multifamily and single-family dwelling units, commercial building types, and air conditioner types.

Table 7. Summary of Urban Infrastructure Scenarios.

Case	Model parameter(s) affected	Low	Medium	High
Growth	Population growth # of new dwelling units per period (3 people per DU) # of additional commercial buildings	1.2 million CA DoF / USGS projection	Average	3.1 million SCAG projection
	Building turnover rate (replacement with new buildings)	0.03% per year	0.3% per year	3% per year
	AC penetration	Central AC in all new buildings from turnover and population growth		
Energy Efficiency	Housing Density Percent allocation of new dwelling units by residential building type.	SFD - 47 SFA - 08 MFS - 24 MFL - 21	SFD - 28 SFA - 05 MFS - 36 MFL - 31	SFD - 09 SFA - 01 MFS - 45 MFL - 45
	Total ratio of (MF/SF) for new DUs	(55/45)	(67/33)	(90/10)
	Residential ACs (all DUs, new and pre-existing)	SEER 16	SEER 19	SEER 21

*Acronyms: United States Geological Survey (USGS), Department of Finance (DoF) Southern California Association of Governments (SCAG), dwelling unit (DU), multi-family (MF), single-family (SF), single-family detached (SFD), single-family attached (SFA), multi-family small (MFS), multi-family large (MFL).

Table 8. Range of Peak Demand Projections for LAC for Residential and Commercial sectors only

Time Period	LAC Total Peak Demand (GW)			
	Finance - Low	Finance - High	SCAG - Low	SCAG - High
<i>Hottest Day</i>				
2010	9.5	12.7	-	-
2040	12.3	15.8	13.1	16.7
2060	13.0	17.3	14.7	19.2
<i>Composite</i>				
2010	-	13.5	-	-
2040	12.9	17.3	13.8	18.4
2060	13.6	18.8	15.4	20.9

Generation

Vulnerabilities in generation were first assessed as potential capacity (MW) losses due to high air temperatures at sensitive generation plants. Sensitive generation plants in LAC were designated as dry-cooled natural gas plants, the dry-cooled portion of combined cycle natural gas plants, and solar PV plants. The location of these plants is shown in Figure 11 (US Energy Information

Administration, 2017), with values as listed in Table 9 assumed relative to $T_{max}=40^{\circ}\text{C}$ (104°F) (D. Burillo, Chester, Ruddell, et al., 2017). Wet-cooled plants were modeled with zero capacity losses for air temperature (Henry & Pratson, 2016). Availability of cooling water, cooling water temperature, potential for mechanical failures, and imports from neighboring regions were categorically out of scope and not considered in this study of air temperature effects on infrastructure within LAC. Vulnerabilities were estimated for individual generators for temperatures in excess of 40°C (104°F) using the composite T_{max} projection images (Daniel Burillo et al., 2018). Derating factors were attributable due to chiller performance at the air intake of dry combustion engines for natural gas plants (Brooks, 2000; Henry & Pratson, 2016; Maulbetsch & DiFilippo, 2006; Sathaye et al., 2012), and due to internal carrier recombination rates from thermal excitation of solar PV modules (Dubey et al., 2013). Hydropower plants are known to be vulnerable to climate change, estimated between 0.4-14% to 2060 in the US, but primarily due to reduced water availability from drought, as opposed to higher air temperatures directly (M. D. Bartos & Chester, 2015; Henry & Pratson, 2016; van Vliet et al., 2016). Therefore, as those types of plants account for only 2% of the generation in LAC, hydropower derating was considered negligible in this study. Capacity losses were tabulated for the LAC generation fleet for both average temperature rises and for temperatures in excess of 40°C (104°F) predicted by 2040 and 2060 under RCPs 4.5 and 8.5.

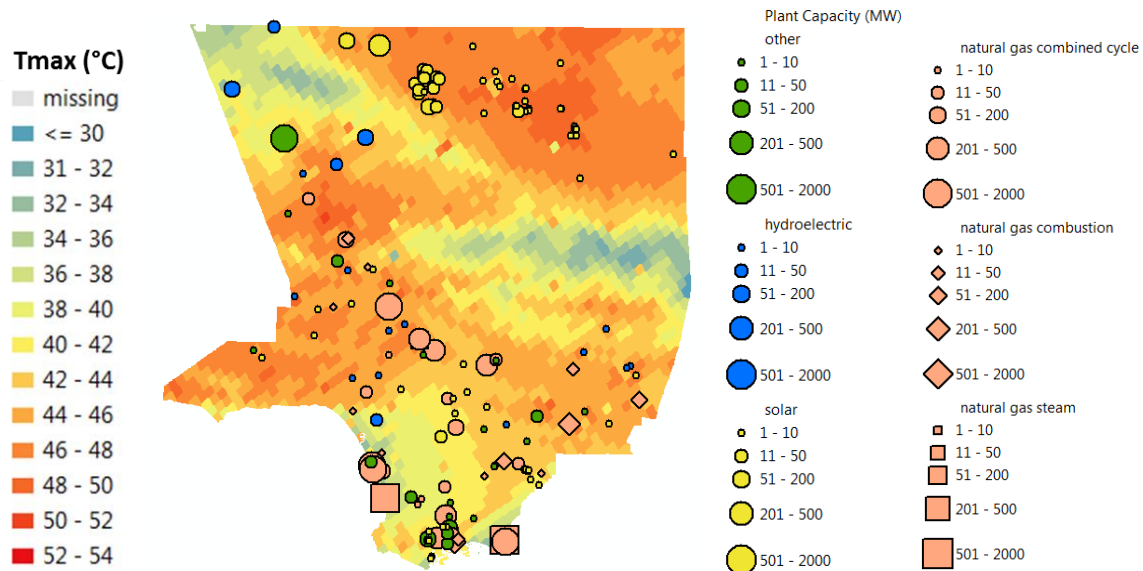


Figure 11. Map of Power Plants by Type and Capacity Overlaid to T_{max} on Historical Hottest Day.

Table 9. Power Plant Capacities by Type and High Air Temperature Derating Factors

Generation type	Count	Power Plants Capacity (MW)	Derating factor (%/1°C- T_{max})
Hydropower	18	284	-
Natural Gas (steam)	3	3,406	-
Natural Gas (combustion)	15	1,044	0.6% ± 0.1%
Natural Gas (combined cycle)*	23	5,742	0.3% ± 0.1%
Solar PV**	91	890	0.35% ± 0.25%
Other***	24	2,137	-
Total	17	4	13,503
			0.20% ± 0.06%

*Includes three “natural gas other” plants with total capacity of 4.4 MW.

**Includes one 3.2 MW solar thermal plant without storage.

***Includes, by size: pumped storage, biomass, other, and petroleum.

Vulnerabilities in generation were also quantified in terms of local reserve margin (LRM), i.e., the amount of generation capacity in excess of peak demand for the region. LRM is important to consider for security reasons, because if there is an outage in the long-distance transmission lines, then cities must have enough local power generation for other critical infrastructure systems, as well as

basic living provisions in residential buildings, or else catastrophic impacts could occur. LRM was projected to decrease for two separate and distinct reasons. First, plants have reduced generation capacity under the stress of higher ambient air temperatures on the hottest days. Second, there will be higher demand for electric power on the hottest days when ambient air temperatures are highest. Peak demand values used in the LRM calculations are listed in Table 8, plus the greater of 5 GW or 50% as a conservative estimate of industrial and other sector processes that could scale with population growth (Daniel Burillo et al., 2018).

Substations

Substation vulnerabilities were first assessed in terms of derated capacity (kVA) of transformers due to rising air temperature only, and second in terms of temperature-adjusted load factors, considering future demand increases. Substation data were obtained from (Homeland Infrastructure Foundation-Level Data, 2017b), and modeled with derating factors of 1% and 1.5% kVA per 1°C (1.6 °F) for $T_{max} > 40$ °C (104°F) (IEEE Standards Association, 2012) for low (66-138 kV) and high voltage (230-500 kV) units. Load factors were estimated for a large sample (50-70%) of the substations owned by SCE where data were available for substation capacity (kVA) and recent historical peak load (Southern California Edison, 2016a). Load factors were defined as peak load divided by capacity, which we assumed was initially for 40 °C (104 °F) unless otherwise specified in our weather-adjustment derating. Composite temperature images were used for future demand forecasts to estimate the highest stress at any

substation. Since we did not have precise data as to which buildings are served by which substations, we allocated prior building peak demand projections, at CBG resolution, (Daniel Burillo et al., 2018) to substations by nearest distance. This was done using a two-layered Voronoi Tessellation clustering approach. Voronoi Tessellation is a method to partition a plane with respect to a set of initial points of reference. The process results in the production of a set of contiguous polygons which define the boundary of the area that is closest to each individual point of reference, in this case the clusters of substations. This approach has been used significantly for optimization problems of substation planning based on substation capacity and load factors (Ge et al., 2015; S. Wang, Lu, Ge, & Wang, 2014; Zhu et al., 2016). Two layers were created such that peak demand was allocated to both high-voltage substations and low-voltage substations by nearest distance and substations within 2 km and 1 km radius were clustered respectively. This approach was an approximation in consideration of both shortest path distance to service loads, as well as parallel and series power flows within the delivery system for high- and low-voltage substations. This process is detailed in a technical appendix of (Daniel Burillo et al., 2018), including verification in which the historical substation load factors estimated were within 15% of SCE DERiM data values. Future scenario load factors were estimated by scaling the load at the substations by the corresponding percentage increase in demand relative to base period demand in each polygon. Weather-adjusted load factor ratings were classified as described in Table 10 for the reasons as listed accordingly.

Table 10. Substation Derated Load Factor Risk Metrics

Load Factor	Risk Level	Reference	Description
n/a	Unknown	n/a	Substation(s) exists in this space according to national database (Homeland Infrastructure Foundation-Level Data, 2017b), but not shown in SCE DERiM (Southern California Edison, 2016a), so load factor data were unavailable.
0.01-0.5	Very Safe	Assumption	Negligible thermal wear, probably n-2 reliable if in parallel/redundant configuration.
0.51-0.85	Safe	15% rule	Very low thermal wear, probably n-1 reliable if in parallel/redundant configuration.
0.86-1.00	Caution	15% rule	Some thermal wear, probably not n-1 reliable.
1.01-1.20	Warning	(IEEE, 2012; Southern California Edison, 2016b)	Moderate thermal wear, component overloaded, automatic switching may occur within 24 hours to 30 days if loading continues at this level depending upon switch gear settings.
1.21-2.00	Emergency	(IEEE, 2012; Southern California Edison, 2016b)	Significant thermal wear, component very overloaded, automatic switching may occur within 30 min depending upon switch gear settings.
> 2	Outage	(IEEE, 2012)	Extreme thermal wear, switchgear will automatically trip to prevent combustion and permanent hardware damage.

Transmission Lines

Transmission line vulnerabilities were assessed as potential decreases in ampacity. Spatial line data were obtained from the Department of Homeland Security in (Homeland Infrastructure Foundation-Level Data, 2017a), rated based on voltages from 66 kV to 1,000 kV. Transmission line capacity (MVA) data were unavailable, therefore we were unable to calculate changes in load factor symmetric with the substation and generator analysis. The IEEE standard steady state thermal balance equations for calculating the current-temperature relationship of bare overhead conductors (IEEE - PES, 2013) was used to consider the effects of air temperature on the maximum safely allowable current.

Lines were classified as above and below 200kV with derating factors of $0.6 \pm 0.3\%$ and $1.5 \pm 0.6\%$ Amps per 1°C per the model sensitivity analysis in (Daniel Burillo et al., 2018) using component parameters from (IEEE - PES, 2013; Nexans, 2014; Southern California Edison, 2016b; US Department of Agriculture, 2009). The basic high-level equation is $q_c + q_r = q_s + I^2RT_c$, where the sum of the convective (q_c) and radiative (q_r) heat loss of the line is equal to the heat gain from the sun (q_s) plus the power flow on the line times the conductor temperature. The power flow on the line is equal to square of the current times the resistance, thus we calculated the ampacity by solving for the current as explained in the IEEE standard. The top five most significant attributes identified in the sensitivity analysis were the conductor resistance at 25°C (77°F), the maximum allowable surface temperature, the conductor diameter, air temperature, and emissivity based on parameter ranges used in the study taken from the IEEE standard, SCE, power line performance specifications and weather data specific to LAC (IEEE - PES, 2013; Nexans, 2014; Southern California Edison, 2016b; US Department of Agriculture, 2009).

Overall

With generation, substation, and transmission capacity sensitivities to air temperatures estimated, and with prior forecasts of changes in peak demand in (Daniel Burillo et al., 2018), we considered overall system vulnerability and adaptation options. The overall vulnerability of the infrastructure was considered in terms of the changes in demand relative to changes in supply with

consideration for reductions in capacity throughout the County. Each component class can potentially constrain the system. For example if there is insufficient generation capacity, then transmission and substation capacities are irrelevant, or if there is insufficient substation capacity, then so on. We estimated the total generation requirement including the additional de-rated generation capacity that would be needed to meet total future demand on the hottest day. We also estimated the need for additional substation capacity, distributed energy resources, or some form of demand side management to reduce and/or shift peak load geographically to keep substations in safe operating conditions with load factor at or below one for the scenario projections considering both air temperatures at 40°C (104 °F) and for our composite image approach for air temperatures.

Results

Generation

Of the 13.5 GW of power generation physically located within the County boundary, shown in Figure 11, up to 240 MW (1.8%) are vulnerable to increases in air temperature. The majority of the vulnerable generation are the 23 combined cycle and 15 combustion natural gas plants located in the San Fernando Valley (northwest) and on the outer basin areas away from the ocean. By 2060, under RCP 8.5, T_{max} at natural gas plants was projected to range from 40-53 °C (104-127 °F) resulting in 3-9% less capacity than 40°C (104 °F) summertime rated values. Total capacity of natural gas plants would be 69-104 MW (0.7-1.5%) less

than present ratings. The 90 solar PV generation plants are also vulnerable, most significantly in Antelope Valley. Maximum temperatures at solar PV plants ranged from 44-54 °C (111-129 °F), and if such extreme temperatures were realized, individual solar PV output could be 1-8% lower than rated. The total capacity loss of solar PV on the hottest day would be 8-45 MW less than present ratings. The estimated capacity loss of the entire fleet on the hottest day was 110 MW, or approximately half of the total vulnerable capacity identified using the composite T_{max} projection images. Based on the range of temperatures already observed in the historical period, 75 MW of capacity is already vulnerable to temperatures in excess of 40°C. Average total plant capacity losses were estimated at 35 MW for average warming by 2060 under RCP 8.5. Los Angeles County's current local reserve margin was estimated to be negative by 1-6 GW, which is not disagreeable with the value estimated in (D. Burillo, Chester, Ruddell, et al., 2017), or presented in (CPUC, 2016) for SCE territory. This means that the county needs to be able to import from neighboring regions 1-6 GW of electric power during heat waves. In practice, imports and exports are not accounted for by county, but LAC had approximately 13 GW of import capability as of 2017 from Arizona, Nevada, the Pacific Northwest, and San Diego Gas and Electric (CPUC, 2016). In the worst-case scenario modeled, the need for additional local generation and/or imports increased to 15 GW by 2060. The full range of simulated LRM values are listed in Table 11, where the minimum increase in peak hour generation capacity needed to meet future peak demand was 3.1 GW by 2040 and 3.8 GW by 2060 for the low growth, high efficiency

scenarios under RCP 4.5. Again, details of factor contributions are explained in (Daniel Burillo et al., 2018). While it is possible to invest in generation capacity outside of LAC and long-distance transmission imports to meet future peak demand, doing so exclusively could result in substantially negative LRMs, such that less than half of the County's peak electricity demand would be able to be met if imports were unavailable.

Table 11. Estimated Local Reserve Margins for Time Period, Population, and Demand Scenarios

Time Period	Local Reserve Margin GW (%)			
	Department of Finance - Low	Department of Finance - High	SCAG - Low	SCAG - High
2021-2040	-3.9 (-29%)	-10 (-77%)	-4.7 (-35%)	-12 (-87%)
2041-2060	-4.6 (-35%)	-12 (-93%)	-6.3 (-47%)	-15 (-115%)

*Base period LRM estimated between -0.8 and -5.7 GW (-6% to -42%)

Substations

Of LAC's 410 substations, 99% are vulnerable to air temperatures over 40 °C (104 °F), including reductions in loadability of up to 20% of their kVA ratings. For worst-case temperature projections, 24 unknown capacity substations (presumably low voltage convective air cooled) and one 138 kV substation, across Antelope Valley, San Fernando Valley, El Monte, and Pomona could experience temperatures up to 51-53 °C (123-127 °F) and be safely loadable at 16-20% less than their summertime 40°C kVA ratings. Substations within 5 km (3.1 mi) of the Santa Monica, Manhattan, and Torrance beaches were projected to have capacity losses no more than 5% as temperatures were not projected to rise above 42 °C (108 °F). As shown in Figure 14, results for different time periods and RCPs were within 2% kVA, 70% of substations were projected to

experience average capacity losses of 1.5-3% kVA due to average warming, and 60% of substations were projected to experience capacity losses of 6-12% during heat waves due to temperatures in excess of 40°C (104 °F).

Over half of SCE's substations were identified as being at risk of overloading with the base-period urban infrastructure in the event of an extreme heat wave. The colored Voronoi polygons in Figure 12 represent the estimated geographic coverage of SCE's substations as listed in the DERiM data set. The grey polygons are areas for substations owned by other service operators (mostly the Los Angeles Department of Water and Power), and the other grey shaded regions are masked as those were places with >50% area classified as protected lands per the 2017 California Protected Areas Database (GreenInfo Network, 2018). A map of service territories by system operator can be seen in the link in reference (SocalEV, 2015). As shown in Figure 12, the majority of SCE's substation areas throughout the region were projected to operate at a weather-derated load factor in the 1 to 1.2 range under the highest historical temperatures.

In all future scenarios, at least a few substations were projected to exceed tolerance for automatic outage trips with a derated load factor in excess of two. With implementation of high efficiency measures, and population growth limited to mostly out-of-basin areas, then most substations in the central basin area were projected to actually realize reduced loading by 2040. But in all other scenarios, either without improved building and AC energy efficiency, or with any form of in-basin densification, most substations were projected to be vulnerable

to emergency (>1.2) or automatic outage (>2) load factors during the peak hour of an extreme heat wave. The loading pattern for 2060 is shown in Figure 15 in the Overall results sub-section for 2060, which is the same but more severe as for 2040.

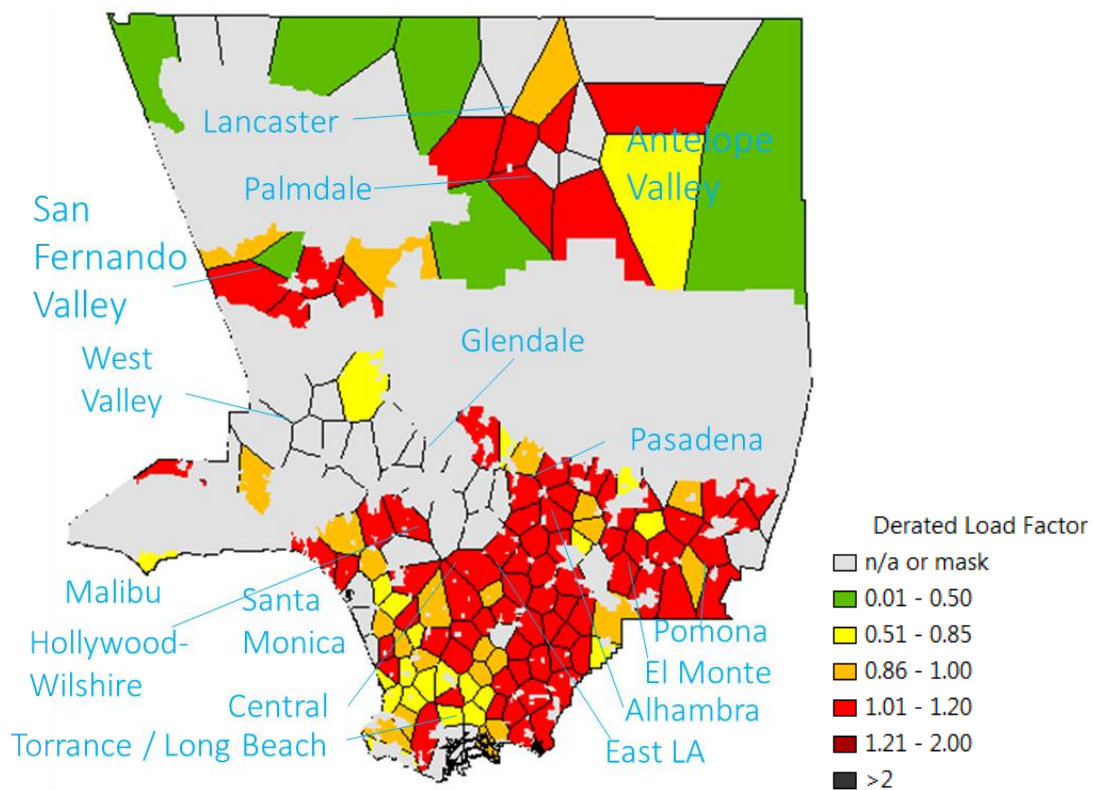


Figure 12. Map of Present Day SCE Substation Vulnerabilities. Current substation load factors derated for composite historical heat waves. I.e., this is what the peak hour could look like this summer in any spot on the map.

Transmission Lines

Of LAC's 185 transmission line segments and 3.5 million meters (2,200 miles) of conductor length, all of the segments and 99% of the length were projected to be vulnerable to air temperatures over 40 °C (104°F). Similar to substations, reductions in ampacity were projected up to 20%. In the highest

temperature projections, the higher voltage lines (230-1,000 kV) across Antelope and San Fernando Valley could experience T_{max} up to 47-54 °C (117-129 °F) and experience 2-13% ampacity reductions from their summertime 40°C ratings. As shown in Figure 13, the lower voltage transmission lines (66-138 kV) were generally projected as more vulnerable than the higher voltage due to higher sensitivity of the lines to air temperatures. Lines located in and around the Hollywood-Wilshire regions were projected to be most vulnerable, with T_{max} up to 47-50 °C (117-122 °F), and corresponding reductions in ampacity of 6-20%. Also similar to substations, and shown in Figure 14, the results only varied by up to 2% of ampacity on any line across time periods and RCPs. The least affected lines were the shorter segments near the Santa Monica Bay and In-Basin areas. Some lines appear to have overlapped colors in Figure 13. This is due to differences in line segment length and the presence of hotspots. I.e. some lines have higher ampacity loss in the same location on the map because those line segments also cross other areas with higher heat exposure.

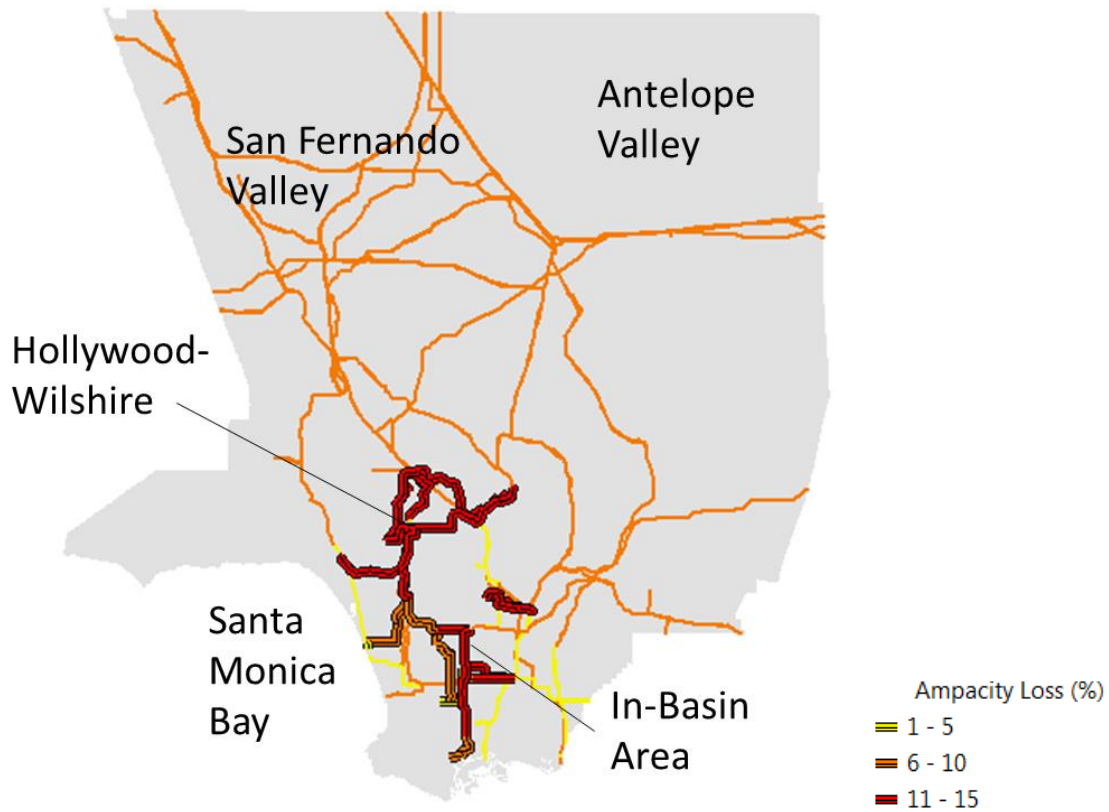


Figure 13. Map of Worst-Case Losses of Transmission Line Ampacity for Composite Temperatures in 2060 RCP 8.5. Percent loss values shown are based on average derating factors. High voltage (230-1,000 kV) lines' values should be considered $\pm 50\%$, and lower voltage (66-138 kV) lines' $\pm 33\%$. I.e., 6% refers to 3-9% or 4-8% accordingly. Low voltage lines are shown in bold stripes in this figure.

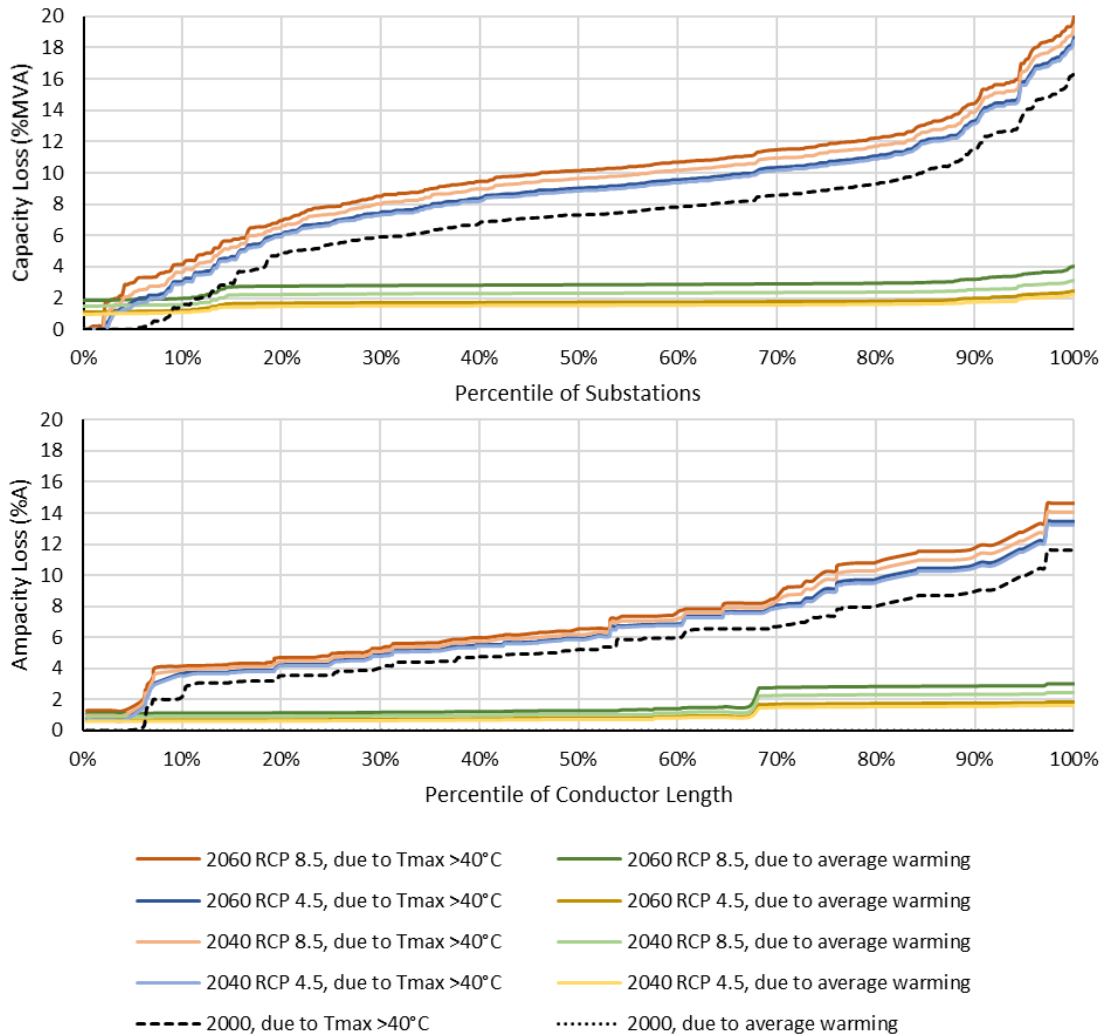


Figure 14. Distribution of Loadability Reductions In Percentile of Substations and Transmission Lines by Time Period and RCP.
Year 2000 average warming values are all equal to zero and may not be visible.

Overall

The overall vulnerability of components in LAC's electricity infrastructure to rising air temperatures is 2-20% loss of capacity by 2060. The only infrastructure in the region that is not at risk of experiencing air temperatures above 40 °C (104 °F) are the components within a few miles of the western-facing coast of Santa Monica Bay. As shown in Figure 15, by considering all the

major potential changes in population, urban infrastructure, and subsequent peak demand along with climate change we were able to project future operational constraints for future weather and demand at the same time.

In all future scenarios, by 2040 and 2060, at least a few substations were projected to exceed tolerance for automatic outage trips with a derated load factor in excess of two. By implementing high efficiency measures, most substation clusters in the central basin area should be able to operate with load factors below one, even during the worst heat wave conditions. The Santa Clarita / San Fernando Valley area was projected to have several substations exceed automatic outage tolerances. Without energy efficiency improvements in this area, both sets of population projections result in a majority of substations being heavily overloaded. Again, even when assuming energy efficiency improvements, the Palmdale and Lancaster areas are expected to be vulnerable to automatic outages by 2060 under the DoF population projections, whereas the basin area is vulnerable to automatic outages in SCAG population projections. Both result in emergency (load factor >1.2) conditions during the peak hour of a heat wave in both locations.

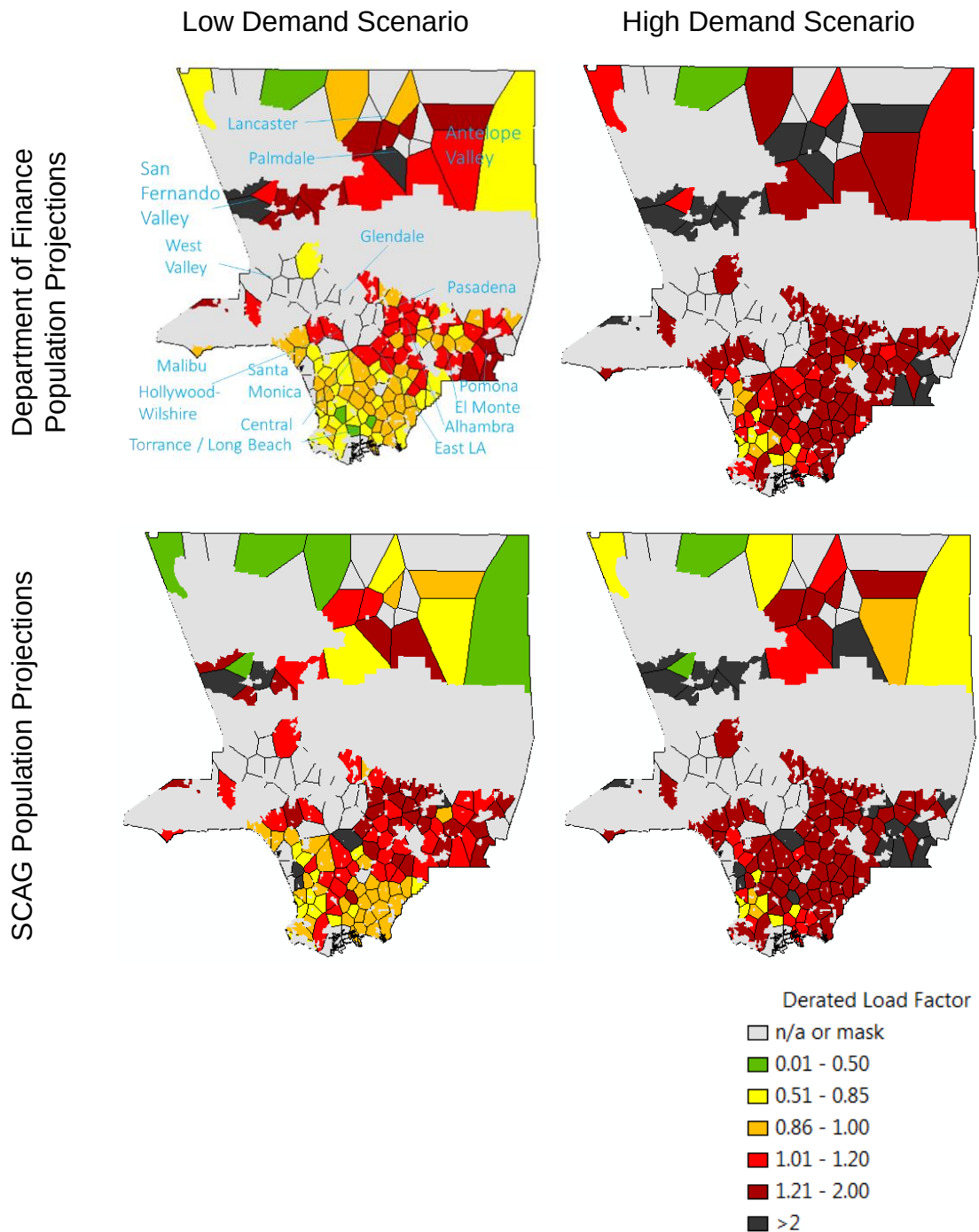


Figure 15. Maps of SCE Substation Risks by 2060.
 Future substation load factors derated for composite worst-case 2060 heat waves. I.e., this is what the peak hour could look like during a heat wave in 2060.

Additional substation capacity, distributed energy resources, or some form of demand side management will be necessary to reduce and/or shift peak load to keep substations in safe operating conditions with load factor at or below one in any future scenario. Table 12 lists the amount by which SCE's high and low voltage substations are overloaded in the model at 40°C (104 °F), and for the composite image temperatures. Consistent with the preliminary analysis of substation loading using SCE DERiM data in the Appendix on Statistics of component loads, no high voltage substations are overloaded during the base period, but several low voltage substations are. The low voltage substation clusters with a load factor greater than one were estimated to be overloaded by a total of 31 MVA at 40 °C (104 °F), and would be overloaded by up to 389 MVA cumulatively for the worst case historical heat wave conditions in the composite images. The values in that table listed do not consider substation clusters with a load factor less than one. The difference between substation capacity with and without considerations for spatial differences in air temperature and climate change is 911 MW in the highest case, SCAG 2060 high demand RCP 8.5. Per the same Appendix, the current total nameplate capacity of SCE's high and low voltage substations is 10,883 MVA and 10,155 MVA respectively, or 21 GVA total. Therefore, the total additional requirement by 2060 using the 40 °C (104 °F) rating approach would be 557—5,260 MVA (3—25%), and using the composite image approach with consideration for warming due to climate change would be 848—6,724 MVA (4-32%).

Table 12. SCE Peak Hour Substation Cluster Capacity Overload (MVA)

Period & Scenario	High Voltage		Low Voltage	
	@ 40°C (104 °F)	w/ Composite Temperatures	@ 40°C (104 °F)	w/ Composite Temperatures
Base	-	-	31	389
2040 DoF - Low	-	-	278	474
2040 DoF - High	312	623	1,834	2,634
2040 SCAG - Low	-	-	410	761
2040 SCAG - High	597	1,003	2,517	3,357
2060 DoF - Low	-	-	557	848
2060 DoF - High	513	1,002	2,733	3,669
2060 SCAG - Low	37	241	1,035	1,570
2060 SCAG - High	1,209	1,762	4,051	4,962

Discussion

Considering rising air temperatures, there are many ways to maintain local reserve margins, safe operating loads on components, and reliable electric power services in general. We considered the preconditions that could result in service outages and identified high priority neighborhood areas to investigate for more detailed circuit-level implementation studies. Several adaptation options are listed categorically in Figure 16, with effects on reliability and other factors important for consideration. The discussion in this section considers effects and trade-offs following that framing. Several recommendations are provided for LAC specifically based on the preceding analyses; however, this list is not intended to be exhaustive nor advocate for any particular option as a one-size fits all solution in regions that may have unique geographic constraints. The aim of this discussion is to inform LAC, California, and the scientific community with regards

to pragmatic options for addressing challenges created by climate change induced heat events that both improves service reliability and are cost-effective.

Options / Effects		Reliability factors					Other factors			
		Peak load, normal	Peak load, heatwave	Load variance	Delivery congestion	Power quality	Total energy consumption	Water use	Air emission	Land use
Electrical systems										
Resources	Distributed - solar PV without VAR control or storage	↓	↓	↓	↓	↓	-	-	-	-
	Distributed - solar PV with smart-inverter & storage	↓	↓	↓	↓	↑	-	-	-	-
	Central - CCNG, nuclear, or other	-	-	-	↑	↑	-	↑	↑	↑
	Imports, long distance transmission	-	-	-	↑	↑	-	-	-	↑
Loads	Appliances: higher energy efficiency	↓	↓	↓	↓	-	↓	-	↓	-
	ACs: peak performance metric	-	↓	↓	↓	-	-	-	-	-
	ACs: dual-systems with ice thermal storage	-	↓	↓	↓	-	-	↑	-	-
	ACs: water-based evaporative systems	-	↓	↓	↓	↑	↓	↑	↓	-
Building stock										
	Growth on fringe (single-family or multi-family)	↑	↑	↑	↑	-	↑	↑	-	↑
	Growth in-basin (densification with multi-family units)	↑	↑	↑	↑	-	↑	↑	-	-
	Improved building albedo and shading	↓	↓	↓	↓	-	↓	-	↓	-
	Improved building thermal insulation	↓	↓	↓	↓	-	↓	-	↓	-

Figure 16. Climate Change Risk Mitigation Options and Effects. Arrows indicate an increase or decrease in the factor. Solid green indicates higher efficiencies and or conservation of limited natural resources. Hollow red indicates the opposite.

Electrical Systems – Resources

The major tradeoffs between generation technologies—distributed solar PV (with storage and power quality controls) and centralized systems—in meeting demand are: land space requirements, delivery congestion relief, water usage, air emissions, and marginal capital costs. Solar PV can be installed on building roofs, whereas centralized systems require their own dedicated land footprint (Bridge, Bouzarovski, Bradshaw, & Eyre, 2013; Carrasco et al., 2006; Fthenakis & Chul, 2009; Ochoa & Harrison, 2011). When implemented at the distribution level, solar can power load directly without going through delivery components that are necessary for central systems. The net effect is a relative decrease in load from the perspective of the grid relative to demand. Yet these

distributed systems beg the question of storage given peak demand occurs once the PV systems decline in production of power. At the same time, this will be an important metric to monitor for reliability purposes going forward—if storage is included -- as those two values have historically been one and the same. The most prominent fast-ramping central generation technology is combined cycle natural gas plants, which both consume water and emit various gasses into the atmosphere. Combustion-only natural gas plants could be implemented, which would not use water, but would be more sensitive to rising air temperatures, as well as less fuel-efficient, and therefore more costly and emissions intensive per kWh. While levelized costs of solar PV are now at or below parity with bulk generation plants on a per kWh basis, the combined costs of solar PV with storage to provide 24/7 dispatchable energy and regulation services are still higher than traditional central generation plants (Penn, 2017). Thus, the best options for new resource procurement across competing objectives, will be those that consider the current and future state of the delivery infrastructure.

Implementing DER with new buildings may be the most cost-effective way to meet demand associated with growth in areas where delivery infrastructure are already over capacity during extreme heat waves. In such areas, some substations may be able to be adapted with improved heat sinks, forced air, or water cooling systems to increase capacity. But some may not, and overhead power line capacity will still be limited to convective cooling. The cost of increasing delivery infrastructure capacity necessary to meet demand through central generation, or long-distance imported power could be quite significant at

\$10-130 million USD per substation and \$1-3 million USD per mile of line length leading all the way out of the urban center (CA ISO, 2012; Mason et al., 2012). For the 848—6,724 MVA of substation overloading, if we assume an average size of 80 MVA per new substation, then an additional 11-84 substations would be required, which would cost \$110 million to \$11 billion USD. With 100—300 miles distance between LAC and neighboring regions (CEC, 1999), the cost of increasing the transmission import capabilities could be another \$100-\$900 million USD, and there would probably be additional costs associated with upgrading distribution-level transformers and power lines as well.

Future work for vulnerable neighborhoods should consider implementation of adaptation options by considering 24-hour load profiles on distribution-level circuits, the total Watt-hours of necessary storage capacity to complement solar PV capacity, and opportunity for network aggregation in supplying ancillary grid services. Circuits with higher portion of commercial and industrial loads may be preferable for the installation of DERs, as their load profiles may more closely match the PV generation profile (peaking at mid-day) allowing for more storage efficiency. Effective implementation of energy storage would reduce load variance by charging during off-peak hours and discharging during peak hours, resulting in a more consistent load, which is more readily manageable by system operators, and therefore has lower operations and maintenance costs (Willis et al., 2001). This could occur through some kind of automated and networked market incentives that are available for wholesale markets as of February 2018 (St. John, 2018).

Implementation of new bulk generation systems and delivery infrastructure may be more valuable in the northern areas of San Fernando and Antelope Valley. The areas are relatively less developed there and so land should be more readily available for construction. Future studies should consider the reliability and security benefits of redundant central and distributed energy systems, and determine what amount of each, including storage, is optimal for different outage risk tolerances.

Electrical Systems – Loads

More energy efficient appliances exist which can reduce use-phase load, load variance, and thus provide benefits to the power system's reliability. To mitigate risks from heat waves however, focus should be directed towards air conditioner units. While differences in lighting and other appliance efficiencies are significant for total annual energy consumption, they accounted for less than a 2% difference in peak demand in the models. By contrast, AC units generally accounted for 60—70% of summertime peak demand within residential buildings, and higher air temperatures resulted in a 3—7% increase in demand per 1°C (1.8 °F). LAC currently has only 45% AC penetration in its residential buildings, meaning that peak demand in just over half of the current building stock does not increase with air temperature. By 2060 almost all buildings could have AC.

Policies that would guide new or replacement ACs based on different performance constraints or different technologies would aid in reducing the risk of excessive peak demand during extreme heat events. It is possible to design AC units that are more efficient under the hottest conditions or that utilize thermal

storage to achieve 'flat' efficiency curves that do not degrade at the hottest temperatures (Bush & Ruddell, 2015; Ruddell et al., 2014). For example, developing a new 'peak performance rating' for ACs at 50 °C (122°F) could be useful to mitigate peak load during extreme heat waves. Doing so could provide incentive for ACs to be optimally engineered for more efficient performance at or near such extreme temperatures. Current standards, SEER and EER (SCE, 2003), are primarily for temperatures at or below 35 °C (95 °F). The current SEER standard, SEER 13, is already optimized to the point that improvements in SEER ratings in the model up to SEER 21 only affected peak demand by a few percent and were slightly counter-effective in some instances where temperatures exceeded 45 °C (113 °F) due to tradeoffs in engineering design optimization. Water-based evaporative cooling systems are another option that uses much less electric power, but requires water to operate, and are often not accepted by users as the sole-source of air conditioning due to insufficient comfort levels when the weather is both hot and humid (Kumar et al., 2016; Parsons, 2003). Further study may be useful to identify the practicality of hybrid designs.

Building Stock

Population growth will increase peak demand, but where and by how much will be significantly influenced by decisions relating to the management of urban systems. Housing demand in less developed areas of northern Santa Clarita and Lancaster, as the DoF forecasted, can be met through either single family or multi-family dwelling units. To meet the SCAG forecast however, most

housing demand would need to be met through new multi-family dwelling units and significant densification. In addition to conserving land space, the benefits of building new multi-family unit residential housing can be as much as a 50% lower peak demand per capita than single-family detached units. Those benefits are due to reduced volume and shared walls, which significantly reduce exposure to extreme heat. In addition, street albedo and widths should be considered for urban heat island impacts.

Further research is necessary for development of both residential and commercial building models. This study had the most uncertainty with respect to commercial building types in both the LAC assessor database and the energy models used. Residential building data and models were much more precise, and while the original models (Janet L. Reyna et al., 2017) were originally calibrated to annual energy consumption, reasonable adjustments were made in this study to calibrate building's peak demand to historical peak demand. Further research would be beneficial to develop residential building energy models, (coupled with street width and albedo analysis) calibrated for all hours of the day as electrification of natural gas appliances, widespread adoption of electric vehicles, and rooftop solar PV will have significant effects on residential loads.

Overall Conclusions

This analysis serves as a timely case study for utilities and governments to assess their climate change vulnerabilities, and develop adaptation plans considerate of future population and technology changes. Utility and other planners should recognize the vulnerabilities identified in this study as valuable in

prioritizing grid modernization projects in places that can meet mutual stakeholder objectives, including reliability, economics, environmental, and security. The analysis should also inform plans for future urbanization and implications for public health, economic burden of the energy transition, and urban form. Future work should expand on this study to consider other forms of climate change, technology, and grid modernization. Entities in other locations can develop their own versions of this study with geographic weather data under climate change, current and future population and building locations, and recent historical infrastructure component capacities and load factors.

Acknowledgements

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CHAPTER 6

SYNTHESIS

The collective work of this dissertation provides several contributions to the literature on electricity infrastructure vulnerability assessment, planning, and climate change. The four chapters each provided insights on the differences in electricity infrastructure systems operations with and without climate change. While the geographic regions considered for the case studies in this dissertation were limited to Los Angeles County, California (LAC) and Maricopa County (Phoenix), Arizona, the approaches developed are generalizable and usable for other regions as well. Moreover, the specific results for these regions are usable in larger regional analyses and as comparison data for future works, whether they be by the same approach or others. The study of the rising air temperatures due to climate change provided results specifically for Phoenix and LAC. All of the methods developed for estimating (change in) probabilities of hazardous conditions, including, component outage rates, cascading failures, excessive peak demand, reduced generator capacity, reduced substation capacity, transmission power line ampacity, reduced local reserve margin, and higher weather de-rated load factors on components are transferrable to smaller scale distribution-level components, or larger-scale interconnection areas, as well as other technology types. The approach to considering adaptation options in terms of supply side technology options, demand side technology options, supply side market incentives, demand side market incentives, building stock, and urban

form are all generalizable and transferrable other regions with varying climate change concerns and geopolitical goals. The numerous innovations and insights developed in this work also provides significant advancements for asking and answering further research questions that are timely and relevant to maintaining reliability in electricity infrastructure systems, for which future operations are subject to many uncertainties in technology, environment, and human behavior.

Understanding rising air temperatures due to climate change using the hottest day and composite imagery approaches, at 2x2 km or other resolution, developed in this dissertation will be useful for other regions to do their own climate change vulnerability assessments and adaptation plans. Not only is this approach useful for characterizing rising air temperatures due to climate change, it is generalizable to other environmental effects of climate change as well. This dissertation quantified how statistical approximations, in the form of 90th percentile historical temperatures (T90), or using city-level weather-station data instead of higher resolution weather data, can limit the accuracy and effectiveness of risk management and planning processes in the electricity infrastructure. A confident upper boundary of higher air temperatures to consider in planning and design processes was developed using ranges of climate change scenarios. Other regions and industries can use the hottest day approach, or other most stressful climate condition day, to understand the highest total stress that their net systems could experience on a single day. Likewise, the composite imagery approach can be used in other regions where downscaled climate data are available to consider the most stressful conditions that any infrastructure

components may be subject to operating under in any region of a large period of time. The benefit of these two types of climate imaging approaches is that they ask and answer the right research questions in a computationally expedient manner that can be readily applied in context for the most stressful conditions that are necessary to understand for risk and reliability purposes. Future research questions that can be asked and answered using these approaches will bolster regional coincidence analyses to go beyond the coincidence of high stress from multiple customer sector activity at the same time and associated human behaviors, to also consider the coincidence of multiple heat waves or other extreme weather events happening in interdependent neighboring regions.

More accurate and precise air temperature forecasts can be useful in developing new local reserve and safety margin requirements as the legacy T90 + 15% approach was based on uncertainty in weather, outages, and industrial services. The legacy approach has been demonstrated in this dissertation to be outdated, as we are now able to confidently state what maximum temperatures would be under various climate change scenarios of increasing air temperature. Hence, future work can consider how to remove the weather uncertainty from the planning equations, and correspondingly reduce the 15% margin to whatever would be appropriate for the remaining (scheduled and unscheduled) outage margin, margin for industrial services, and margin for security risks.

A complete high-level systems understanding of how electricity infrastructure systems are vulnerable to future heat waves due to climate change was developed. From generation to end-use, critical processes were identified,

individual component sensitivities to air temperature were characterized, and relationships were quantified that could result in failures. The approach developed for estimating probabilities and change in probabilities of component outages and cascading failures was a modular statistical approach applicable to any electricity system or any other system that could result in service interruptions due to excessive loading conditions and or hardware failures on multiple components. Several methods for considering the exposure time of high heat and high loading on components mean time to failure or failure rate were identified. Further work could characterize magnitudes of exposures on specific components, and or use performance characteristics of component thermal exposure times, to consider accelerated material wear under climate change resulting in failure. The probability distribution of excessive component loading could be further developed to consider the probability and duration of automatic outage trips resulting in N-x scenarios that could further result in cascading failures. Additional system vulnerabilities could be identified by including in the model component recovery or repair times in the case of outages due to trips and/or outages that require field dispatch. Further development of this type of approach can be useful for problems of N-x contingency analyses, field dispatch optimization problems, preventative maintenance, spare part inventory optimization problems, as well as consideration for backup power systems in other interdependent infrastructure systems such as water treatment and water pumping.

The structural equation modeling approach developed in this dissertation for estimating peak demand and local reserve margin as a function of high ambient air temperature is a form of statistical regression analysis and is readily implementable for other regions to do the same analysis. Thanks to recent developments in public availability of data, researchers can use regression analysis techniques to solve for the parameters of the peak demand model developed in this dissertation. The data necessary for the peak demand model includes hourly electricity demand data, which is at least provided publically at the balancing authority level by the US Energy Information Agency if not maintained privately by most utilities. Also daily weather data are necessary, which are readily available for weather stations around the world, and counts of residential and commercial buildings in the territory, which are also generally available through the public domain or utility service providers. Because peak demand is an order of magnitude more sensitive to changes in ambient air temperature than electricity generators, using linear approximations, such as those presented in the section for natural gas and solar PV, are sufficient for other utilities or geographic regions to conduct the same type of analysis. Other regions can therefore do a full local reserve margin estimation for higher air temperatures due to heat waves, and further consider vulnerabilities in resource adequacy across large geographic regions as import demands will increase and export capabilities decrease under the scenarios of multiple coincident heat waves at unprecedented high temperatures.

The structural equation model developed in this dissertation also provided new insights into AC operations, including the effects of different AC technologies in the motors on power performance at high temperatures, as well as thermostat settings and building shell thermal insulation properties. Further study could estimate the effects of new standards in AC performance on total annual energy consumption in regions as well as on peak electricity demand. These results could be extrapolated into studies of total costs to the ratepayers, and cost-benefit analysis of changes in AC performance standards, building insulation standards, and risk management of over-demand hazards. Moreover, as inferences were made of the general difference in AC thermostat setting preferences from LAC to Phoenix, such human behavior patterns could be further extrapolated in other regions. Understanding of thermostat preferences could be used in behavioral economics studies of demand-side management programs, which could be better engaged by certain occupants with one set of indoor air temperature preferences over another. Thermostat preference data could also be useful in advancing building energy models to better forecasts of hourly loads and improve grid service planning and reliability.

The methods developed in this dissertation for forecasting change in peak demand utilizing the bottom-up building energy models, composite imagery, and spatial allocation are generalizable for other building types, geographic areas, projection scenarios, energy demand forecasting problems, and will be useful for researchers, utilities, urban planners, and regulators globally. The building energy models utilized were calibrated for Los Angeles annual electricity

demand, and in this dissertation further calibrated for peak demand based on historical records. The accuracy of this approach can be improved with hourly data from smart meter records to improve building energy models, hourly load forecasts, and therefore reliability in systems as planners and operators will have more accurate and precise data to work with. The software platform EnergyPlus has become common for doing similar building energy modeling simulations, but in order to do this work a special approach for utilizing the hourly input weather files was developed that is not a current feature of the software. The software input weather files currently exist in the format of 8760 consecutive hours for a complete year, and only by having full data will the program run a building energy simulation. By modifying the weather input files to make 24 hour periods correspond to daily air temperature patterns with days of incrementally higher maximum temperature, the performance of individual buildings was able to be characterized for days with different daily maximum air temperatures. Doing so was a new and useful application of the tool beyond characterization of annual energy consumption, and will be useful for further calibration of peak, hourly, and sub-hourly electricity demand for the EnergyPlus software suite or other similar software suites. This approach further enabled allocation of peak electricity demand across a map of LAC utilizing the resolution of the county assessor database of buildings at census block group scale and air temperatures at 2x2 km resolution. This allocation could have been done at even higher resolution had such data been available. Adjustments in resolution of building allocations from census block group to match neighborhoods or utility delivery circuits will be

useful for urban planners and utilities. Regulators and policy makers can benefit from the general approach in terms of evaluating efficacy of programs that may affect individual parameters within the EnergyPlus software, such as air temperatures, building vintage, building size, and AC efficiency. For example, it was quantified how higher SEER rated air conditioner units actually perform worse than some lower rated units at very high temperatures ($> 44^{\circ}\text{C}$ 111°F) in the software. Regulators may wish to use this information to explore developing a complementary peak performance rating for air conditioner units that would result in different engineering optimizations, power curves, and annual energy consumption attributes. Moreover, the same efforts can be applied to commercial buildings to develop a suite of calibrated models for that sector of buildings. The commercial buildings used in this study were explicitly not calibrated for energy consumption; however, thanks to publically available data about the sector, reasonable estimates were developed with qualified uncertainty. Therefore, as residential building models have developed over time, future research can continue to develop incrementally better models of commercial buildings such that utilities may better plan for coincident loads on shared circuits. Similarly, building energy models can be updated to consider rooftop solar, onsite energy storage, and electric vehicle charging and/or discharging. More general application of the greater approach to spatial electricity demand forecasting provided insights into the effects of population growth on peak demand and therefore infrastructure capacity requirements throughout the county. Other cities and government entities can apply this approach in collaboration with urban

planners and infrastructure companies in order to better facilitate growth and commerce for successful achievement of multiple goals.

The next value-add for cities and the utility sector developed in this dissertation, after developing a high-resolution peak demand forecast, was to consider the impact on delivery infrastructure loading and the potential for capacity shortage issues due to heat waves from climate change. This was done using geospatial analytics techniques to assign the weather and peak demand projections to the transmission-level delivery infrastructure, including generator plants, transmission lines, and substations. This was possible thanks to infrastructure data made publically available geospatially by the Department of Homeland Security, the US Energy Information Agency, and the utility Southern California Edison. Further data exists both publically and privately for smaller distribution-level asset classes, for which the same type of vulnerability assessment and adaptation plans can be developed. Geospatial assignment of various parameters, including spatial coverage of substations and peak demand at the census block group level, can be further refined with more accurate substation coverage mapping that utilities should be able to provide.

Transmission line load factors, and potential for overloading, was not estimated due to a lack of information for recent historical load factors as was available for substations. If utilities were to provide such information, then future work could estimate the same changes in load factors for lines as was done for substations. Moreover, the parallel and series operations of component loads and load factors was approximated in this study with an even split above and below the 230 kV

level, but collaboration with utilities could improve upon this approach by comparing results to more precise network power flow simulations. Tradeoffs exist between time-series and static modeling (this dissertation) in planning and forecasting efforts. Namely, computational time, but as computational speed continues to improve exponentially into the future, then researchers should aim to merge these two types of approaches and create software simulation platforms that create the insightful value of both and more.

The combined results of component derating for rising air temperatures due to climate change and component load factors / capacity shortages developed in this dissertation enabled long-term strategic considerations of urban planning, utility asset planning, and overlapping environmental goals. Because urban form and utility infrastructure assets are generally immovable after construction, forecasting and planning are extremely important. While one-size fits all approaches are extremely rare, solution implementations often only get one chance in that cities are general stuck with the results for the foreseeable future (at least in terms of land-use) which can also be catastrophic if all the failure scenarios were not sufficiently identified and planned for. Therefore, further development of these techniques will highly valuable to coordinate with grid modernization efforts, including non-dispatchable variable intermittent generation from solar and wind sources, as well as proliferation of electric vehicles. The techniques developed in this dissertation for understanding component load factors will be useful in siting and sizing these new technologies, peak shifting/shaving programs, and community micro-grids in ways that can enhance

system reliability and avoid unnecessary outages or failures. The work can be built upon to consider use of limited natural resources such as water and land space, as well as emissions from different generation technologies.

In general the approach to considering adaptation options in terms of supply side technology options, demand side technology options, supply side market incentives, demand side market incentives, building stock, and urban form is a framework transferrable other regions with varying climate change factors and geopolitical goals. As was stated explicitly in the body of the dissertation, the purpose of developing that framework for analysis, and specific recommendations for LAC, was not to advocate any particular solution, but rather to advance the public discourse in a clear and structured manner. Cities around the world face challenges in terms of advancement of technology, markets, and urban form, wherein there will always be suppliers, demand-side consumers, and some form of governance. Likewise, there are numerous climate change challenges that affect the electricity sector, and other infrastructure systems, beyond rising air temperature, including rising water temperature, more severe storms, rainfall, wind speed, change in sea level, and change in river flow. To advance the literature and implementations in practice it is important to address the knowledge of these challenges both individually and collectively. This dissertation focused scope tightly on one very specific parameter associated with climate change, and as future works do the same with others, then they will effectively be brought together in a way that all stakeholders can understand the

contributions of individual aspects and evaluate adaptation options as they affect other economic, environmental, and social goals.

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APPENDIX

APPENDIX A

BUILDING ENERGY MODELING CHARACTERIZATION

The content in this appendix is in review at the California Energy Commission as part of a larger report with the citation (pending) as follows: Burillo, Daniel, Mikhail Chester, Stephanie Pincetl, Eric Fournier, Daniel Walton, Fengpeng Sun, Marla Schwartz, Katharine Reich, Alex Hall. (University of California Los Angeles). 2018. ***Climate Change in Los Angeles County: Grid Vulnerability to Extreme Heat***. California's Fourth Climate Change Assessment, California Energy Commission. Publication number: CEC-XXX-2018-XXX.

Building peak electricity performance was characterized for commercial and residential buildings using the US DOE's EnergyPlus and BEOpt simulation software. A total of 45 commercial building models (EnergyPlus files), and 153 residential building models (BEOpt files) were used. Peak hour electricity consumption (kWh or kW per hour) was estimated for all building models using the weather profile EPW files created. Building peak demand performances were characterized over a range of daily T_{max} , from 20°C to 60°C, as the average of the noon-6pm hourly profiles observed in the simulation results for the respective T_{max} .

Residential Buildings

Previous work conducted by Reyna and Chester in (Janet L. Reyna et al., 2017) developed 1,071 residential building models (using BEOpt and Energy Plus) calibrated specifically for LAC to estimate change in electricity use for various climate and urban infrastructure future scenarios. Those models were

developed categorically for 4 types of building dwellings: single family detached (SFDD), single family attached (SFAD), small multifamily (MFSD), and large multifamily (MFLD); 5 CEC climate zones (6, 8, 9, 14, 16); 7 construction time-periods based on the county assessor's database; and 21 appliance configurations for heating, cooling, and lighting efficiency. The consolidated 51 “archetypes” of different building shell properties are listed in Table 1. All appliance usage patterns were kept at the default settings, including thermostat set point equal to 25°C (77°F). The 21 appliance configurations were defined as closely as possible with the options available in the software to fit the California Residential Appliance Saturation Survey (RASS), and were allocated by climate zone, building type and vintage (CEC, 2009). The 51 archetypes were then calibrated for LAC specifically by adjusting building shell parameters such that when the total $51 \times 21 = 1,071$ models were run, simulation results were within 10% of total annual electricity sales for several recent years – aggregated by building count and or square footage for the LADWP service territory.

Table 1. Residential Simulation Archetype Divisions and Names. Note: CZ = Climate Zone.

Multifamily Small (MFS), apartment or condo (2-4 units)						Multifamily Large (MFL), apartment or condo (5+units)				
	CZ 6	CZ 8	CZ 9	CZ 14	CZ 16	CZ 6	CZ 8	CZ 9	CZ 14	CZ 16
<1940	6MFSD-5	8MFSD-4	9MFSD-5	14MFSD-5	16MFSD-4	6MFLD-5	8MFLD-5	9MFLD-5	14MFLD-5	16MFLD-4
1940-1949	6MFSD-5	8MFSD-5	9MFSD-5	14MFSD-5	16MFSD-4	6MFLD-5	8MFLD-5	9MFLD-5	14MFLD-5	16MFLD-4
1950-1959	6MFSD-5	8MFSD-5	9MFSD-5	14MFSD-5	16MFSD-4	6MFLD-5	8MFLD-5	9MFLD-6	14MFLD-5	16MFLD-4
1960-1969	6MFSD-5	8MFSD-5	9MFSD-6	14MFSD-5	16MFSD-4	6MFLD-6	8MFLD-6	9MFLD-6	14MFLD-5	16MFLD-4
1970-1982	6MFSD-6	8MFSD-6	9MFSD-6	14MFSD-5	16MFSD-6	6MFLD-6	8MFLD-6	9MFLD-6	14MFLD-5	16MFLD-4
1983-1997	6MFSD-6	8MFSD-6	9MFSD-6	14MFSD-5	16MFSD-6	6MFLD-6	8MFLD-6	9MFLD-6	14MFLD-6	16MFLD-4
1998-2008	6MFSD-6	8MFSD-6	9MFSD-6	14MFSD-5	16MFSD-6	6MFLD-7	8MFLD-6	9MFLD-7	14MFLD-6	16MFLD-4
Single family detached (SFD)						Single family attached (SFA), townhouse, duplex, etc.				
	CZ 6	CZ 8	CZ 9	CZ 14	CZ 16	CZ 6	CZ 8	CZ 9	CZ 14	CZ 16
<1940	6SFDD-5C	8SFDD-5C	9SFDD-5C	14SFDD-5C	16SFDD-7	6SFAD-6C	8SFAD-6C	9SFAD-6C	14SFAD-6M	16SFAD-7
1940-1949	6SFDD-5C	8SFDD-6C	9SFDD-6C	14SFDD-5C	16SFDD-7	6SFAD-6C	8SFAD-6C	9SFAD-6C	14SFAD-6M	16SFAD-7
1950-1959	6SFDD-5M	8SFDD-6M	9SFDD-6M	14SFDD-5C	16SFDD-7	6SFAD-6C	8SFAD-8M	9SFAD-7M	14SFAD-6M	16SFAD-7
1960-1969	6SFDD-7M	8SFDD-7M	9SFDD-7M	14SFDD-7M	16SFDD-7	6SFAD-6C	8SFAD-8M	9SFAD-7M	14SFAD-6M	16SFAD-7
1970-1982	6SFDD-7M	8SFDD-7M	9SFDD-7M	14SFDD-7M	16SFDD-7	6SFAD-7M	8SFAD-7M+9SFAD-7M	9SFAD-7M	14SFAD-6M	16SFAD-7
1983-1997	6SFDD-8M+8SFDD-7M+9SFDD-7M	8SFDD-7M+9SFDD-7M	9SFDD-7M	14SFDD-7M	16SFDD-7	6SFAD-6M+8SFAD-7M+9SFAD-7M	8SFAD-7M+9SFAD-7M	9SFAD-7M	14SFAD-6M	16SFAD-7
1998-2008	6SFDD-8M+8SFDD-7M+9SFDD-8M+14SFDD-8M+16SFDD-8	8SFDD-7M+9SFDD-8M+14SFDD-8M+16SFDD-8	9SFDD-8M+14SFDD-8M+16SFDD-8	14SFDD-8M+16SFDD-8	16SFDD-8	6SFAD-6M+8SFAD-7M+9SFAD-8M+14SFAD-6M	8SFAD-7M+9SFAD-8M+14SFAD-6M	9SFAD-8M+14SFAD-6M	14SFAD-6M	16SFAD-7

This study used the 51 core building archetypes (in BEOpt) with four AC configurations, to characterize peak demand. This consolidation was done for both technical reasons to reduce computational time, and for practical purposes to define urban infrastructure scenarios. The original 21 appliance configurations included 20 different AC types, and no AC. AC unit efficiency effects on peak demand were characterized for AC types as shown in Figure 17. The AC technology comparison showed approximately 2x energy efficiency gains from SEER 8 to SEER 16, and diminishing returns at higher SEER ratings with the most efficient being the central AC (CAC) SEER 21. Minor efficiency trade-offs were inconsistent between 2-stage & variable-speed motors, as well as CAC to air source heat pump (ASHP). Peak demand from room air conditioners (RACs) saturated between $T_{max} = 30$ and 35 °C. AC technologies were accordingly

labeled as low-, medium-, and high-efficiency (SEER 8, 16, 21) in the residential building models for each archetype for a total of $51 \times 3 = 153$ simulation models. Peak demand for the 51 archetypes with no AC was calculated post simulation, with the same peak demand value for all T_{max} . The AC technology categorization is summarized in Table 2 with high-level statistics of the base case allocation for LAC at large.

Relative differences in AC performance were consistent when tested in other residential building types as well, as shown in Figure 18. Note: MFLD buildings include 12 DUs, and MFSD and SFAD buildings include 4 DUs. Spikes at low T_{max} are due to indoor heating. All models assumed 34% CFLs and 66% incandescent lighting, and a thermostat set point of 25°C (77°F) in the software. This assumption is maintained as the difference is not significant to peak demand. Relative to 34% CFL, BEOpt lists 100% CFL using $\sim 1/3^{\text{rd}}$ less power, and 100% LEDs as using another $\sim 1/7^{\text{th}}$ less power. Dwelling units with the base 34% CFL penetration were listed at $\sim 1,000$ kWh/unit/year, Therefore, ~ 3 kWh/day over ~ 10 hours, makes for ~ 0.3 kW contribution to peak load, or ~ 0.1 kW difference in lighting efficiency. For peak demand of approximately 6 to 25 kW per residential dwelling unit, this is $\sim 1\%$ effect on peak demand. Therefore, a reduction of 1% for peak demand can be included post processing as a source of uncertainty for potential improvements in lighting efficiency.

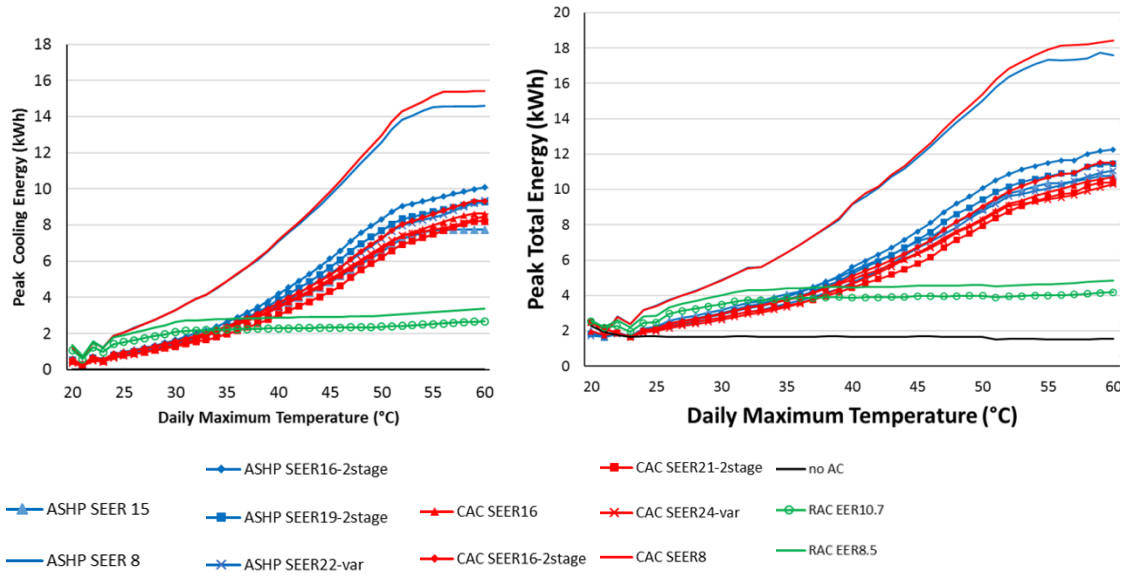


Figure 17. Comparison of AC Technologies on Building Peak Demand Performance for 6SFDD-8M+.

Abbreviations: ASHP – air source heat pump, CAC – central air conditioner, RAC – room air conditioner.

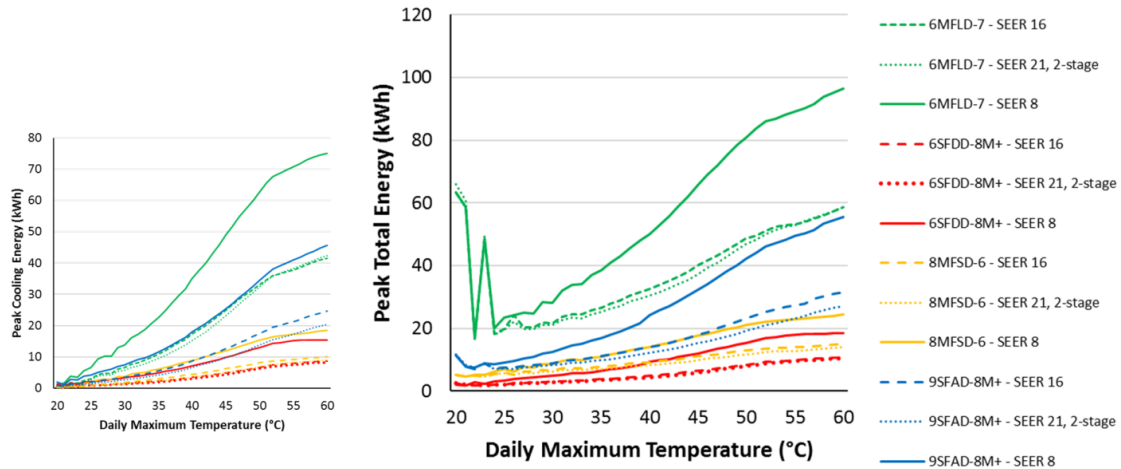


Figure 18. Comparison of AC Technology on Residential Cooling and Total Peak Demand for 4 Major Building Types.

Table 2. AC Technology Categorization.

AC type	Definition	Clustering of (Reyna & Chester)	Base case allocation
No AC	No AC	No AC	44%
Low efficiency	SEER 8	All SEER 10 or less + ½ of all RACs	26%
Medium efficiency	SEER 16	All SEER >10 + ½ of all RACs	30%
High efficiency	SEER 21	n/a	0%

Characterization Results

In most cases, the building energy simulation results show the newest vintage building consumes the most energy for each building type within each CAZ. This is primarily due to the increase in square footage of buildings over time, i.e. more efficient per square foot, but more square feet, as listed in Table 3.

Table 3. Residential Building Prototypes Square Footage

Code	ft ²	Beds	Units	New
Single Family Detached				
6SDFDD-5C	1200	3	1	0
6SFDD-5M	1360	3	1	0
6SFDD-7M	2065	3	1	0
6SFDD-8M+	1940	3	1	1
8SFDD-5C	1260	2	1	0
8SFDD-6C	1300	3	1	0
8SFDD-6M	1402	3	1	0
8SFDD-7M	1775	3	1	0
8SFDD-7M+	1820	3	1	1
9SFDD-5C	1694	3	1	0
9SFDD-6C	1411	3	1	0
9SFDD-6M	1505	3	1	0
9SFDD-7M	2135	3	1	0
9SFDD-8M+	3010	4	1	1
14SFDD-5C	1175	3	1	0
14SFDD-7M	1720	3	1	0
14SFDD-8M+	2600	4	1	1
MtnSFDD-7C	1930	3	1	0
MtnSFDD-8	3615	4	1	1

Single Family Attached				
6SFAD-6C	840	2	4	0
6SFAD-7M	1228	2	4	0
6SFAD-6M+	1196	3	4	1
8SFAD-6C	924	2	4	0
8SFAD-8M	1200	2	4	0
8SFAD-7M+	1200	2	4	1
9SFAD-6C	1040	3	4	0
9SFAD-7M	1250	2	4	0
9SFAD-8M+	1496	3	4	1
14FAD-6M	1196	3	4	1
MtnSFAD-7	1092	4	4	1
Multi-family small				
6MFSD-5	870	2	4	0
6MFSD-6	910	2	4	1
8MFSD-4	840	1	4	0
8MFSD-5	800	1	4	0
8MFSD-6	1050	2	4	1
9MFSD-5	928	1	4	0
9MFSD-6	918	2	4	1
14MFSD-5	896	2	4	1
16MFSD-4	1020	1	4	0
16MFSD-6	1800	1	4	1
Multi-family large				
6MFLD-5	625	2	12	0
6MFLD-6	750	2	12	0
6MFLD-7	1435	2	12	1
8MFLD-5	675	1	12	0
8MFLD-6	840	2	12	1
9MFLD-5	725	2	12	0
9MFLD-6	812	1	12	0
9MFLD-7	1200	2	12	1
14MFLD-5	775	2	12	0
14MFLD-6	775	2	12	1
16MFLD-4	870	1	12	1

Simulation results are shown below grouped by CAZ and building type for SEER 8 efficiency ACs.

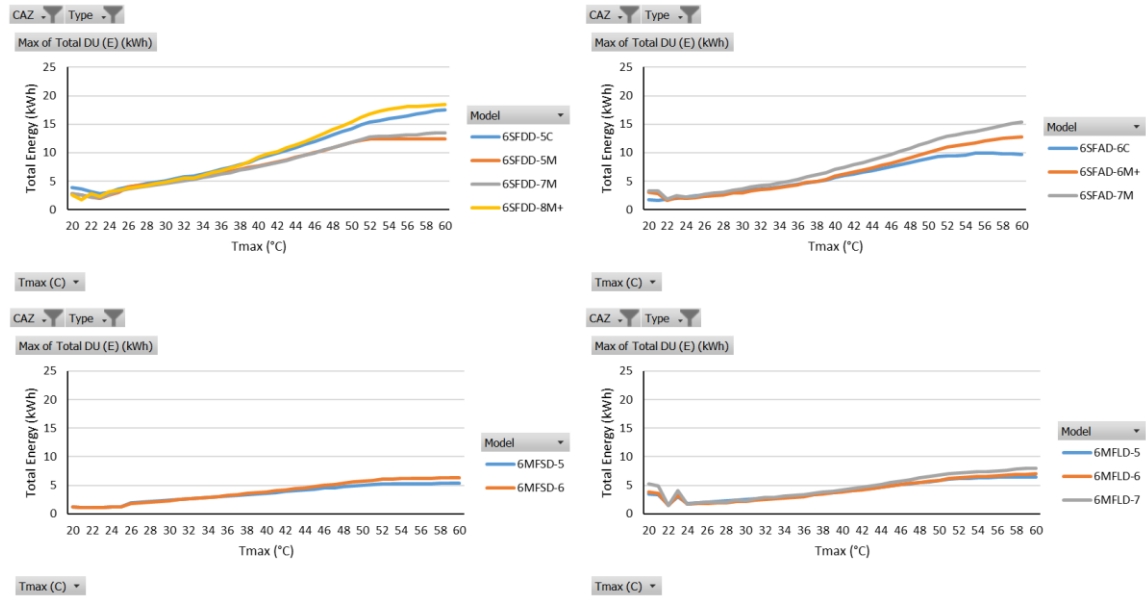


Figure 19. Residential Building Performance for CAZ 6.

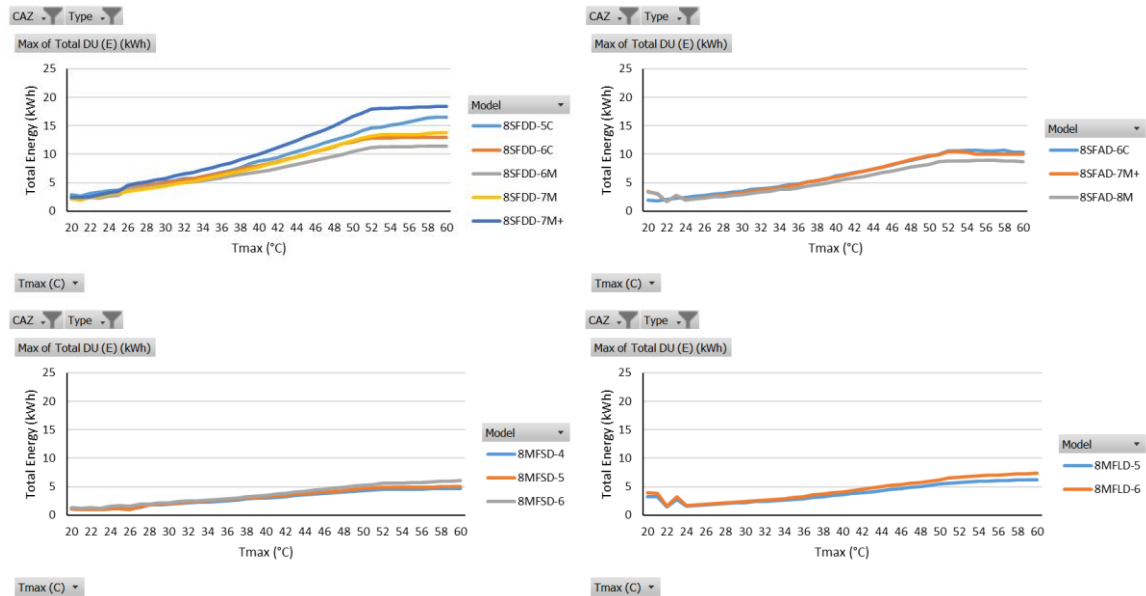


Figure 20. Residential Building Performance for CAZ 8.

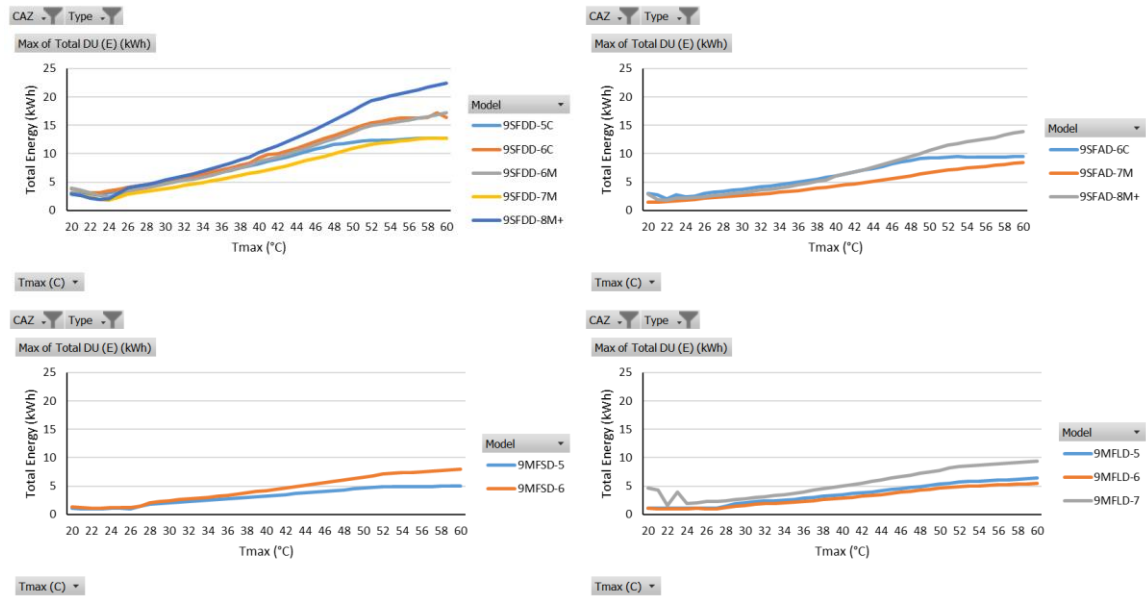


Figure 21. Residential Building Performance for CAZ 9.

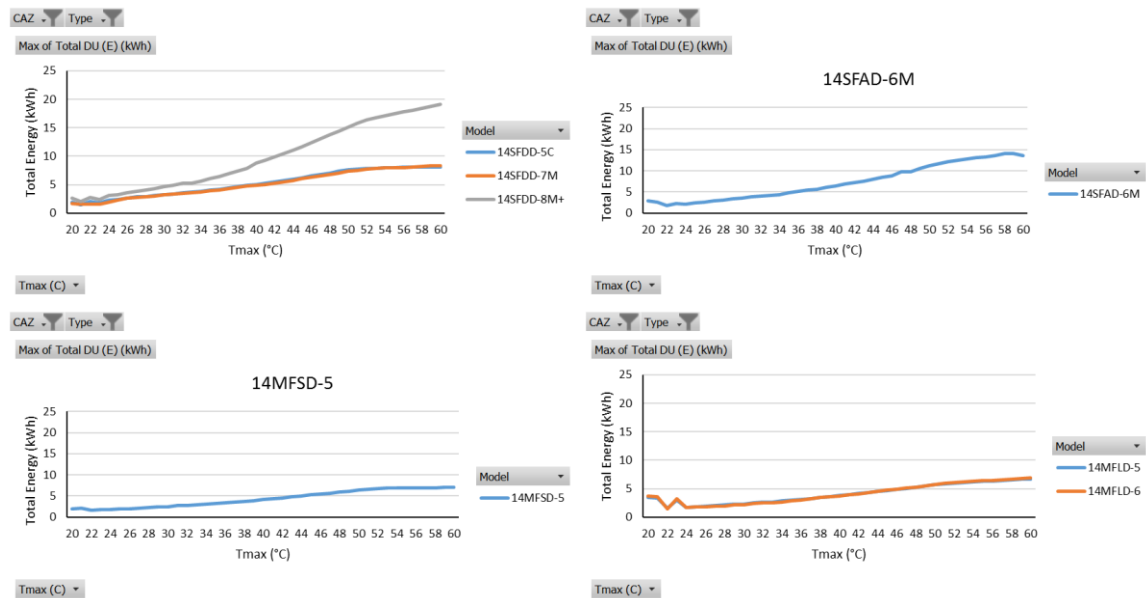


Figure 22. Residential Building Performance for CAZ 14.

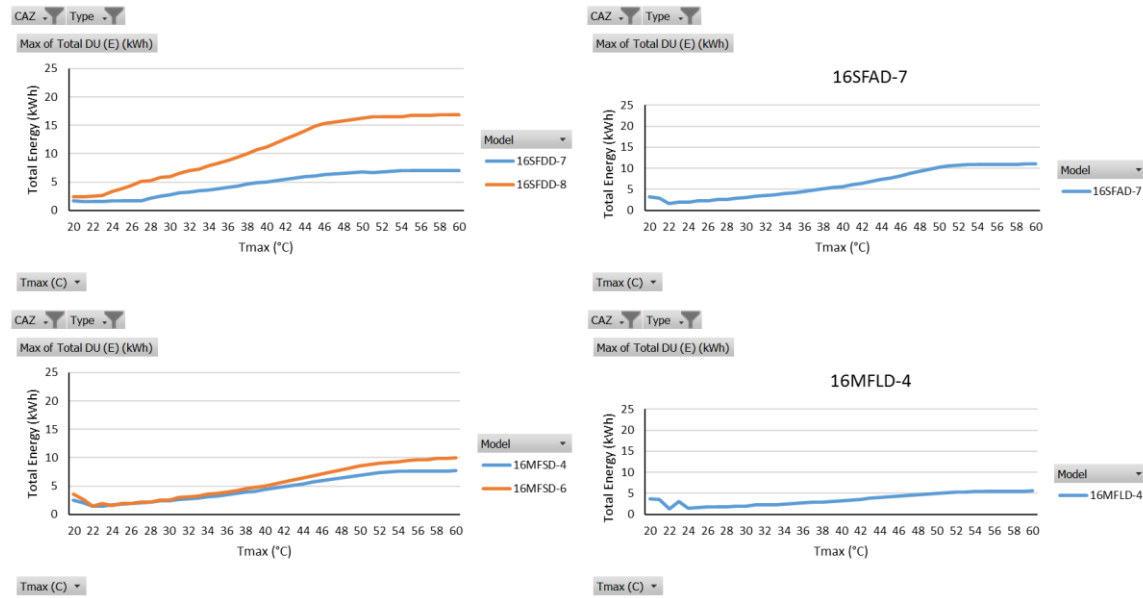


Figure 23. Residential Building Performance for CAZ 16.

Comparing the newest vintage of buildings for SEER 8 and SEER 21, in all cases the SFDD type has higher peak demand per dwelling unit than any form of attached unit. In most cases SFAD consumes the next most energy per dwelling unit. In some cases the MFSD consumes the least, and in some cases the MFLD consumes the least per dwelling unit.

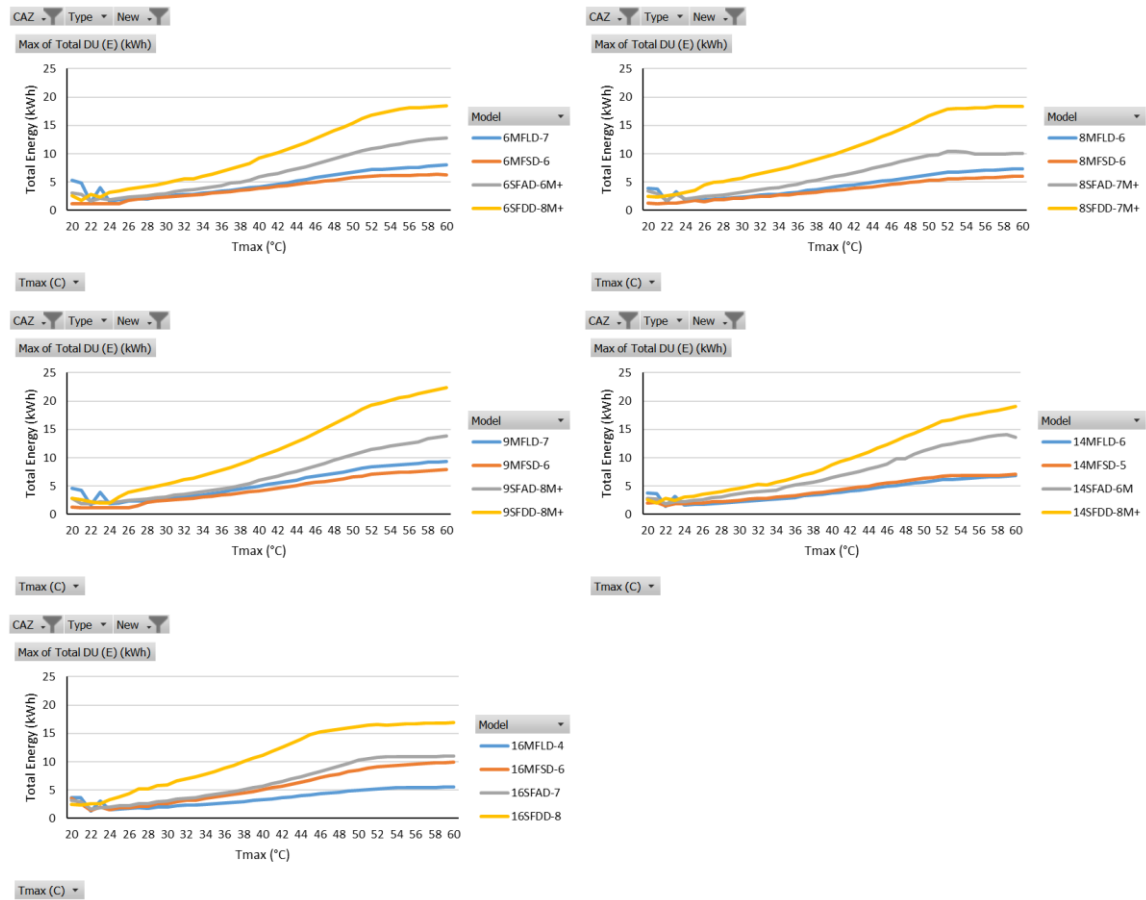


Figure 24. Residential Building Performance for SEER 8.

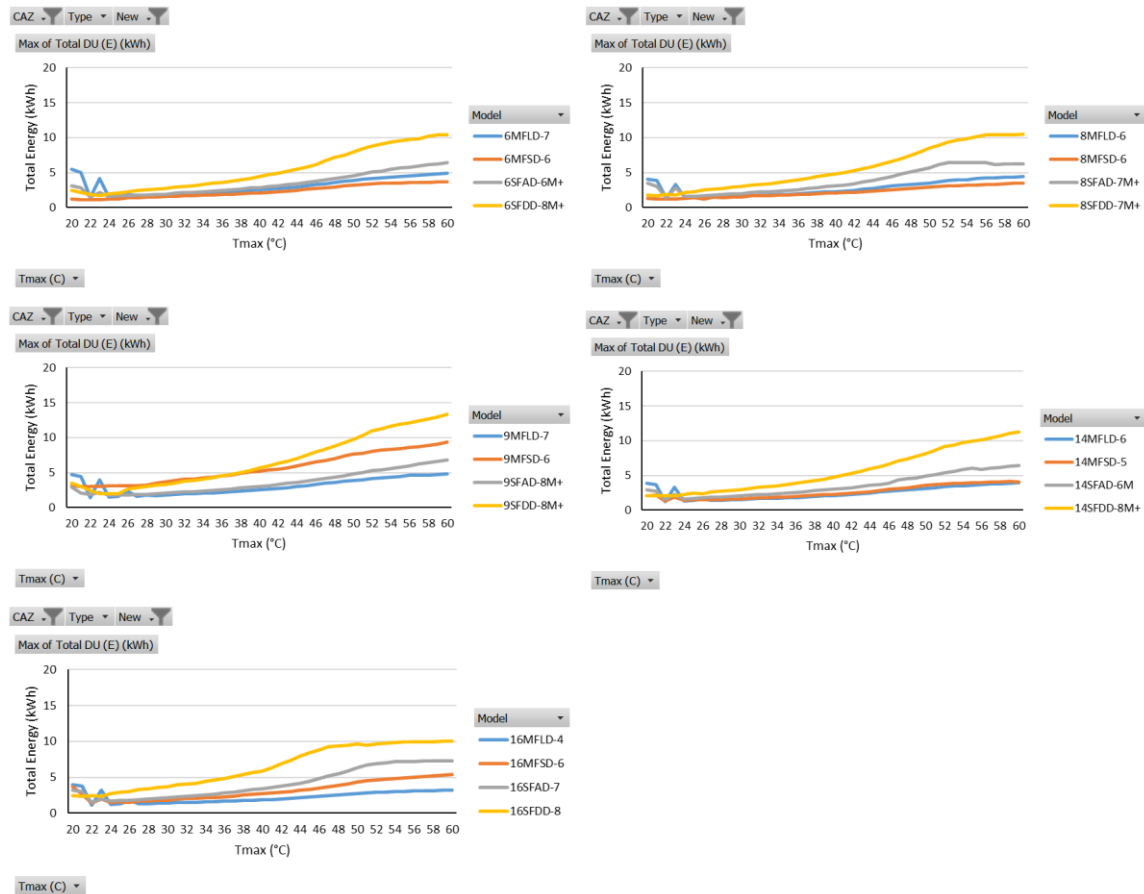


Figure 25. Residential Building Performance for SEER 21.

Commercial Buildings

The commercial building models used in this study were produced by NREL and published by DOE (Department of Energy, 2017) for use in Energy Plus. The 15 types of commercial building models used are listed in Table 4. DOE has published models with building performance characteristics calibrated for several regions. The models calibrated for Los Angeles specifically were used; however, the details of those calibrations are not for the purposes of this report. These models were used as they were the best-known models available at the time. Moreover, DOE has published three versions of these models based

on vintage for: pre-1980, post-1980, and post 2004. Thus, a total of 45 models (EnergyPlus files) were used. Characterization figures for peak demand in each commercial building type are shown in Appendix A.1. No patterns were particularly identified other than that electricity demand generally increased with daily maximum temperature. Inconsistencies in peak demand between building vintage may be explained by differences in appliance technologies and use profiles. To best calibrate the results to the validation data for commercial buildings, the lowest peak demand values were used in this assessment for any of the 3 vintages of the 15 building types at any temperature.

As stated in the documentation (Deru et al., 2011),

Intended uses

“The reference building models will be used for DOE commercial buildings research to assess new technologies; optimize designs; analyze advanced controls; develop energy codes and standards; and to conduct lighting, daylighting, ventilation, and indoor air quality studies.”

“They also provide a common starting point to measure the progress of DOE energy efficiency goals for commercial buildings.”

Uses not intended

“These reference building models are not intended to represent energy use in any particular building. Rather, they are hypothetical models with ideal operations that meet certain minimum requirements.”

“The reference building model definitions are not intended to act as targets to rate the energy performance of single existing or proposed buildings.

The models and weighting factors are not appropriate for analysis at the state level, as the datasets used to generate the models and the weighting factors are too small to form a valid statistical model at this level.

Variations of these models and weighting factors could be created for such purposes, but that is not the objective of this project.”

Thus, the use of these models in this research, and the decisions made by staff as to how to use these models consistently with historical data, is both insightful in terms of the climate change assessment, as well as the DOE research community in advancement of the models themselves. A detailed audit of the plug and process load characterization in the source models is beyond the scope of this work.

Table 4. Commercial Building Types.

Type	Description	Floor Area (ft ²)	Number of Floors
1	Large Office	498,588	12
2	Medium Office	53,628	3
3	Small Office	5,500	1
4	Warehouse	52,045	1
5	Stand-alone Retail	24,962	1
6	Strip Mall	22,500	1
7	Primary School	73,960	1
8	Secondary School	210,887	2
9	Supermarket	45,000	1
10	Quick Service Restaurant	2,500	1
11	Full Service Restaurant	5,500	1
12	Hospital	241,351	5
13	Outpatient Health Care	40,946	3
14	Small Hotel	43,200	4
15	Large Hotel	122,120	6

*Midrise Apartment excluded from analysis due to redundancy with residential category large multifamily unit (MFL)

Characterization Results

Commercial building model performance was characterized for a range of daily high temperatures from 20°C to 60°C. Table 5 lists descriptive statistics of the area, stories, and count of building types in the historical base period. The following figures show the daily peak electricity consumption for building cooling only as well as the entire facility for each building type for New (2004+), Post 1980, and Pre 1980 models.

Table 5. Commercial Buildings

Index	Building Type	Area (m ²)	Stories	Historic Count Pre 1980	Historic Count Post 1980	Historic Count Post 2004	Historic Count Total
0	Midrise Apt. (not used)	3,135	4	528	514	79	1,121
1	Large Office	46,320	12	2,719	1,350	265	4,334
2	Medium Office	4,982	3	5,247	1,414	657	7,318
3	Small Office	511	1	6,553	4,303	1,444	12,300
4	Warehouse	4,835	1	16,221	2,409	1,332	19,962
5	Stand-alone Retail	2,294	1	1,415	1,374	392	3,181
6	Strip Mall	2,090	1	2	2	0	4
7	Primary School	6,871	1	478	126	42	646
8	Secondary School	19,592	2	144	175	99	418
9	Super Market	4,181	1	4,086	759	241	5,086
10	Quick Service Restaurant	232	1	363	22	14	399
11	Full Service Restaurant	511	1	104	12	2	118
12	Hospital	22,422	5	386	64	8	458
13	Out Patient	3,804	3	185	162	173	520
14	Small Hotel	4,014	4	528	514	79	1,121
15	Large Hotel	11,345	6	2,719	1,350	265	4,334

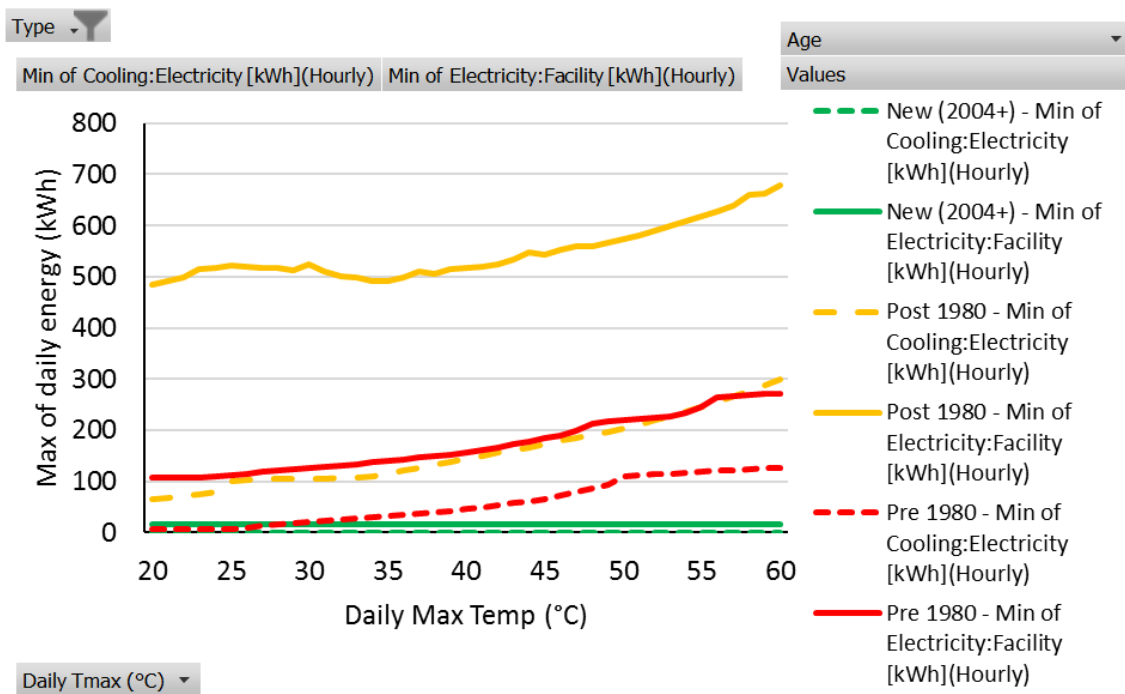
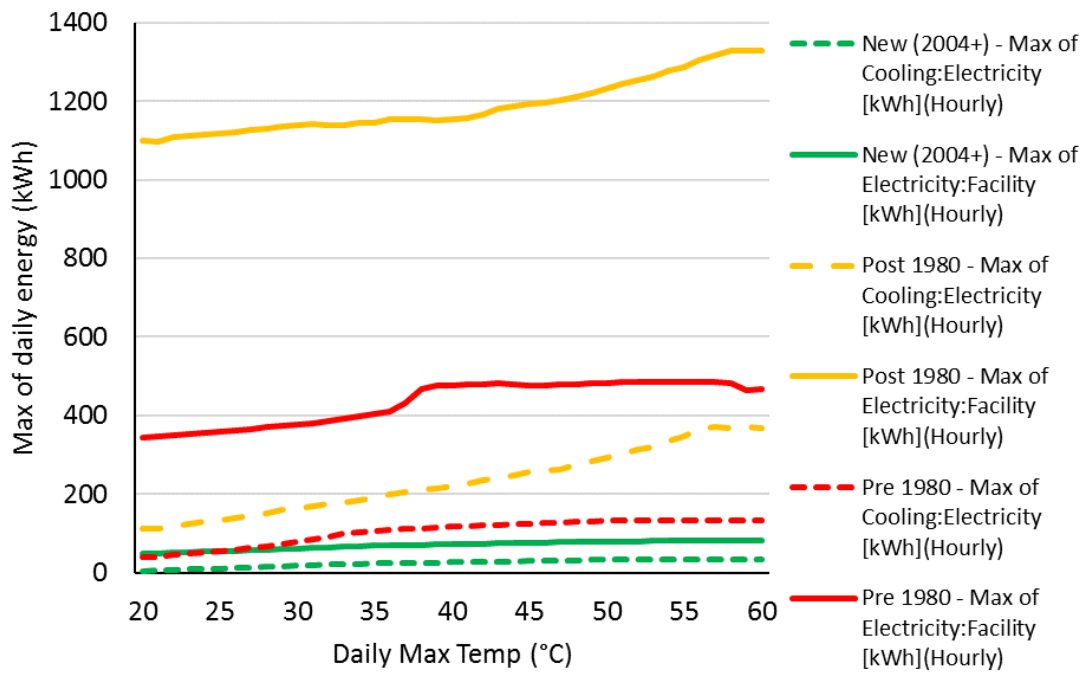


Figure 26. Full Service Restaurant.

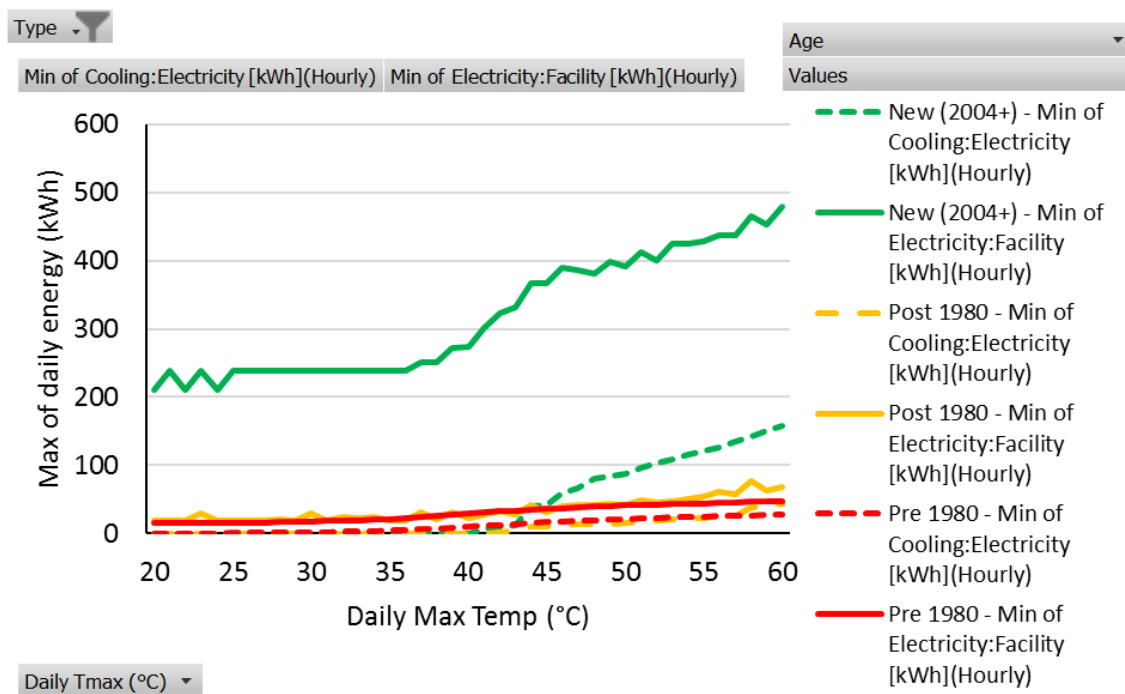
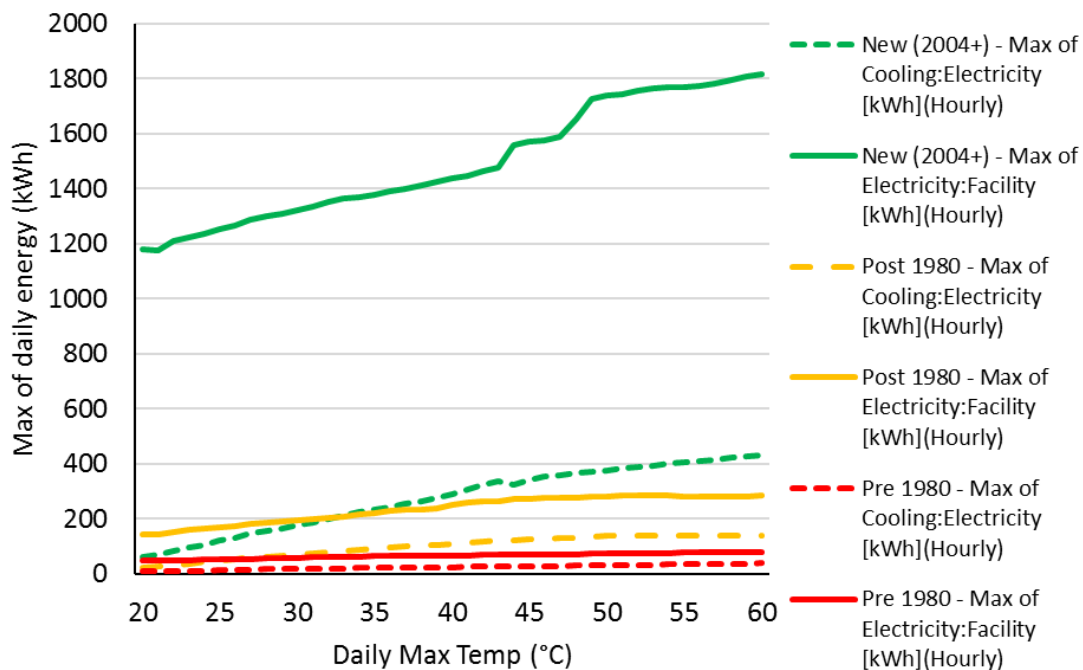


Figure 27. Hospital

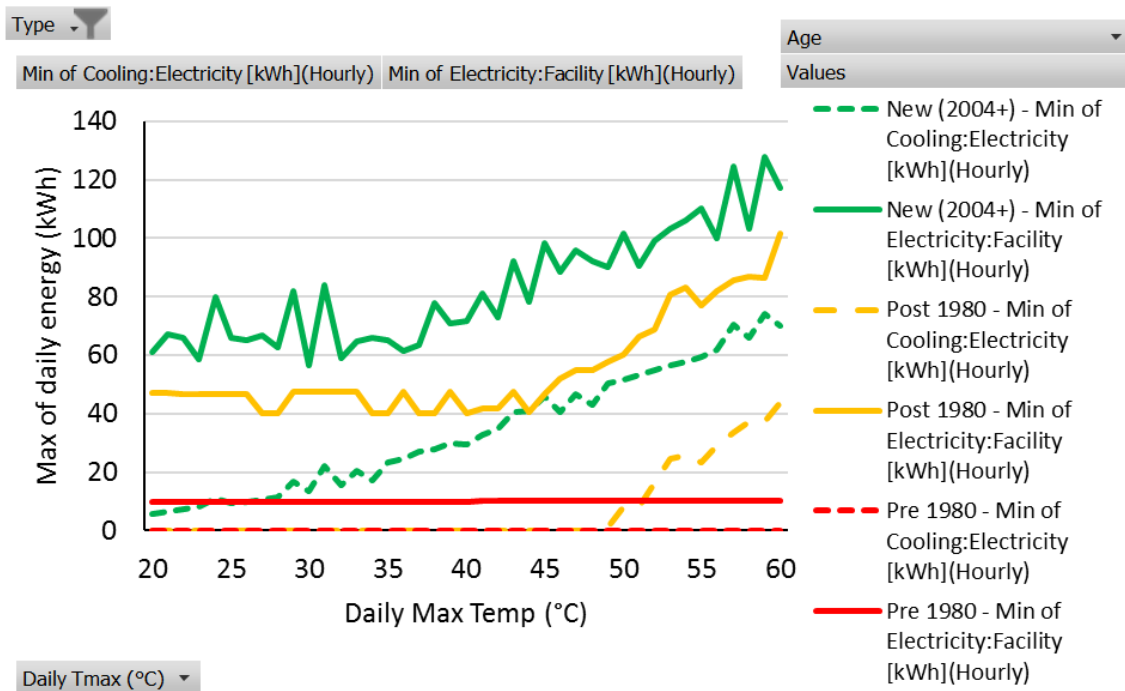
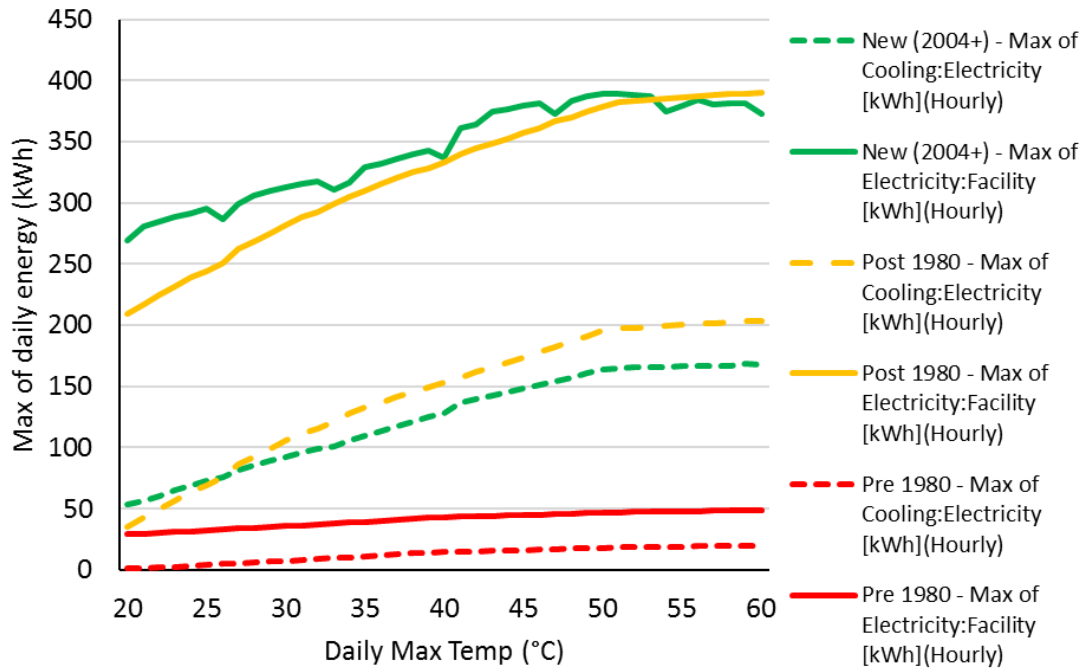


Figure 28. Large Hotel

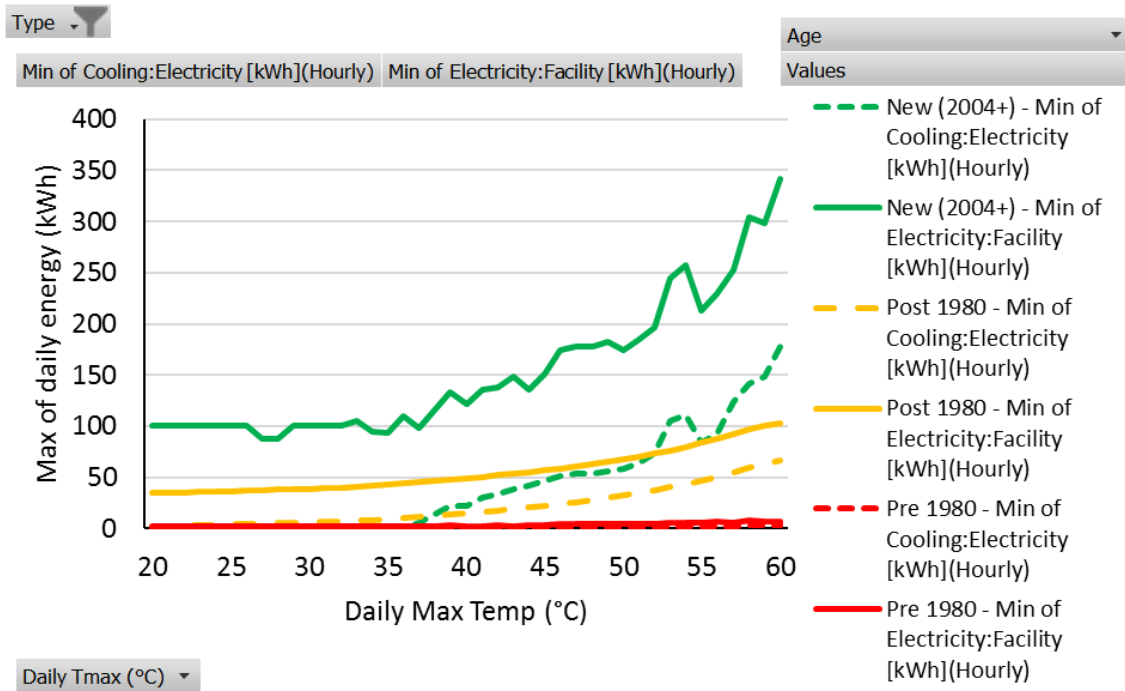
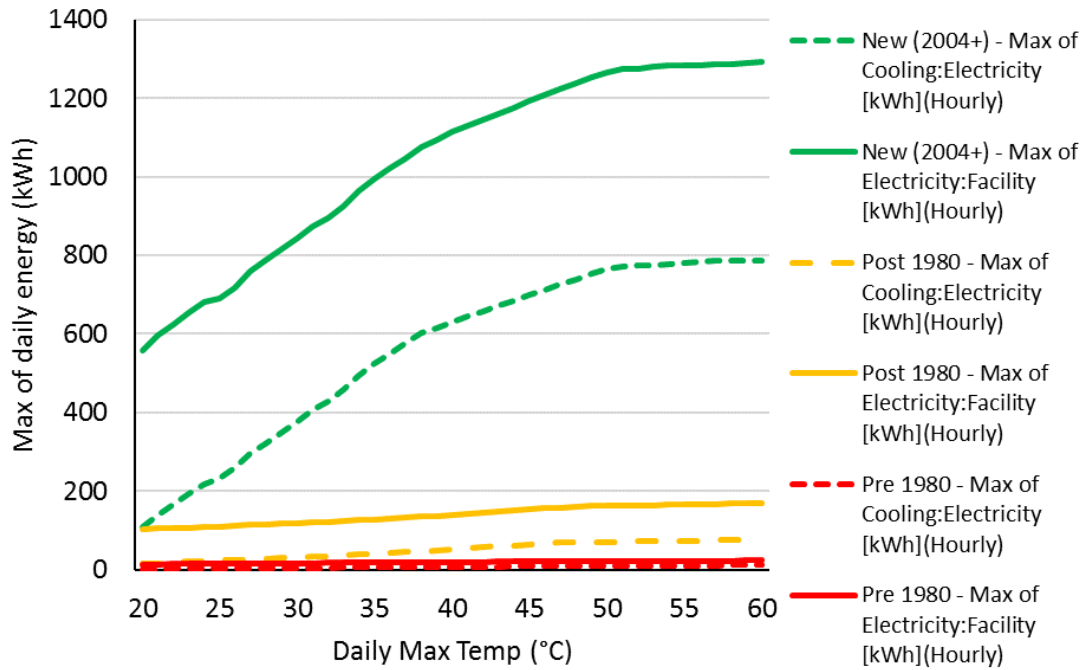


Figure 29. Large Office

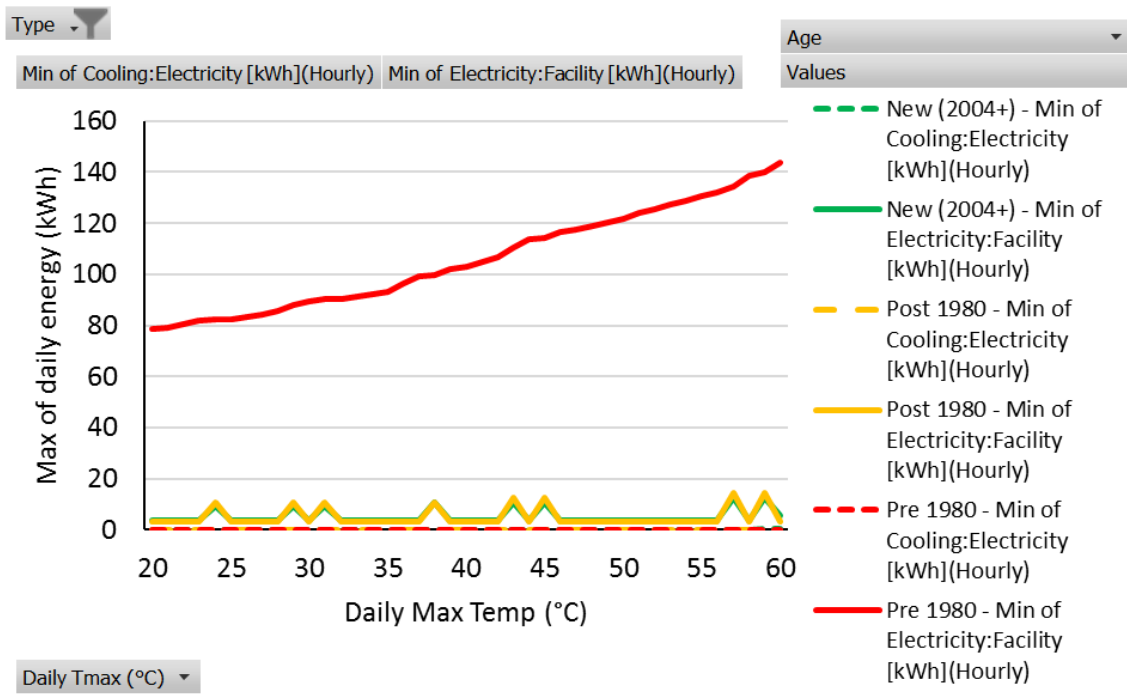
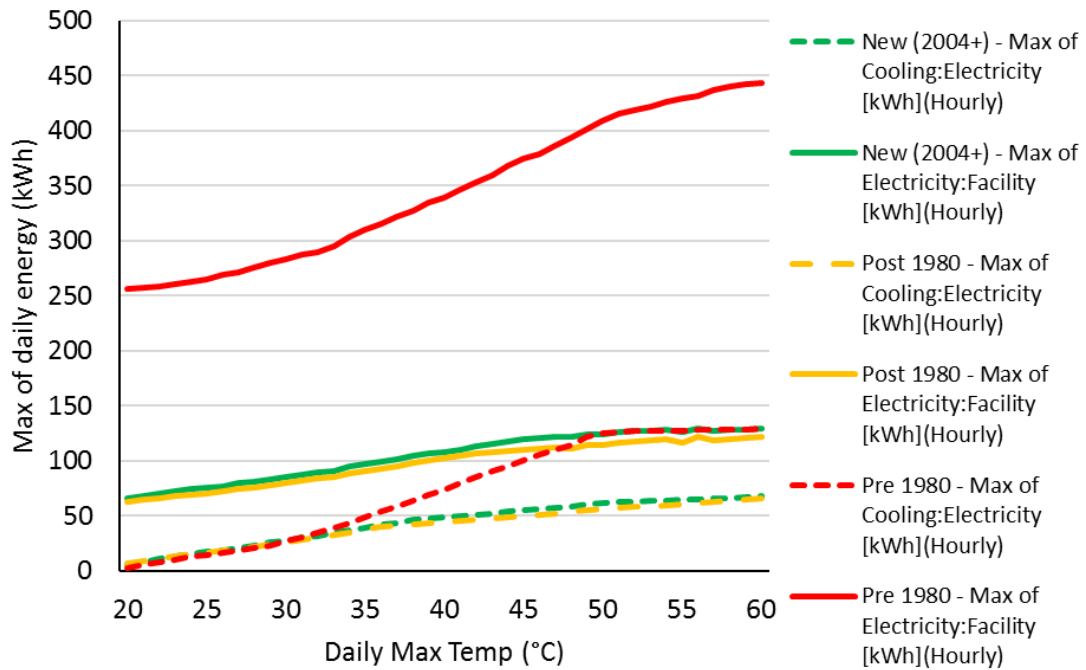


Figure 30. Medium Office

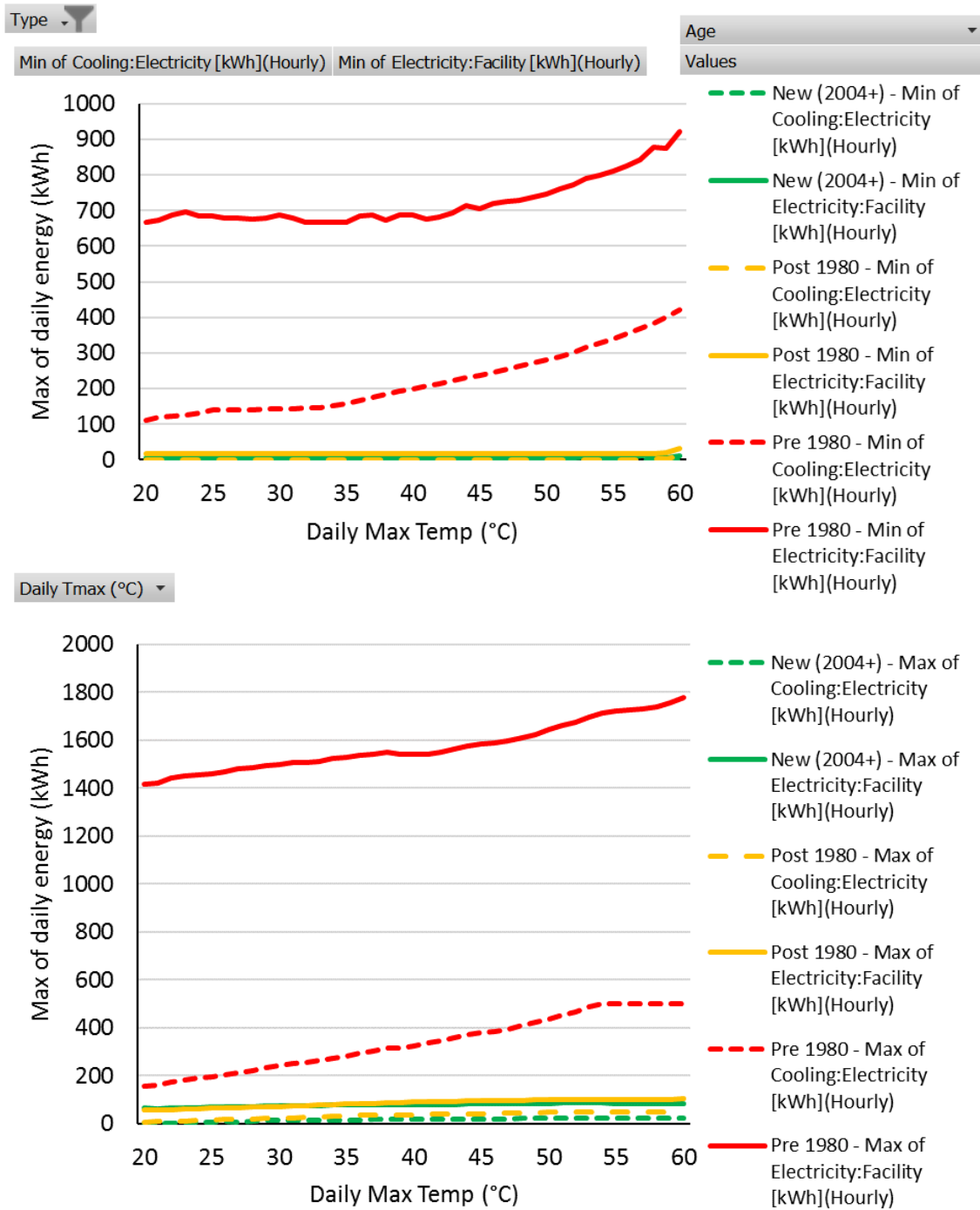


Figure 31. Midrise Apartment

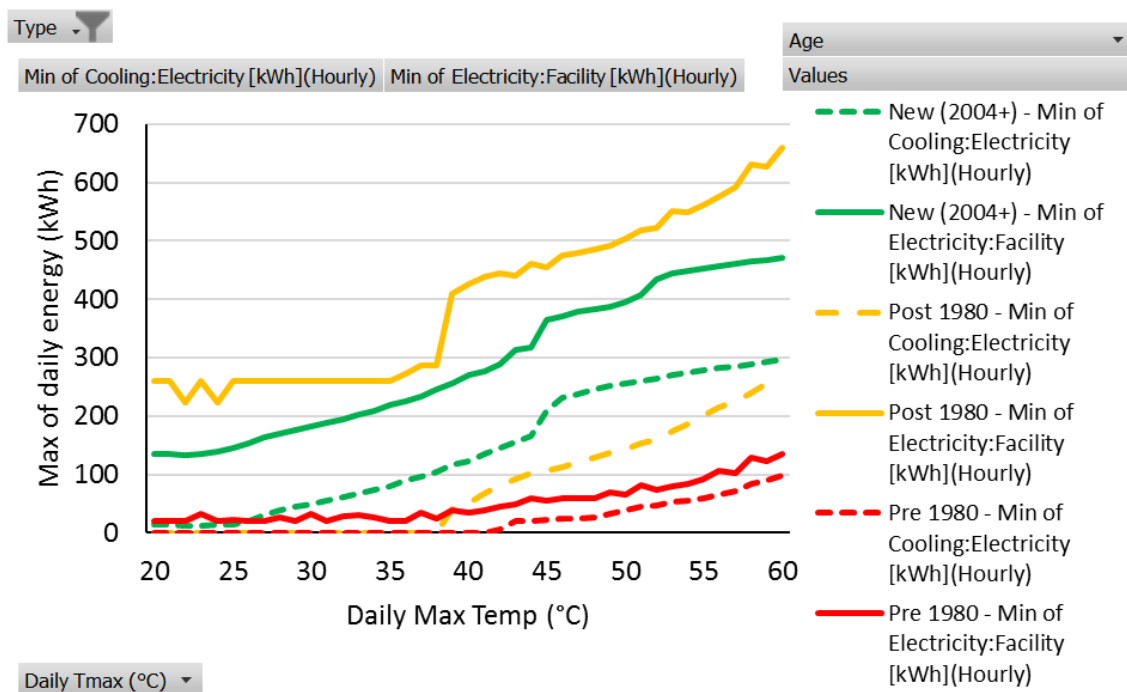
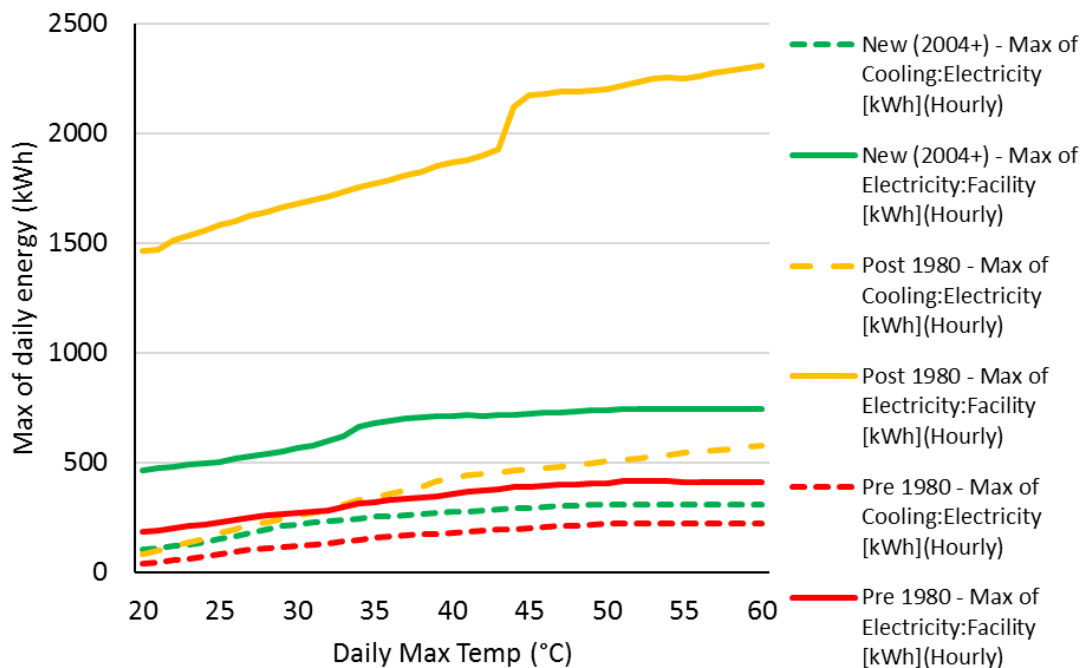


Figure 32. Out Patient

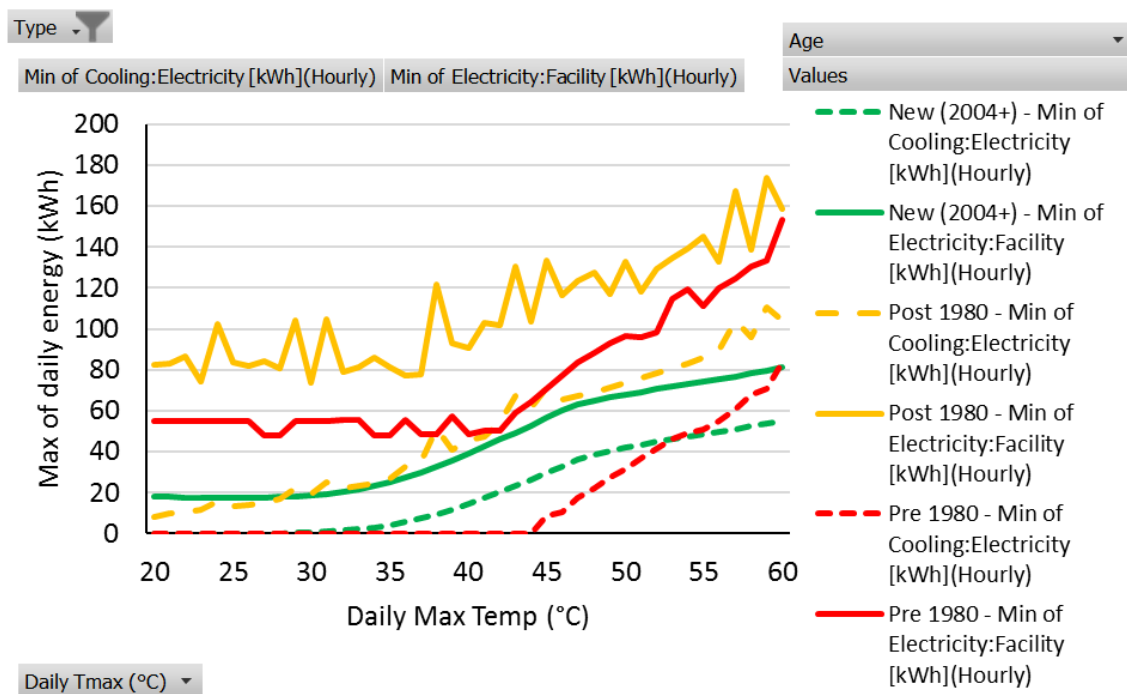
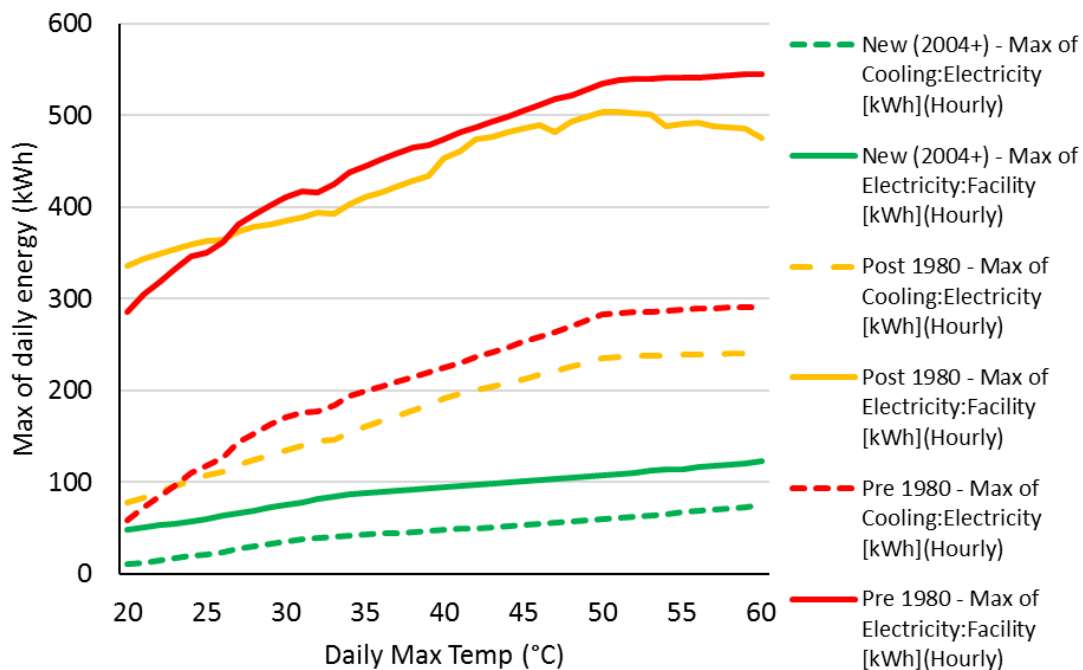


Figure 33. Primary School

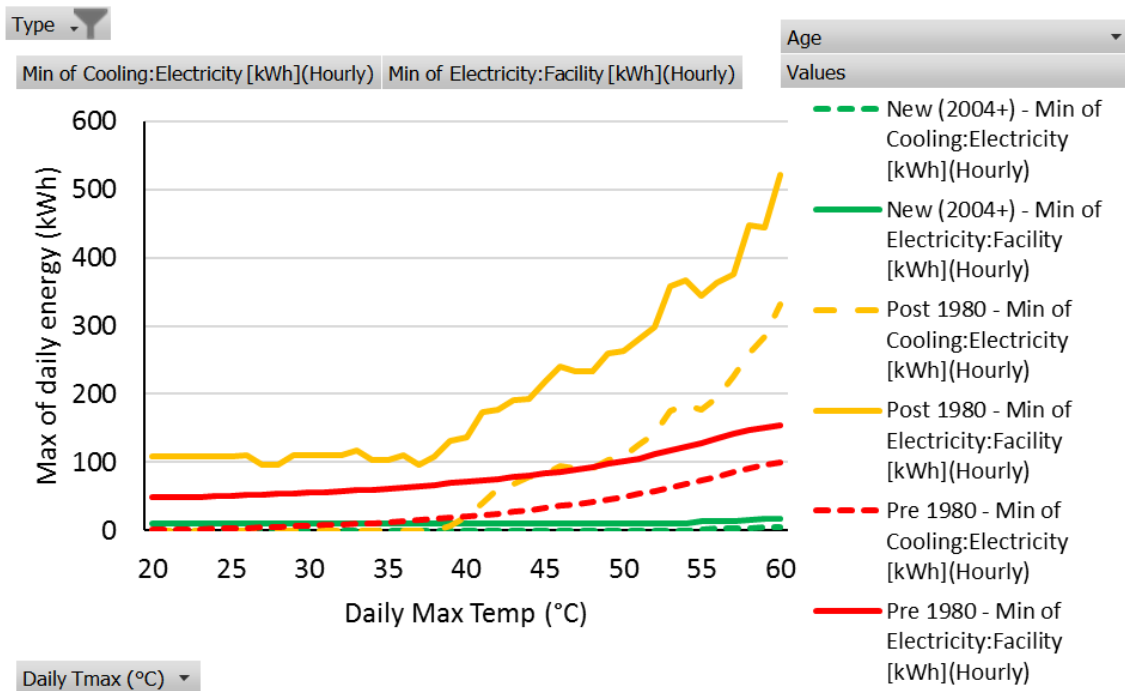
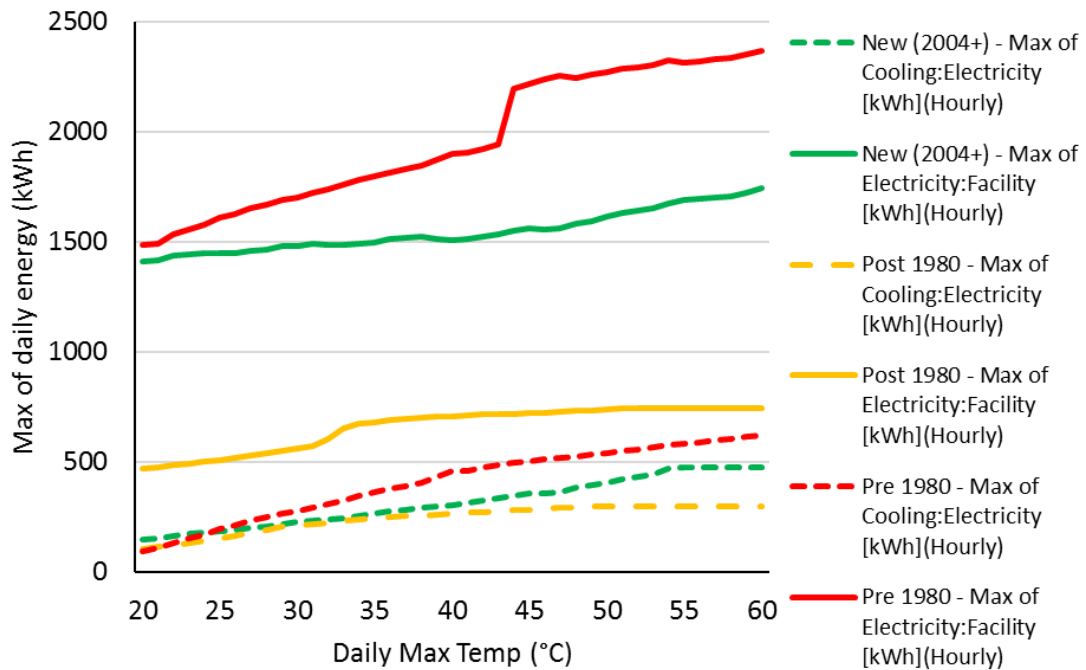


Figure 34. Quick Service Restaurant

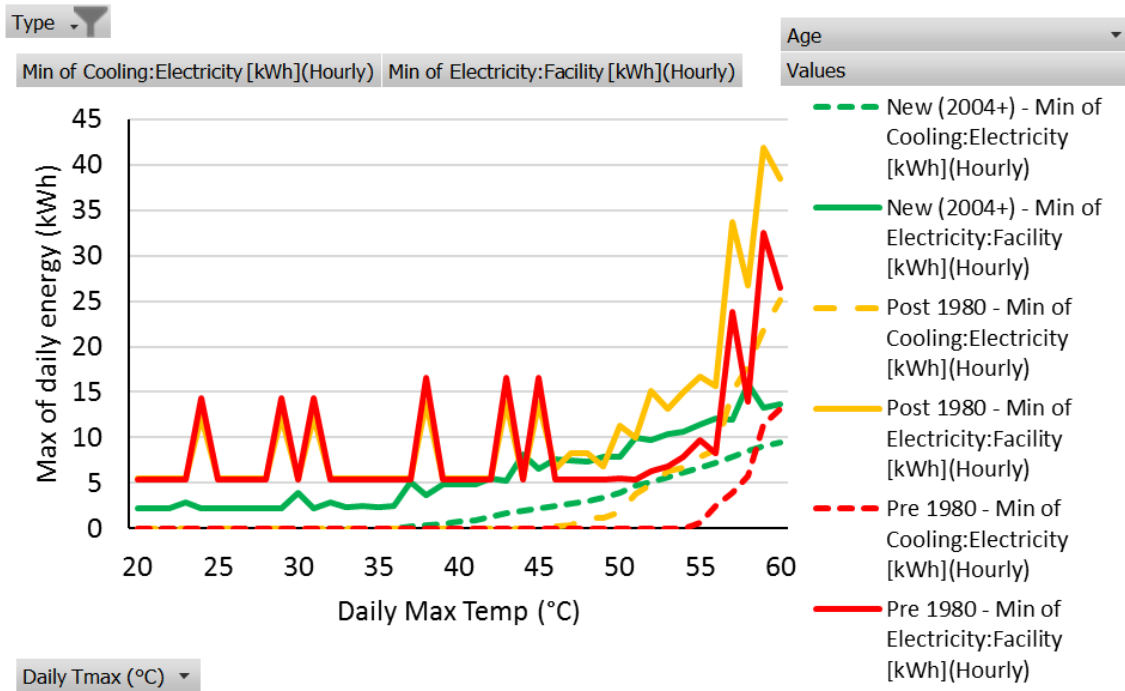
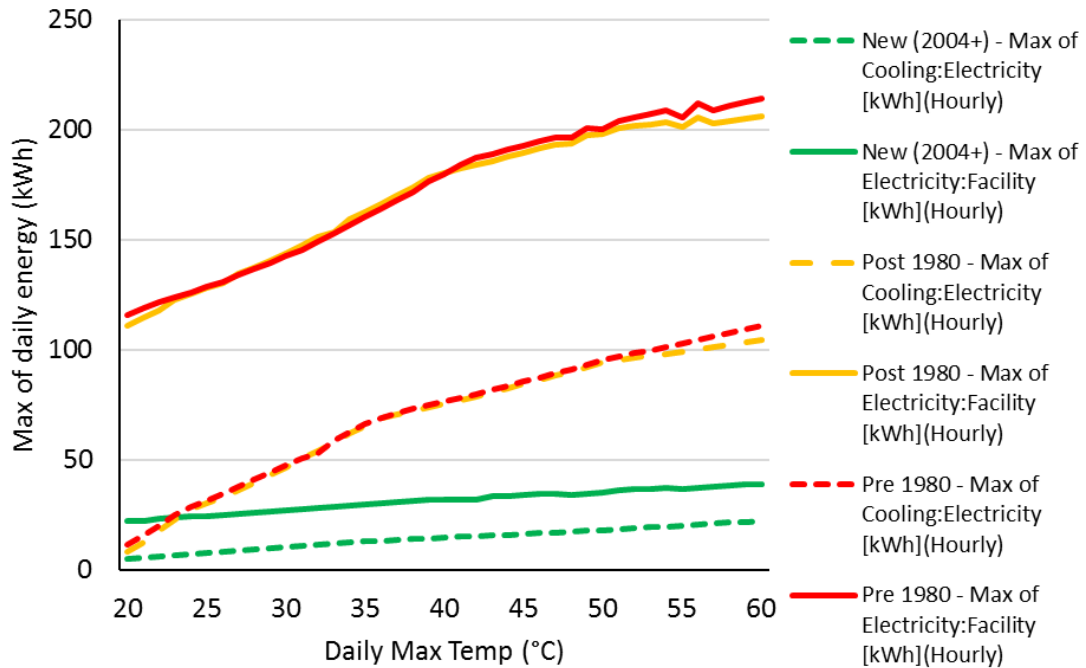


Figure 35. Secondary School

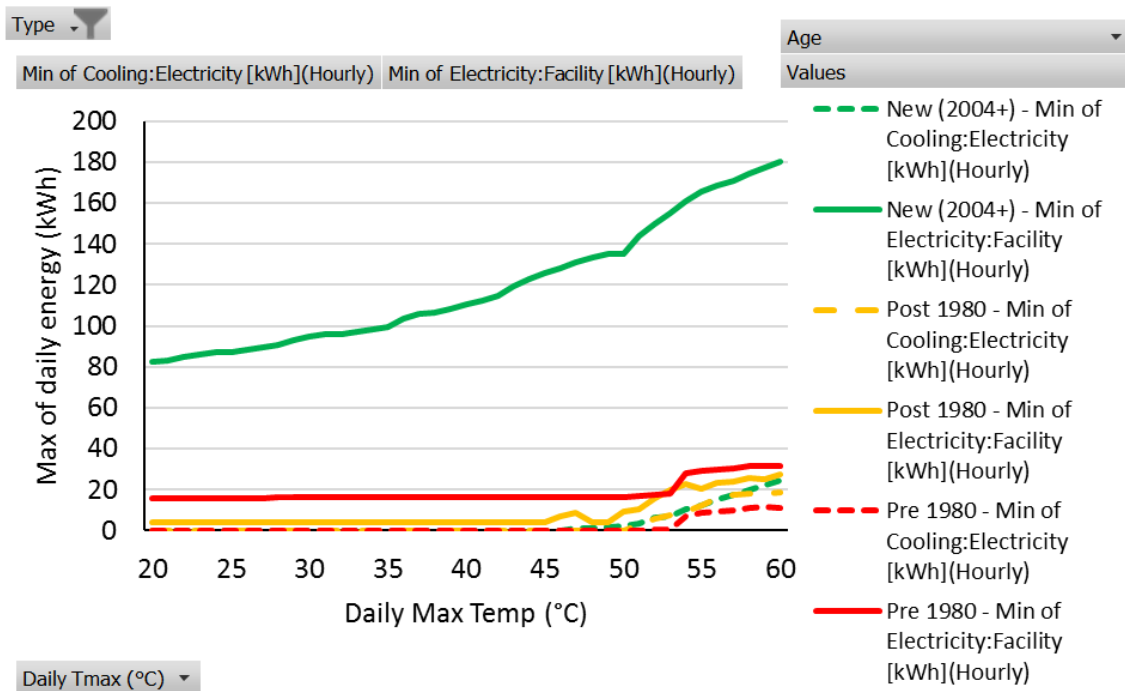
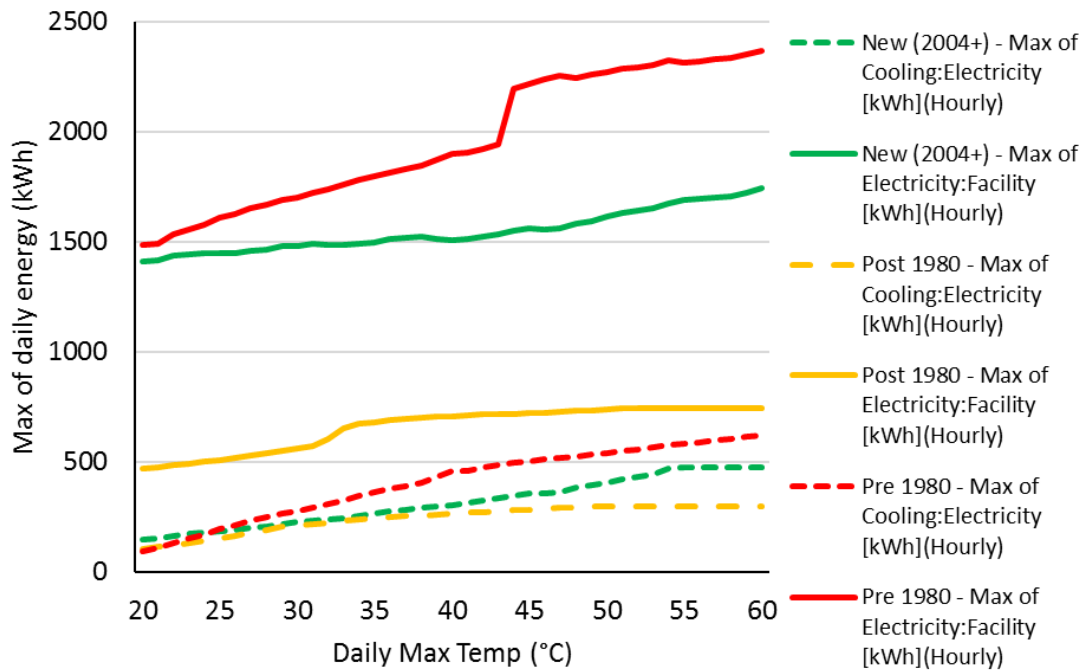


Figure 36. Small Hotel

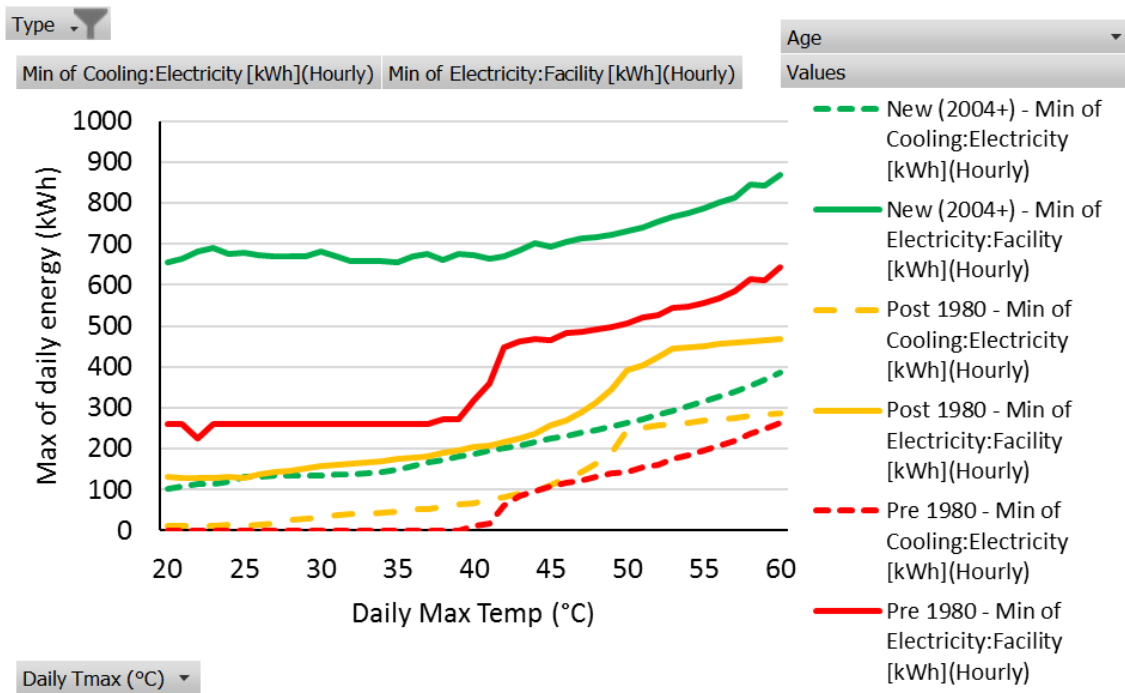
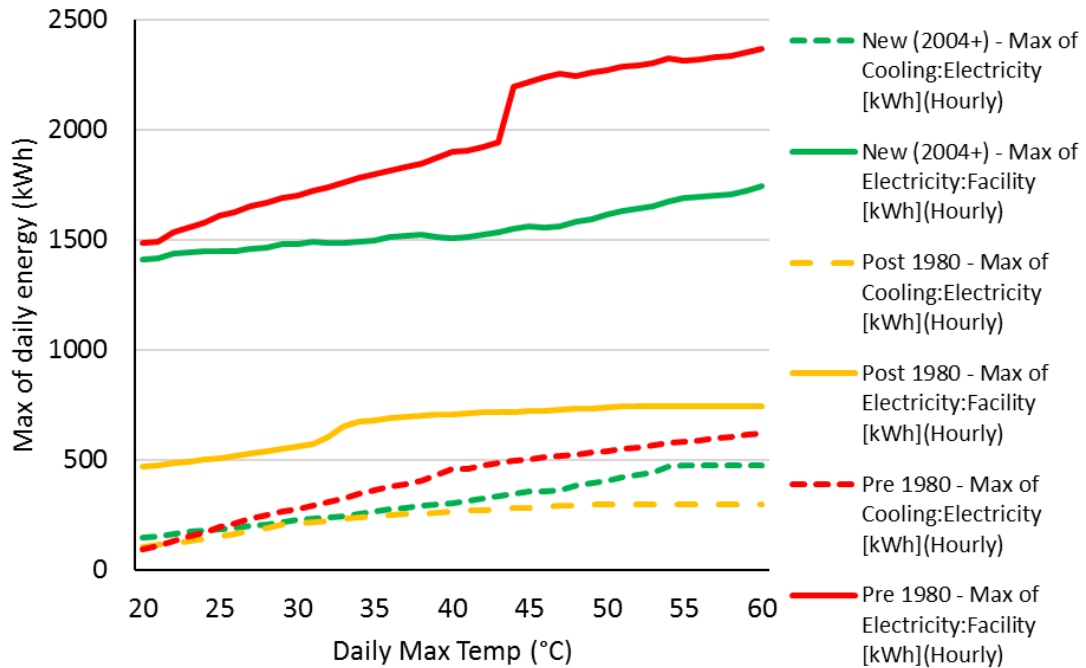


Figure 37. Small Office

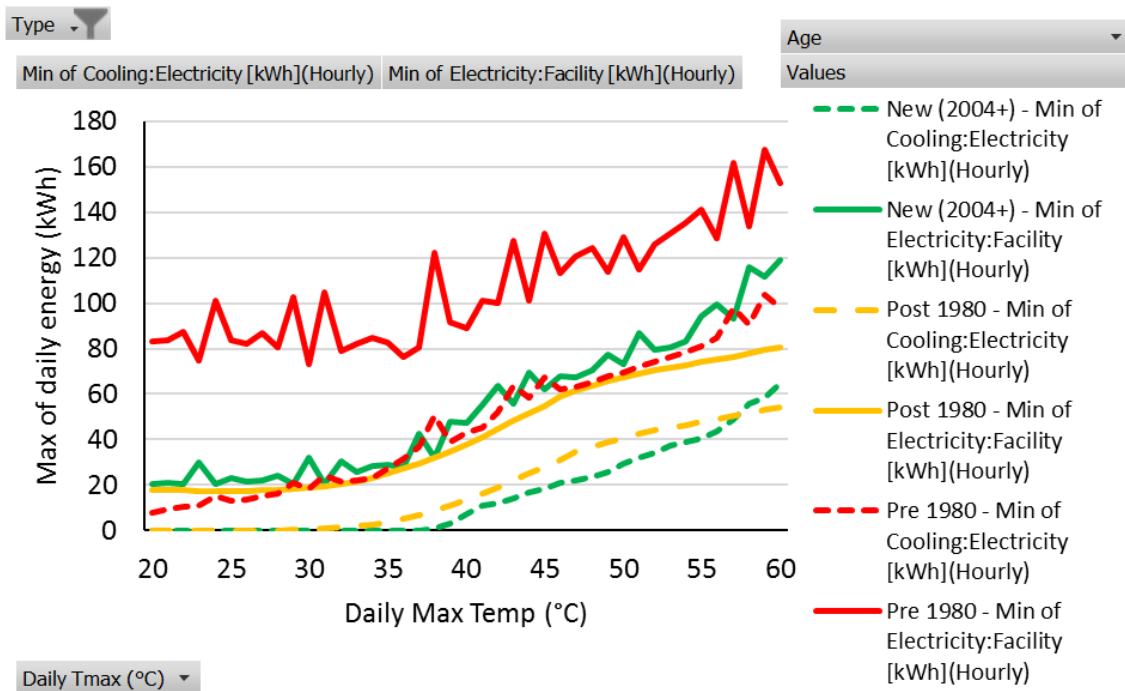
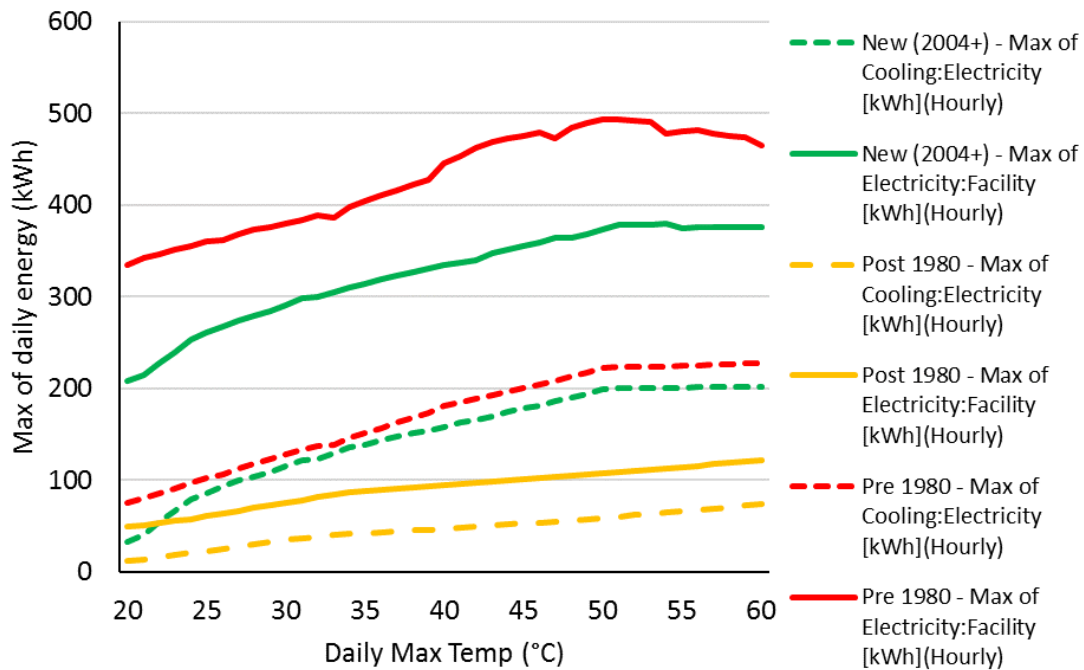


Figure 38. Stand-Alone Retail

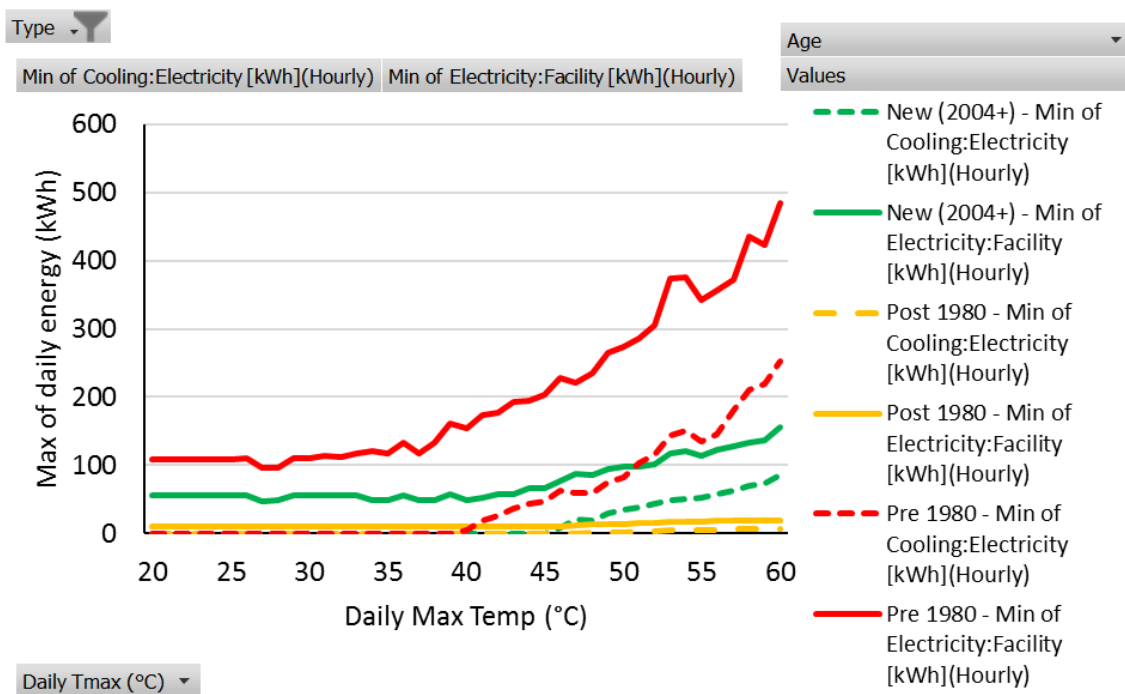
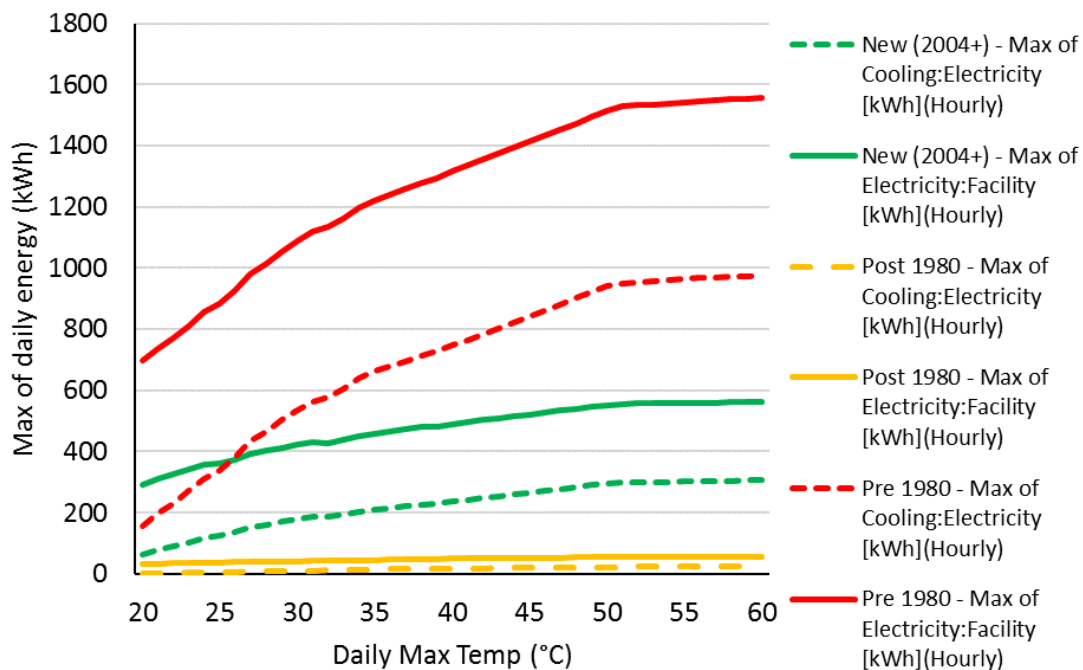


Figure 39. Strip Mall

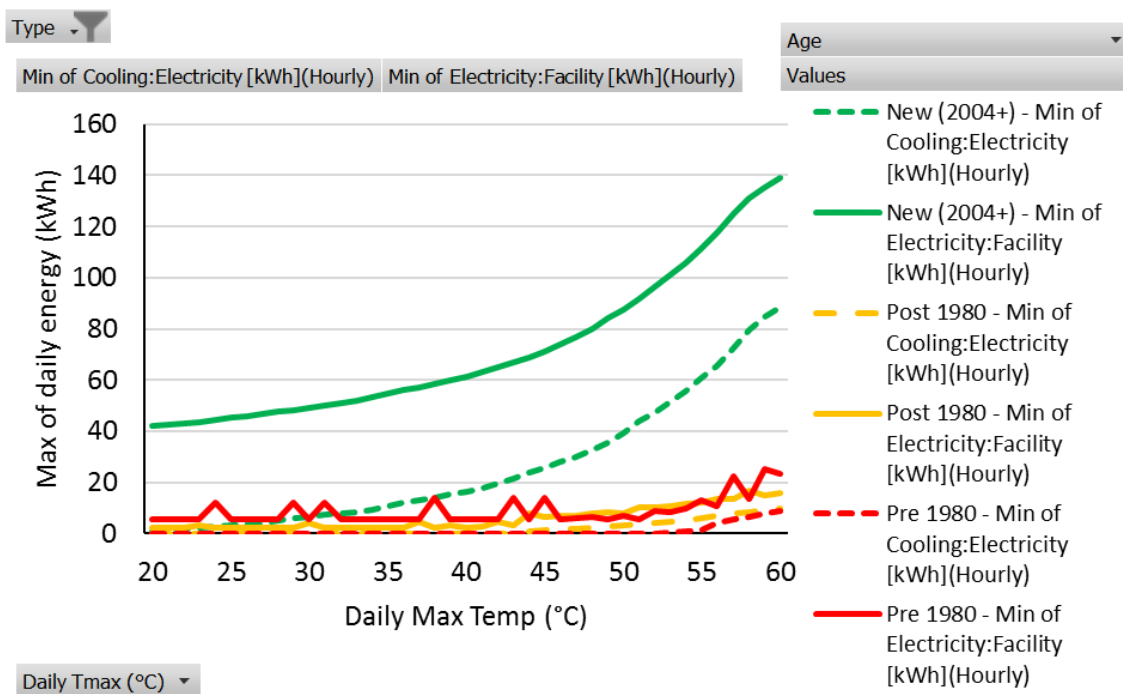
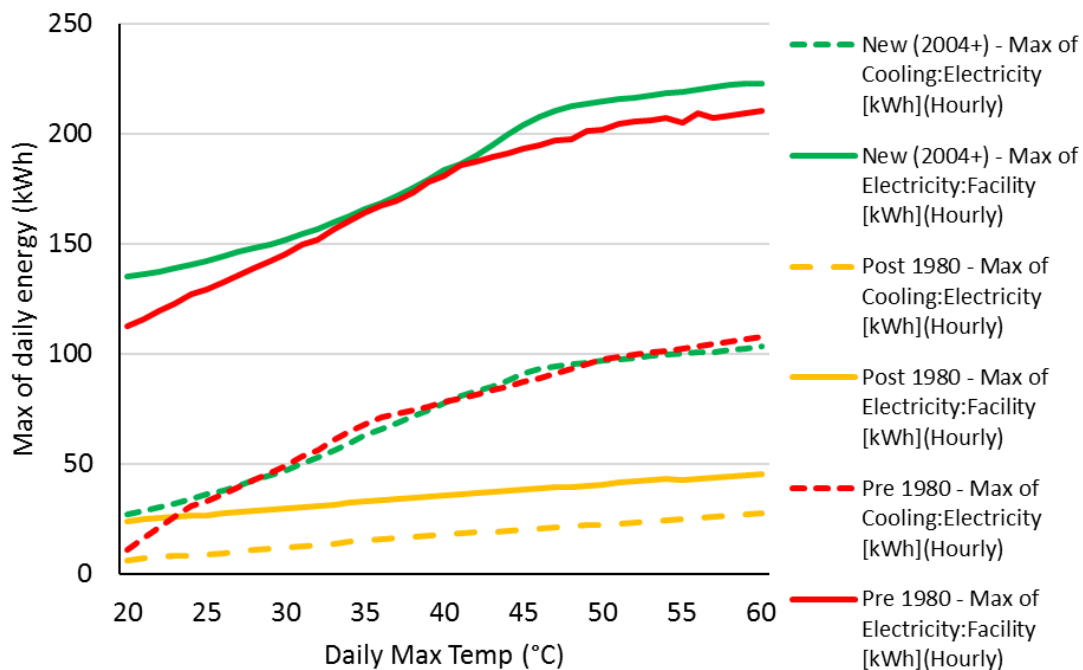


Figure 40. Super Market

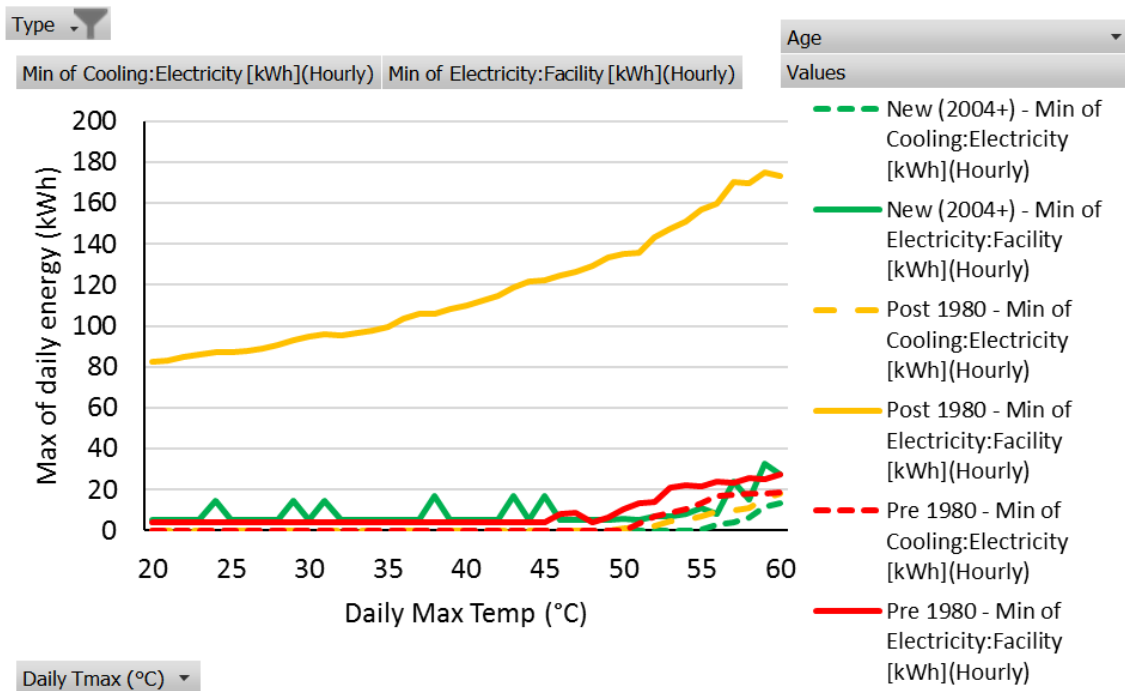
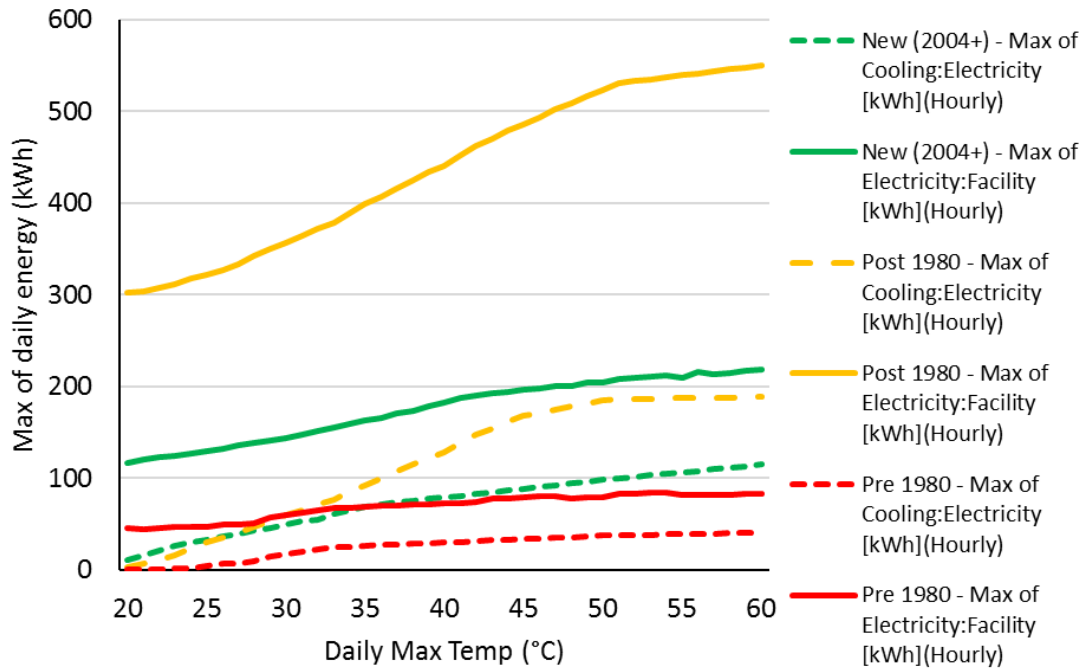


Figure 41. Warehouse

APPENDIX B

STATISTICS OF COMPONENT LOADS

This appendix is in review at the California Energy Commission as part of a larger report with the citation (pending) as follows: Burillo, Daniel, Mikhail Chester, Stephanie Pincetl, Eric Fournier, Daniel Walton, Fengpeng Sun, Marla Schwartz, Katharine Reich, Alex Hall. (University of California Los Angeles). 2018. *Climate Change in Los Angeles County: Grid Vulnerability to Extreme Heat*. California's Fourth Climate Change Assessment, California Energy Commission. Publication number: CEC-XXX-2018-XXX.

Instructions are for ArcMap Desktop 10.5.

Start with EIA / homeland security data set (Homeland Infrastructure Foundation-Level Data, 2017b), as shown in Figure 42 below. Notice transmission lines from (Homeland Infrastructure Foundation-Level Data, 2017a) are overlaid in figure.

- 410 substations total
- 102 have voltage ratings
 - 66-69 kV, count = 25, all but 9 are listed with connections to one or more lines
 - 115-138 kV, count = 18, all but 7 are listed with connections to one or more lines
 - 230-500 kV, count = 59, all but 5 are listed with connections to one or more lines
- 308 unknown are assumed to be medium to low voltage, i.e. ≤ 138 kV

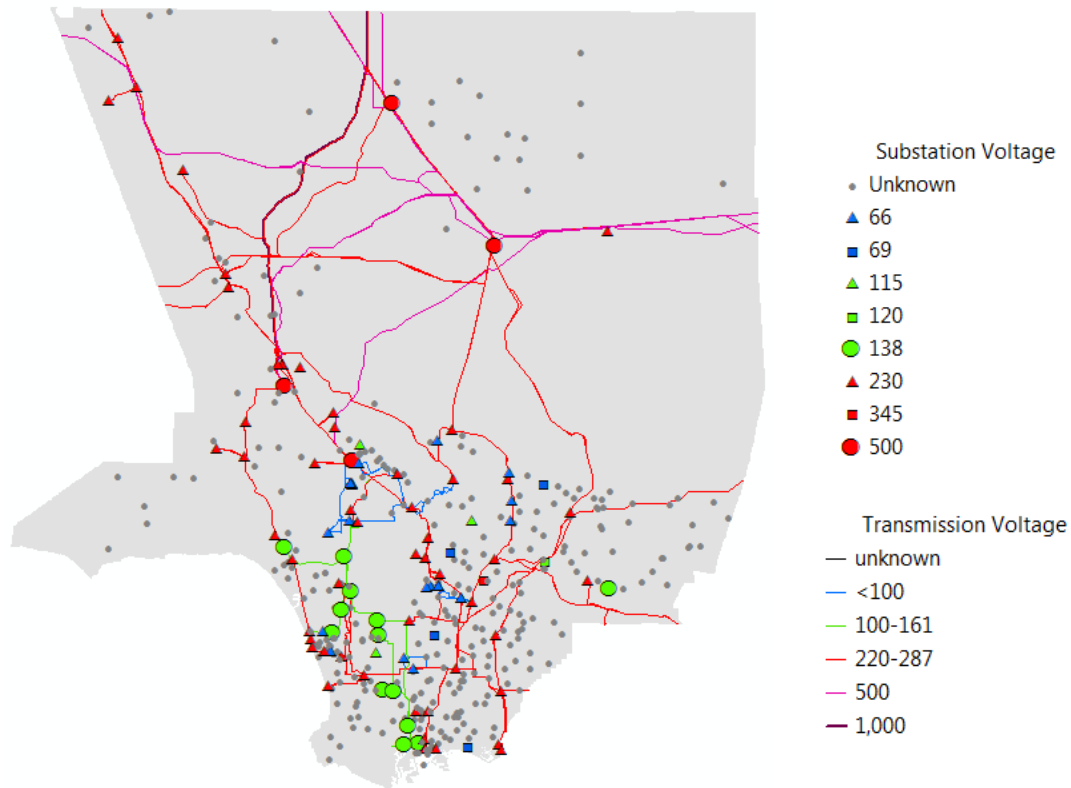


Figure 42. LAC Substations with Transmission Line Overlay.

Note: not all components may be visibly identifiable due to close proximity.

Separate substations into two layers, high voltage and low voltage per the Preliminary Analysis of Substation Loading below.

- High voltage: 230kV and up
- Medium and low voltage: rest including unknown

High Voltage

1. Use “Integrate” tool on high voltage layer with 2km tolerance, and then “collect” to produce new layer as shown in Figure 43. The 59 substations will be consolidated into 36 clusters. Substations are grouped together in

this manner to prevent creation of nonsensically small polygon areas in the following step.

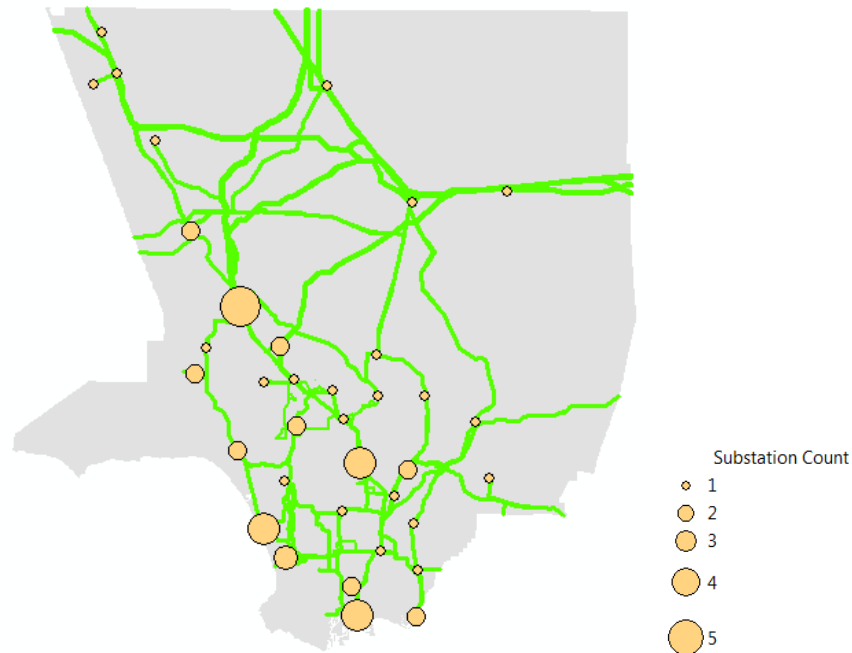


Figure 43. Clustered High Voltage Substations Only with Transmission Line Overlay

2. Use "Create Thiessen polygon" to run Voronoi Tessellations and allocate substations to land area coverage, and then "clip" to LAC as shown in Figure 44. Add the attribute of Area for square meters.

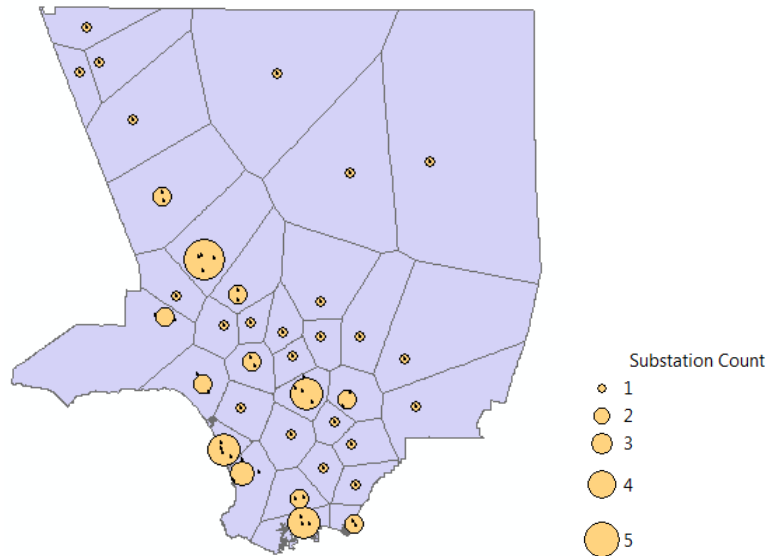


Figure 44. Clustered High Voltage Substations with Voronoi Polygons

3. Use the “intersect” tool assign the CBG peak demand composite image for the base period. Make sure peak demand is available in terms of (W) and that the areas of the CBGs are in that shape file.
4. Create a new column for area of the intersected space in terms of square meters.
5. Create a new column for the peak demand (W) to allocate to the Voronoi polygon. Calculate it as the product of peak demand (W) in the CBG and the ratio of intersection area to CBG area.
6. “Dissolve” the layer by the FID of the Voronoi polygons, and sum the peak demand (W). Base case shown in Figure 45 for 13.5 GW.

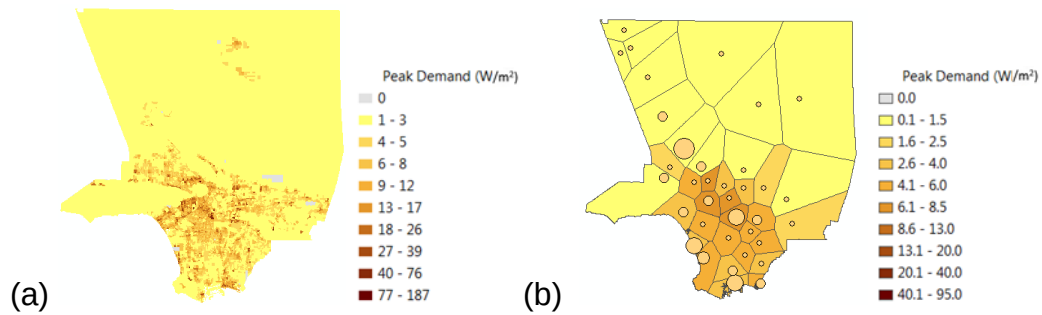


Figure 45. Sample Transform of Peak Demand from CBGs to High Voltage Substation Voronoi Areas.

Comparison of substation allocations with SCE DERiM data is shown in Figure 46. Total peak demand estimated in the model at substations corresponding to the same geographic locations was 10% less than values estimated from the DERiM data, 6,388 MW versus 7,098 MW. The majority of that difference was 250MW at the three clustered substations in the southwest LA Fresa (x2) and El Nido substations, and 180MW at the Antelope substation in the north.

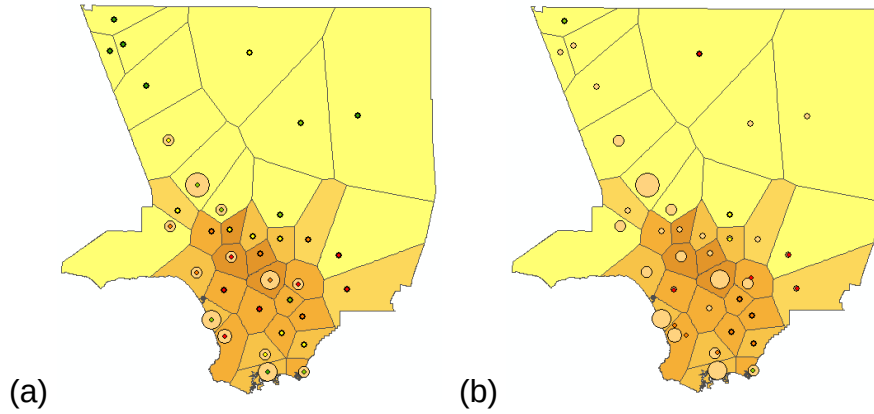


Figure 46. Overlay of Substation Clustering, Voronoi polygons with base period demand allocation (W/m^2)

to (a) model estimated peak load, and (b) SCE DERiM peak load estimates.

Medium and Low Voltage

Repeat steps for high voltage.

Cluster 351 substations into 173 Voronoi polygons by grouping within 1km proximity, Figure 47.

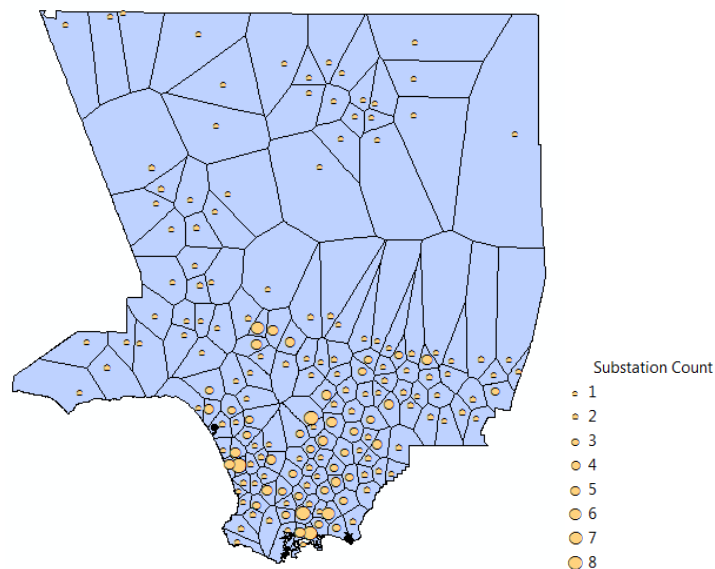


Figure 47. Clustered Low Voltage Substations with Voronoi Polygons

Comparison of demand allocation shown in Figure 48.

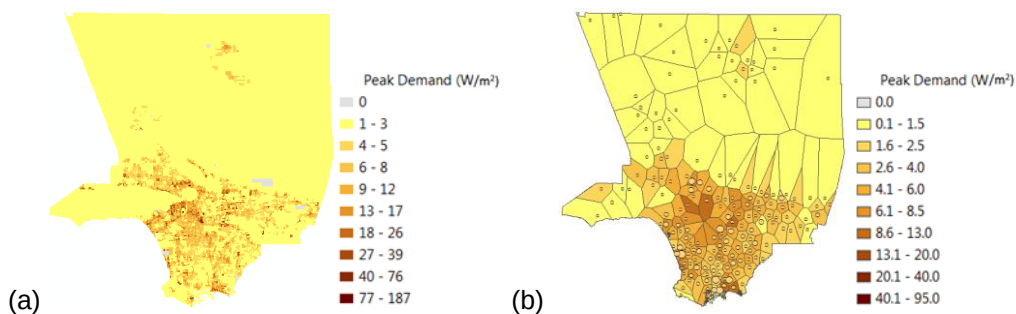
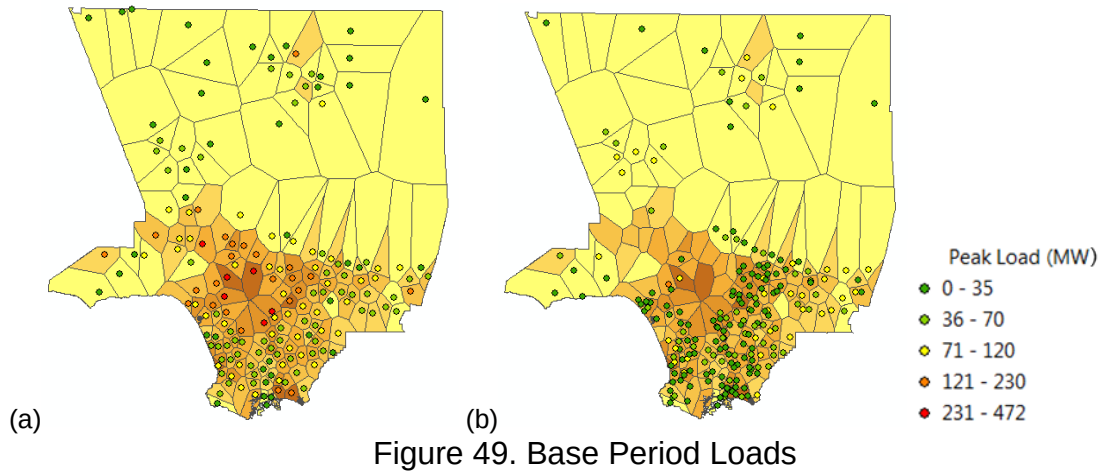


Figure 48. Sample Transform of Peak Demand From CBGs to High Voltage Substation Voronoi Areas.

Of the 173 substation clusters, 133 overlapped with the SCE DERiM's distribution substations, with a combined model peak demand of 9.94 GW, 15% higher than the DERiM's 8.62 GW. Comparison of loads on substations and substation clusters is shown in Figure 49. Most of that difference was due to Voronoi polygons that included LADWP substations in the clustering.



for (a) model composite demand on substation clusters, and (b) SCE DERiM distribution substations and estimated peak load.

Preliminary Analysis of Substation Loading

This section details how substation load, capacity, and load factor estimations were developed for the base period. The EIA / Homeland Security substation data set, as previously described, was used as representative of LAC's installed components in terms of location and level in the delivery system. Components were separated into high voltage and low voltage layers in an attempt to represent parallel operations within each layer and series operations across the layers. Obviously this is not a perfectly accurate method, but given the data and tools available to work with this was considered a reasonable approach, within limits, as follows. The SCE DERiM data set (Southern California Edison, 2016a) was used as a representative sample because data were available to estimate load, capacity, and load factor as detailed in the next paragraph. Shown in Figure 50, the DERiM's 21 "sub-transmission" substations were geo-located within 100m of the EIA's 59 high voltage $\geq 230\text{kV}$ substations, with matching names in

the data. All but three were labeled as 220/66 kV, two were labeled 66/66 kV, and one as 12/66kV. Of the DERiM's 245 "distribution" substations, 202 were geo-located within 100m of the EIA lower ≤ 138 kV and unknown voltage substations, 171 were listed as 66/16 kV or 66/12 kV, 73 as 16/4kV or 12/4kV, and 1 as 16/33 kV. Obviously, there is some amount of power flow in series amongst those substation layers, as there is between 500 kV and 230 kV substations. Again, this approach is an approximation. Of the EIA's 351 lower voltage substations, 37 had "unknown" names, otherwise unique, and 161 had names that matched to the DERiM's 245 substations. The DERiM data had 74 substations listed with the same name and different voltage ratings as the EIA data. Therefore, DERiM data were assumed representative of approximately 1/3rd of the high voltage substations, and 70% of the low voltage substations in LAC.

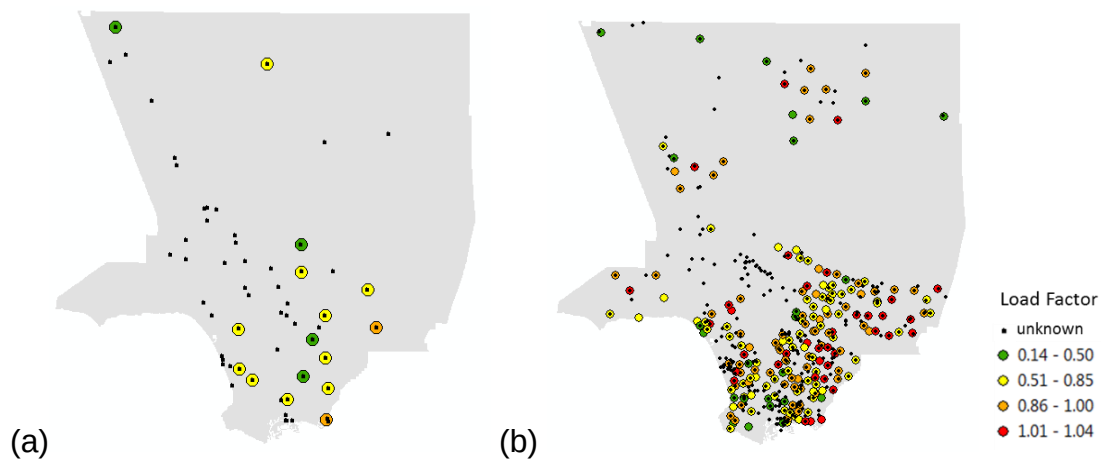


Figure 50. Overlay of EIA and SCE Substations for (a) high voltage and (b) low voltage layers. EIA substations are shown as black dots, and SCE substations as colored circles.

Substation load, capacity, and load factor estimates were developed from the published DERiM data, and ranges allocated to the remaining substations in

243

the LAC infrastructure. Equations for estimated values are listed in Table 13 below. Peak Load was a straightforward estimation per the definitions from SCE's data dictionary (Southern California Edison, 2016a) quoted in the bullets points below. The formula for Nameplate Capacity was assumed for a temperature adjusted loadability factor equal to 1 at 40°C. SCE's interconnection handbook guidelines (Southern California Edison, 2016b) state 40°C in sections for Ambient conditions, and Transformer Emergency Ratings are stated as permissible with 10-20% overloading for 1-30 days. These values are consistent with the range of high voltage AC switchgear operations described in IEEE Std C37.30.1-2011 (IEEE, 2012). Load Factor is a straightforward calculation based on the previous two estimates. Descriptive statistics of results are summarized in

Table 14, and shown in Figure 50, Figure 51, and Figure 52. Note: 7 substations were discarded from sample as Load Factor values were not considered reasonable equal to zero or greater than 2. UNIVERSAL 66/12 kV, TAHITI 66/16 kV, REDMAN 66/12 kV, NAVY MOLE 66/12 kV, GOULD 16/33 kV, GANESHA 66/12 kV, AUTOBODY P.T. 16/4 kV. Of the 238 remaining substations, the 72 substations labeled 16/4 kV and 12/4 kV had a total peak load of 509 MW (6% of the sample), capacity of 677 KVA (7% of the sample), and single largest capacity of 17 kVA.

Table 13. Equations Used in Estimating Substation Load Factors

Equation #	Expression	Units
1	Peak Load = Total Generation / Current Penetration Level * 100	MW
2	Nameplate Capacity = Existing Generation + Maximum Remaining Generation	MW
3	Load Factor = Peak Load / Nameplate Capacity	%

- Total Generation (MW) - “This value represents the sum of both Existing and Queued Generation. Total Generation includes all downstream [distributed energy] resources. For example, Total Generation at a substation includes all Existing and Queued Generation connected to all circuits fed from that substation.”
- Current Penetration Level (%) - “This value represents the ratio of generating resources to peak load, expressed as a percentage. For example, if a circuit has a peak load of 10 MW, along with 4 MW of Total Generation (this includes existing and queued generation), the current penetration level is 40%.”
- Maximum Remaining Generation (MW) – “This value represents the maximum amount of generation that the system may be capable of supporting within existing planning guidelines and criteria. The maximum remaining generation capacity often requires system upgrades to be fully realized.”

Table 14. Summary of SCE DERiM Substation Estimated Values.

Attribute	min	mean	max	total
<i>High voltage (21/59)</i>				
Peak Load (MW)	40	338	759	7,098
Nameplate Capacity (MW)	215	518	911	10,883
Load Factor (0-1)	0.188	0.632	0.893	0.652
<i>Low voltage (245/351)</i>				
Peak Load (MW)*	1	36	143	8,537
Nameplate Capacity (MW)	1	43	387	10,155
Load Factor (0-1)	0.145	0.807	1.042	0.841

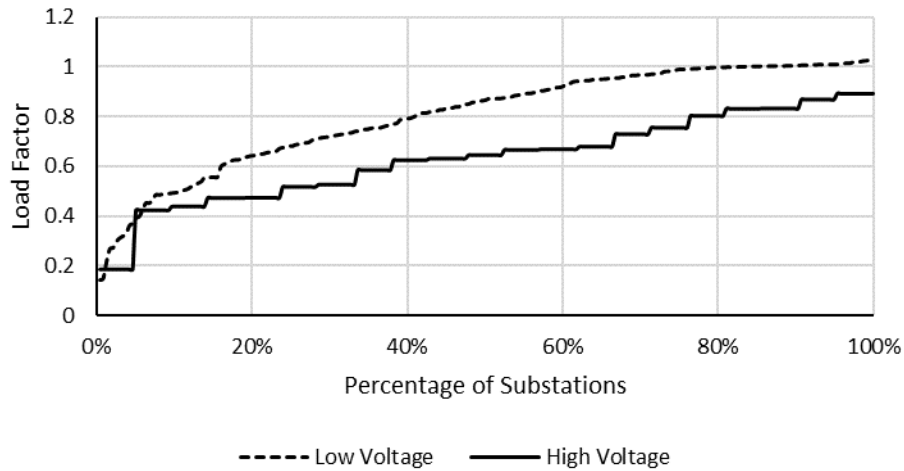


Figure 51. Probability Density Function of Load Factors on SCE Substations

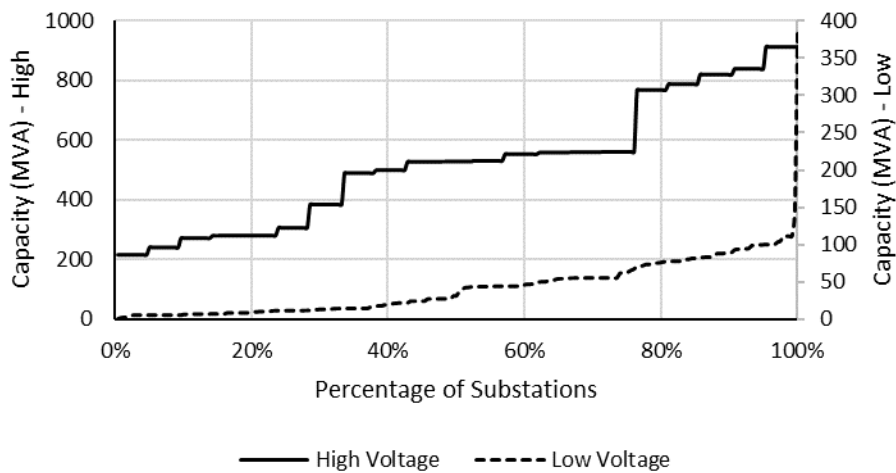


Figure 52. Probability Density Function of Load Factors on SCE Substations

Total values for peak load for SCE at high- and low-voltage levels were considered as within a reasonable range to use for approximate verification purposes. Previous work in Task 3 estimated the range of base period peak demand for LAC as 15-20 GW. If the total peak demand for SCE's high voltage substations is proportionally representative of the county, then total county peak demand on the high voltage layer would be equal to $7.1 \text{ GW} * 59/21 = 19.9 \text{ GW}$.

If the total peak demand for the low voltage substations is proportionally representative of the county, then total county peak demand on the low voltage layer would be equal to $8.5 \text{ GW} * 351/245 = 12.2 \text{ GW}$. Possible explanations for the 25% shortfall at the low-voltage level are that SCE has about 1-2 GW of installed Solar PV capacity (Desert Renewable Energy Conservation Plan (DRECP), 2017),(Southern California Edison (SCE), 2009) that is skewing the peak load lower in SCE substations relative to the rest of LAC, the other distribution substations may have disproportionately higher loads, and or the source data may erroneous beyond the 7 outliers identified.