

Article

Evaluating the Impact of the COVID-19 Pandemic on Residential Energy Use in Los Angeles

Michael J. Klopfer ¹, Joy E. Pixley ¹, Armen Saiyan ², Amir Tabakh ², David Jacot ² and Guann-Pyng Li ^{1,*}

¹ California Plug Load Research Center (CalPlug), California Institute of Telecommunications and Information Technology (Calit2), University of California, Irvine, CA 92697, USA; mklopfer@uci.edu (M.J.K.); jpixley@uci.edu (J.E.P.)

² Los Angeles Department of Water and Power (LADWP), Los Angeles, CA 90051, USA; Armen.Saiyan@ladwp.com (A.S.); Amir.Tabakh@ladwp.com (A.T.); david.jacot@ladwp.com (D.J.)

* Correspondence: gpli@uci.edu; Tel.: +1-(949)824-9073

Featured Application: This work is potentially useful for updating residential energy usage models, considering presented energy impacts of the COVID-19 pandemic.

Abstract: The 2020 COVID-19 pandemic provided an opportunity to assess energy use during times of emergency that disrupt daily and seasonal patterns. The authors present findings from a regional evaluation in the city of Los Angeles (California, USA) with broad application to other areas and demonstrate an approach for isolating and analyzing residential loads from community-level electric utility feeder data. The study addresses effects on residential energy use and the implications for future energy use models, energy planning, and device energy standards and utility program development. In this study we review changes in residential energy use during the progression of the COVID-19 pandemic from four residential communities across Los Angeles covering approximately 6603 households within two microclimate sub regional areas (Los Angeles Basin and San Fernando Valley). Analyses address both absolute and seasonal temperature-corrected energy use changes while assessing estimated changes on energy usage from both temperature-sensitive loads (e.g., air conditioning and electric heating) and non-temperature-sensitive loads (e.g., consumer electronics and major appliance use). An average 5.1% increase in total residential energy use was observed for non-temperature sensitive loads during the pandemic period compared to a 2018–2019 baseline. During mid-spring when shelter in place activity was highest a peak monthly energy use of 20.9% increase was seen compared to a 2018–2019 composite baseline. Considering an average of the top five warmest summer days, a 9.5% increase in energy use was observed for events during summer 2020 compared to summer 2018 (a year with similar magnitude summer high heat events). Based on these results, a potential trend is identified for increased residential load during pandemics and other shelter-in-place disruptions, net of any temperature-sensitive load shifts with greater impacts expected for low-income communities.

Keywords: residential energy modeling; COVID-19; coronavirus pandemic; temperature sensitivity; energy security

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1. Introduction

In 2020, changes in energy use and emissions were seen worldwide as a direct effect of the COVID-19 pandemic [1–6]. Mandatory stay-at-home periods globally reduced jet and aviation fuel by 50%, gasoline by 30%, and electricity (on average) about 10 percent during the early pandemic where shelter-in-place (SIP) orders were widespread across many regions. This reduction was followed by partial rebounds for all mentioned energy types later in 2020 [2,7–11]. While commercial transport and mobility to support com-

mercial activities (e.g., commuting for work) were greatly reduced by a curtailment in overall business activities, the impact on residential energy use is harder to directly assess from publicly available electrical grid regional operator data. Preliminary results from studies early in the pandemic suggest increased residential energy use, but results vary [12–14]. Further, little attention has been paid to understanding the mechanisms leading to this change in energy use during both the early pandemic SIP periods and periods following, in addition to regressive periods due to regional re-closures due to increased COVID-19 cases.

Analysis of total energy use for a given region provides conclusions for macro trends. However, analyzing data comprised of heavily mixed sectors (residential and commercial loads) and as a combined set across all day types (weekends and weekdays) provides limited utility for sector-based analysis, and complicates actionable model adjustments for energy planning and conservation efforts. Approximately 21% of energy use nationwide is from residential customers [15]. Residential energy efficiency is a substantial focus for utility programs, but sector changes can be obscured within direct regional load figures. While a general decrease in energy use was broadly observed across most regions worldwide during the 2020 COVID-19 pandemic, modeling and planning difficulties when predicting future demand led to service disruptions. Most notably, poor forecasting models for pandemic-related changes in energy use directly led to widespread rolling blackouts in California in mid-August of 2020 during a substantial heat-wave [16,17]. The 2020 pandemic period exhibited increased reliance on non-dispatchable, low carbon energy sources, with increases of 22.3% solar production and 13.5% wind production in the US compared to 2019 [18]. Understanding sector-focused changes in energy use helps improve demand predictions for future widespread lockdown events in an era of increasing effects of climate change and increased reliance on non-dispatchable and distributed generation.

Residential electric load is primarily comprised of the following major load categories: electricity-driven space conditioning (air conditioning, ventilation/forced air circulation, and electric heaters), lighting, major appliances, miscellaneous (plug) loads, constant building loads, and electric transportation. Of these categories, only space conditioning is directly temperature sensitive. Demand from three other categories—lighting, major appliances, and plug loads—is largely driven by occupancy without substantial regard to ambient temperature. With 42% of US residential use due to space conditioning, ambient temperature is a primary driver of residential electricity use, especially with high air conditioning penetration [15,18,19]. Despite the mild climate in Southern California, Chen et al. assessed a substantial (69% estimated) regional household penetration for air conditioning [19,20]. This includes residential air conditioning systems in different form factors and cooling capacities. For temperature-sensitive loads, both increased occupancy and the reaction of occupants to change in the ambient temperature affect energy use. For the remaining categories, changes in daily occupancy rates (occupied by none versus one or more individuals) and resulting changes in device use behavior (i.e., which loads or devices are used and how they are used) are the main considerations.

Residential occupancy shifted substantially for much of the population during the pandemic, particularly early in the pandemic timeline. While exact assessments of stay-at-home rates are difficult, general trends show higher rates of SIP compliance early-on following the first COVID-19 case wave with proportional compliance (SIP compliance compared to present active COVID-19 cases) generally dropping during the following COVID-19 case waves throughout 2020. In Los Angeles County, mobility data indicates estimated stay-at-home rates of 50.6% of individuals on April 11 and dropping to 35.5% of individuals by September 1 (compared to approximately 25% during mid-February) [21]. Similarly, in a national Gallup study, 49% of respondents reported being likely to shelter in place if asked to during a third surge in late 2020, compared to 67% in early April 2020 during the first surge [22]. SIP restrictions reduced leisure activities in evenings and especially on weekends, but primarily impacted weekday occupancy

through three mechanisms: a shift toward working from home, reduced access to educational facilities for students and educators, and increased unemployment [23]. During 2020, Los Angeles experienced a maximum unemployment rate of 18.8% in May 2020 with a recovery to 12.3% by December 2020 compared to a pre-pandemic level of 4.9% in February 2020 (non-seasonally adjusted) [24]. The majority of jobs lost across the USA (as in other countries) were in leisure, hospitality, entertainment, manufacturing, and food services sectors, with pandemic-related job loss disproportionately impacting women, younger workers, and workers with less education [25]. Minor shifts in population impacting household size also occurred during the early pandemic: in a June 2020 Pew Research Center study 6% of respondents reported gaining a household member and 3% reported moving because of the pandemic. Of those who moved, 61% of respondents reporting moving into a family member's home. The shutdown of college campuses (25%), the desire to be with family (20%), and financial related reasons (18%) were major relocation catalysts, and relocations were highest among young adults (ages 18–29) [26].

The current study analyzed energy use data from distribution station feeder loads, specific to defined geographic areas in the city of Los Angeles, accessed using generalized utility supervisor control data acquisition (SCADA). Such grouped load data is often the only measure available. Prior investigations have identified limitations in using it in standard linear regression-based energy prediction models due to autocorrelation and homoscedasticity. There are also limits when relying on temperature data at high time scale resolutions (e.g., per day), given the shifts in energy use corresponding to behavior variation over the course of the day. However, for certain use cases comparing daily average energy use to daily temperature data has been demonstrated to provide satisfactory estimation figures [27,28]. Here, the authors demonstrate an approach for analyzing grouped load data and daily temperature values to provide insight into how energy use changes due to widespread emergency conditions such as the COVID-19 pandemic.

With a diverse population and a warm, dry climate and typically temperate spring, Los Angeles provides a near-ideal environment to assess the impact of the pandemic on residential utility customers, especially assessing non-temperature sensitive load contribution to total residential energy use. In addition, the city of Los Angeles provides a useful case study because it was substantially impacted by the COVID-19 pandemic in both number of COVID-19 cases in addition to state and local restrictions on business, services, and travel. California's aggressive stay-at-home order was initiated on 19 March and was followed by a relaxation in June, a partial reinstatement in July (following the start of a second wave of COVID-19 cases), a relaxation in September and an amended limited stay at home order issued in late November following through the end of the year (in response to a third wave of COVID-19 cases). Los Angeles County (the major regional health reporting resource covering the city of Los Angeles) suffered three successively increasing waves of COVID-19 case peaks in 2020, occurring on 8 April, 22 July, and 27 December with this one county representing 32% of all cases statewide (note that approximately 25.5% of California's population lives in Los Angeles County) [29,30]. As of 31 December, 7.7% of the LA county population had been infected with COVID-19. The city of Los Angeles regularly maintained stricter controls on business activities to reduce population movement compared to both state and county COVID-19 guidelines [30,31]. A follow-up SIP order to the one issued in spring focused on Los Angeles, beginning 30 November and continuing through 31 December, this was the strictest order in the state of California, effectively banning most outdoor gatherings, restricting employment travel, and reducing retail capacity. Accordingly, the city of Los Angeles provides a rich opportunity to draw transferrable lessons on energy responses to major behavioral shifts.

2. Materials and Methods

2.1. Feeder and Data Selection

This study used Los Angeles Department of Water and Power (LADWP) municipal electrical substation 4.7 kV customer distribution feeder net loads (reported in hourly average kW load values) servicing a designated geographic territory within the city of Los Angeles to provide serviced population load data. Comparison baselines were created from composites of 2018 and 2019 load data from individual feeders, while the evaluation period was initiated with the California SIP order on 19 March 2020 and continued through the end of reporting on 31 December 2020 [31,32]. For comparison as needed an evaluation period beginning on 1 January 2020 is used to report energy use change with respect to calendar year. To compare heatwave-related events, period to period comparisons between single years were used. From a pool of all available feeders the authors performed a two-tier screening process. The first tier selected for feeders that serviced primarily residential customers (greater than 90% residential customers with largely negligible pre-pandemic observable commercial loading patterns). The second tier selected for diversity across the city considering community location, community income, and community building types. Feeders were then excluded for substantial service interruptions or for major changes from 2018 through 2020 rendering those periods non-comparable, including substantial changes in customer base, major new construction, building demolition, or zoning changes. Feeders were also excluded for exhibiting great heterogeneity of income across neighborhoods served by the same feeder, with the exception of Feeder A providing service to Section 8 subsidized low-income housing in Watts. Four feeders were ultimately selected for the current analysis, serving distinct communities across Los Angeles with a total residential customer base of approximately 6603 combined residential customers covering areas with a range of median incomes (see Table 1).

Table 1. Summary of sampled feeders including feeder service area and service demographic information.

Feeder	Location (ZIP Code) ¹	Residential Customers	Region, WS ICAO Code ²	Median Income (Specific Feeder) ³
A (primary)	Watts (90059)	2563 (91.1%) ^{4,5}	LA Basin, KCQT	\$51,635 (\$15,584)
B (primary)	Southeast LA (90037)	1086 (90.1%) ⁴	LA Basin, KCQT	\$44,965 (\$37,004)
C (primary)	Toluca Lake (91602)	1214 (96.5%) ⁴	SF Valley, KVNY	\$109,254 (\$49,039)
D (primary)	Burbank (91601) ⁶	1740 (90.0%) ^{4,7}	SF Valley, KBUR	\$72,868 (\$51,003)
E (example)	Central Wilshire (90036)	1320 (94.6%) ⁸	LA Basin, KCQT	\$117,596 (\$103,242)
F (example)	Downtown (90014)	0 (0.0%) ⁹	LA Basin, KCQT	N/A
NPL	All Los Angeles City	1.24 M (90.7%)	Entire city (KCQT, reference)	\$62,142

Refer to Supplementary Table S1 for additional details. ¹ Presented with community name, reference zip/postal code tabulation area (ZCTA) inclusive of served feeder area; note that Los Angeles-Long Beach Census tract codes inclusive of feeder service area are presented in the supplementary extension of this table. ² Los Angeles (LA) Basin or San Fernando (SF) Valley; NWS weather station (WS), ICAO airport code used for identification; temperature reference and corresponding microclimate region. ³ Median income of service area inclusive ZCTA, and specific feeder service area median income. ⁴ Feeder service area includes single and multi-family homes, small apartment complexes. ⁵ Feeder service area includes public housing. ⁶ This feeder corresponds to a service area bordering North Hollywood (Los Angeles) and Burbank and is served by LADWP. ⁷ Single and multi-family homes, small apartment complexes near commercial district. ⁸ Feeder service area includes a large apartment community, low rise with numerous common facilities. ⁹ Pair of mid-rise buildings mixed retail, mercantile, offices, buildings in LA Jewelry District.

Feeders were evaluated across the period of investigation from 2018 through 2020. Customer construction permit records indicate <6% mid-day solar load contribution total, with slow growth, and 2017 motor vehicle records showed <5% average customer EV penetration average across all primary evaluated feeder service areas (see Table S1). Both factors suggest a low overall impact such that the change between the pandemic and pre-pandemic periods for the evaluated feeders and accordingly the differential impact from solar and EV loads are treated as negligible. The majority of the building types represented were a mixture of single-family homes and small multi-family properties hosting several units, with a smaller proportion of low-rise apartment complexes. The communities assessed represented two microclimates: the Los Angeles Basin and San Gabriel Valley. The California Energy Commission designates two of these feeders (A and B) in climate zone (CZ) #8 and two (C and D) in CZ #9 [33]. Typically, temperature data would be collected from a weather station in the same CZ. However, the neighborhoods served by Feeders A and B are on the border of CZ #9 and exhibit more similarity with the weather station in CZ #8 than with the closest weather station in CZ #9, which is farther away and on the coast. For this reason, the closest weather station is used for all analyses, regardless of designated CZ.

Along with the residential distribution feeder data (listed as primary feeders) used in these analyses, two example feeders are provided for additional context in the discussion section, representing a large apartment complex and a commercial zone.

System-wide net power load (NPL) was sourced directly from LADWP. Reported NPL summarizes full system net load (not including customer onsite co-generation) on an hourly basis for 2018 through 2020. All power data was analyzed with ambient temperature data, which was sourced from local National Weather Service (NWS) weather stations via a third party sourcing utility, MesoWest/SynopticLabs [34]. Load data was temporally correlated with weather data interpolated to the nearest hour using Universal Translator 3 (UT Online, Pacific Energy Center, Pacific Gas and Electric Corp., San Francisco, CA, USA) [35] and Easy Data Transform (Oryx Digital Ltd., Swindon, Wiltshire, England, UK) [36] software packages. When city data is not available with respect to COVID-19 caseloads and stay-at-home rates, data scoped at the inclusive Los Angeles County or California state level is used.

2.2. Load Evaluation

First, individual feeders' average loads were compared on a monthly or weekly basis (using an ISO 8601 defined week – see Table S4) across the period of study without temperature normalization or restriction. Major holidays were excluded from categorization. Analysis of input data and calculations were performed in kW and kWh.

For temperature analyses, hourly average temperature values were used along with monthly degree day values, which were assessed from local NWS observation weather station monthly reports (see Table 1 for data source information). Interpolative re-sampling was used to correlate temperature data to load data. Temperature data and derivative units were converted from °F to °C for final reporting and rounded to the nearest 0.1 °C for reported values.

Two effects of temperature on load must be distinguished in these analyses. First, the expected effect of temperature on electricity use (particularly cooling on hot days) must be considered when comparing across periods with different temperature patterns. Second, higher residential occupancy rates can increase households' response to temperature, making the effect of hot days stronger during the stay-at-home periods than otherwise.

Temperature models to assess sensitivity to load change due to temperature change were created using 2018 and 2019 daily average load data (for counterfactual models) discretely processed with ambient temperatures corresponding to feeder weather station source. As individual household loads are not available, reporting is performed in percent change compared to the counterfactual model used as a baseline for 2020 observed

data. Depending on the specific application, temperature data was used as average period temperature or relative to heating or cooling degree days with a customary balance point of 18.3 °C (65 °F). In average-temperature regression models, the mean static temperature (MST) temperature was used rather than the customary degree day balance point value in calculation. Processing was performed as an average daily load considering daily average temperature (computed average of all periods as opposed to average of minimum and maximum daily observed temperature approach, which is used with degree-day calculation). Hourly models were used for direct comparison of specific, short-term periods. Being more stable, daily models were used in the linear modeling methods used in this report, consistent with similar observations in previous method comparisons [19,27].

For the relationship of energy usage to ambient temperature, piecewise regression corresponding to ASHRAE RP-1050 type linear change-point regression [37,38] was used to determine the 5-parameter models used (corresponding to three segments marked by two change points (CPs)—representing three regressed periods of load versus temperature), see Equation (1):

$$\begin{aligned} y &= m_1x_1 + b_1 \text{ (inf. to low CP bound, } t_1), \\ y &= b_2 \text{ (low CP bound, } t_1 \text{ to high CP bound, } t_2), \\ y &= m_2x_2 + b_3 \text{ (high CP bound, } t_2 \text{ to inf),} \end{aligned} \quad (1)$$

where y is an average feeder load (kW), m_1 is a regressed constant (kW/temp), x_1 is a period average temperature value (below the low CP bound), m_2 is a regressed constant (kW/temp), x_2 is a period average temperature value (above the high CP bound), b_1 and b_3 are a set of regressed intercept values corresponding to load at the CP bounds (kW) and b_2 is average constant load (kW) across temperature range between CP bounds.

This model accounts for temperature effects on energy use for heating and cooling as well as temperature ranges where load is not substantially affected by temperature. Regression analyses were performed using the open-source Energy Charting and Metrics (ECAM) (ECAM v.6.6, Bonneville Power Administration, Portland Oregon, OR, USA) calculation engine for Microsoft Excel (Excel v.14.0 (32-bit), Microsoft Corp., Redmond, WA, USA) [39] with an 80% confidence interval (CI) used for both temperature change point determination and data boundary determination. Testing showed that an 80% CI provided a balance between valid model calculation convergence and data inclusivity for all feeders analyzed. The calculated midpoint temperature between the determined change points corresponds to the MST. As data is analyzed, CI boundaries are similarly passed through calculations to provide error estimation for multi-step calculations. Temperature-based correction was used to normalize the influence of temperature such that all data sets are corrected to a value representing MST on a daily or hourly basis (as previously discussed) and compared. This approach estimates non-temperature-sensitive load. In addition, a reporting-period basis calculation provides estimates of post-period energy difference considering pre-period basis. This calculation used ECAM's internal engine implementing modified ASHRAE Guideline 14, model guidelines [28,40]. Analyses compared 2020 energy use to baseline data in 2018–2019 (for either the 2020 calendar year period or 2020 COVID-19 pandemic subset period) to normalize the impact of temperature between the evaluation and baseline periods in comparison. By removing this substantial factor, this provides a means to assess differences in load due to the changed factors (namely occupancy) during the COVID-19 pandemic period compared to the baseline period.

A separate two-term linear regression (see Equation (2)) was performed to model the impact of temperature on load as a function of heating degree day (HDD) or cooling degree day (CDD) values on a daily basis. Raw calculated values were limited such that values with CDD or HDD values less than 1.1 °C (2 °F) were removed from the model to reduce the bias from non-temperature related load variance. A CDD or HDD value

would be mutually exclusive for a given day. Analyses were performed using a multiple linear regression in Origin Pro 9.0 (Origin Lab Corp., Northampton, MA, USA). Regression results were modeled for impact across an inclusive range of HDD and CDD values for both the baseline and evaluation period and presented as a simple percent difference for change comparing the differences between evaluation and comparison period with the same change in simulated CDD and HDD values:

$$y = m_1x_1 + m_2x_2 + b, \quad (2)$$

where y is the total feeder daily energy use (kWh), m_1 is a regressed constant (in kWh per HDD), x_1 is the HDD (single day) value, m_2 is a regressed constant (kWh per CDD), x_2 is the CDD (single day) value and b is regressed energy independent of HDD or CDD change (kWh).

2.3. Temperature Restricted Load Calculation

Temperature restriction is an approach used to filter values outside a pre-defined temperature range where limited correlation exists between temperature and elevated energy usage for each hourly temperature value. This method is appropriate when ambient temperatures largely remain near 18.3 °C (65 °F), which is the conventional degree-day calculation reference value customarily used by the US NWS. In the current analyses, a 4 °C range above and below the balance-point temperature was used for the restriction cut-off. Temperature-restricted 2020 evaluation period load data was compared to the combined 2018 and 2019 composite counterfactual model on a monthly or weekly basis considering day-type scope (all days, weekdays, or weekends/weekend days) or illustratively to a 2018 or 2019 single year baseline. Calculations of energy usage change were performed in the same manner as that used in the previously discussed temperature normalization process.

3. Results

Stay-at-home behavior generally tracks early public directives and provides the framework for interpreting shelter in place (SIP) response and the impact on energy usage. An LA County state of emergency was declared on 3 March while a California-wide state of emergency was declared on 4 March in response to rising regional case numbers. An SIP executive order was initiated in California on 19 March, and modified for provisions for essential workers on 4 May [32]. A follow-up tightening of restrictions followed on 2 July. Estimates of SIP response rates based on smartphone data (reported from early February through early September) show approximate alignment with LA County first wave COVID-19 reported case values (see Figure 1).

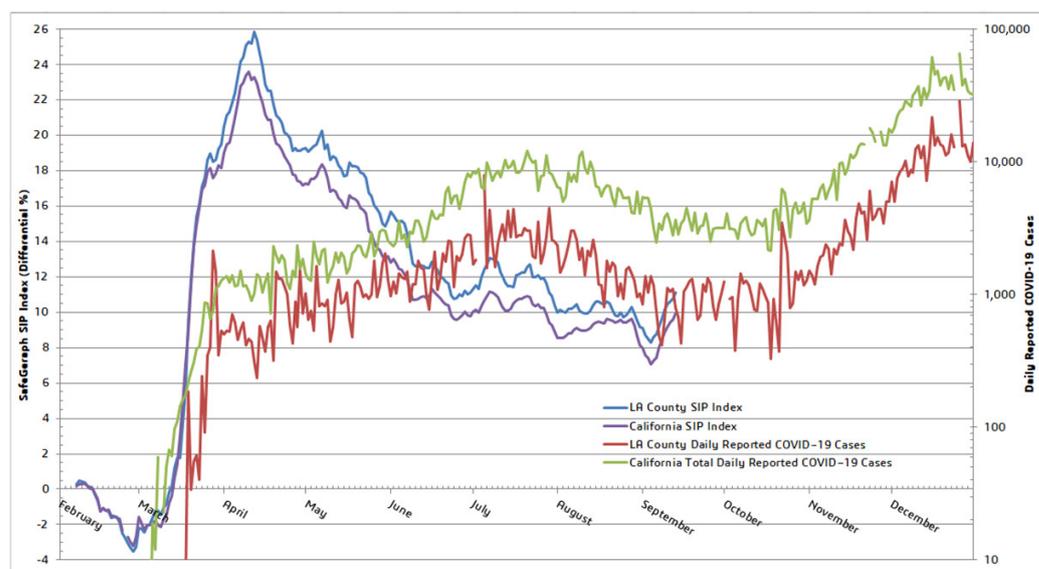


Figure 1. Comparison of LA County and all of California for shelter-in-place response and COVID-19 diagnosed cases over time. Data sources: California Department of Public Health [41], SafeGraph, Inc. [21]. The SIP Index represents the change (as a difference) in the % of people staying home compared to pre-pandemic baseline. The index ranges from -100% to 100% , where 0 (zero) is no change from a pre-pandemic baseline.

SIP response for the observed period peaked on 12 April [21,41], and decreased through late June. SIP response, measured as stay-at-home rate, is designated as no commuting or transit observed via mobile phone tracking. A pre-pandemic baseline rate of approximately 25% stay-at-home corresponds to a SIP index of 0. On 13 July commerce was restricted during the second case wave. Compared to the initial SIP response and despite the severity of the second wave (July through August), at nearly an order of magnitude higher than the first wave (mid-March through April), the population reaction was weaker, with less than a 5% increase in SIP response as compared to California and LA County at the pandemic onset, with a nearly a 15% decrease comparing the peak of COVID-19 case count during the second wave to that of the first wave. The magnitude increase of successive COVID-19 case peaks for each wave is so substantial that Figure 1 uses a y-axis logarithmic plot scaling to present this. Comparatively, SIP data is presented with a y-axis linear plot scaling. This smartphone based measure of SIP response over time closely resembles other indicators of stay-at-home behavior, such as keyword search histories for topics related to baking and home improvement, providing anecdotal evidence on activities performed by individuals with more available time and resources during the peak SIP period [42,43].

3.1. Unnormalized Load Comparison

The first set of load analyses use gross energy use data, not normalized for temperature. Energy use for Feeders A, B, C, and D for the pandemic period compared to the comparison period was higher by 10.0% for all days of the week considered together and by 10.4% during weekdays alone (see Table 2).

Table 2. Change in energy use for 2020 compared to a comparison baseline for Feeders A-D showing monthly energy use. Values are not normalized for temperature. Positive values indicate higher 2020 energy use compared to the counterfactual model constructed using the 2018–2019 baseline during the comparable monthly period. See Figure S2 for the yearly summary of individual feeders and Figure S3 for a weekly summary chart for individual feeders.

Month	All Days	Weekdays	Weekend Days
January	0.7%	1.2%	−0.4%
February	−10.3%	−10.1%	−10.6%
March (14–31 March)	2.6% (8.6%)	3.2% (9.5%)	1.1% (6.2%)
April	13.4%	13.1%	15.6%
May	20.9%	22.4%	17.3%
June	6.2%	9.1%	−0.4%
July	−10.5%	−12.7%	−5.3%
August	12.1%	8.0%	22.5%
September	25.4%	27.6%	20.6%
October	18.0%	20.9%	10.8%
November	5.0%	5.6%	3.6%
December	1.4%	1.0%	2.2%
Yearly Average	6.9%	7.2%	6.3%
COVID-19 Period Average	10.0%	10.4%	9.3%

Evaluating temperature differences while considering occupancy differences for the same period helps differentiate the causes of energy use change (see Figure S1 for monthly summarized temperature information for the LA Basin feeders). As shown earlier, stay-at-home rates for LA County rose swiftly in late March, peaked in April, reduced but remained high in May and June, and fell to a lower plateau for the rest of the summer. As shown in Figure 2, average temperatures were fairly similar in the 2020 period as in the 2018–2019 comparison period. Energy use was 2.6% higher for the whole month of March, but 8.6% higher for the second half of the month, after the initial SIP order (see Figure 2). Average temperatures were somewhat higher in April (1.8 °C, not significant) than in the composite 2018–2019 comparison period.

However, during most parts of the day and night temperatures were near the 18.3 °C (65 °F) nominal balance point, where the load is least impacted by temperature. Temperatures were much higher in May: a weighted average of 20.9% warmer (4.2 °C) with an average 2020 temperature above the balance point of 18.3 °C, indicating cooling-related energy use as a driver for the increase of 13.4% in average load that month. June 2020 had an average temperature within 1 °C of the counterfactual (weighted), but an average of 6.2% increase for 2020 against the counterfactual, suggesting increases in non-temperature-sensitive loads. Summer 2020 had generally reduced stay-at-home rates compared to spring with a substantially cooler July compared to the same period in the counterfactual. During August 2020, an extended warm period mid-month increased the average monthly temperature, which would have otherwise been a month cooler than the comparison monthly period. During this month, yearly record-high energy use in California was recorded. Increased occupancy compared to the comparison period with extended periods of high temperature led to increased energy use during these extreme heat events.

In fall and early winter, October and November both had monthly averages for 2020 within 1 °C of the monthly comparison periods but have 18% and 5% respective increases in energy use over the comparison periods for each month. December, with <1 °C of the monthly comparison period, despite the high COVID-19 cases had an energy usage increase within 2% as compared to the comparison period.

In general, monthly average load correlates with temperature change, consistent with expected temperature-driven load increases in hotter periods, particularly if higher occupancy rates lead to stronger response to ambient temperature. However, higher energy use in March provides a tell-tale indicator of increased load in these residential

neighborhoods due to SIP activity during a period of relatively consistent temperature. By comparison, the overall LADWP NPL decreased during March and April in large part due to a reduction in commercial activities, which use a higher proportion of total energy load than residential customers (see Figure 3, top portion).

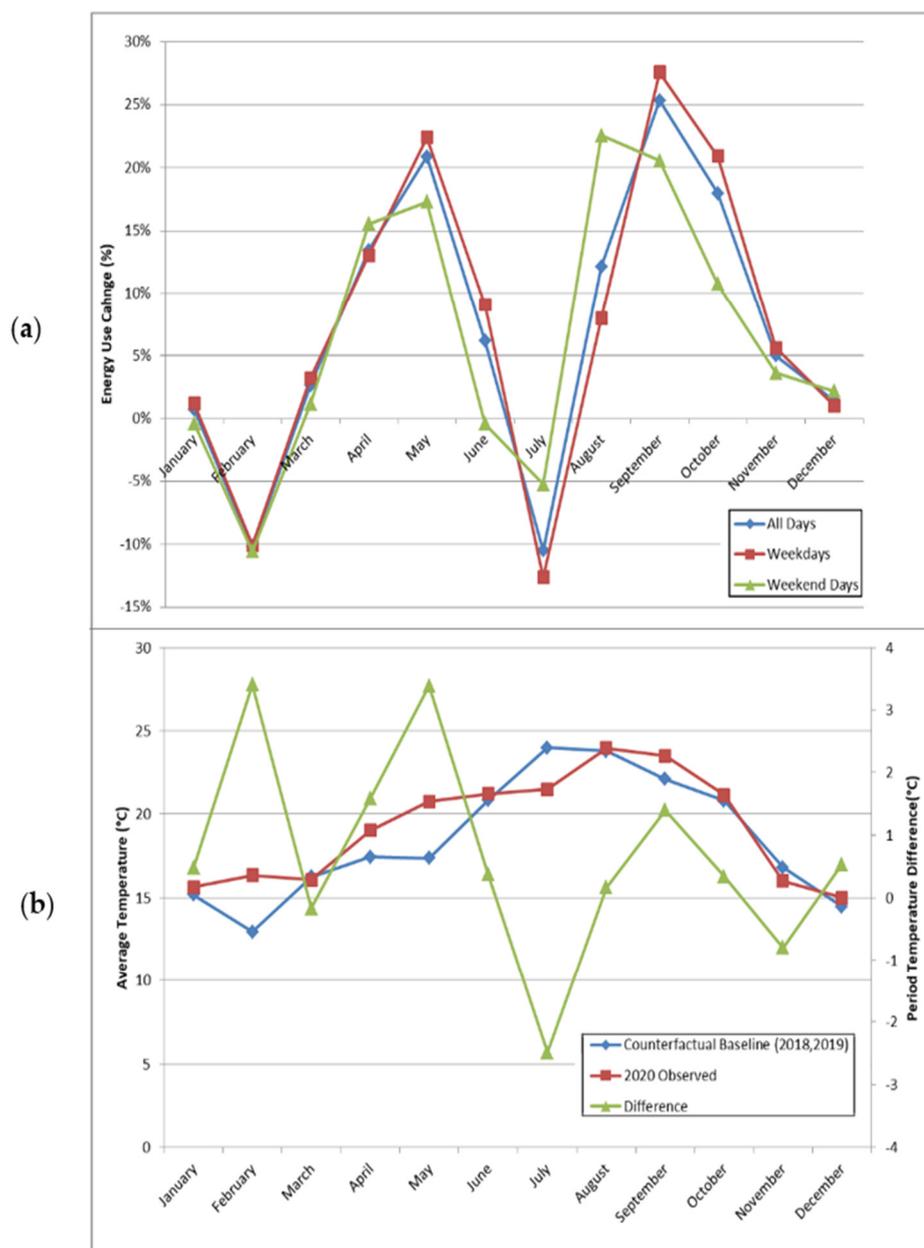


Figure 2. (a) Energy usage across all evaluated communities (simple composite average, not temperature normalized) with 2020 observation compared to a 2018–2019 comparison baseline, showing higher energy use. (b) Average monthly temperature as measured at weather data source KCQT in downtown Los Angeles observed for 2020 and comparison periods. Energy use strongly follows temperature change in relation to the mean static temperature (MST).

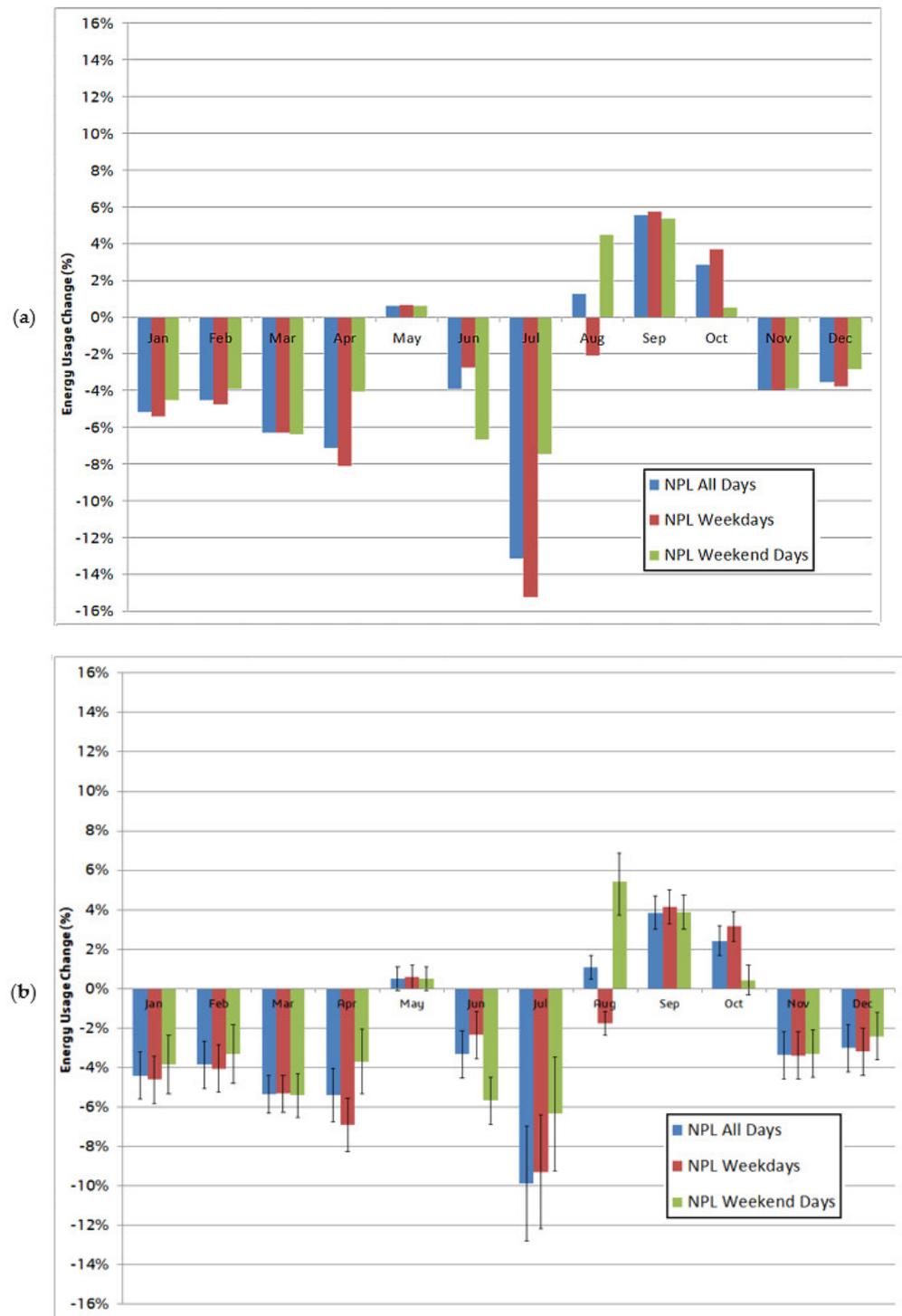


Figure 3. Monthly net load (NPL) including residential and commercial customers for Los Angeles Department of Water and Power for the pandemic compared to a counterfactual model using a 2018–2019 baseline. **(a)** Presented without temperature correction, and **(b)** presented with normalization to MST against a corresponding monthly counterfactual value, showing 80% CI boundaries in error bars as a result of temperature normalization.

3.2. Temperature Normalization

Temperature normalization compensates for the impact of temperature on energy use, to better estimate the impact of non-temperature sensitive loads. However, as temperatures can vary across larger measured areas that combine residential and commercial loads, use of this technique on highly distributed loads such as NPL can lead to poor

correlation (see Figure 3, bottom portion). Correlations between temperature and commercial loads are generally weaker than for residential because commercial buildings tend to have a higher proportion of temperature-insensitive process loads and large scheduled or sensed ventilation loads regardless of ambient temperature.

Residential energy use presented as a total for the evaluated feeders is shown in Figure 4 and Table 3. Total load yearly average difference against the baseline is 3.6% for 2020 for a scope of all days and 5.1% for the pandemic period against the comparison baseline. During the pandemic period, the average increase due to non-temperature sensitive loads is estimated at 5.6% for weekdays and 4.8% for weekend days. During the spring months of March through June, when SIP response was the highest, average total loads for these residential feeders were higher by 5.2% for all days, with a much higher increase for weekdays (6.2%) than for weekends (3.6%). When the 80% CI regression coefficients are evaluated for temperature and normalized for each MST value, a general pattern develops in the 2020 pandemic period of a smaller static temperature range with a higher comparable static load (greater temperature insensitive load proportion) compared to the baseline. Energy use is higher at low temperatures for all 4 feeders for temperatures adjacent to the upper temperature boundary for 2020 weekdays compared to counterfactual model values for weekdays. The nature of the data shows a distribution for 2020 with a large spread and bias to high load shifts in early spring compared to the comparison data considering the same sub-periods of evaluation. With lower temperatures in July 2020 compared to the counterfactual baseline, temperature range under-sampling occurred, resulting in low temperature data biasing the 2020 data. The limited number of days with high average temperatures in July 2020 compared to the baseline period results in variability as low temperature data is substantially influencing average daily the temperature-to-load relationship.

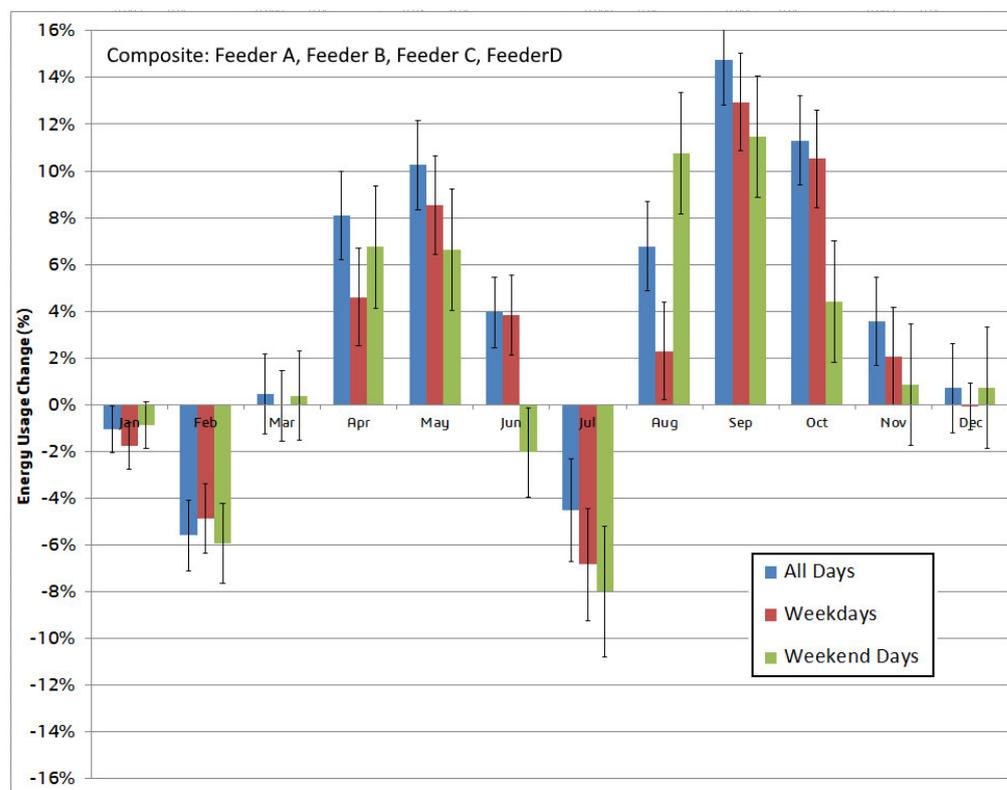


Figure 4. Total residential estimated non-temperature sensitive energy change for 2020 compared to a counterfactual using a 2018–2019 baseline, presented on a monthly basis as a simple composite average of feeders.

Table 3. Change in energy use for 2020 compared to a 2018–2019 baseline for Feeders A–D showing monthly energy use after temperature normalization. Positive values indicate higher 2020 energy use compared to the counterfactual model values.

Month	All Days	Weekdays	Weekend Days
January	−1.1%	−1.0%	−1.6%
February	−4.4%	−5.1%	−6.9%
March (14–31 March)	1.0% (3.5%)	1.3% (3.9%)	0.1% (2.3%)
April	6.9%	7.5%	7.5%
May	9.4%	10.5%	7.4%
June	3.4%	5.4%	−0.4%
July	−4.2%	−6.2%	−3.6%
August	5.0%	3.3%	11.2%
September	13.2%	15.1%	12.5%
October	10.0%	12.4%	6.3%
November	2.9%	3.4%	2.2%
December	0.7%	0.7%	1.9%
Yearly Average	3.6%	3.9%	3.0%
COVID-19 Period Average	5.1%	5.6%	4.8%

ECAM’s native engine was used to generate a predictive model of total load change for the entire pandemic period against a counterfactual model of the comparison period (Figure 5). Energy use change reported is consistent with the temperature normalization method and within 2% for all individual feeders across the evaluation period. Results show relatively constant non-temperature load for the COVID-19 pandemic period in 2020 compared to the counterfactual in the 1–5% range considering all days (weekends and weekdays) (see Figure 5).

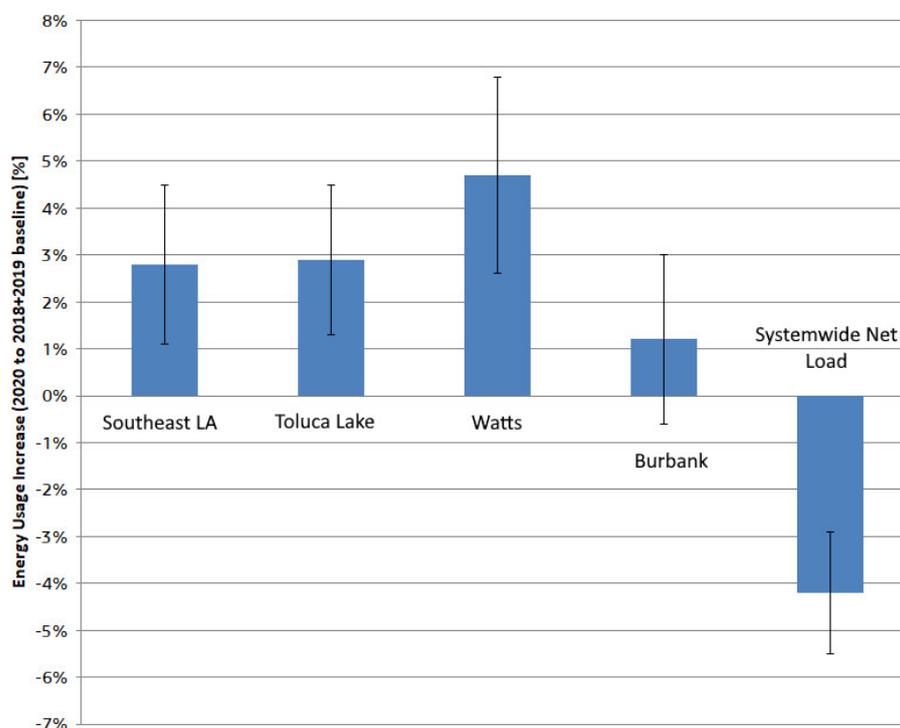


Figure 5. Total estimated non-temperature sensitive energy change during the COVID-19 pandemic period compared to a 2018–2019 comparison baseline for each analyzed feeder in addition to system wide LADWP NPL load. Error bars represent 80% CI bounds propagated.

Comparing change in energy use to median household income for each feeder (Figure 6), a weak trend develops suggesting higher impacts for temperature-insensitive loads for feeders in communities with lower median income. This may be due to disproportionate impact within this population of unemployment or population shift due to the pandemic. The Burbank feeder (Feeder D), while servicing primarily residential buildings, has a business artifact from an auto dealership on the periphery of the feeder territory which caused a small reduction in load early during the early COVID-19 pandemic period in 2020 compared to the counterfactual baseline.

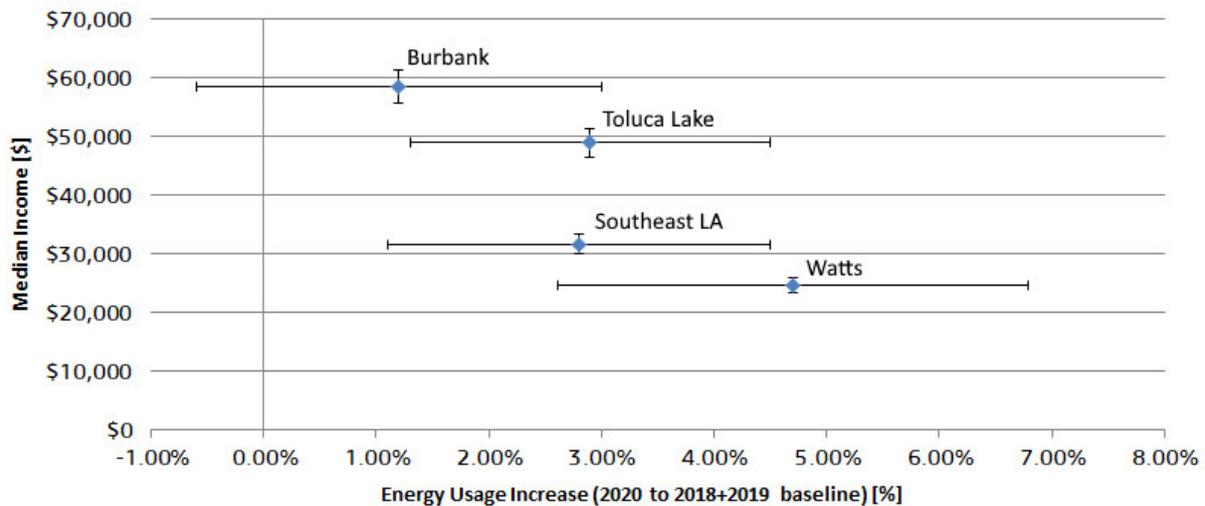
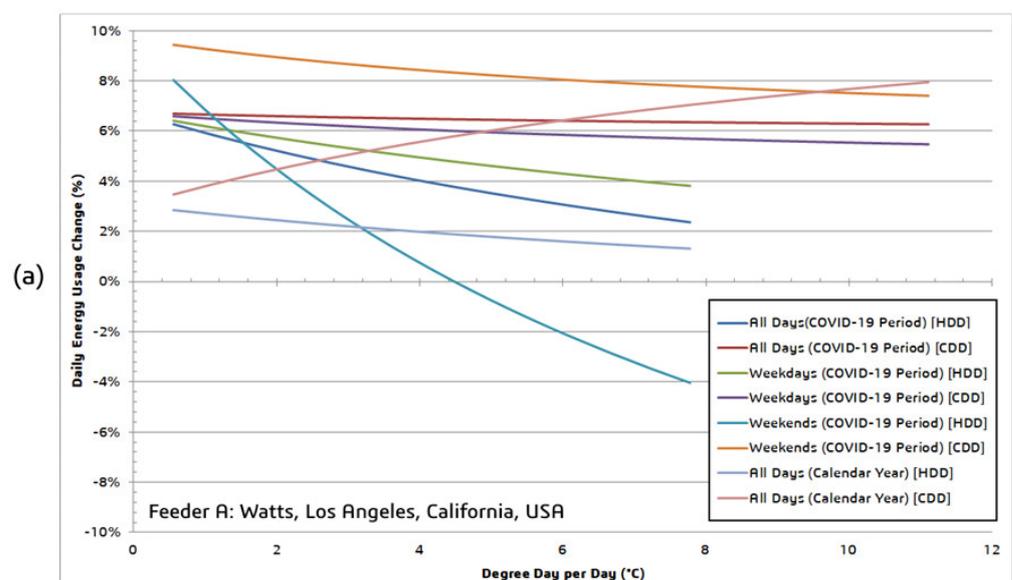


Figure 6. Energy change compared to feeder service community median income with a consistent 5% shown in the vertical error bars and the 80% CI shown in the horizontal error bars. The analysis scope was the COVID-19 pandemic period of Mid-March through December.

Estimation of energy use as a function of heating and cooling use change showed modest changes in the impact of load as a function of average HDD and CDD compared to the counterfactual period considering only the COVID-19 pandemic period as well as all of 2020 considering weekends and weekdays separately or combined (Figure 7).



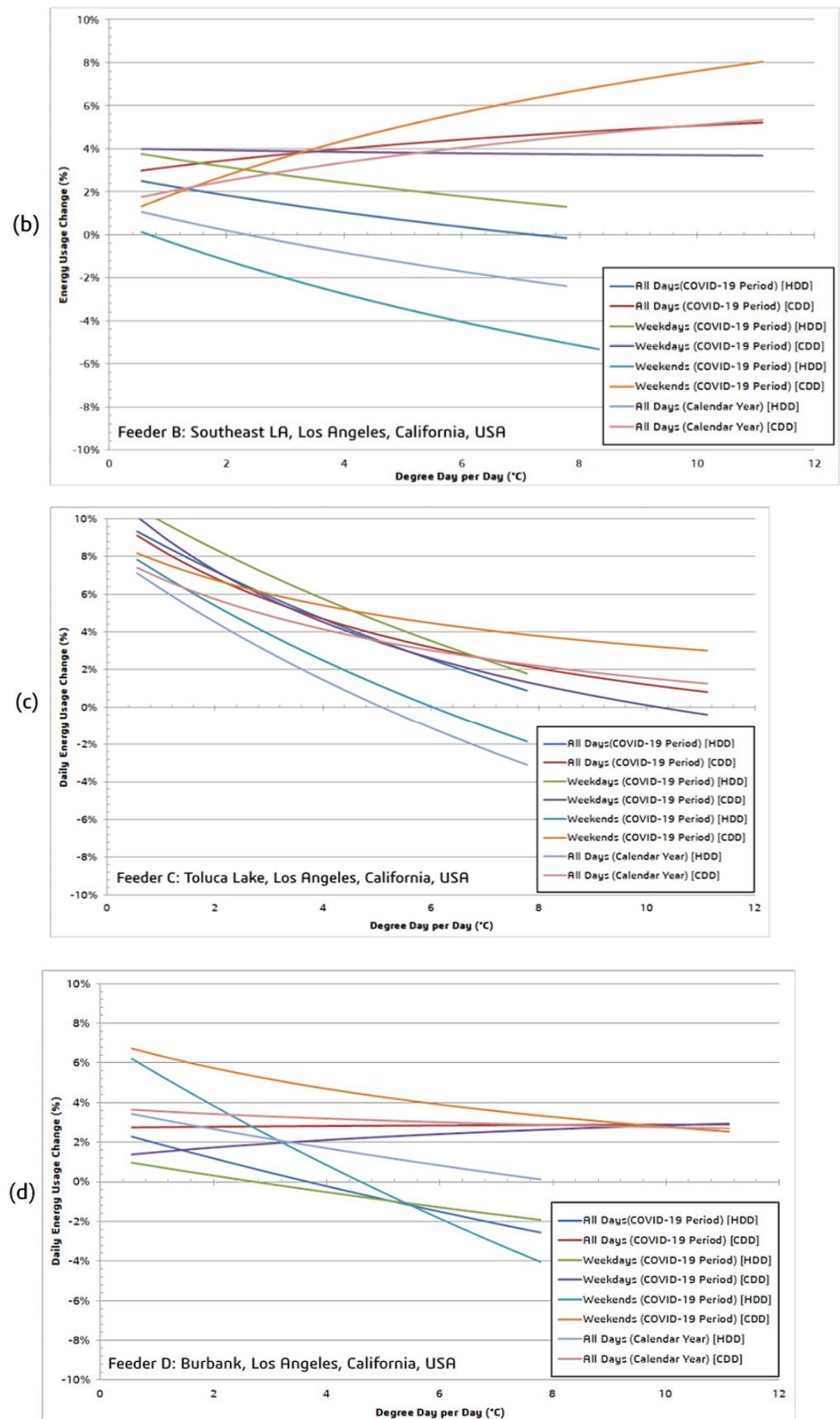
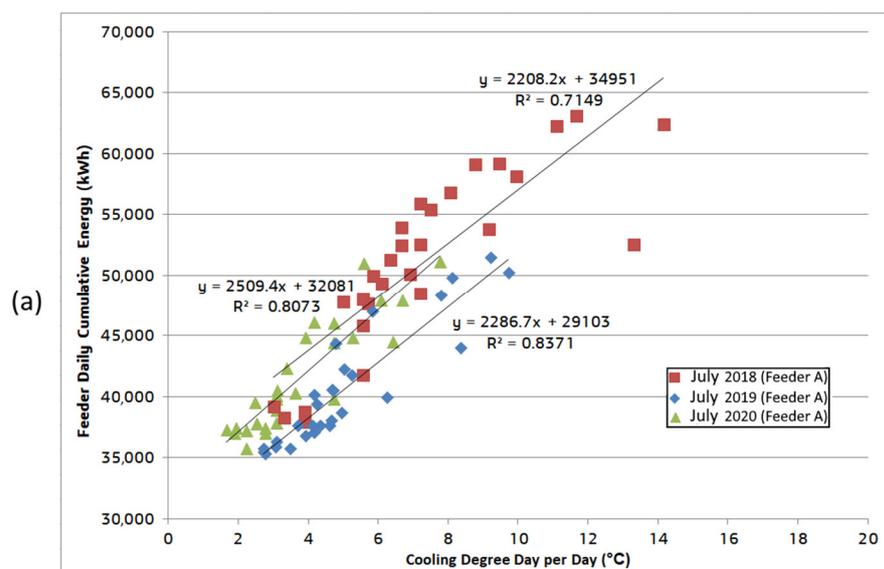
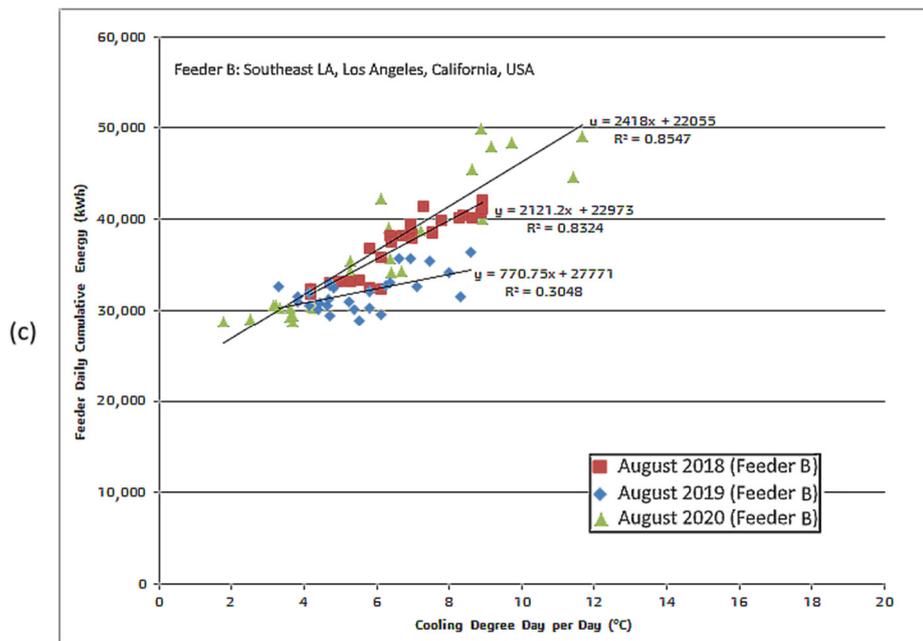
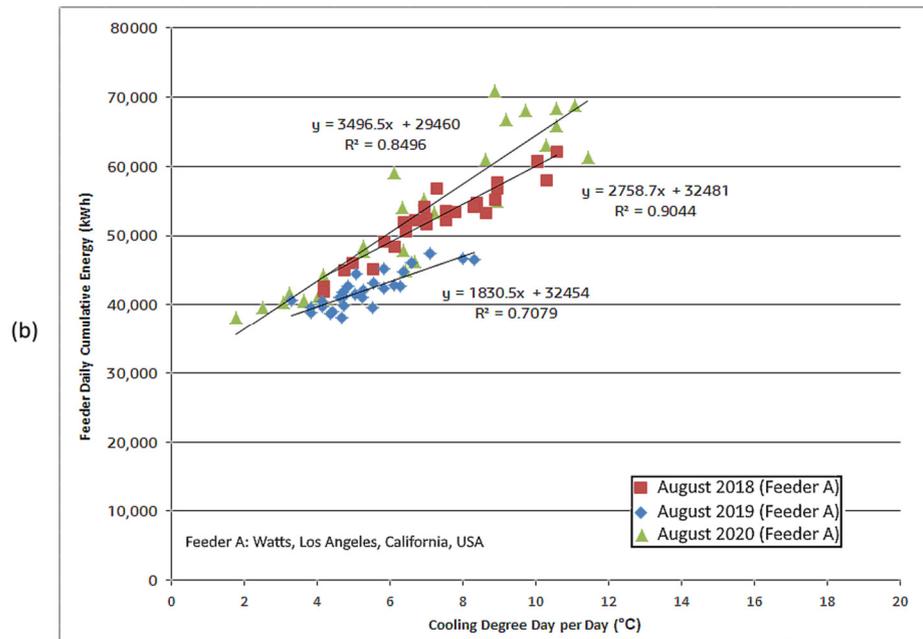


Figure 7. (a–d) Modeled normalized load change for 2020 compared to the baseline period for both calendar year periods (2020 to a 2018–2019 baseline) and subsets of mid-March through December for all periods comparing change in load relative to the baseline for a range of CDD and HDD

values for each of the four feeders (a) Feeder A, (b) Feeder B, (c) Feeder C, (d) Feeder D. See Figure S2/Table S3 for a similar presentation of this data using normalized MST values and average daily temperatures as opposed to HDD and CDD values.

The HDD impact from heating loads decreased in all cases as presented. As noted earlier, 2020 was warmer in early spring leading to potential model bias during the period where SIP would have had the greatest impact on energy use. Electric heating (primarily portable space heaters) is a minor heat source in the region, with natural gas heating being predominant. Another region with higher heating requirements may provide better data for impact analysis. As expected, cooling loads for most scopes increase as temperatures rise from moderate to high, but plateau at very high temperatures, after air conditioning use is saturated. With this said, high heat events did distinctly show an increase in load for a given CDD value; this is especially apparent in the feeders in the LA Basin. For the Burbank feeder, a leveling off of increasing load is observed as the result of limited reserve cooling capacity—all available cooling having already been activated and in use (see Figure 8). Per Chen et al., warmer areas in Southern California, such as the San Fernando Valley, are less temperature sensitive compared to cooler areas. The current results suggest this phenomenon similarly carries over to a more limited change in energy use during extreme heat events during the COVID-19 pandemic period as compared to other more temperature sensitive areas.





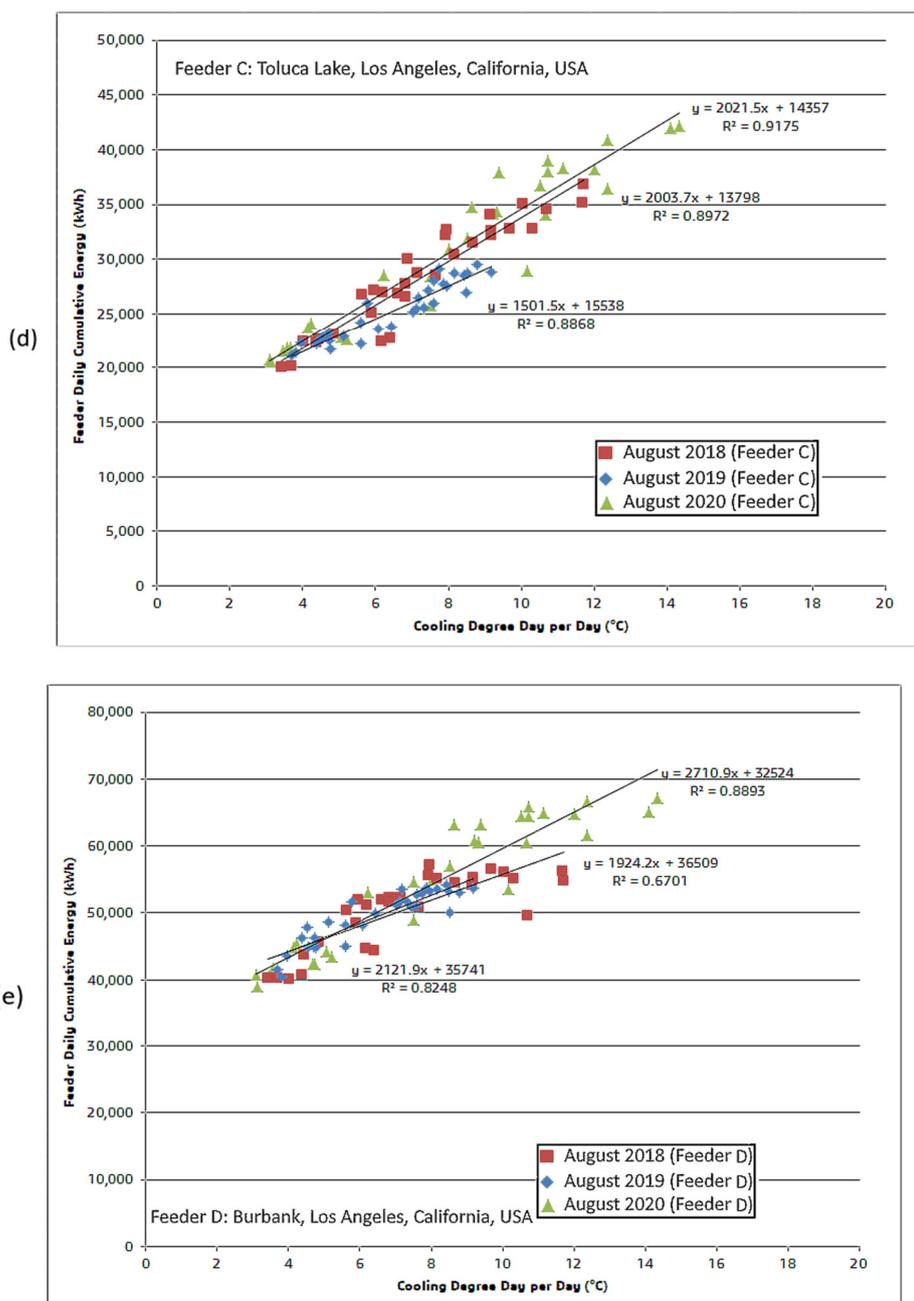
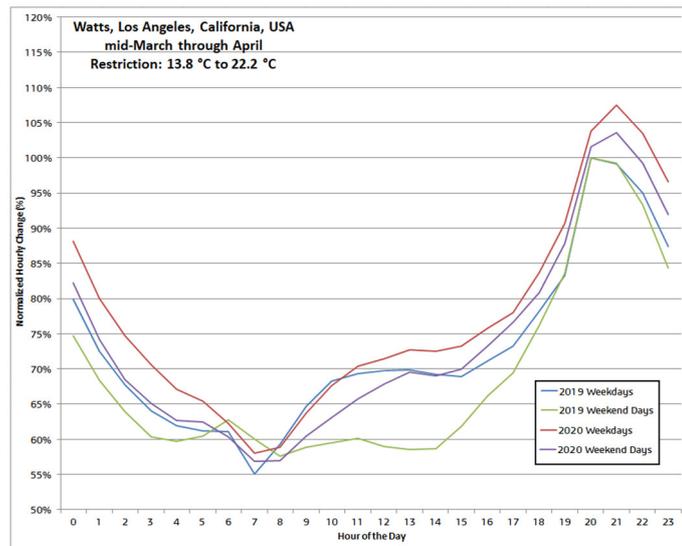


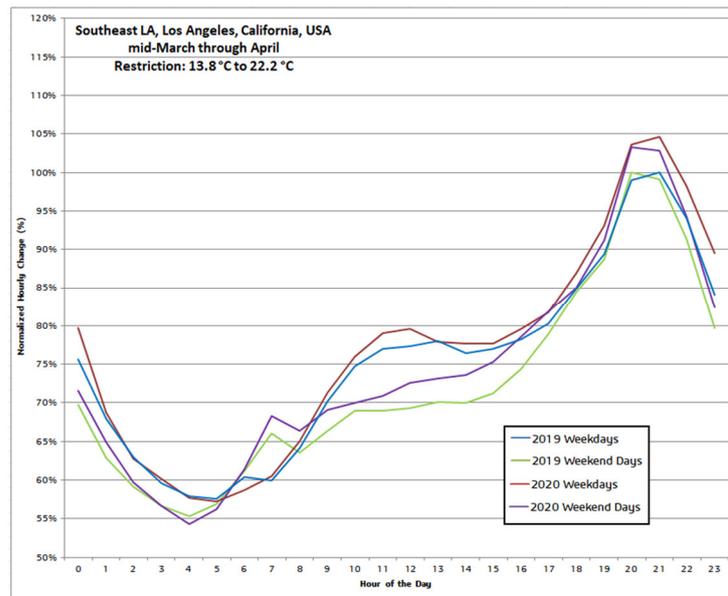
Figure 8. Comparison of feeder daily energy use for 2018, 2019, and 2020 for observed CDDs for (a) the month of July for Feeder A; and (b–e) presenting the month of August for Feeders A–D.

3.3. Temperature Restriction

Estimation of non-temperature sensitive loads on an hourly basis provides indication for granular energy use change based on changes in behavioral patterns that can only be observed at an hourly (versus a daily) level. Removing heating and cooling loads by restricting points when these loads are likely active reduces the temperature variability and helps present impact due to behavior change during SIP and the impact on non-temperature sensitive loads. Mid-day energy use is increased on weekdays (Figure 9) for most feeders. Weekend data is typically noisier than weekday data given relative under sampling compared to weekdays. Early evening peaks are moderately higher and weekday morning peaks are reduced. The values found via this direct analysis (Table 4) are largely similar to the estimated change due to non-temperature sensitive loads (Table 3).



(a)



(b)

Figure 9. Baseline peak normalized (separately for weekdays and weekends) energy use change comparing 2020 to 2019 baseline for mid-March through April using a temperature restriction. Examples presented for (a) Feeder A and (b) Feeder B within the LA Basin microclimatic region.

Table 4. Energy use difference for mid-March through April comparing 2020 against a counterfactual baseline of 2018–2019. The all-day average for Feeders A–D was 5.3%.

Source	Weekday Change	Weekend Day Change
Feeder A	5.0%	3.1%
Feeder B	2.8%	2.0%
Feeder C	9.9%	13.9%
Feeder D	2.8%	2.0%
Average (A–D)	5.1%	6.1%
Feeder E	7.2%	4.8%
Feeder F	−28.0%	−24.8%
NPL	−6.2%	−4.2%

4. Discussion

While major fuel and energy sources were observed to show a net decrease in use early in the pandemic, the opposite was largely observed for residential energy use. These findings were consistent with that of earlier studies such as those performed by Pecan Street [14] in Austin, TX, with 113 panel-instrumented homes: study results showed an approximate 42% (~300 W) mid-day increase in April 2020 for non-temperature sensitive loads such as consumer electronics, appliances, miscellaneous electric loads (plug loads), and lighting, compared to a baseline of the previous year, reflecting increased occupancy with increased load during both weekdays and weekends. Full-day energy use increase is likely closer to ~14%, estimating from Pecan Street provided figures. Similarly, this Pecan Street study identified an increase in temperature sensitivity across March and April identified by average home kWh/cooling degree day (CDD) of the evaluated period with a value of 0.7 in April 2020 compared to a value of 0.56 for the average of April 2017, April 2018, and April 2019, a comparative 25% increase in load for each CDD change [14]. These results match the general trends observed in our study, albeit with higher magnitude changes between 2020 observations and past baselines. Much of this difference is likely related to Pecan Street's use of instrumented single-family, higher-income housing combined with regional climatic variance (e.g., impact of humidity and higher regional temperatures on cooling behaviors). Also, days with potential heating and cooling activity in shoulder periods (often with low CDD or HDD values) can incur bias from the dominant space conditioning energy load used during the period, as previously mentioned. Energy use for this scenario can increase for low HDD or CDD values; our tests showed that using a threshold value of 2 CDD or HDD substantially reduced this impact. The temperature in Los Angeles in April rarely requires air conditioning usage, whereas Austin, Texas experienced a warm and humid spring during the highest SIP period.

Load impact from non-temperature-sensitive loads during the early pandemic were estimated from sampled feeders through both temperature restriction (Table 4) and temperature normalization (Figure 4) resulting in estimated increases of 5.3% and 5.7%, respectively (mid-Mar through April, all days), less than that reported by Pecan Street. With the exception of Feeder C, change in weekday load was more impacted than weekend load compared to the 2018–2019 baseline during the early pandemic (Table 4). Non-temperature loads were a substantial component of energy used which is evidenced by the similarity in total load change (Table 3) to temperature restricted load change (Table 4). Heavy mixtures of both HDD and CDD during this period complicate regression analyses (of the type used in Figure 7). This is because the nature of the degree day metric is not exclusive to heating or cooling, but is the balance point difference computed between the range from daily highs and lows. When temperature fluctuates enough over a 24-h period to require both heating and cooling, that day may be labeled with a low value for HDD, CDD, or both. This effectively skews energy use per HDD or CDD when using multiple regression models. Temperature normalization based on average daily temperature regression performs marginally better with respect to these temperature variations.

When temperatures increase, increased occupancy (even at lower levels compared to the mid-April peak) drives loads higher. This is clearly illustrated in Figure 8b representing Feeder A. The load events with CDD values between 9 °C and 11 °C required 9.2% more load compared to similar events in this same temperature range in 2018, consistent with the idea of higher home occupancy rates driving higher demand for cooling on hot days. The effect of SIP response can differ for weekend and weekday loads. This is illustrated with the highest heat day in this figure, which has substantially less load than the second highest load event: note that this day falls on a weekend (for which occupancy shifts due to SIP should be reduced) versus higher impacts on adjacent weekdays during this extended extreme heat event. Mixing weekdays and weekends for analysis results in model variance challenges due to substantially different activities for these two day

types. This is especially true during typical, non-SIP periods such as the baseline. Clearly, increased occupancy drives up cooling requirements during extreme heat events. Capturing a representative spectrum of temperatures and loads for each month while occupancy was varying due to SIP response to allow direct calculation is challenging. For example, as illustrated in Figure 8a, the high heat events observed in July 2018 and 2019 were not replicated in July 2020, which weakens any comparison across these months to assess 2020 SIP response effects on energy use.

Daily energy use patterns were strongly impacted early in the pandemic. Compared to the counterfactual model, energy use was slower to rise in the early morning and was higher during mid-day hours, with a moderate increase in daily peak energy use across all feeders (see Figure 9). Assessed with restricted temperature analysis, the impact of these features decreased with a slow resumption toward baseline energy use as SIP response reduced.

Energy usage impacts for large multi-family apartment complexes is likely different from that for the single family and small multi-family residences studied above. Figure 10 shows results for an additional example, Feeder E, representing a large apartment complex. During the early pandemic period, energy use for this case largely tracked other residential loads. By summer, the shutdown of many shared-use areas within these buildings to reduce potential community spread of COVID-19 reduced the cooling burden to these buildings, resulting in a net drop compared to the baseline during the period when the cooling burden is the highest (mid-summer). This effect, plus the centralization of cooling and heating, are likely substantial divergence points comparing large apartment complexes and high-rises to low- and medium-density homes and low-rise apartments, which have limited shared facilities and individual heating and cooling supplies.

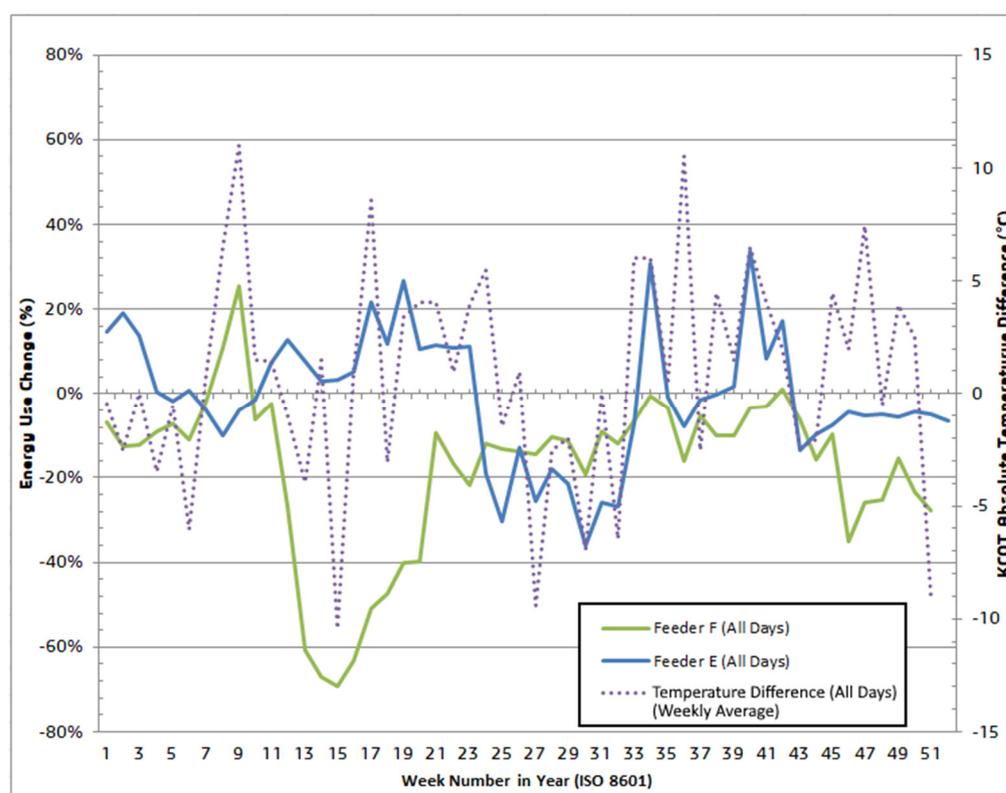


Figure 10. Direct change in energy use (non-normalized for temperature) for Feeder E (large apartment complex) and Feeder F (commercial building).

Commercial energy use, a major component represented in the NPL figure, is illustrated by a single mid-rise building source (see Feeder F in Figure 10). This example is included as a contrast to the residential feeders analyzed above, as an approximate in-

indicator for impacts of SIP on non-essential business activity (jewelry manufacture and distribution). For this commercial feeder, a major drop in energy use occurred during week 12 of 2020 (16–22 March), corresponding to the initiation of SIP restrictions, which is when residential energy use increased. By mid-June (Week 21) energy use in the commercial feeder had greatly increased. This follows a weakening of SIP response, previously discussed. The second-wave restrictions did not substantially reverse the increase in energy use, which showed continued growth until early fall. The lower energy use in November and December of 2020 compared to the 2018–2019 counterfactual composite baseline may reflect the reduction of typical high-intensity holiday shopping during those months, including extended hours.

The current findings show limited evidence of a higher increase in non-temperature sensitive load over the COVID-19 period for lower income areas than higher income areas. The expected effect of SIP response on energy by income is not clear, as various factors predict mixed results. For instance, more highly educated, higher-income professionals were more likely to be able to shift to working from home, while less-educated workers were more likely to either continue working outside the home (e.g., in essential service or manufacturing) or lose their jobs. Lower-income households tend to have more members to use devices if everyone is at home, but higher-income households have more square footage and more devices to be used per person; furthermore, lower-income households spend less money (and time) on entertainment and dining outside the home than higher-income households normally, and would thus experience less change. Residential use of portable space heaters and window AC units, more common among older housing stock in lower-income areas, also adds to electricity use. Given the limited number of neighborhoods sampled here and the small observed effect, this result is considered questionable, but suggestive of further consideration; additional research would be required to clearly ascertain the income differences in effect of SIP response on energy use. However, it is worth noting that even the same or lower increase in energy use is a greater hardship for lower-income households, as they already experience a significantly higher energy burden (that is, the proportion of their income spent on energy bills) and have little or no discretionary income to cover unexpected expenses.

Overall, SIP compliance was initially strong, but this effect was temporary. Approximately one month elapsed between the rapid ramp-up of SIP response and a long-term decrease and eventually leveling out of SIP compliance. This occurred even with daily briefings from health experts and government officials reporting increasing caseloads in the LA area. Energy models considering change in occupancy must expect a ramp-up, peak, and an extended dynamic equilibrium for general change in occupancy. Considering the near future of the COVID-19 timeline, stay-at-home rates will continue to subside into an extended equilibrium that is likely higher than pre-pandemic levels. This suggests that increased telecommuting from home will continue to raise the energy burden during high heat events. Mid-day energy use, compared to a pre-COVID-19 baseline has had a modest increase—this can help offset the increasing glut in solar energy mid-day during normal conditions. However peak conditions, especially in late afternoon when solar is switching to spinning reserves can still impact energy supplies during this critical ramp-up and source switching period.

5. Conclusions

This research adds to the growing body of knowledge on how the COVID-19 pandemic has affected human behavior and the resulting impact on energy usage. Increased residential occupancy has impact on energy use. Over the course of the 2020 pandemic period, fatigue with SIP compliance led to a rebound toward earlier pre-pandemic occupancy rates (reduced SIP response) and a substantial rise in regional COVID-19 active cases. It is reasonable to assume that in future pandemic events, similar behaviors are to be expected. The potential for extended SIP activity for extended periods has limits. The timing of an SIP period can strongly affect energy use change. During temperate periods,

limited heating or cooling impact will likely be observed with a constant increased non-temperature sensitive load increase. Even with occupancy patterns trending more toward normal, impacts on energy used for cooling during heat events was observed. As the current analysis examined only electricity, and space heating in this region is largely fueled by natural gas, observed stay-at-home impacts on heating were minimal. However, as electrification development continues, increased reliance on electric heating should be reflected in larger impacts of residential occupancy on electrical energy use. As long-term work at home activity continues, increased residential energy use during weekdays will continue for applicable households. Modeling this change is outside the scope of this study but relevant to future expected household energy change and population impacts. The results suggest the possibility of a higher impact of stay-at-home behavior on energy change for communities with lower median income level, however, evidence is weak and further research would be necessary to confirm such a relationship.

Continued efficiency measures for miscellaneous electric loads can help reduce non-temperature sensitive loads. Focus on reducing wasteful energy use (i.e., devices not properly entering low-power mode when not in use) is a major potential area of research. The analysis this study has provided on residences is also applicable to businesses, to highlight opportunities for better managing plug and process loads, especially while not in use, and may be a fruitful area for follow-up study. Follow-up studies using similar approach methodology with data for areas with substantial heating and cooling loads would help draw the maximum impact of stay-at-home behaviors when considering temperature sensitive loads as a major energy load contributor.

Supplementary Materials: The following are available online at www.mdpi.com/2076-3417/11/10/4476/s1, Numeric tools, calculation scripts, and calculation workbooks as well as extended data subsets used within this report are available at: <https://github.com/CalPlug/CovidResEnergyAnalysis2021>. Supplementary Report Contents: Table S1: Extended feeder summary table showing solar and EV installation penetration within the bounding ZCTA for each feeder, Table S2: Change in energy use for 2020 compared to a counterfactual 2018–2019 comparison baseline showing change in energy usage by communities, Figure S1: Monthly temperature summary for Los Angeles across all periods used for analysis, Table S3: Summary of regression segments (80% CI) and temperature change point values for both comparison and pandemic evaluation periods. Table S4: Specific dates for the ISO weeks for 2018, 2019, and 2020. Figure S1: Monthly temperature summary for Los Angeles across all periods used for analysis. Data sourced from KCQT (Downtown LA), NWS. Figure S2: Comparison model of the effect of ambient temperature on feeder energy use—MST normalized to 100%. Figure S3: Non-temperature normalized energy use for all feeders presented on a weekly basis. Table S5: Report abbreviation and acronym list.

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