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Residential electricity demand on CAISO Flex Alert days: a case study of voluntary emergency demand response programs

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Abstract

The California Independent System Operator (CAISO) utilizes a system-wide, voluntary demand response (DR) tool, called the Flex Alert program, designed to reduce energy usage during peak hours, particularly on hot summer afternoons when surges in electricity demand threaten to exceed available generation resources. However, the few analyses on the efficacy of CAISO Flex Alerts have produced inconsistent results and do not investigate how participation varies across sectors, regions, population demographics, or time. Evaluating the efficacy of DR tools is difficult as there is no ground truth in terms of what demand would have been in the absence of the DR event. Thus, we first define two metrics that to evaluate how responsive customers were to Flex Alerts, including the *Flex Period Response*, which estimates how much demand was shifted away from the Flex Alert period, and the *Ramping Response*, which estimates changes in demand during the first hour of the Flex Alert period. We then analyze the hourly load response of the residential sector, based on ∼200 000 unique homes, on 17 Flex Alert days during the period spanning 2015–2020 across the Southern California Edison (SCE) utility's territory and compare it to total SCE load. We find that the Flex Period Response varied across Flex Alert days for both the residential (−18% to +3%) and total SCE load (−7% to +4%) and is more dependent on but less correlated with temperature for the residential load than total SCE load. We also find that responsiveness varied across subpopulations (e.g. high-income, high-demand customers are more responsive) and census tracts, implying that some households have more load flexibility during Flex Alerts than others. The variability in customer engagement suggests that customer participation in this type of program is not reliable, particularly on extreme heat days, highlighting a shortcoming in unincentivized, voluntary DR programs.

1. Introduction

In California, the state's largest balancing authority, California Independent System Operator or (CAISO), utilizes a voluntary demand response (DR) tool known as Flex Alerts. When a Flex Alert is issued, electricity consumers are asked to voluntarily reduce their electricity usage for a specified period in time to reduce strain on the grid during periods when grid reliability is threatened [1]. The Flex Alert program has become an important tool for managing California's electric grid, which has been challenged by an increasing frequency and intensity of extreme heat events, in conjunction with a rapid increase in variable renewable energy, which provide challenges for reliable grid operation.

Flex Alerts have helped avoid rolling blackouts by reducing total system load during times of grid stress particularly on hot summer afternoons when air-conditioning (AC) use is high [1, 2]. During heat waves, electricity demand often surges as customers turn on AC to stay cool [3]. To avoid disruption, grid operators must secure enough generation resources to meet rising demand, at the same time that electricity generators themselves might experience reduced capacity because of the high temperatures. For example, extreme heat can reduce reliable thermal power plant operation via lower power plant efficiencies [4], or in extreme cases, due to inadequate or disrupted cooling water resources [5]. The efficiency of solar photovoltaic panels are also reduced on hot days [6]. When extreme heat occurs during periods of drought, low hydropower resources can further exacerbate reductions in generation capacity [7]. Heat may also cause losses in transmission lines through both lowered line ratings and a need to de-energize in instances of wildfire risk [8, 9]. Extreme heat events in the past have forced utilities to resort to involuntary load shedding (i.e. rolling blackouts) when available power generation was inadequate to meet demand [10–12]. While rolling blackouts can effectively stabilize the power grid, they pose significant public health risks and have been shown to more adversely affect minorities and populations with lower socioeconomic status [13].

In addition to extreme heat, high penetrations of variable renewable energy, namely solar, on California's electric grid have prompted a set of emerging challenges that can threaten supply–demand balancing, particularly during periods of peak demand. These challenges are especially acute on high electricity demand days in the early evenings when solar PV generation falls at the same time that net demand (i.e. total demand less total variable renewable generation) approaches its peak. To accommodate the rapid increase in net demand, electricity generators from other (typically more dirty) resources have to quickly ramp up their generation, which can threaten grid reliability as there are physical constraints on the rate at which fast generators can be dialed up [14]. Conversely, in mid-day periods when solar resources are high and net load is at a low, CAISO has been challenged by solar overgeneration (i.e. periods when solar generation exceeds what the grid can accommodate), typically on sunny Spring days when hydropower and/or wind resources are also high [15]. During these periods system operators often curtail this load to avoid damage to the grid [16].

Flex Alerts can alleviate some of the stress of fossil fuel power generator ramping and solar overgeneration by encouraging customers to shift electricity demand from on-peak to off-peak hours. In CAISO, shifting load to off-peak hours when solar and wind output is high has the added benefit of increasing the amount of load met with emissions-free renewable generation. For some loads, this temporal shifting might cause a net increase in daily electricity usage, for example if customers precool their homes by running their air-conditioners more intensely in early afternoon in efforts to relieve cooling during on-peak hours [17]. (However, since electricity is cleaner and cheaper prior to Flex Alerts, there are likely indirect emissions and cost benefits in addition to grid reliability benefits, even in these cases [18]).

Most analyses of CAISO Flex Alerts have focused on impacts to systemwide or regional demand, and therefore, do not capture how participation in each DR event may have varied across sectors, spatial and temporal extents, or population demographics. CAISO itself has stated that there have been significant drops in overall demand during typical ramping hours on Flex Alert days, suggesting that they are a useful tool for shedding load [2, 19, 20]. However, an energy consulting firm released a load impact evaluation of California's Flex Alert program in 2014 using PG&E load data from three different Flex Alert days in 2013, roughly 10 years after program deployment, and did not find a statistically significant difference in the load, compared to reference days [21]. In recent years, there have been calls by the California Public Utilities Commission (CPUC) and investor-owned utilities (IOUs) to study consumer awareness of the program [22], but there has very little analysis on the efficacy of or participation in CAISO's Flex Alert program, in part due to the lack of high-resolution, publicly available data at a regional scale. As a result, our understanding of how different populations of electricity consumers respond when Flex Alerts are issued is limited.

In this research we aim to both evaluate the effectiveness of Flex Alerts as well as define what it means for a Flex Alert to be 'effective', as there exists no standard metric in the literature. We use five years of hourly smart meter electricity data from approximately 200 000 homes in Southern California to analyze the energy demand of residential customers on Flex Alert days. The following research questions are addressed: (1) how effective have Flex Alerts been in reducing pressure on generation fleet ramping ('Ramping Response') and residential sector demand ('Flex Period Response') during Flex Alert hours? (2) do factors including daily maximum temperature, weekend–weekday scheduling, and frequency of Flex Alert issuance affect Flex Period Responses on Flex Alert Days?, and (3) what subpopulations of customers are most likely to change their behavior during Flex Alert Periods? the results of this study will provide insight into the efficacy of voluntary DR programs and how they can be tailored to better engage and motivate different groups of residential customers.

2. Background

While few studies have analyzed the CAISO Flex Alert campaign specifically, many studies have attempted to quantify the full potential of residential DR by simulating or modeling energy behavior and customer response to certain signals [23–26]. These studies focus on how 'flexible' certain loads could be (i.e. how much of demand could potentially be shifted to other hours), but the results of these analyses do not give insight into how actual electricity users behave when DR events are called. Energy behavior, especially in the residential sector, is driven by a multitude of factors and is highly variable and unpredictable [27]. In the case of DR programs, users will not always respond to price signals or incentives consistently or in the most economical way [28]. A review of residential engagement in DR trials and programs found that modeling studies generally have optimistic assumptions about consumer engagement that are not realized, meaning the real-world customer response is lower than estimates in the peer-reviewed literature [29].

To gain better insight into how electricity users and different subpopulations will actually respond to DR, many studies analyze the load data of customers who participated in DR pilot programs and trials [30–34]. For example, one study evaluated the response of 483 residential customers to critical-peak pricing in California, finding that users with higher electricity demand and users in cooler climate zones were more responsive to critical-peak pricing and reduced their demand by larger percentages, compared to users with smaller loads and in warmer locations [30]. However, the number of participants enrolled in these DR pilots are not typically representative of an entire region (e.g. a couple hundred to a couple thousand homes [35–38]), which limits insight into the overall efficacy of the program or how responses differ within a region. Further, they focus on pricing or incentive driven programs [34, 39, 40] rather than programs like Flex Alerts where customers are called on to voluntarily reduce demand without incentive [41, 42].

Voluntary DR programs that offer no financial incentive for customers who shift or shed their load, such as Flex Alerts, are far less common in practice and in the literature. However, it has been shown that customers can be persuaded to conserve energy without incentive when emergency situations occur. In 2009 when a transmission line was severed in Juneau, Alaska, the town's residents responded to conservation requests and decreased their electricity use by 30% compared to the same time in the previous year [42]. Similarly, California developed a statewide public information campaign, titled *Flex Your Power*, during its 2001 energy crisis, that urged residents and businesses to reduce both their overall and peak demand. As a result of the campaign, additional DR programs, and efficiency measures, the peak electricity demand was reduced by an estimated 6,369 MW, with 2,616 MW reduction being credited to voluntary conservation alone [43]. These examples indicate that voluntary DR programs can be an effective tool to help avert energy emergencies, but to replicate their success, further analyses of the factors that impact the level of response are needed.

Evaluating the efficacy of DR programs is difficult because there is no precise ground truth of what energy demand would have been in the absence of the DR tool since variables such as temperature and other meteorological conditions, day of the week, holidays, etc. influence day-to-day and hour-to-hour demand. Most studies establish a reference case (e.g. predicted demand [30], demand from similar, non-participating customers [34], or a constructed baseline determined from demand during a reference period [32, 33, 39, 42, 44]) to serve as a proxy that can be compared to the observed demand to estimate how successful a DR program was. However, a more robust, standardized analytical method that assesses the extent to which customers engaged in DR events would be useful to systematically quantify and compare the efficacy of DR programs across time, space, and customer demographics and the role DR can play in achieving system reliability.

3. Methods

3.1. Datasets

Flex Alert data were retrieved from CAISO's Grid Emergencies History Report for the years 2015–2016 and 2018–2020 [45]. (These time periods were selected to align to our available hourly household-level electricity dataset described below). Data regarding the CAISO Flex Alert issuance date, targeted period (e.g. 4pm–9pm), and regional coverage (e.g. all of CAISO vs. Southern California) were extracted. In total, 18 Flex Alerts were issued during the study period with regional coverage that included Southern California. We chose to omit one Flex Alert (20 June 2016) from the study because the length of the alert (issued from 10 am to 9 pm) was markedly longer than others. We kept another Flex Alert, issued on 7 September 2020, in the analysis, although it occurred on a major holiday (Labor Day), which we acknowledge may have impacted customer response level.

Residential sector data comprised of hourly-smart meter electricity records for roughly 200 000 unique homes across the entire Southern California Edison (SCE) Investor-Owned Utility (IOU) service area were selected to be statistically representative of the SCE region with 99% certainty. SCE provided the smart-meter dataset with matching street-level addresses for the years 2015–2016 and 2018–2020. Data were stored on a high security data account to abide by the privacy requirements of the SCE. These household-level data were analyzed to evaluate how responsive the residential sector and subpopulations within the residential sector were to Flex Alerts. In this analysis, we use the normalized shape of our hourly smart meter dataset (i.e. after aggregating customer load at each hourly increment) as a proxy for SCE's normalized residential sector load and refer to it as the 'residential load'.

Total hourly load data for SCE, which encompasses all end-use sectors, on each Flex Alert day were retrieved from CAISO as a reference to compare to the residential smart meter data (referred to as 'total SCE load').

Local and regional temperatures were used in this analysis to investigate the impact of temperature on customer response during Flex Alerts and to identify similarly hot days to use as reference. Three sources of land-based weather station networks were used in this study: CIMIS, EPA AQS, NOAA. In total, historical dry bulb temperature records were retrieved from 112 different stations throughout the study region [46–48], and each household was matched to the nearest weather station. Daily average and maximum temperatures were computed on Flex Alert days for every census tract in the study area, as well as for the study area as a whole, by taking the average of each household's assigned temperature in the area of interest. The temperatures were used to compare weather conditions across Flex Alert days and determine comparable days (described in the following section). Daily temperatures were assumed to be equal for the residential load and total SCE load analyses. Each house was also matched to its corresponding California climate zone, as defined by the California Energy Commission, to gain insight into how consumer response varied across micro climates [49].

Census tract level data from CalEnviroScreen 3.0 and the U.S. Census Bureau were retrieved to compare energy consumption behavior across different subpopulations [50, 51]. These data include poverty percentile, education percentile (e.g. the percent of households in a census tract where a resident has at least a high school education—shown in SI), and income. Each household is characterized by the census tract it is situated in, as household level socioeconomic data is not available.

3.2. Response metrics

To define how 'responsive' a household was to the Flex Alerts, it was prudent to define a reference scenario to estimate what hourly electricity usage behavior might have been in the absence of the Flex Alert. Since it is impossible to know what actual electricity use behavior would have been in the absence of a Flex alert on a Flex Alert day, we assigned three '*comparable* days' to each of the 17 Flex Alerts studied. The set of comparable days were selected based on 4 criteria, including that they (1) occurred in the two weeks leading up to or two weeks following the given Flex Alert, (2) shared the same 'day type' (i.e. weekday or weekend) as the Flex Alert, (3) were not classified as a Flex Alert day, and (4) represented the three hottest days based on the region's daily maximum temperature. Every census tract was also assigned three comparable days for each Flex Alert day using the census tract's daily maximum temperature. Thus, the assigned comparable days may differ across census tracts but are always the same for every household within a census tract.

The electricity demand of each unique customer i on each of the three comparable days, $E_{i,h}^{(C1)}$, $E_{i,h}^{(C2)}$, and $E_{i,h}^{(C3)}$, respectively, is averaged to generate an estimate of the electricity demand of each customer in hour h on the Flex Alert day had the Flex Alert *not* been issued. We refer to this as the reference electricity demand, $E^{(R)}{}_{i,h}$ described in equation (1). We use this metric as a proxy to estimate hourly demand across the reference day in equations (2)–(4)

$$E_{i,h}^{(R)} = \frac{E_{i,h}^{(C1)} + E_{i,h}^{(C2)} + E_{i,h}^{(C3)}}{3}. \tag{1}$$

Two metrics were developed to evaluate how responsive customers were to each Flex Alert. The metrics were calculated for the SCE's entire service territory and at the census tract level to explore how the response varied across spatial extents and subpopulations. (Note: In equations (1)–(5) no summation across customers i is required when calculating the Flex Period Response and Ramping Response of SCE's total load data as these data are already aggregated into hourly values representing all customers and all sectors in SCE territory).

The first metric, described by equation (2), is referred to as the *Flex Period Response* and is a proxy to estimate the change in the percent of total daily demand that took place during targeted Flex Alert hours on the Flex Alert day, F, compared to the same day if a Flex Alert was not issued (i.e. the reference day, R). Hence, to calculate the Flex Period Response, we calculate, $P^{(F)}$, representing the percentage of total daily demand that occurred within the Flex Alert period by summing the total amount of electricity demand by customers across the spatial extent of interest (i.e. census tract or total SCE region) between hour s, defined to be the start of the Flex Alert period, and hour e, the end of the Flex Alert period, and divide by the total daily electricity usage of all customers in the dataset on the Flex Alert day, as shown in equation (2). Then we repeat the calculation in equation (3) to calculate the same value for the percentage of demand occurring within the Flex Alert hours on the reference day referred here to as $P^{(R)}$

$$P^{(F)} = \frac{\sum_i \sum_{h=s}^{e} E_{i,h}^{(F)}}{\sum_i \sum_{h=0}^{23} E_{i,h}^{(F)}} \times 100. \quad (2)$$

$$P^{(R)} = \frac{\sum_i \sum_{h=s}^{e} E_{i,h}^{(\mathrm{R})}}{\sum_i \sum_{h=0}^{23} E_{i,h}^{(\mathrm{R})}} \times 100. \quad (3)$$

The Flex Period Response (units of percent change) represents the difference between, $P^{(F)}$ and $P^{(R)}$as shown in equation (4)

$$Flex\, Period\, Response = P^{(F)} - P^{(R)}. \quad (4)$$

The second metric, described as the *Ramping Response* (units of percent change) in equation (5), is a proxy to estimate the difference in how demand changed across the first hour of the Flex Alert Period (i.e. the hour spanning $h = s$ to $h = s + 1$) on the actual Flex Alert day versus the reference day

$$Ramping\, Response = \left(\frac{\sum_i E_{i,h=s+1}^{(F)} - \sum_i E_{i,h=s}^{(F)}}{\sum_i E_{i,h=s}^{(F)}} - \frac{\sum_i E_{i,h=s+1}^{(R)} - \sum_i E_{i,h=s}^{(R)}}{\sum_i E_{i,h=s}^{(R)}} \right) \times 100. \quad (5)$$

The Flex Alert period varied across Flex Alert days so the targeted period in equation (2) through (4) reflects the period defined by the unique Flex Alert listed in CAISO's Grid Emergencies History Report [45]. For example, on June 30th, 2015 the alert was issued to begin at 2 pm and end at 9 pm (i.e. $s =$ 2pm to $e =$ 9pm) and on 14 August 2020, the alert was issued to begin at 3 pm and end at 10 pm (i.e. $s =$ 3pm to $e =$ 10pm). For each set of comparable days, the s and e values are defined based on the corresponding Flex Alert day.

4. Results and discussion

The Flex Period and Ramping Responses of both the residential load and the total SCE load were calculated to understand the varying success of the program and identify factors that might have motivated customer engagement. In figure 1, the Flex Period Response of the (a) residential load and (b) total SCE load on each Flex Alert day is plotted against the study region's daily maximum temperature on the day of the Flex Alert. In figure 1(c), a timeline of the Flex Alerts across the five years of data is shown with the corresponding Flex Period Response on those days (note: desired Flex Period Responses are negative, representing reductions in load). The shape of the points on the scatter plot represents whether the date was a weekday or weekend, and the shade of each point refers to the order within each year that the Flex Alerts were issued. (We were interested in understanding the frequency and timing of Flex Alerts throughout the year to see if there might be fatigue across the customer base when many Flex Alerts were issued within a short duration of time). Points that are outlined in red represent Flex Alert days that were hotter in temperature than all three of their comparable days.

The scatter plots show that there is a correlation between the study region's Flex Period Responses and the region's daily maximum temperature, and the slope and r value of the line of best fit can give insight into how dependent and correlated the Flex Period Responses are to daily maximum temperature. In general, the residential load and total SCE load were more likely to reduce demand during Flex Alert hours on days with relatively cooler temperatures (i.e. higher magnitude, negative Flex Period Response). When compared to total SCE load, the Flex Period Response of the residential load is more strongly dependent on (slope of 0.52 versus 0.34) but less correlated to (r value of 0.58 vs 0.69) the daily maximum temperature. No observable trends were noted across weekday/weekends, the number of Flex Alert issued in the year, or whether the Flex Alert was the hottest day of the comparable days. Additionally, the timeline in figure 1 does not show any trend of consumers being less responsive on consecutive days of issued Flex Alerts (i.e. there was no response fatigue after multiple consecutive days of Flex Alerts).

Table 1 summarizes Flex Alert days and the responses of both the residential sector and all SCE customers. Compared to the Flex Period Response, the Ramping Response was much less strongly dependent on the region's daily maximum temperature, with a slope of 0.07 and 0.05 for the residential load and the total SCE load. On average, the Ramping Response also has a lower magnitude, negative value for both the residential SCE and total SCE load. It is important to note that the shape of the load profile on the three comparable

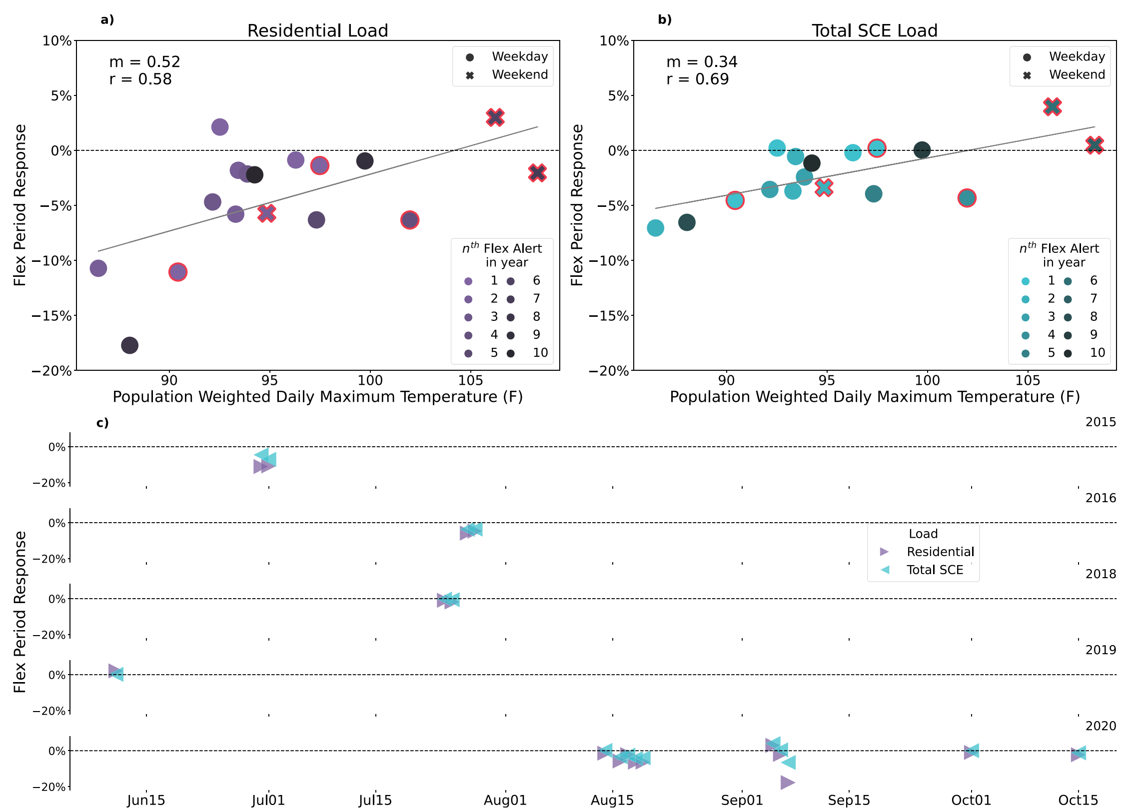

Figure 1. Flex Period Response of the (a) the residential SCE load and (b) total SCE load on each Flex Alert day issued in 2015–2016 and 2018–2020 versus the region's daily maximum air temperature. (c) A timeline of when each Flex Alert was issued with the corresponding Flex Period Response.

days strongly impacts the Ramping Response, and if the demand peaks earlier or later than is typical it could lead to an under or overestimation of the responsiveness. For example, on 11 June 2019, the demand on one of the three comparable days is already declining before the start of the Flex Alert period, which increases the value of the computed Ramping Response (i.e. positive or lower magnitude, negative value). Because there is no ground truth to compare against, this is a difficult limitation to avoid. (Note: the hourly load profiles of the residential load and total SCE load on all of the Flex Alert days are available in the SI).

Table 1 also highlights that the overall Flex Period Response of both the residential and total SCE load is inconsistent, and certain Flex Alert days appear to be effective (i.e. a negative Flex Period Response) while others are not. On the most effective Flex Alert days (apart from the Flex Alert that fell on a major holiday), the Flex Period Responses of the residential loads are −11% (30 June 2015 and 1 July 2015), but most days have more modest values, or even positive Flex Period Response values, indicating that load actually increased during the targeted period when compared to the estimated reference day. The average Flex Period Response of the residential and total SCE load are −4% and −2%, respectively. It is likely that large industrial and commercial loads are already participating in existing SCE DR programs (e.g. [52]) that incentivize them to shift or shed their large loads (and possibly on selected comparable days, in addition to Flex Alert days), which might partially explain why these customers have a lower average Flex Period Response and less sensitivity to temperature.

While the days with positive Flex Period Reponses may seem like days in which the program was ineffective, our reference day demand is only an estimate of what demand would have been in the absence of a Flex Alert, so we have no precise ground truth for comparison. Thus, it is possible that customers still used less demand during the Flex Alert period on these days than they would have in the absence of a Flex Alert, particularly on days where the Flex Alert day was hotter than the three comparable days used to calculate the reference.

As observed in figure 1, the Flex Period Response of both the residential and total SCE load varies across the Flex Alert days. Figures 2(a) and (b) highlights the load profiles of the residential load and total SCE load on two different Flex Alert days (30 June 2015 and 1 July 2015), which had the largest flex period responses in the sample of Flex Alerts studied (both −11%). The load profiles of the comparable days, used to calculate the reference day hourly load, are also shown for context. As a note, the three comparable days exhibited strong consistency in the shape of their load profiles for a corresponding Flex Alert day (refer to the SI for the

Table 1. Summary of CAISO's Flex Alerts from 2015–2016 and 2018–2020 with the corresponding Flex Period Response and Ramping Response of SCE's residential load and total load.

			Residential SCE Load		Total SCE Load	
Date	Day of week	Daily max temp (F)	Ramping Response	Flex Period Response	Ramping Response	Flex Period Response
30 June 2015	Tuesday	90.4	−9%	−11%	0%	−5%
1 July 2015	Wednesday	86.5	−1%	−11%	−2%	−7%
27 July 2016	Wednesday	93.3	−2%	−6%	0%	−4%
28 July 2016	Thursday	92.2	−1%	−5%	1%	−4%
24 July 2018	Tuesday	96.3	1%	−1%	2%	0%
25 July 2018	Wednesday	93.4	1%	−2%	2%	−1%
11 June 2019	Tuesday	92.5	0%	2%	1%	0%
14 August 2020	Friday	97.5	0%	−1%	3%	0%
16 August 2020	Sunday	94.9	−3%	−6%	−2%	−3%
17 August 2020	Monday	93.9	−1%	−2%	−1%	−2%
18 August 2020	Tuesday	102	−2%	−6%	−1%	−4%
19 August 2020	Wednesday	97.3	−1%	−6%	−1%	−4%
5 September 2020	Saturday	106.2	−2%	3%	2%	4%
6 September 2020	Sunday	108.3	−3%	−2%	−1%	0%
7 September 2020[a]	Monday	88	−7%	−18%	0%	−7%
1 October 2020	Thursday	99.7	−1%	−1%	2%	0%
15 October 2020	Thursday	94.2	1%	−2%	5%	−1%
Average response			−2%	−4%	1%	−2%
Median response			−1%	−2%	0%	−2%
Slope of response metric to temperature metric			0.07	0.52	0.05	0.34
r value of response metric to temperature metric			0.11	0.58	0.16	0.69

[a] Flex Alert fell on a federal holiday.

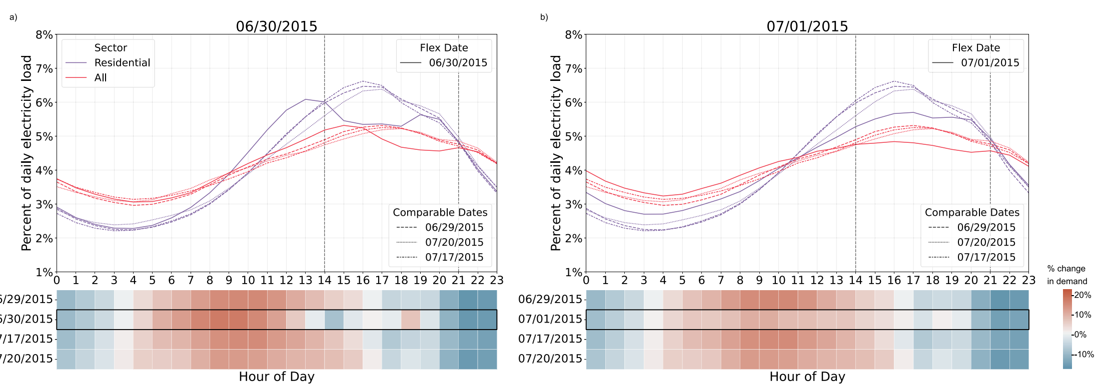

Figure 2. (a), (b) Normalized hourly electricity load profile of residential load (purple) and total SCE load (red) on two different Flex Alert days (solid lines) compared to the hourly load profiles on the comparable days (dashed lines). (c), (d) And hourly percent change in electricity demand on two Flex Alert days (outlined in black) and their corresponding comparable days.

load profiles of the comparable days on all Flex Alert days). The Flex Period Response suggests that the DR event was effective on both of these days; overall, customers used less of their daily load during Flex Alert hours than they did on comparable days, reducing the generation resources needed during those periods.

While significant Flex Period Responses were observed during Flex Alert hours on both days in figure 2, the shape of the responses differs. On 30 June 2015, the residential load sharply fell in the hours leading up to and after the first hour of the Flex Alert and remained relatively low before peaking again in the final hours of the Flex Alert. The heat maps in figures 2(c) and (d) underscore this behavior, illustrating a significant decrease in demand occurring between hours 14 and 15, followed by an increase between hours 18 and 19, which is markedly different from the patterns of changes in hourly demand on the three comparable days occurring before or after the 30 June Flex Alert. In contrast, on 1 July 2015 there is no sharp drop in the residential load; instead, the demand is consistently lower than the comparable days leading up to and throughout the hours of the issued alert. However, on both Flex Alert days, there are ramping benefits meaning that hourly increases in load during the initial hours of the Flex Alert are less than comparable days.

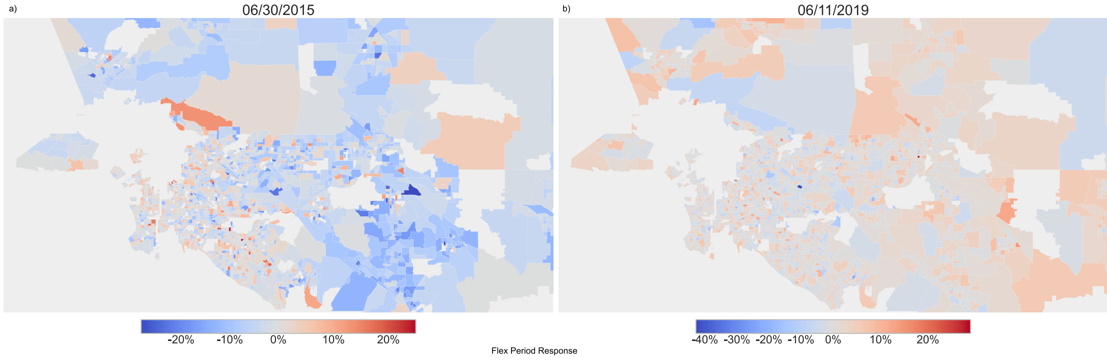

Figure 3. (a), (b) Choropleth map of the census tract level Flex Period Response of SCE's residential load on two different Flex Alert days. Areas in blue consumed a lower percentage of their total daily electricity demand during Flex Alert hours than they did on reference days, while areas in red used a higher percentage of their total daily electricity demand during Flex Alert hours than they did on reference days.

However, we observe slight penalties, in the case of the June Flex Alert, when demand spikes in the final hours of the Flex Alert period.

The load profiles also highlight some differences in how the residential sector consumes energy throughout the day versus all sectors. While both normalized load profiles show peaking behavior in the late afternoon through evening hours, the residential load's peak is significantly higher than the total SCE load's peak. Hence, the residential sector drives much of the peaking behavior that occurs during typical Flex Alert hours, as much of the residential sector's demand is driven by AC use. While it might be difficult for some households to shift or shed their load when temperatures are hot, the high percentage of demand that takes place during the hours of interest underscore the opportunity that residential consumers present for participating in DR programs aimed to reduce peak electricity consumption.

The response to Flex Alerts across residential customers is not uniform. To observe variations across both the microclimates of the study region and subpopulations, the residential Flex Period Response of each census tract was mapped across SCE territory. The choropleth maps of the residential load's Flex Period Response on two different Flex Alert days are depicted in figure 3. Figure 3(a), represents 30 June 2015, a day where the alert prompted a relatively large Flex Period Response of −11% for the residential load (compared to the average residential load's Flex Period Response across all Flex Alert days of −4%). On this day, the response in the study region is relatively consistent with reductions in loads across most census tracts. Conversely, on 11 June 2019, the average Flex Period Response for residential customers across SCE's service region was +2%, meaning that there was an average increase in load during the Flex Alert compared to electricity consuming behavior on similar days. However, when the responses are mapped at the census tract level, there are many census tracts that were responsive to the Flex Alert (i.e. had a negative Flex Period Response value).

We also investigated how socioeconomic factors influence a customer's participation in Flex Alerts. Figures 4(a) and (b) depict the hourly residential load in MWh by electricity demand percentile and income percentile, respectively, (binned according to total annual demand in each year) on a Flex Alert day, 30 June 2015. Figures 4(c) and (d) depict the percent of daily residential electricity load split across each hour of the day by electricity demand percentile and income percentile, respectively, on the same Flex Alert day. From the load profiles, we observe that higher income and higher demand customers have larger demand reductions during Flex Alert hours than customers with lower income and demand. The heat maps in figures 4(e) and (f) show percent change in hourly demand on the same Flex Alert day, again by demand and income percentiles. Here we see that high income, high demand customers have a steeper decline in demand during the initial hours of the flex alert than low income, low demand customers. These results can be explained in part by previous studies on energy poverty, which have found differences in the energy behavior of low-income and high-income utility customers. Low-income customers typically use significantly less energy than their high-income counterparts and more consistently engage in energy limiting behaviors to reduce costs [53]. Thus, when DR events occur, it is difficult for low-income customers to further reduce their demand.

These results illustrate that average households in some census tracts likely have greater flexibility to respond to Flex Alerts than in others. Despite the wide disparities in climate, housing stock, and population demographics across and within both the census tracts and subpopulations studied, we can draw some conclusions on some common characteristics of the households most likely to respond. For example, customers with larger demand (who also tend to be higher income) are more likely to modify electricity

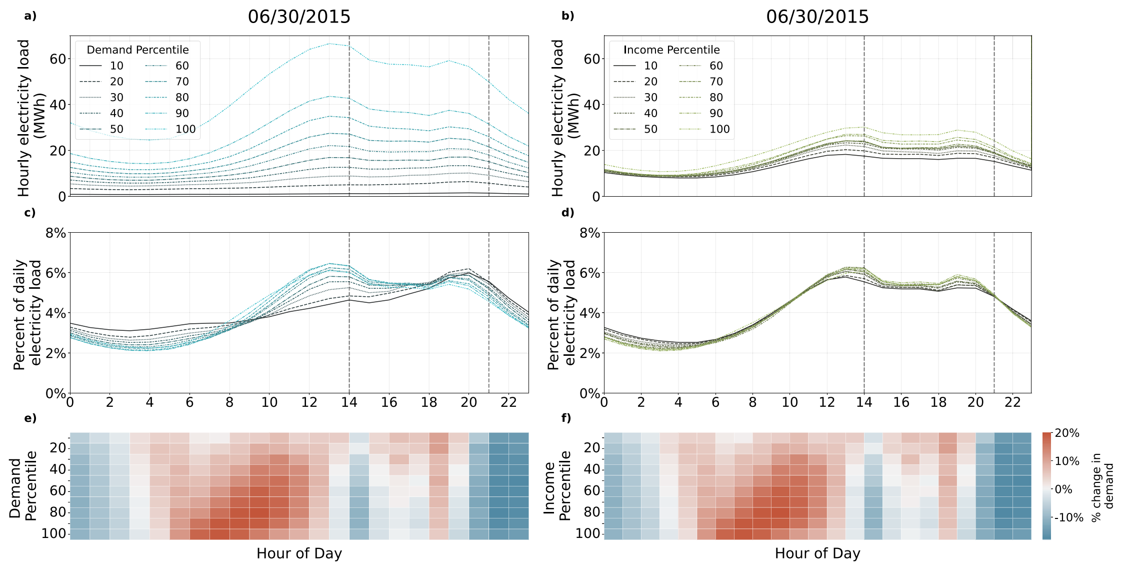

Figure 4. Hourly residential electricity load by (a) income percentile and (b) demand percentile and normalized hourly residential electricity load by (c) income percentile and (d) demand percentile. Heat maps of hourly percent change in demand by (e) income percentile and (f) demand percentile on a Flex Alert day, 30 June 2015. Note: the 10th percentile refers to the lowest income and demand percentiles, and the 100th percentile refers to the highest income and demand percentiles.

consuming activities and might have access to technology that enables flexibility [54]. In contrast, a customer that is already very energy conscious and/or has few discretionary electric loads (who also tend to be lower income) might not be able to shift much of their load to other periods of the day. These results, on one hand, indicate that the households with the largest potential to contribute large reductions in peak demand (i.e. high consumers) are typically the households that are most likely to respond to Flex Alerts, which is valuable for program success. However, on the other hand, our census tract results across the SCE region indicate that responsiveness to Flex Alerts on extreme heat days (particularly in the hottest regions) tend to be lower than Flex Alerts issued on comparatively cooler days (and in cooler regions). Hence, the Flex Alert program might not be very effective on the most extreme heat days when grid resources tend to be most strained.

5. Conclusion

The results of this study show that voluntary DR programs, even without financial or other incentives, can significantly influence energy behavior, especially in the residential sector, where peak electricity usage tends to be high compared to other sectors. On the Flex Alert days with the greatest percent reduction of daily consumption during the Flex Alert hours, the residential load and total SCE load had Flex Period Responses of −11% and −7%, respectively (excluding the Flex Alert that fell on a federal holiday). These values represent meaningful decreases in the percent of daily demand used during Flex Alert hours suggesting that Flex Alerts have provided a valuable tool to help maintain grid reliability on days when the grid has been stressed. However, there are also days when responsiveness appears to have been somewhat negligible and regional results suggest that Flex Alert responsiveness tends to be reduced on days and in locations experiencing extreme heat (and electricity resources were presumably most strained).

Our investigation of differences across subpopulations and census tracts implies that some households have more flexibility or ability to shift or shed their load and that this flexibility can vary significantly across Flex Alert days. While we do not have full transparency into what drives these differences, which are likely due to variety of factors (e.g. outdoor temperature, higher efficiency homes, more flexible schedules, more discretionary loads during Flex Alert hours, and the health, wealth, and age of occupants, etc), we can generate some broad insights. From our analysis we see clear overlaps between household income, total electricity demand, and Flex Period Response; customers with large electricity demand often also have high income, and hence, more demand flexibility. However, future analyses should focus on teasing out the other factors that drive differences in customer engagement and literacy in the program across subpopulations to gain a better understanding of what factors influence customer participation so that messaging for future events can be tailored to increase engagement. Future work might also look into the efficacy of trying to drive larger Flex Alert responses in cooler regions on extreme heat days, when responsiveness in the hottest regions is likely to be muted.

This study underscores some of the shortcomings of unincentivized, voluntary DR programs, since it difficult to predict how much additional capacity can be gained by issuing Flex Alerts, limiting their benefits to grid operators for longer term planning. As the frequency and intensity of extreme heat events grow, a viable, dynamic grid will likely require more flexibility than a program such as Flex Alerts can provide, meaning robust, incentivized DR programs with reliable participation are needed to ensure resources are available during periods of high demand. Most incentivized DR programs in California over the past decade have been geared towards industrial and commercial customers with large loads for load shedding and load shifting, but the results of this study show that there is huge potential for demand-side management programs through the aggregation of smaller residential load reductions. Currently, DR programs are decentralized and administered by either the state's three IOUs, CPUC jurisdictional entities, or commercial DR providers, and residential customers can elect to participate. However, the future of California's electricity systems will likely include a more formal approach to DR, such as universal opt-in access to real-time energy and capacity pricing, as was outlined in the CPUC Energy Division's 2022 'CalFUSE' proposal [55]. (Note: In May 2022, the California Public Utility Commission launched a pilot program administered by a customer's IOU, called 'Power Saver Rewards' that pays customers in bill credits when they respond to Flex Alerts [56]. That incentivized pilot program was not implemented during the period of study).

As markets for incentivized DR are developed, attention should be given to how to best optimize these programs as there are conflating factors that can limit their overall success. For example, although wealthier customers have the capability to load shift, studies have shown that they are harder to incentivize financially [57]. And while lower income customers are more likely to respond to pricing signals, their participation does not offer as much flexibility to the grid as higher income customers because their loads are generally smaller [58, 59]. Further, low-income, energy insecure customers may already be engaging in energy limiting behaviors due to their own financial constraints. Thus, it is important to design programs that distribute the benefits to vulnerable households, whose ability to participate is limited [60], and hence, will not benefit equally from financial incentives or lowered electricity prices in comparison to wealthier, higher consuming users [61]. Still, regardless of who participates, successful DR programs that shift load to off peak hours benefit the whole customer base through reductions in overall electricity costs that reflect a transfer of wealth from electricity generators to electricity consumers [62, 63].

Data availability statement

The data cannot be made publicly available upon publication because they contain sensitive personal information. The data that support the findings of this study are available upon reasonable request from the authors.

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