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Quantifying the Demand Response Potential of Residential Loads in India

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Highlights

- Smart meter data from residences in Pune City is analyzed for estimating urban residential load in India.
- Appliance ownership data is exploited to infer electricity usage and peaks in the load curve for each household.
- Potential of demand response (DR) programs is studied using this data set to shave peaks by load shifting.
- Load composition of residences contributing to system peak is studied to estimate their DR potential.

Abstract

The paper investigates how residential loads in India contribute to grid peak load and how to manage such peaks. Algorithms that process smart meter data from residential loads and compute attributes that capture their contribution to the system peak are devised and demonstrated in the paper. Specifically, a distribution system is considered based on a study on households in Pune, India. To enhance the household dataset for analysis, a synthetic data generation technique is employed. The algorithms developed here are applied to this system to showcase their capabilities. Results show how simple attributes such as peak amplitude and peak duration can extract sufficient information to ensure households that contribute to system peak are appropriately identified. Moreover, these attributes offer insights into appliance ownership, supporting the development of effective DR programs. A demonstration of how shifting of individual peaks can significantly impact system peak is also provided. The results lay the foundation for designing meaningful DR programs leveraging the smart meter data.

Keywords: demand response, residential loads, peak load shaving, load shifting

Introduction

The residential consumption in India accounts for about 24% of the total electricity in the country [1]. There are multiple categories of appliances owned by these households. Understanding the appliance penetration in individual households and studying their load curve can help the utility to manage the efficient dispatch of power for the system. For instance, when a few households consume high power at the same time, it could result in high demand. This demand is met by activating high-cost generators, leading to increased generation costs for the utility and, thus, higher electricity bills for consumers. Managing the system peak is a concern for all utility operators; it can be managed via an effective generation dispatch, leveraging storage and/or demand side management. This paper is concerned with the last category.

Demand side management and demand response (DR) programs motivate the consumers of households to reduce or shift their electricity usage from peak periods to off-peak periods by providing financial incentives or by responding to time-varying electricity prices. DR programs are an intelligent way used by the system operator to balance supply and demand to make decisions to operate low-cost generators to fulfill the estimated household demand. There are multiple methods by which end users are engaged in DR programs. Time-based electricity pricing, like time-of-use (ToU) pricing, critical peak pricing (CPP), and real-time pricing (RTP), is a way in which the consumer is motivated to shift the appliance operation based on electricity tariff information. Direct load control programs provide flexibility to the utility to control high consumption loads like air conditioners (ACs) and water heaters (WHs) by turning ON and OFF during intervals of system peak in lieu of financial incentives.

The potential for DR among residential consumers increases with the growing penetration of flexible and controllable loads like electric vehicles (EVs) and cooling and heating appliances such as ACs and WHs. DR programs, leveraging advanced metering infrastructure (AMI) and other innovative technologies, can alter the electricity consumption patterns of households by shifting, shedding, or shaping the load curve [2]. However, engaging consumers in DR programs can be challenging, especially in terms of which consumers to enrol. DR implementation requires the installation of smart meters and communication capability to enable the exchange of information between the grid and the end user. Smart meters allow improved management and control over the electricity grid. Meter data can help utilities to identify appropriate residential consumers for the DR program.

Residential DR programs that show a reduction in peak load by controlling operations of WHs [3] have been studied in the literature. Experimental results covered in [4] show a drop in peak demand by 3% to 6% when using ToU pricing and a 13% to 20% drop in peak demand when using CPP. The survey presented in [4] for the United States mentions a change in metering infrastructure for implementing DR in the retail electricity market and emphasizes that about 60% of the investment can be covered by savings in distribution system costs. The remaining amount could be recovered by reducing power generation costs which could be achieved by DR. A survey conducted in [5] has assessed appliance use behaviour and DR preferences to simulate DR potential by using the survey data in a Home Energy Management System (HEMS) optimization tool. A peak reduction of 33% was observed with the use of HEMS for DR.

The success of electricity DR programs is found to be correlated with the extent of urbanization of the area where it is implemented and annual economic growth rates. The DR programs in the future can be made more effective by deploying DR programs in urban areas with the capability to afford infrastructure and coupling the program with economic policies and urban development planning [6]. To address the potential of implementing DR for large industrial and commercial customers, a bottom-up engineering approach that assesses the individual user's peak load is studied in [7]. The customer survey-based approach reported in this paper uses the responses to evaluate the likelihood of end users participating in DR programs. Evaluation of the DR potential of heating, ventilation, and air conditioning (HVAC) systems is studied in [8], which considered a DR event period, and load adjustment in the DR period was evaluated by ensuring consumer preferences. A simulation tool for estimating DR potential from residential loads is presented by modelling occupant behaviour relating to residential activity patterns and residential loads [9]. A study in [10] estimates the impact of change in the setpoint of HVAC in implementing DR programs. The household information available in [11] is leveraged to build a demand curve for individual households. Their behavioural patterns and appliance ownership information are used to create a demand curve for individual households. The case study focuses on peaks generated in the utility demand curve and observes the peaks of households to study the appliance level contribution on individual peaks and harness the information to save during peak price periods by shifting the operations to low pricing intervals.

From the literature reviewed above, it can be concluded that smart meter data analysis can be leveraged to assess DR potential. Due to the absence of sufficient smart meter data for residential DR in the Indian context, this paper leverages information on household type and appliance ownership along with recorded smart meter data from select houses in Pune to generate representative synthetic household consumption data. A hypothetical total system load is computed using the recorded data from the select houses and synthetic data. This time series system load, along with individual household time-series load data, is analysed to understand the DR potential of households having high-consumption appliances such as WHs and ACs. The role such houses play in shaping the system load peak is comprehensively studied using easily computable metrics: peak amplitude and peak duration. Finally, the appliance ownership information available [11] is leveraged to infer appliance usage and contribution to individual peaks, and a rudimentary load-shifting application is presented to potentially shave the peak by load-shifting intervals.

Preliminary Data Analysis

Dataset

eMARC dataset [11] is used to construct the load data for the analysis presented in this paper. The dataset encompasses power consumption information of 5 cities having 115 households for a period of two and half years from Jan 2018 to June 2020. The data includes both the daily consumption power as well as 15-minute block aggregate power consumption dataset for individual households in each city. The 15-minute block dataset for all the cities is considered for this paper. This dataset includes the basic as well as high power rating appliance ownership information like the number of lights, fans, WHs, ACs, and other appliances present in each household. From the review literature, the DR potential of residential appliances like WH and AC is established. Therefore, for this study, load data from households with AC and WH appliance ownership are considered, and hence data from Pune & Pune City comprising of 67 households are used. To avoid having to tackle with large volumes of missing data, only 55 households having less than 30 days of missing data are included in this analysis. Information on the income of households is unavailable and may not be disclosed due to privacy issues.

Data Pre-processing

The raw data of the considered households has missing data points for some intervals. Every household is expected to have 96 data points showing aggregate load power for each day. For each household, daily load curves having at least 90 data points are considered for the analysis. The remaining days with fewer data points are replaced with the data of the day having the nearest temperature of that corresponding day. For the days that have up to 6 missing data points, the linear interpolation method [12] is used to impute the missing data. After data pre-processing, the dataset comprises 15-minute interval power consumption profiles of 55 households over 365 days, starting from 1 January 2019 until 31 December 2019.

Appliance Usage and Synthetic Data

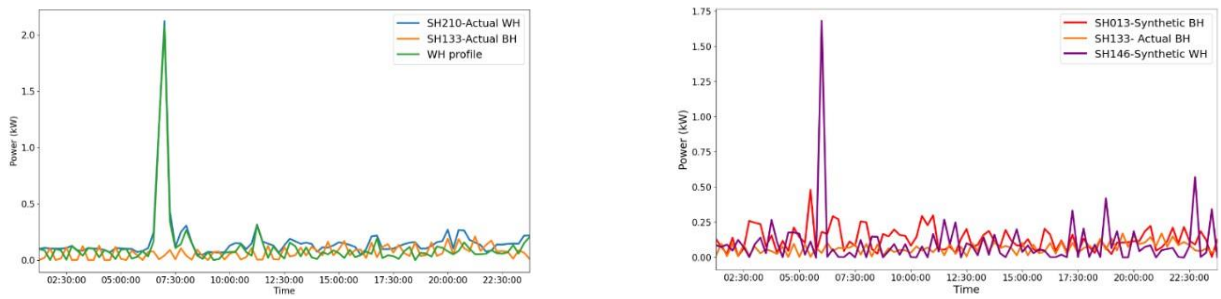
The initial dataset comprising of 55 households is used to generate a collection of 245 synthetic household data to enrich the analysis of the study. From the eMARC dataset [11], the shortlisted 55 households are categorized based on ownership of WHs and ACs: 6 households have AC ownership only, 12 have WHs only, 8 households own both WH and AC, and 29 basic households (BH) have neither AC nor WH ownership. The appliance ownership information allows for appliance usage patterns to be inferred to aid the synthetic data generation.

The synthetic data generated for this work is derived from an adaptation of the Generative Adversarial Network (GAN) model [13]. The adapted model takes as inputs the original daily load curves of basic households from the eMARC dataset and typical daily appliance usage patterns for WHs and ACs. Through statistical techniques, the load curves are reproduced with suitable time shifts and scaling as needed, with appliance usage patterns superimposed on them if necessary. In this way, basic household load data can be processed to generate load data for another hypothetical house that is either basic or has WH, AC, or both appliances.

To illustrate the synthetic data generation process, consider WH household (SH210) and basic household (SH133) from the eMARC dataset. The appliance ownership of both is presented in Table 1: it is evident that the households are nearly similar in all aspects, such as number of occupants, house area, and number of appliances, except for the WH presence in SH210. Assuming that the energy consumption of both households is only differentiated by WH appliance operation, the two datasets are subtracted and suitably rounded off to derive the WH energy consumption patterns as shown for a typical day in Figure 1(a). The load data of SH133 can then be processed along with appliance consumption data, thus derived in the adapted GAN model to generate data for a basic synthetic household and a synthetic household with WH. Figure 1(b) shows the typical daily load curve for all three households: SH133, synthetic WH house SH146, and synthetic basic house SH013.

Table 1: Appliance data and other relevant information of two example households

H.No.	Area	Rooms	People	ACs	Air cooler	WH	Fans	Lights	WM	Mixer	Iron
SH133	575	3	2	0	0	0	3	11	1	1	0
SH210	600	3	2	0	0	1	3	9	1	1	1



(a) Extracting appliance consumption pattern *(b) Generating synthetic load curve*

Figure 1: Daily load profile and load duration curve

The AC usage patterns are harder to extract from real data; rather, these are simulated using ambient temperature, occupancy, and rated power of AC for each house along with an assumed setpoint temperature using the standard equivalent thermal parameter model such as the one proposed in [14]. This way, the power consumption of the AC for each time interval is derived by making suitable assumptions on the time of the day and months of the year when the AC would be ON. With AC and WH consumption profiles thus generated, the original dataset comprising of 55 households is processed to generate synthetic data for an additional 245 hypothetical households. Table 2 shows the description of actual and synthetic datasets with respect to appliance ownership. The household distribution is approximately informed by the original distribution of household ownership types, effectively capturing the diverse proportions of basic, WH-only, AConly, and AC-WH ownership configurations.

Table 2: Household information for the complete dataset

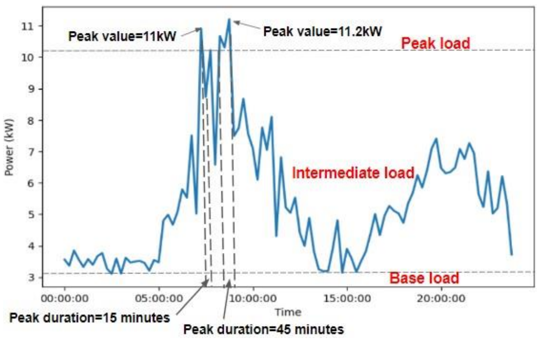
Dataset (Count)	Basic (Count)	WH only (Count)	AC only (Count)	WH & AC (Count)
Actual (55)	SH109-SH137 (29)	SH205-SH216 (12)	SH240-SH242 (3)	SH287-SH297 (11)
Synthetic (245)	SH001-SH108; SH298-SH300 (111)	SH138- SH204 (67)	SH217- SH239 (23)	SH243-SH286 (44)

Methods

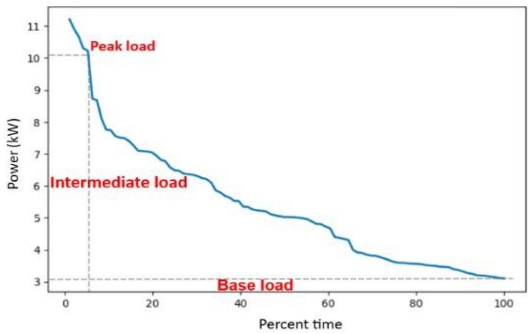
Load duration curve (LDC)

Suppose the load is recorded for T samples each day. The LDC represents the statistical distribution of the load over a specified period. For instance, consider a typical daily load curve based on 15 minutes of sampled data, as shown in Figure 2(a). The LDC is obtained by rearranging the recorded load values in descending order and translating the X-axis to percent time [15], as shown in Figure (b). The minimum demand needed to supply is termed the base load. The peak load is assumed to occur 5% of the time. The power between peak load and base load is known as intermediate load. Figure 2(b) shows the base, peak, and intermediate load values.

Load curve can be plotted for a year also. It helps the utilities to identify the day and time during which the system load was at peak values in that year. If this peak load can be reduced or shifted, then it can help the utilities to reduce the burden on their generating stations.



(a) Daily load profile



(b) Load duration curve

Figure 2: Daily load profile and load duration curve

Peak Associated Attributes

The following are the peak associated attributes are considered based on LDC and time-series data:

1) Peak value: The magnitude on the y-axis on the LDC for 5% time represents the peak value. 2) Peak duration: The duration for which this peak occurs is defined as the peak duration.

For the load curve in Figure 2(a), these peak attributes are plotted for reference. The peaks that are generated for individual households and the entire system can be studied to identify the appliance level contribution. The days and intervals that contribute to the top 5% of time are considered. Two algorithms are proposed to study the peak attribute information for these days. Algorithm 1 is proposed to identify the contribution of households to the peaks and infer the dominant appliance operating at the peak day. Algorithm 2 calculates the duration of peaks that occur for households with and without AC.

Algorithm

Consider H number of households for D days. Each day, D has T data points at timesteps of 15 minutes. Here, H, D, and T are 300 households, 365 days, and 96 data points, respectively. Let the notation for household be h. Let P be the peak load of the total system load in kW and $p \in P$ be the subset of the 0.5% time of the LDC. Considering i as the instance of date and time, p_i represents the i^{th} instance of p. Let h_{ji} be the household $j \in \{1,2,\ldots,H\}$ at i^{th} instance of date and time. The peak load in kW of household j at instance i is given by $p(h_{ji})$. Let δ be the allowable threshold in kW that captures the power consumption of ACs and WHs. Typical values of δ are obtained from [16] and observed to be over 1.5 kW.

Algorithm 1 shows the steps to identify the households that contribute to the high demand peak for 0.5% time. Algorithm 2 is used to calculate the duration of peaks for households with and without AC. For households with AC, the threshold Δ is introduced to capture any drop in power consumption of AC due to a change in the setpoint and duty cycle of the AC. These algorithms are used to analyse the data set.

Algorithm 1 Identifying contribution of peak load

Require: $H, D, T, p_i, p(h_{ji}), \delta$

for $p_i \in P$ do

  Identify the households h_{ji}, $j \in \{1,2,\ldots,H\}$, that are the highest contributors of p_i

  Arrange h_{ji} in decreasing order of $p(h_{ji})$

  Calculate the total percentage contribution of the households as $(\sum p(h_{ji})/p_i) \times 100, p(h_{ji}) \geq \delta$

  Based on the ownership information of h_{ji}, the appliance operating at i^{th} instance are inferred

end for

Algorithm 2 Identifying peak instances and duration for households with and without AC

Require: $H, D, T, p_i, p(h_{ji}), \delta$

for $h_{ji} \in H$

  for $p_i \in P$ do

    Consider the timeseries data for the same date of i^{th} instance

    Consider the k consecutive instances of p_i such that $p(h_{ji}) \geq \delta$

      if ownership is AC then

        Define threshold Δ as the allowable decrease in power from p_i

        The peak duration is calculated as the k consecutive instances of p_i such that $p(h_{ji}) \geq \delta p_i - \Delta$

      else

        The peak duration is calculated as the k consecutive instances of p_i such that $p(h_{ji}) \geq \delta$

      end

    The peak duration in minutes is obtained by multiplying k with 15

  end for

end for

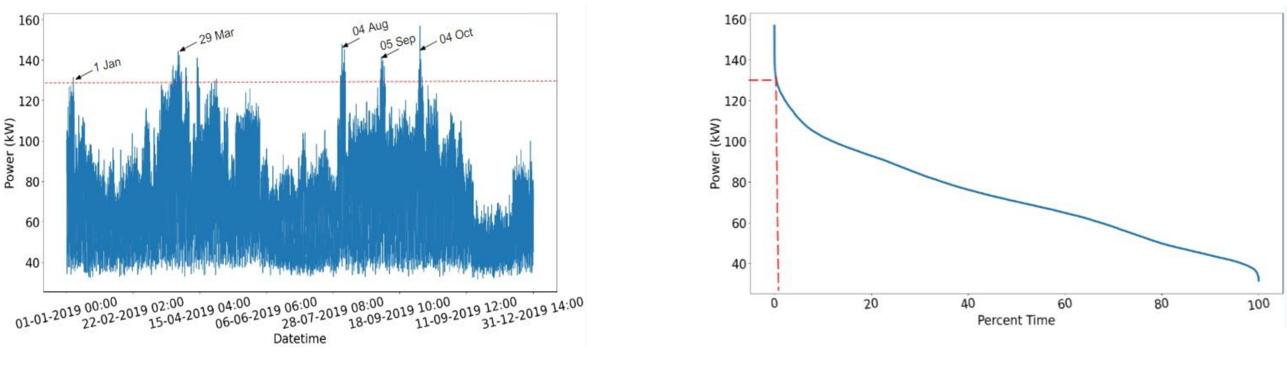
Results and Discussions

Daily consumption profile

The daily load profile for all the households in the dataset is added to compute the total system load of the utility servicing these households. The system losses are ignored, and the utility is assumed to be supplied to these residential households only. Figure 3(a) shows the daily system load curve for the whole year under study (2019).

Load duration curve

To identify the peak days and time, the yearly system load time series is rearranged in descending peak load values to generate the LDC, as shown in Figure 3(b). The highest peak load of 155.86 kW occurs on 4th October 2019 at 5:15 am. Using Algorithm 1, the peak value corresponding to 0.5% time is observed to be 130 kW and marked as in Figure 3(b). A few days with load values above 130 kW are marked in Figure 3(a): the second highest peak load of 152.97 kW also occurs on 4th October at 7:00 am, followed by peak load instances recorded for 4th August, 7:45 am with 146.97 kW, and so on.



(a) Daily load profile *(b) Load duration curve*

Figure 3: Daily load profile and load duration curve for complete dataset

Peak load contribution

Using the peak information obtained from the system LDC and yearly time series data, the contribution of individual households in the considered peaks in total demand is analysed for the date and time corresponding to peak load instances.

As per the LDC shown in Figure 3(b), 4th Aug. 2019 at 7:45 am shows one of the highest peak load values. During the system peak of 146.97 kW at 7:45 am, households SH280, SH283, SH285, SH282, SH290, SH250, and SH138 also show a high load value for the same interval. Figure 4 shows the daily load curve for these households and the system load curve for this day. The peak load contribution of these households is shown in Table 3 in descending order.

Table 3 includes the appliance ownership information of the peak contributing households. The load values for the selected households show that WH and AC usage play a major role in causing the system to peak. The consumption of all the households mentioned in Table 3 contributes to 27.49 kW in aggregate, implying that these 10 households, out of 300, contribute to 18.7% of the total peak load value.

From the LDC in Figure 3(b), the prominent days of peaks are noted on the time series load curve in Figure 3(a). Observing the power consumption of individual households during these peak intervals, the contribution of appliances to system peak can be studied, and the potential of DR of these loads can be estimated.

To observe the impact of ownership of appliances, peak durations corresponding to different dates of the year are considered. The date of the year and time of the day can be used to draw inferences on the status of appliances for each household. For the system peak intervals, the households with the highest load values are considered. The peak attributes for these households are computed; these along with the appliance ownership information, are studied to understand the DR potential.

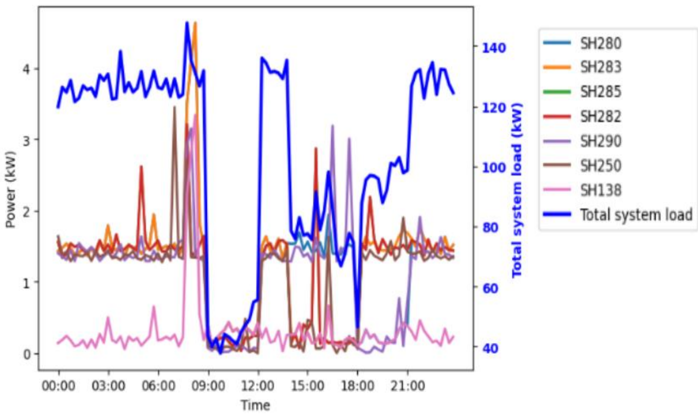


Figure 4: Load curve of households on 04 Aug 2019

Table 3: Peak load of households on 04 Aug 2019

Household No.	Ownership	Peak load (kW)
SH280	WH, AC	3.514
SH283	WH, AC	3.514
SH285	WH, AC	3.207
SH282	WH, AC	3.207
SH290	WH, AC	2.928
SH250	WH, AC	2.718
SH138	WH	2.237
SH207	WH	2.171
SH258	WH, AC	2.011
SH256	WH, AC	1.982

Table 4: Household information for peak intervals

Month	January 2019	March 2019	September 2019	October 2019	October 2019
Date-time	01 Jan, 7:30 am	29 Mar, 7:15 am	05 Sep, 7:45 am	04 Oct, 5:15 am	04 Oct, 8:00 am
Peak (kW)	130.60	143.15	139.1	155.86	150.14
Individual household load (kW)	SH253 (4.4) SH158 (3.27) SH283 (2.80) SH191 (2.12) SH251 (2.30) SH138 (2.01) SH270 (1.91) SH207 (1.87) SH215 (1.74) SH241 (1.70)	SH287 (5.09) SH285 (4.89) SH142 (3.79) SH282 (3.56) SH264 (2.97) SH291 (2.77) SH246 (1.92) SH169 (1.64) SH228 (1.63) SH260 (1.62)	SH283 (3.52) SH280 (3.51) SH278 (3.02) SH268 (2.97) SH291 (2.59) SH138 (2.43) SH207 (2.42) SH215 (2.29) SH183 (1.93) SH273 (1.88)	SH243 (4.23) SH287 (4.14) SH285 (4.09) SH282 (4.02) SH253 (3.22) SH148 (2.91) SH142 (2.83) SH140 (2.75) SH185 (2.26) SH247 (2.01)	SH280 (4.81) SH283 (4.65) SH281 (4.52) SH284 (4.31) SH207 (3.22) SH224 (1.74) SH225 (1.71) SH226 (1.69) SH217 (1.66) SH229 (1.60)
Percentage contribution	18.5	20.8	19	20.83	19.92
Ownership (majority)	WH, AC	WH, AC	WH, AC	WH, AC	WH, AC

Table 4 shows the analysis for a few peak instances shown in Figure 3(a). Each column shows the total peak load and the contribution of households to the peak for the days that experience high consumption. The total percentage contribution of high-consumption households shows that they contribute dominantly to the corresponding peaks. Based on the ownership information, the appliances that are responsible for generating the peaks are inferred in Table 4. It can be observed that a few of the households frequently operate at their peak when the system experiences peak load values for the corresponding date and time. As mentioned in Table 3 and Table 4, SH283 and SH207 contribute significantly to system peaks. SH283 has the appliance ownership of WH & AC, while SH207 has ownership of WH only. Similarly, SH280, SH287, and SH285 are observed to contribute to the highest peak load instances. These households have ownership of WH & AC. The other households contributing to the peaks have a majority of WH & AC ownership. On analysing the daily load curve of these households for the date and time mentioned in Table 4, it is observed that the peak values are mainly due to the coinciding operation times of WH & AC.

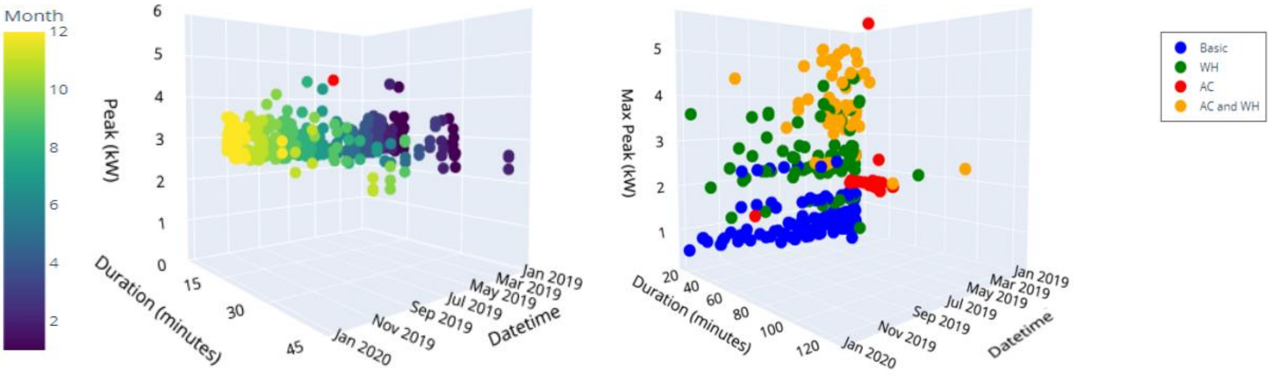
From Table 4, it is clear that households with high-consumption appliances contribute significantly to the system peak. Deferring the operation time of high-rating appliances can potentially reduce the peaks and help flatten the system load curve.

Peak amplitude information

The scatter plot for household SH291 is shown in Figure 5(a). The x-axis represents the peak duration, the y-axis represents the timing of the peak, and the z-axis represents the amplitude of the peak. The plot gives information on the variation in the highest 1% peak values of the household occurring throughout the year, along with the duration of peaks. The data points in the plot are coloured in accordance with the month of the year. The resultant projection point for this household considering maximum peak amplitude is shown in red colour in Figure 5(a). Since SH291 has ownership of both appliances, AC and WH, the duration of peaks on different days is scattered. The short-duration peaks can be attributed to the usage of WH, and longer-duration peaks can be the result of AC consumption.

The households that frequently show high load demand for system load greater than 130 kW are obtained from the LDC. The projection points using the maximum peak amplitude of the highest contributing households in LDC are marked in Figure 5(b). The colour of the data point represents the appliance ownership type of the household. This plot gives us insight into the power consumption behaviour based on appliance ownership. Some clusters within households of similar ownership types can be observed in the scatter plot, which indicates the prominent usage pattern of appliances with similar duration and peak power consumption behaviour. From Figure 5(b), it can be observed that basic households are not significant contributors to system peak and experience short peak durations. Households having ownership of only AC show high peaks in wide ranging amplitudes and duration in the month of May. However, peaks of the households with only WH are evidenced across the year, show a wide range of power consumption values, and persist for shorter durations between 15 and 45 minutes in line with expected usage of WH. Finally, for households with both AC and WH, high peaks for shorter durations that can be attributed to WH usage and peaks with longer durations that occur due to the operation of AC are seen.

A similar plot can be obtained by considering the maximum duration of the peak for all households. Analysis of the scatter plot in Figure 5(b) can be done by suppressing the datetime axis and obtaining the 2D plot of the peak amplitude and duration of the households. Figure 6 shows the resultant 2D plot containing projection points of the maximum amplitude and duration of peaks for all the households. The households with ownership of only WH have clustered at short peak duration intervals. Households with AC have a relatively higher duration of appliance usage and contribute highly to power consumption. Basic appliances, excluding AC and WH, do not have high power ratings, and the duration of operation of the appliances also varies across the day. The clustering observed amongst households containing both AC and WH gives a high indication of the usage of the appliance. Households with WH contribute to shorter duration peaks occurring for less than 45 minutes, while AC operation may be prominent for a longer duration that may be indicative of households with AC.



(a) Peak projection point for household SH291 *(b) Peak projection point for all households*

Figure 5: Peak projection using maximum peak amplitude for households.

The information on the date and time of peaks can be used as in Figure 5(b) to verify the category of appliance used in the household. Inferences can be made on ownership of households that contribute to peak amplitude and duration using Figure 5(b) and Figure 6.

This analysis can help to identify the households to perform DR to shave the system peak and avoid using high-cost generators. The projection points for individual households using the information on peak amplitude, duration, and datetime can be calculated by considering maximum peak amplitude and maximum peak duration, similar to Figure 5(b). Considering both the duration and amplitude of the projection points, Figure 7 provides added information on the duration of peaks. This can be used to infer information on the duration of the peaks of the households that are considered in Figure 6. The dominant factor that contributes to the peaks in households with ownership of both AC & WH can be estimated using the plots. Households like SH282 and SH285 have short-duration peaks with high amplitude, as shown in Figure 6. This may be a result of operating WH only, while households like SH250 and SH295 have peaks with higher duration, as shown in Figure 7, that may occur due to the operation of AC & WH.

In the subsequent section, the algorithm introduced is applied in a case study, utilizing ownership information to implement DR.

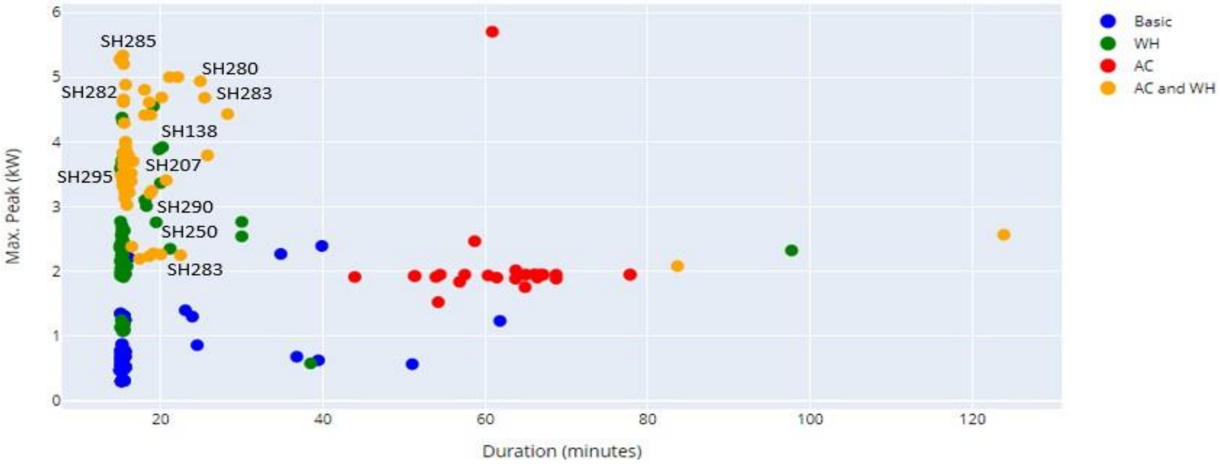


Figure 6: Scatter plot for households using projection on maximum peak amplitude

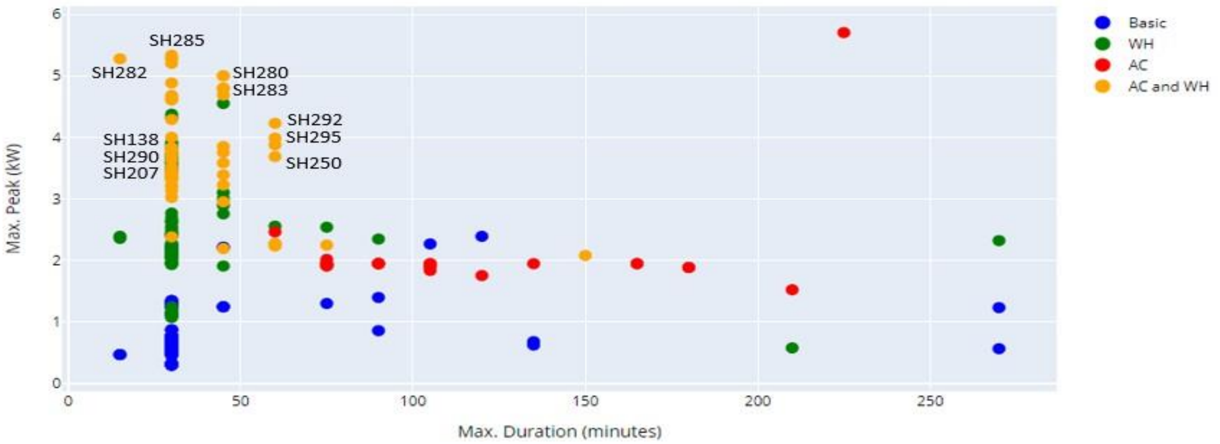
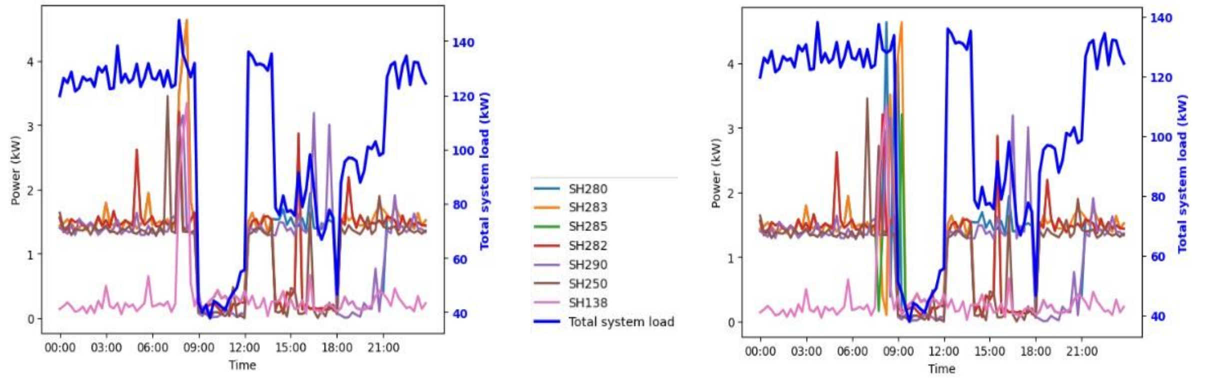


Figure 7: Scatter plot for households using projection on maximum peak amplitude and duration

DR potential of WH to remove peaks

Figure 8(a) shows the households that contribute to the system peak on 04 Aug. 2019 at 07.45 am. Table 4 shows that the top 10 households for the same interval account for 18.7% of the system peak. Considering the morning time and with the knowledge of ownership of WH in these households, the potential of eliminating the peak by shifting the operating intervals of the WH is explored. According to the survey in [5], WH offers a great DR possibility due to significantly high energy consumption. The turn ON time of WH can be shifted to off-peak intervals, ensuring the least loss of comfort for the consumers [5]. Assuming that only the WH was ON at 07.45 am in the households, the total power consumption of the household is assumed to be equal to the power consumption of the WH in this interval.



(a) Household load profiles with WH without DR *(b) Household load profiles with WH with DR*

Figure 8: Peak reduction using DR for households with WH

The load profile of households with WH without the implementation of DR is shown in Figure 8(a). By constraining the shifting time of WH to at most 30 minutes, the system peak at 07.45 am can be reduced by almost 6.5% by deferring 5 WHs operation as can be observed in Figure 8(b). Table 5 shows the potential reduction in system peak on 04 Aug. 2019 at 07.45 am by shifting the operating time of WH if DR is implemented with the objective to reduce peaks. The deferral period ensures minimum loss of comfort and also results in significant peak reduction. Peak reduction can be achieved by designing DR objectives carefully to ensure that households do not shift the operating time of appliances to low price periods together, which may result in a shift in peak.

Table 5: DR potential in WH

Peak values (kW) on 04 Aug 2019 07.45 am							
Strategy	SH280	SH283	SH285	SH282	SH290	SH250	System peak
Without DR	3.514	3.514	3.207	3.207	2.928	2.718	146.97
DR using 1 WH	1.474	3.514	3.207	3.207	2.928	2.718	144.61
DR using 5 WH	1.474	1.836	1.410	1.410	1.346	2.718	137.48

DR programs are implemented by either publishing the time-varying prices of electricity a day ahead of time or by providing incentives to the consumers to shift the consumption from peak intervals to off-peak intervals. The pricing information can be exploited to schedule the appliance operation to ensure the minimum electricity consumption cost and reduce peaks in the system. This can be realized using an HEMS that is integrated into smart meters installed in households by fetching the electricity prices from the utility. An analysis of the change in consumption patterns of household appliances using the system load information and time-varying prices can be conducted to study the effect of different pricing schemes used in DR programs.

Some Remarks

The analysis performed herein leads to two findings: First, high-consumption appliances such as WHs and ACs may contribute to nearly a fifth of the peak. Second, analysing the peak amplitude and peak duration of individual households may lead to the discovery of a cluster of households that are significant contributors to the system peak load. For more conclusive results, the analysis should be performed for the top 5% system load values – in this case, it is loads over 110.27 kW. Due to page limits we skip this detailed analysis here.

Conclusions and Future Work

The study presented in this paper focuses on households from Pune region in India. A hypothetical system load is constructed based on data from actual houses as well as synthetically generated data. The algorithms presented in this paper use the information encapsulated in the system load curve and the individual household load curves to identify the households that are suitable candidates for DR programs. Our results show that the households contributing to system peak load possess high-consumption devices such WHs, ACs, or a combination of both. We also observe that the peak loads lasting for shorter durations can be typically attributed to the households having WH ownership, while those with longer durations can be attributed to households with AC ownership. Both WH and AC loads exhibit inherent flexibilities that can be exploited to implement DR. In this paper, a simple load-shifting possibility is demonstrated to affect a peak shaving of 6.5%.

The dataset with some missing information for households in Pune & Pune City has been considered for the study. A richer dataset containing information on appliance ratings and user preferences can be used to quantify savings at the appliance level. The study of the frequency of occurrence of the peak would add more information to this analysis.

Similarly, using other attributes like mean values and peak-to-average ratio can lead to a more detailed analysis. The paper can be scaled to a larger set of households to study the potential savings using DR programs. This is future work and is out of the scope of this paper.

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