Revisiting Selection of Residential Consumers for Demand Response Programs

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ABSTRACT

Electrical utilities depend on Demand Response programs to manage peak loads by incentivizing consumers to voluntarily curtail a portion of their load during a specified period. Utilities first categorize consumers based on their energy consumption patterns into different clusters and then request consumers of a particular cluster to participate in the demand response program. At a coarse level, clustering approaches do well, but we may not be able to correctly predict which cluster's profile will fit that day's power availability. We address this issue by examining the *consistency* of consumer's consumption patterns across several consecutive days. We demonstrate that measuring consistency quantitatively helps to understand predictability of consumer's energy consumption.

In the rest of the paper, we provide details of our proposed consistency metric. Further, we propose a methodology to select a few consumers among the consistent ones such that they have a peak at the time specified by the demand response program. We validate our approach using real-world energy consumption data from residential buildings.

CCS CONCEPTS

• **General and reference** → **Metrics**; • **Mathematics of computing** → *Time series analysis*;

KEYWORDS

Demand response program, Time-series consistency, Peak detection

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1 INTRODUCTION

Backup generators used by electricity grid authorities to meet the peak demand are inefficient, expensive, and extremely polluting. A Demand Response (DR) program is run by utilities to curtail a portion of the peak demand by shifting the energy usage. Advanced Metering Infrastructure (AMI) meters introduced early for billing purposes were seen as enablers of DR programs [7]. A recent Federal Energy Regulatory Commission (FERC) report shows a 40.6% penetration rate of AMI meters in the US and is still going on [10]. It further highlights that DR programs in 2014 resulted in peak reduction of 31 GW in the US with a breakdown of 26%, 20%, 53% in residential, commercial, and industrial sectors respectively. AMI meters make it possible to log electricity consumption data for analysis and to extract insights about usage pattern, energy saving opportunities, malfunctioning symptoms, and failures of energy consuming appliances [2–4, 6, 12].

A DR program is run to ensure grid stability and avoid brownouts[1]. To ensure the success of DR, utilities target a group of consumers who voluntarily participate or are encouraged to deter their consumption by curtailment or to defer elastic loads. In return, participating consumers are provided incentives in the form of reduced bills or with direct payments [8]. The selected consumers consume a significant amount of energy and use deferrable appliances at DR time normally. The usage behavior of a consumer is easily obtained with the analysis of smart meter data [1]. A recent work identifies the potential set of deferrable appliances, which can be used as criteria for the selection of consumers in DR [11].

Utilities identify DR consumers by clustering all consumers according to their similarities in consumption patterns. A simple approach to find the set of DR consumers is to select those clusters which show peak consumption at the desired DR time. Utilities believe that selected consumers are likely to follow the same behavior on DR day, which usually happens to be the next day. Accordingly, selected consumers are informed one day ahead of the actual DR run. It is possible that a selected consumer was wrongly classified for DR due to clustering approach and hence will get the perks without any load curtailment. In these cases, it is a loss for a utility and gain for a consumer. Although the clustering approach identifies a group of DR consumers at a coarse level, clustering criteria do not consider the consistency of a consumer with respect to the consumption pattern across several consecutive days. Quantifying consistency in consumption pattern is important as it indicates the likelihood of a consumer following the historical pattern on DR day and time.

In this paper

(1) We propose a consistency metric which only considers historical consumption data of several days. This metric is computed by calculating statistical features like mean and standard deviation.
(2) We develop a methodology to select the consumers who have peaks at desired DR time among the consistent consumers. It is possible that a consistent consumer has peaks at different times of day instead of target DR time.

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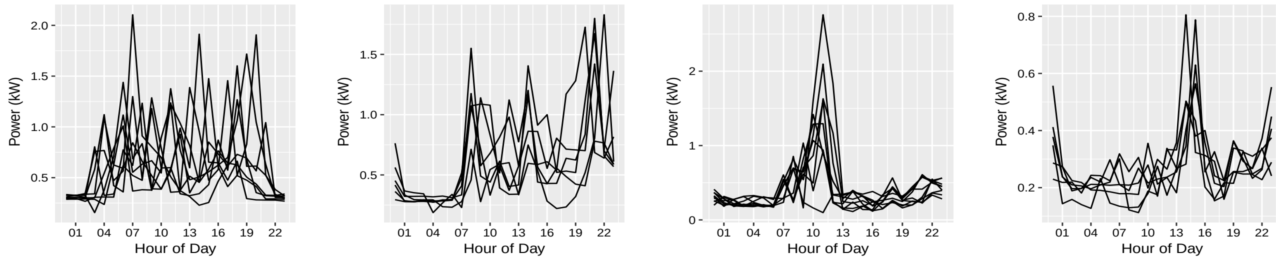


(a) (b) (c) (d)

Figure 1: Energy consumption patterns of four consumers on six consecutive days. Each wiggly line represents the hourly energy consumption of a consumer on a different day.

(3) We show the effectiveness of our metric by using data from a residential building consisting of 60 apartments.

2 RELATED WORK

In [9], consistency in usage pattern of a consumer is measured with entropy metric. The authors compute possible profiles (consumption patterns) of a consumer by means of clustering. Each profile represents the center of a different cluster. Therefore, the number of profiles for a consumer equals the number of clusters. The approach requires calculation of the profiles of a consumer beforehand, which is difficult if complete yearly data is not available. Calculating profiles depends on the clustering approach, i.e., the value of k (# of clusters) or other thresholds. In clustering, cluster centers are the representatives of other cluster members. A lower value of k results in lesser number of large size clusters, while a higher value of k results in a large number of small size clusters. Small cluster members are compact and represent maximum similarity in usage pattern whereas big cluster members are sparse and represent coarse similarity in usage pattern. Therefore finding profiles with clustering approach is hard as it depends on the value of k, and finding an optimal value of k for different consumers is difficult.

Instead, we propose a simple approach to quantify the consistency in usage pattern across multiple days. This approach only needs to calculate average consumption and the standard deviation across N consecutive historical days.

3 PROBLEM DEFINITION

Given a set of consumers C with their historical energy consumption, find all $c_i \in C$ who have highly consistent energy usage pattern across days and hence are predictable. Figure 1 shows energy consumption patterns of four different consumers over consecutive days, where c_1(Figure 1(a)) follows a random energy consumption pattern across all days, c_3 and c_4 (Figures 1(c), (d)) follow a perfect consistent pattern as peak occurs at the same time on all days, and c_2 (Figure 1(b)) follows a mix between random and consistent pattern, i.e., up to 8 A.M. it follows a consistent pattern and after 8 A.M. random pattern is observed. In the literature, we do not find a quantitative metric which can summarize consistency in the energy consumption across days. In the rest of the paper, we design such a consistency metric and evaluate its effectiveness.

We find this problem interesting because of its following applications

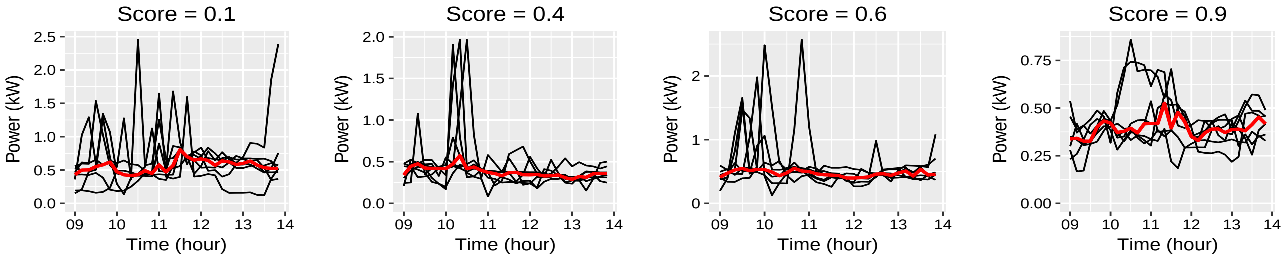
• *Consumer Selection*: Consumers are incentivized in DR through time-based pricing. The selection of consumers is done by their historical energy consumption behavior. Therefore, it is always better to ensure that the selected consumers have consistent energy usage pattern and will consume energy according to the utility's expectations during DR timings. Random energy usage consumers may show unpredictable consumption behavior, and this may prevent utilities in achieving DR objectives.

• *Deterministic Power Allocation*: Consider a typical office building which has Z zones, where each zone $z_i \in Z$ consumes power differently due to different occupancy schedules. Assume Figures 1(a) and (c) represent the power consumption patterns of two zones z_1 and z_2 respectively on different days of a month. Figures show that z_2 follows a deterministic consumption pattern over consecutive days as each day has a peak of 1.5 kW approximately from 10 A.M. to 1 P.M., and for remaining hours usage remains below 0.5 kW consistently. While as nothing can be said deterministically about the consumption of z_1 as it changes almost every day every hour.

The proposed consistency metric can represent the deterministic nature of the power consumption pattern of z_1 and z_2 quantitatively and hence can assist building manager to decide how she should allocate power among contending zones of a building on a crisis day. The higher the consistency score of a zone, more confidently she can select the zone and allocate the power required (computed using historical usage) as compared to a zone with less consistency score.

• *Energy Forecasting*: Energy forecasting starts with building prediction models which involve the selection of right variables among weather (temperature, pressure, humidity), occupancy, calendar, seasonality, historical consumption, etc.

To decide whether historical consumption variable should be included in the prediction model, researchers either use complex regression analysis or use "correlation technique". Correlation measures only the correlation coefficient for a pair of variables/days and not for N days' consumption simultaneously. As a result, it requires interpreting $\binom{N}{2}$ correlation coefficients. Our proposed consistency metric can measure correlation for all the days in one shot and provides an easy to interpret value between [0 - 1]. The higher the correlation value, the higher are the chances that the historical consumption accounts in energy forecasting.



(a) (b) (c) (d)

Figure 2: Energy consumption patterns of 4 consumers on consecutive days. Red line represents the average consumption. Consistency score is above the graph.

Algorithm 1: Consistency Score of a Consumer

Input: $X[\,]$: Vector containing N days historical power consumption data of a consumer $c_i \in C$, where each day contains T power consumption readings

Output: Consistency score in the range [0 - 1]

1 Transform input $X[\,]$ into matrix $Y[1:N][1:T]$

2 Compute mean and standard deviation across columns of Y
$M[j] = mean(Y[\,][j]), \forall j \in \{1, \cdots, T\}$
$S[j] = \sigma(Y[\,][j]), \forall j \in \{1, \cdots, T\}$

3 $Cnt \leftarrow 0$ `/* No. of consistent days */`

`/* Calculate total no. of consistent days */`

4 **for** $h = 1$ *to* N **do**

5   **if** $(Y[h][j] \leq M[j] + n * S[j]$ & $Y[h,j] \geq M[j] - n * S[j])$, $\forall j \in \{1, \cdots, T\}$ **then**

6         $Cnt \leftarrow Cnt + 1$

7 $C_s = Cnt/N$ `/* Consistency score */`

8 return C_s

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4 METHODOLOGY

To run DR, electric utilities need to identify the potential group of consumers who have consistent energy usage patterns across days for easy predictability, and have peaks at desired DR timings. Firstly, we explain the methodology to identify consistent consumers and later we discuss the steps to identify consistent consumers who have peaks at desired DR timings.

Consistency Metric: Our methodology takes power consumption data of N days as input and outputs the consistency score in the range $[0 - 1]$. Algorithm 1 summarizes all the steps of the methodology. The steps involved in computing consistency score for a consumer $c_i \in C$ are:

(1) *Input Data:* Input time-series power consumption data of N days as a vector $X[\,]$. Assume sampling rate is T readings per day.
(2) *Data wrangling:* Transform input vector X into Matrix Y containing N rows and T columns, i.e., each row of Y stores data of a separate day. Data wrangling is essential to compute the subsequent statistical operations.
(3) *Feature calculation*: Compute statistical features – mean ($M[1:T]$) and standard deviation($S[1:T]$) – along rows of Y. Both M and S vectors contain T values corresponding to T readings of each of N days.
(4) *Compute Score*: Firstly, count the number of days for which all of the T readings lie within n standard deviations (Algorithm 1, Steps 5 - 6) and represent count as cnt. Next compute consistency score C_s by dividing cnt with total number of days N.

The higher the value of C_s for c_i, the higher are the chances that the mean consumption M of c_i represents its baseline/actual energy usage pattern and implies higher chances of predictability.

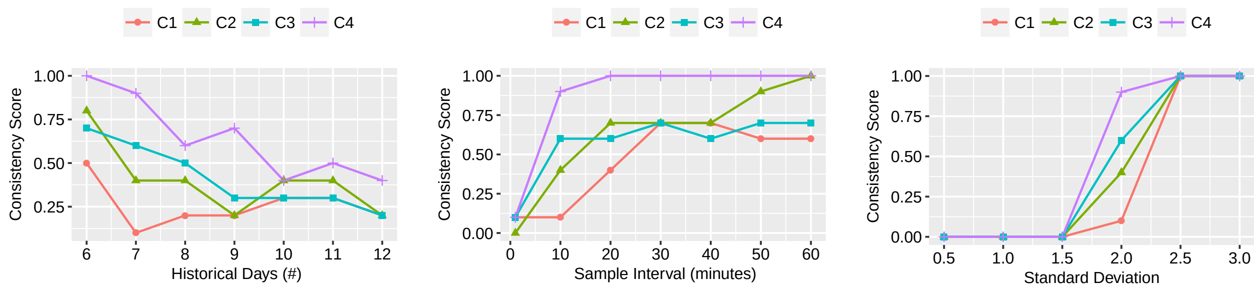
Peak Detection: Once a consistent group of consumers is found using consistency metric, the next step is to find consumers who have peaks at desired DR time window. The peaks are identified by using a peak detection procedure, which gives the magnitude of peaks and their actual time of occurrence in a day. The following steps are used to detect peaks:

(1) Fit a non-polynomial regression line $\widehat{M}$ using LOESS (Locally weighted Scatter Plot Smoother) [5] on mean consumption M. LOESS also provides a knob to control the smoothing level of the regression line.
(2) Find local maximas of $\widehat{M}$ denoted as M^{max} using a rolling window. This step essentially calculates all moving maxima over $\widehat{M}$.
(3) Store timestamps (indices) of $\widehat{M}$ in P wherever $\widehat{M}$ equals to M^{max}. These timestamps represent locations of peaks in T consumption window.
(4) Use P to find the magnitude of all peaks from M and then store these peak magnitudes in $Mag[\,]$.

Therefore using three parameters (C_s, P, Mag) computed via Consistency metric and peak detection methodology a utility can decide whether to include c_i in DR or not.

5 EXPERIMENTAL EVALUATION

To evaluate the effectiveness of the proposed approach, we use a dataset of one of the residential buildings at our Institute campus. This building consists of 60 apartments, each apartment is alloted to an Institute faculty and is instrumented with a separate AMI meter. The sampling rate is 5 seconds, but for the evaluation of proposed methodology, we down-sampled data to ten minutes. All results were computed while setting the number of historical days N and the number of standard deviations n (Algorithm 1, Step 5) to 7 and 2 respectively. The effect of these parameters on C_s is analyzed separately.



(a) (b) (c)

Figure 3: Effect of various parameters on consistency score: (a) Historical days, (b) Sampling Interval, (c) Standard deviation

Figure 2 depicts power consumption patterns of 4 different consumers between 0900 − 1400 hours, where the thick red line shows the mean power consumption M across days. The consistency score is just above the graph. Consumer c_1 (Figure 2(a)) has a score of 0.1 because everyday follows a different pattern in energy consumption, while as c_4 (Figure 2(d)) has a score of 0.9 as everyday almost follows a similar pattern in energy consumption. Consumers c_2 and c_3 (Figures 2(b) and (c)) have a score of 0.4 and 0.6 as the pattern deviated significantly at different hours from the mean consumption M on a few days. This shows that the proposed consistency metric is able to quantify the underlying power consumption pattern of a consumer across days.

Sensitivity analysis of C_s: Consistency score C_s depends on three parameters: Number of historical days N, data sampling interval, and the number of standard deviations n.

• *Effect of* N: Figure 3(a) shows the effect of change in N on C_s of different consumers $c_i \in C$. As the number of historical days N increases, the chances of deviation in energy consumption among different days also increases due to change in user behavior or season. So C_s decreases with the increase in N.

• *Effect of sampling interval:* Figure 3(b) shows the effect of change in sampling interval on C_s in the different $c_i \in C$. At higher sampling frequency, frequent deviations in the power consumption from mean consumption M decrease C_s whereas during down-sampling these frequent deviations disappear due to averaging (down-sampling function). Therefore, C_s increases as we increase the sampling interval.

• *Effect of* n: Figure 3(c) shows as the number of standard deviations n increases the consistency score also increases. At lower n, a small change in power consumption from the mean consumption M reduces C_s whereas as n increases these small changes are not perceived as a deviation from M so C_s increase.

The optimal value of N, sampling interval, and n can be decided by a utility manager while considering the program requirements.

6 CONCLUSION

Peak electricity demand often stresses grid stability and can lead to blackouts or brownouts. Utilities use DR programs to handle this peak demand among other options such as using standby generating stations and transformers. In DR, utilities select a group of consumers who satisfy certain criteria. At a coarse level, consumers are selected by using clustering approaches. We argue that during this selection process consumers are not screened for their consistency in energy consumption, i.e., to obtain the confidence that a selected consumer will show desired effect on the DR day based on its historical consumption. In this regard, we proposed a quantitative metric which calculates the consistency score of a consumer in the range [0 - 1]. The higher the consistency score, the higher are the chances that the selected consumer will show desired behavior on scheduled DR timings.

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