Want to Reduce Energy Consumption, Whom should we call ?

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ABSTRACT

Power shortage is a serious issue in developing nations. During periods of high demand, utilities need to motivate the consumers to curtail their consumption for maintaining grid stability and avoiding blackouts or brownouts. Identification of suitable candidates is essential for such events, as the budget set aside by utilities for Demand Response (DR) events for providing incentives to the consumers should not exceed the added production cost due to peaks. Similarly, from the consumers' point of view, participation comes with the compromise to their convenience. Hence, the selection criteria should be such that it minimizes the peaking cost to the utility without affecting consumer comfort.

In this paper, we present SmarDeR, a smart DR consumer selection strategy which considers several factors and consolidates them into a single function which can work in different modes to strategically choose the candidates for the DR event based on the goals specified by the utility. We evaluate different policies and metrics for approaching the right consumers for participating in the DR events. Thereby, we can maintain a fair distribution of requests among the most relevant and reliable users. Experiments with smart-meter data from apartments in our campus demonstrates the effectiveness of our SmarDeR approach.

CCS CONCEPTS

• **Hardware** → **Energy distribution**; • **Computer systems organization** → Real-time system architecture;

KEYWORDS

Demand Response, Smart Meter data, Selection Optimization, Consumer Analysis

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1 INTRODUCTION

When the total demand in the electric grid exceeds the total supply, it leads to grid instability. Meeting this peak demand in the grid is expensive for the utilities, since the excess demand is usually met by running backup generators or buying from the spot market. Running backup generators is highly polluting as they run on fossil fuels. Buying from spot market is also not a preferred solution since the energy is traded at high prices and are dynamic for short-term demands. So the power deficits are handled through rolling blackouts, where a service area is divided into subareas, each of which is denied power during a designated time in the day. Today, smart grids provide the opportunity of avoiding complete blackouts, either by asking every consumer to reduce consumption by an amount proportional to the total deficit or requesting a subset of consumers to reduce their consumption. Such events are collectively termed as Demand Response (DR). The success of such events is measured as the ratio between required target met versus achieved target level. Current event yields are low, in the range of 10% to 30% [12]. The success of the DR events is determined by the identification of consumers who are both likely to agree to reduce their consumption and use deferrable appliances during peak hours. Thus, the selection of consumers for a DR event is a critical step. This paper introduces SmarDeR, with the aim of achieving a smarter selection of customers for effective DR.

Utilities entice their consumers into participation in DR events by providing them incentives in the form of discounts or direct payments [9]. Traditionally, consumers were recruited based on their monthly consumption data, and those with higher bills were their regular targets [13]. The availability of Advanced Metering Infrastructure (AMI) allows the design of more informed approaches. AMI allows two-way communication between utilities and consumers while logging electricity consumption data for analytical purposes. This logged data can be used for drawing useful insights to target consumers for DR programs [7].

Most of the DR approaches make use of differential pricing schemes to prompt consumers to modify their usage behavior [4]. Some utilities charge consumers for the time of usage along with the demand charges. This scheme penalizes a consumer for exceeding maximum demand. In our campus, we pay around 0.6 million USD annually for demand charges. Demand charges are calculated based on the highest demand occurred in a month. If the highest demand crosses the sanctioned demand for the month, then additional charges are imposed. Similarly, for the time of usage pricing, we pay approximately 7000 USD. Figure 1 presents the peak values observed in our campus electricity consumption during different

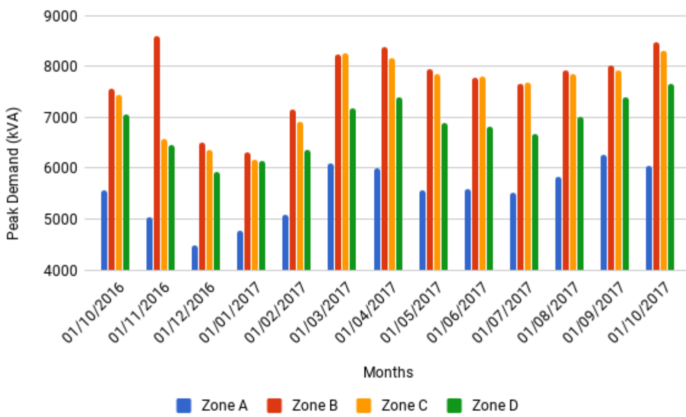

Figure 1: Peak usage occurrence across various months. Zone A (00:00 - 06:00 & 22:00 - 24:00), Zone B (06:00 - 09:00 & 12:00 - 18:00), Zone C (09:00 - 12:00), Zone D (18:00 - 22:00)

months of 2016-2017. The zones in the Figure 1 are divided based on time of usage charges in the ascending order of the rates. Real-time pricing is another alternative, where the price of electricity is varied on hourly or half-hourly frequency with the prices being announced on a day before or hour ahead basis [1]. This calls for an immediate reduction in the peak demand and shifting the appliance usage to off-peak hours. The consumer needs to be smart enough to benefit from such pricing schemes. There is a trade-off between shifting demand from high-cost period to low-cost period to minimize the time of day charges and to reduce the maximum demand to minimize demand charges.

Currently, utilities run DR either by asking an entire region for voluntary participation or using computational approaches to select potential high energy consumers. None of these approaches incorporate consumer satisfaction or historical behavior of consumers for their selection. We argue that a successful DR event is a function of many features and hence all these features should be considered for consumer selection. In this paper, we propose SmarDeR, an informed approach for consumer selection:

- We propose a DR selection function, which takes into account several features such as availability, consistency, peak contribution, etc., to identify prospective DR consumers. (We will explain each term in subsequent sections.) The utilities can specify the features to be taken into consideration and the function will select the consumers accordingly. Figure 2 shows an overview of the SmarDeR selection process.
- We introduce three indices, namely, response index, request index and exhaustion index to measure the likelihood of a consumer participating in a DR event.
- We introduce two metrics, namely *risk* and *unfairness*, to quantitatively measure the performance of the DR selection algorithms and aid the utility to make effective changes in their selection policy and keep customers actively involved in DR events.
- We demonstrate the effectiveness of our SmarDeR approach by using smart-meter data from a residential building consisting of 60 apartments.

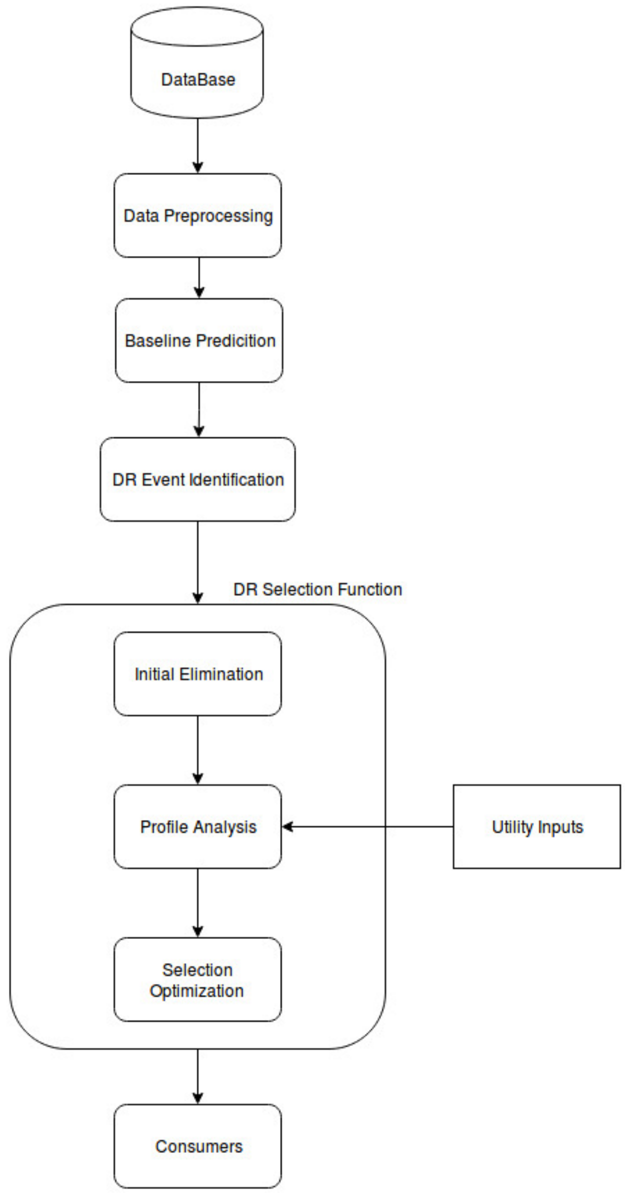

Figure 2: Flow Chart of the proposed DR selection process.

The rest of the paper is organized as follows. Section 2 details the related work. Section 3 introduces the problem. Section 4 details the DR event processing. Section 5 provides an empirical evaluation of our model and Section 7 provides concluding remarks and the future work.

2 RELATED WORK

From the social perspective, the primary objective of demand response programs is to improve the comfort obtained by each consumer and to minimize the expense imposed to the power utility. Thus, the social welfare maximization is to maximize the consumer's utility minus the power utility cost and the energy storage operational cost [5]. Consumers always prefer to increase their level of satisfaction and decrease their electricity bill. There are various approaches to solve the residential DR problem. One of the popular approaches is to cluster the consumers based on their similarities in consumption pattern and select those clusters which exhibit peak consumption at the desired DR time[11]. The selected consumers are informed in advance of the DR event. The major drawback of this method is that it does not take into account the consistency in consumption pattern of a consumer. Rashid et al. [14] introduced a consistency metric to indicate the likelihood of a consumer to follow the historical pattern on the DR day and time. They also presented a methodology to select the consumers who have peaks at desired DR time among the consistent consumers. In Kwac et al. [12] developed an algorithm to choose potential consumers by trade-off between DR availability and DR reliability for a budget.

Authors of [3] proposed an inclusive DR system which respects the end users' convenience and considers their propensity for participating in a particular DR event while altering the consumer demand. They rank the consumers according to the flexibility of their appliance usage in an attempt to target those consumers who would be least inconvenienced by the reduction requests. In their stochastic framework, they determined the consumers probability of participating in the event by analyzing the consumers response history to previous DR signals sent to them. The Stochastic framework ensures fairness on the basis of DR contract. If the consumer has specified the limit for the total number of times they receive a request for a particular time slot t in the contract, they will be exempted when the limit is reached. Similarly, in their rule-based strategy, they sort the consumers in the ascending order of their expected reduction and choose the consumers just enough to meet the targeted reduction in the overall baseline. The fairness is ensured by setting the same percentage demand reduction target over the baseline consumption for each of the consumer.

The electric grid utilities need to maintain a balance between demand and supply. Grids have peak as well as low demand intervals. Storing energy during periods of excess supply (or low demand hours) can serve the need of peak hours, however, scalability is still a matter of concern due to higher storage costs [15]. Alternatively, utilities (grid) can resort to DR programs that stabilize the grid at a lower cost.

The existing [8, 11, 14] DR approaches select consumers based on their historical consumption only and do not consider other contextual features such as their historical DR-related behavior or comfort. As a result, utilities do not achieve the targeted reduction [12]. We argue that incorporating contextual features for each consumer separately will improve the DR participation rate and make it successful. So, we propose a Smarter DR (SmarDeR) approach, which first "senses" four contextual features pertaining to each consumer and then selects most suitable consumers on the basis of these features.

Parameter	Meaning
i	Represents a consumer
j	Represents a DR event
t	Time slot in a day
$A_G(t)$	Available grid power during time slot t
$D_G(t)$	Predicted demand in grid for time slot t
$R_G(t)$	Consumption reduction required in grid for time slot t
$R_T(t)$	Targeted consumption reduction in grid for time slot t
$D_C(t, i)$	Predicted demand of consumer i at time slot t
$Ex(t, i)$	Exhaustion index for consumer i for time slot t
$R_C(t, i)$	Consumption reduction required for a consumer i for time slot t
$R_E(t, i)$	Expected reduction in consumption by consumer i for time slot t
$Cons(t, i)$	Consistency index for consumer i for time slot t
$Cont(t, i)$	Contribution index for consumer i for time slot t
$Rel(t, i)$	Reliability index for consumer i for time slot t
$Req(t, i)$	Request index for consumer i for time slot t
$Res(t, i)$	Response index for consumer i for time slot t
$O(t, i)$	Overall Score for consumer i for time slot t
$P(t, i)$	Performance of consumer i for time slot t during a DR event
M	Number of selected consumers
N	Total number of consumers
$N_{total}(t)$	Total DR events occurred until time slot t
$N_r(t, i)$	Number of requests received by consumer i until t
$N_{rmax}(t, i)$	Maximum number requests that can be sent to consumer i for t
$S(j)$	List of selected consumers for a DR event j
T	Total number of DR requests sent

Table 1: List of Parameters

3 PROBLEM DEFINITION

The power distribution system discussed in this paper is organized like a tree, rooted at the entity to which the DR program j is applied, for example, an educational campus like ours, or a suburb of a city. The leaves of the tree are the consumers N who have signed up to participate in Demand Response events. Our goal is to find the subset of consumers M that must be targeted for a DR program j. The asset being distributed is the available power at that point of time. The objective function is to keep the power consumption within the available power supply without affecting the quality of service experienced by the consumers. The consumers selected for a DR program can be from a residential or industrial sector.

Let $D_C(t, i)$ be the expected demand of a consumer i at time t. If the aggregate demand of all N consumers exceed the available grid power supply $A_G(t)$, i.e., when $\sum_{i=1}^{N} D_C(t, i) > A_G(t)$, utility has to choose some of the consumers M to reduce their power consumption so that grid will stabilize. **The problem can be defined as, given N consumers, find a subset of $M(\leq N)$ consumers whose combined reduction in consumption will compensate for the shortfall in supply.**

$$\sum_{i=1}^{M} R_E(t, i) \geq R_G(t) \tag{1}$$

where $R_E(t, i)$ is the expected reduction associated with a consumer i for time t and R_G is the target reduction which is the difference between total demand $\sum_{i=1}^{N} D_C(t)$ and the total power supply $A_G(t)$ in the grid. All terms used in this paper are defined in Table 1

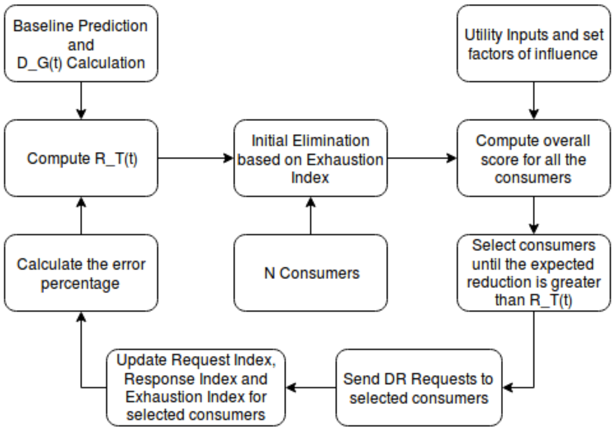

Figure 3: Overview of DR Event Processing

appear in the following order: variables, grid parameters, consumer parameters and other associated terms.

In order to account for the consumers who might not reduce their consumption as required after receiving a DR request, the target reduction limit is increased by a factor, Δ_t. Δ_t denotes the percentage of consumers who have not met their reduction requirements in the past DR events. Therefore the targeted reduction during DR is:

$$R_T(t) = R_G(t)(1 + \Delta_t) \tag{2}$$

Thus, more consumers are being considered by setting a high reduction target than required and the operation yields can be improved. But, DR algorithm should meet the target reduction causing inconvenience to the least number of consumers. To quantitatively measure the chance of failure and inconvenience caused to the consumers we define three metrics namely Risk, Unfairness and Total DR Requests sent.

Risk measures the chances of failure of a DR Request sent to the consumer. **Unfairness** is defined as the ineffective distribution of DR requests among the consumers. **DR Requests sent** is the total number of consumers selected for a DR event. An ideal DR algorithm should minimize the above metrics to ensure that there is a minimum chance of failure of the DR event's goals and minimum inconvenience is caused to the consumers.

4 DR EVENT PROCESSING

We present SmarDeR to systematically pick suitable consumers for DR event giving due importance to the inconvenience caused to them. Figure 3 provides the overview of DR event processing. Throughout the paper, i represents a consumer and t represents a time slot in a day.

4.1 What is the expected demand?

The DR baseline is an estimate of the electricity that would have been consumed by the consumers in the absence of demand response event. The measurement and verification of the demand response baseline is the most critical component of any DR program

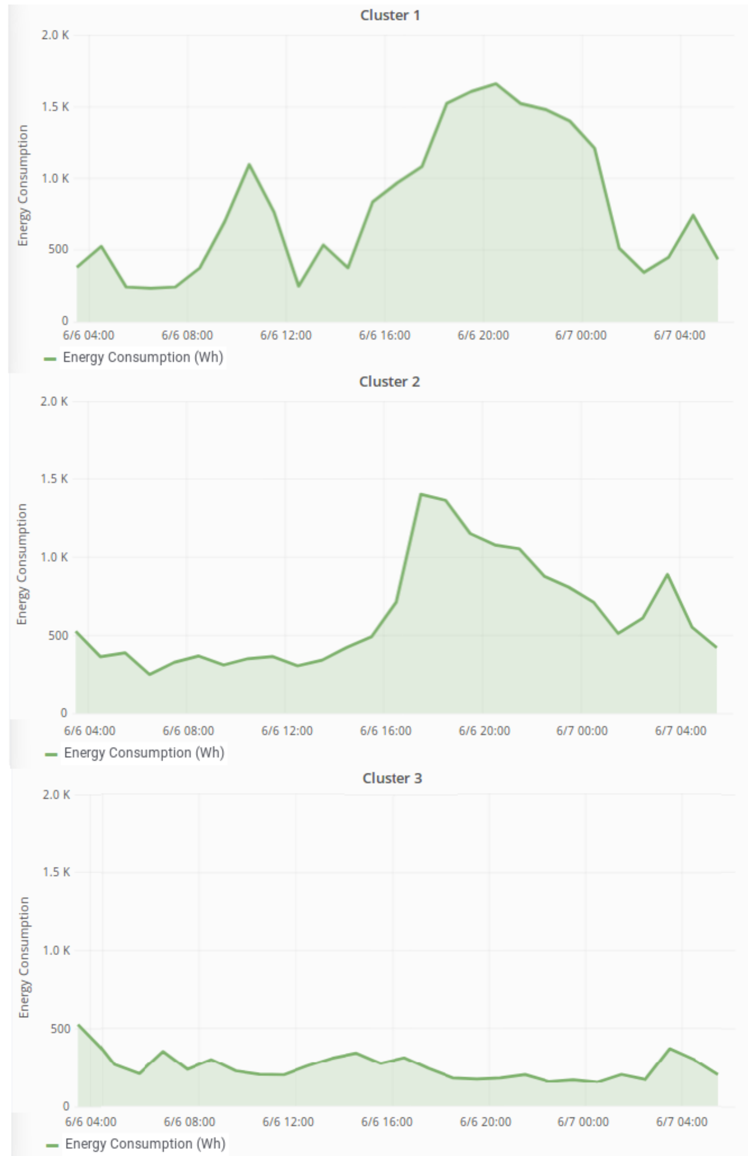

Figure 4: Residential Clusters, where each graph represents the average apartment consumption within a cluster

since the amount of DR curtailment and associated financial reward are determined with respect to this baseline estimate [2]. The baseline consumption is estimated by using a suitable algorithm, for example, see [6].

4.2 When is Demand > Supply?

A DR event is initiated if the total predicted demand in any time-slot is greater than the grid supply. The utility then identifies consumers who can help in reducing growing demand. In such situations, total reduction $R_C(t)$ needed by the grid for a time t, can be calculated using the following formula:

Algorithm 1 Proposed DR selection algorithm

Input: Power consumption of N consumers
Output: List of M suitable DR consumers
Data preprocessing
Compute baseline $D_G(t)$ and total grid supply $A_G(t)$
Compute $R_G(t)$ and $R_T(t)$
$R_G(t) = D_G(t) - A_G(t)$
$R_T(t) = R_G(t)(1 + \Delta_t)$
Filter consumers with various criteria and add filtered ones to initial list L_{init}
for each consumer i in L_{init} **do**
    Compute Consistency index $Cons(t, i)$
    Compute Request index $Req(t, i)$
    Compute Response index $Rel(t, i)$
    Compute Contribution index $Cont(t, i)$
    Compute the Overall Score, $O(t, i)$ based on the selected mode
Sort the list in the decreasing order of their $O(t, i)$ score
Select M consumers from the list in order until $\sum_{i=1}^{M} R_E(t, i) \geq R_T(t)$ and add to the final list $S(j)$
return $S(j)$

$$R_G(t) = D_G(t) - A_G(t) \tag{3}$$

where $D_G(t)$ and $A_G(t)$ are the predicted baseline and the grid supply for t respectively.

4.3 Which consumers should be targeted for reducing consumption?

If a consumer specifies a maximum number of DR requests that can be sent for a time slot t in a day, further requests will not be sent once the limit on DR requests is reached. Exhaustion index $Ex(t, i)$ for each consumer i is calculated as

$$Ex(t, i) = \frac{N_r(t, i)}{N_{rmax}(t, i)} \tag{4}$$

where $N_r(t, i)$ is requests accepted by a consumer i until t and $N_{rmax}(t, i)$ is the maximum number of requests that can be sent to consumer i for a specific time period e.g a month. When $Ex(t, i)$ equals 1, consumer i will be filtered out from the current DR selection process and will be added in the next period.

4.4 Which consumers should be considered for DR?

The algorithm first analyses power consumption profile of each consumer and computes various features such as consistency score, response index, request index and contribution index for the time slot t. Then, it uses each of the calculated features to find the target consumers. An overview of the complete consumer selection process is shown in Algorithm 1. First, we will explain each feature in detail and then the selection function.

• *Contextual Features*: Our "fairness" policies are inspired by a typical income tax system to find the contextual features. A good DR customer selection algorithm should possess the following desirable features:

- Asks the consumers with higher consumption to reduce more compared to a consumer with low consumption.
- Ensures that a particular section of consumers does not get targeted every time.
- Does not disproportionately benefit those who are already benefiting at the expense of the rest.
- Should not take advantage of the consumers who have already participated often.

These can be ensured by computing following features for each consumer:

Consistency index, $Cons(t, i)$ measures the consistency of customer i's consumption profile during time-slot t and is calculated using statistical features like mean and standard deviation. The complete algorithm for consistency calculation is given in [14]. The time-slots in which the consumer has participated in a DR event should be excluded from the consistency calculation since the consumer is asked to deviate from their normal consumption during DR intervals.

Request index, $Req(t, i)$ is the ratio of number of times a consumer received DR requests ($N_r(t, i)$) to the total DR events occurred ($N_{total}(t)$). This can be used to give priority to the least selected consumers.

$$Req(t, i) = \frac{N_r(t, i)}{N_{total}(t)} \tag{5}$$

Response index, $Res(t, i)$ indicates average DR performance of the consumers in the past DR events. This quantitatively measures the interest of a consumer in participating in DR events. DR performance, $P(t, i)$ is the ratio of actual reduction to the expected reduction in consumption for time slot t, if the actual reduction is greater than or equal to expected reduction, DR performance is set as 1. It is calculated as the ratio of summation of the DR performances in the past DR events to number of DR requests received ($N_r(t, i)$) by consumer i during time slot t,

$$Res(t, i) = \frac{\sum P(t, i)}{N_r(t, i)} \tag{6}$$

Contribution index $Cont(t, i)$ measures the predicted contribution of each consumer towards the predicted peak load of a DR event, $R_C(t)$. This factor can be used to prioritize consumers with high energy consumption.

$$Cont(t, i) = \frac{R_C(t, i)}{R_G(t)} \tag{7}$$

where $R_C(t, i)$ is the contribution of consumer i to $R_G(t)$.

• *Selection of DR Consumers*: This step involves ranking consumers for the DR event. The idea is to minimize the discomfort felt by the consumers while allowing the utility to meet its reduction targets. The ideal approach chooses the minimum number of consumers that the utilities should target for time slot t. In real scenarios, utilities will have to target only a small percentage of customers for a DR event. The ranking is done by calculating a consolidated score of Consistency, Response, Request and Contribution indices. Overall score $O(t,i)$ at time t is calculated as

$$O(t,i) = \alpha_1 * Cons(t,i) + \alpha_2 * Cont(t,i) + \alpha_3 * Req(t,i) + \alpha_4 * (1 - Req(t,i)) \tag{8}$$

where α_1, α_2, α_3 and α_4 are weights (which can take values between 0 and 1) assigned to reflect the utility's preference and policies. Consider the following three modes of operation:

- **Optimistic Response Mode**: This is the ideal response case where we assume that all the requested consumers will participate in the event and reduce their energy consumption as asked by the utility. In future smart grids, demand response programs will be implemented through pre-configured smart-contracts, where the decisions will be taken automatically. In such cases, the response index can be ignored for all the consumers.

- **Stochastic Response Mode**: Every consumer participates at their own convenience, there can be instances where a consumer gets a DR Request and doesn't reduce consumption. There can also be instances where the selected consumer might reduce the energy consumption to a lesser extent than required or in some cases more than required. Hence, the response factor for selected time t varies based on the participation and reduction. This is the recommended working mode, as each of the consumers will have different responses to a DR event.

- **Stochastic Response Mode with constraints**: This mode is similar to Stochastic Response Mode and also allows the utility to set separate thresholds for each of the features, which is analogous to adding filters inside the function before calculating the score. If the utility has mentioned that they need the consumers with certain requirements, consumers not meeting the requirements will be filtered out and the score is calculated only for the rest.
  In some cases, there are chances that not enough consumers are selected to meet the target with this criteria. In such cases, the function will also select the consumers having the values close to the threshold and whose selection will reduce the peak to the extent required.

Once the overall score is calculated, the consumers are sorted in decreasing order, and top M consumers are selected based on this score until

$$\sum_{i=1}^{M} R_E(t,i) \geq R_T(t) \tag{9}$$

Where $R_E(t,i)$ is calculated based on the reduction in consumption during the past DR events. If two or more consumers have the same combined score, utility can use any one of the following techniques to resolve the conflicts:

- Earliest Selected Consumer First
- Consumer with high consumption First
- Least Selected Consumer First

etc.

Thus, we can make sure that fewer interruptions occur in consumers' daily lives and delays the onset of demand response fatigue among the consumers while meeting the energy suppliers demands.

4.5 Performance Metrics

SmarDeR should select the consumers who are most likely to reduce their energy consumption, cause less inconvenience to the consumers and benefit as many consumers as possible. The performance features can be categorized as

Risk: This factor will quantify the chance of failure of the Demand Response program in terms of selecting consumers who are not likely to reduce their energy consumption. In other words, it is the likelihood of not meeting the reduction target. A good selection procedure reduces this risk factor by selecting consumers who are most likely to reduce their energy consumption. Risk factor for a DR event is calculated as,

$$Risk = \frac{\sum_{i=1}^{M}(1 - Rel(t,i)) * 100}{M} \tag{10}$$

M represents the consumers chosen for the DR event. Ideally, the risk should be 0. Reliability index, $Rel(t,i)$ is a joint measure of consistency and response, which is obtained by taking the average of both the scores.

$$Rel(t,i) = \frac{Cons(t,i) + Res(t,i)}{2} \tag{11}$$

In the worst case risk can be 100%, where all the selected consumers have low probability to reduce their energy consumption.

Unfairness: As in most of the cases, incentives are provided to the consumers who participate in the DR events. Unfairness can be defined as the number of people who did not receive DR requests and thereby did not benefit from the DR events. Unfairness ratio can be calculated as,

$$Unfairness = \frac{X}{N} \tag{12}$$

where X represents the consumers who are not selected and N is the total number of consumers.

Number of **DR Requests** Sent: It measures the total number request sent to consumers selected for DR events. This factor can be used to measure the inconvenience caused to a consumer resulting from participating in a DR event. To keep the consumers interested in participation, the algorithm should make sure that minimal number of requests are sent to the consumers, so that there will be less interruptions in their daily lives. It is calculated as,

$$T = \sum_{j=1}^{n} M_j \tag{13}$$

M_j is the number of consumers chosen for jth DR event. The maximum value for T is $n * N$, when all consumers are selected in all the DR events.
Ideally, all the above scores should be minimum for a good DR algorithm.

4.6 Complexity

The DR selection should have a low execution time. The size of the input can be measured in the number of consumers i.e, N. The complexity is varied through various stages with respect to proposed heuristics. The operations in the algorithm include first stage filtering, calculating the overall score, sorting the consumers in decreasing order based on their score and selection of consumers. Each has complexity of $O(N)$, $O(N)$, $O(NlogN)$ and $O(N)$ respectively. Thus the complexity of the overall DR selection process is $O(NlogN)$.

5 EVALUATION ON A REAL DATASET

In this section, we describe the dataset used for evaluation and the experimental settings. We show by running the function in various modes that the combination of all the four features results in better DR candidate selection.

5.1 Description of Dataset

The performance evaluation is done by using a campus residential building's energy consumption dataset. It is a high-rise building comprising of 60 apartments, each instrumented with a smart-meter, logging data at a sampling period of 5 seconds. For the purpose of evaluation, we collected data during 2016 - 2017 and down-sampled it to one hour granularity.

We used K-means to divide 60 apartments of the dataset into three clusters and to obtain representative load shapes of the clusters as shown in Figure 4. Cluster 1 contains a minor peak in the morning hours and a major peak in the evening hours. Cluster 2 has a similar pattern to cluster 1 except for the minor peak in the morning hours. Cluster 3 has an almost flat energy consumption profile. Cluster 1 contained 21% of consumers, Cluster 2 contained 44% of consumers and Cluster 3 contains about 35% of the consumers. Clustering gave a clear picture of the types of consumers used in this dataset.

To check the scalability of our proposed approach, we created a larger virtual dataset from the 60 apartments dataset using a similar method mentioned in [10]. We placed a tumbling window of size 14, denoting 14 days for each apartment and considered the data within each window as a separate virtual consumer's consumption after removing the weekends. Out of this new dataset, we selectively choose 500 virtual consumers' data after skipping consumers with missing values. Further, we ensured that each virtual consumer's consumption is different from one another and hence allowing us to run our approach on varied energy consumption patterns.

5.2 Experimental Settings

The time slot t for a DR events is one hour. Maximum number of requests that can be sent to a consumer for the time period is 5, after which the consumer is filtered out from the selection process. We define a flat supply threshold A_G across all time slots, where A_G equals to the 90% of the maximum demand on the DR day. Expected reduction for every consumer is 40 percentage of their total consumption. Initially Δ_t is assigned zero and is updated in the subsequent iterations based on the responses in the previous iteration. The response index and request index are created using a random function, that takes values between 0.1 and 0.9 respectively. Experiments are run in a Stochastic Response Mode for 10 DR events. Each time a consumer gets selected, it's request index and response index are updated using equation 5 and equation 6. Consumer's expected reduction for every DR event is calculated using a function based on their average performance in the past DR events$\pm a$% randomly, where a takes values from 1 to 10, multiplied by 0.4.

5.3 Experiments

For evaluation, all possible combinations, i.e., ${}^4C_1$, ${}^4C_2$, ${}^4C_3$ and ${}^4C_4$ of features in Section 4.4 are taken. For simplicity, while calculating the overall score, all features under consideration are given same alpha values i.e, 1 and rest to 0. All these combinations results in 15 different approaches.

The performance metrics (Section 4.5) are measured for all these approaches using equations 10, 12, 13. Maximum possible value for T (Number of DR requests) is 5000 which occurs when DR Request is sent to every consumer in all DR events. The maximum risk which can be obtained is 100% and worst case unfairness will be close to 500.

6 RESULTS

In this section, we explain results obtained on all the 15 approaches with metrics: *Risk*, *Unfairness* and *number of DR requests sent*. Figure 5 represents average risk over 10 DR events, Figure 6 represents the aggregate unfairness over 10 DR events and Figure 7 represents the total DR requests sent over 10 DR events. We analyze results in the order of the combinations of features taken. The including features: Consistency, Contribution, Request and Response index are denoted by Cons, Cont, Req and Res respectively in Figures 5, 6, and 7.

• *Analysis of ${}^4C_1$ Combinations:* Here, we compare the performances of individual features, i.e., Cons, Cont, Req and Res. Approaches Cons, Cont, Req and Res of Figure 5 show that lower *risk* can be achieved using *response* index as it gives priority to consumers who have reduced their consumption satisfactorily in the previous DR events. It also shows that *risk* is higher for *contribution* index owing to the fact that choosing less number of consumers based on high consumption factor has higher chance of failure. Figure 6 shows that *Unfairness* is also high for *contribution* index as it repeatedly selects the same consumers and thereby sending fewer DR requests. Fair distribution of requests can be obtained using *Request* index because it gives weights to the consumers who are least selected.

• *Analysis of ${}^4C_2$ Combinations:* From Figures 5, 6, 7 we observe that when taken in combinations of two features, there is less impact of *Consistency* score on performance metrics, but when combined with other features reduces *risk*. It can be seen that when *contribution* is considered with any other features, then the number of *DR requests sent* are decreased. Combining *request* with other features also marked a reduction in *unfairness*. We can also observe that combination of *response* and *consistency* has fewer risks, combination of *request* index and *consistency* has less unfairness, and the combination of *contribution* index and *consistency* has least DR requests sent.

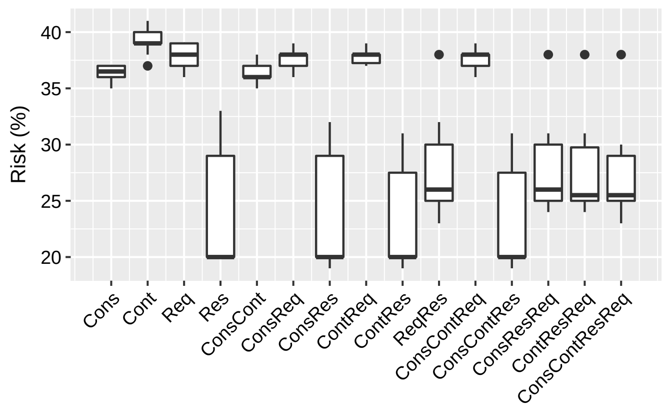

Figure 5: Risk on 500 apartments dataset.

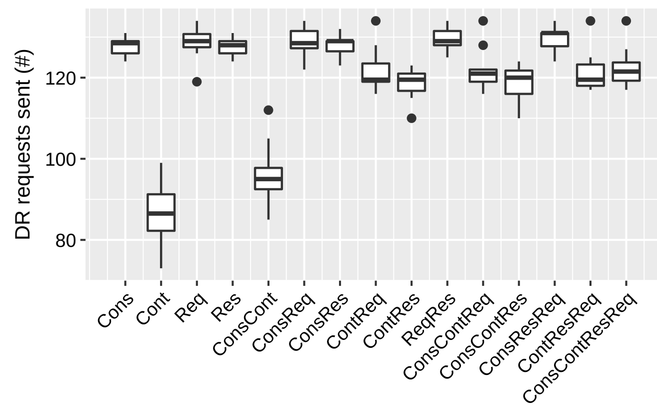

Figure 7: Number of DR Requests Sent on 500 apartments dataset.

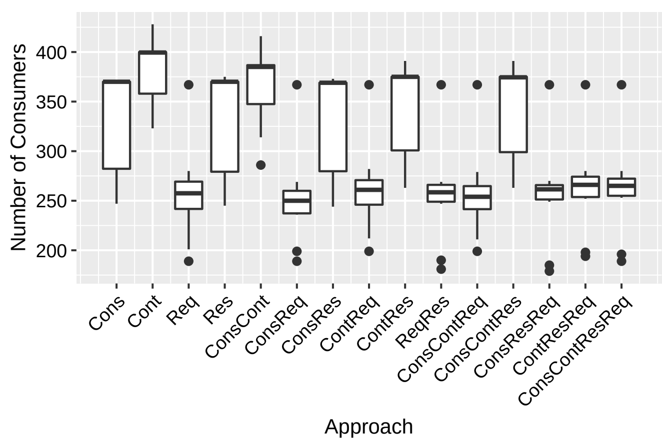

Figure 6: Unfairness on 500 apartments dataset.

Reduction requirement	Cont	Cons	Req	Res
Risk	×	✓	×	✓
Unfairness	×	×	✓	×
No of Requests	✓	×	×	×
Risk & Unfairness	×	✓	✓	✓
Risk & No of Requests	✓	✓	×	✓
Unfairness & No of Requests	✓	×	✓	×
Risk & Unfairness & No of Requests	✓	✓	✓	✓

Table 2: Recommendations for various requirements

• *Analysis of $^4C_3$ and $^4C_4$ Combinations:* Figures 5, 6, 7 show when the features are taken in combinations of 3 and 4, the combination of Cons, Cont, and Req, has least Unfairness and number of DR requests sent. The combination of Cons, Cont and Res shows that risk performance is same as the combination of Cons and Res.

6.1 Insights

We find following insights from our experiments:

(1) Figure 5 shows that approaches Res, ConsRes, ContRes, ReqRes, ConsContRes, ConsResReq, ContResReq and ConsContResReq perform better in terms of reducing the *risk*. The only common factor among these approaches is inclusion of *Response index*. Thus, we conclude that if the utility wants to minimize the *risk* then utility should give priority to response factor while finding suitable DR consumers.
(2) Figure 6 depicts that approaches Req, ConsReq, ContReq, ReqRes, ConsResReq, ContResReq and ConsContResReq are less *unfair* in choosing the consumers. The common factor among these approaches is the usage of *Request factor*. Thus we conclude that utility should incorporate request factor to minimize the *unfairness* among potential DR consumers.
(3) Figure 7 shows that approaches Cont and ConsCont send fewer DR requests to consumers as compared to remaining approaches. Analysis of these approaches implies that to reduce the number of DR requests send, the *contribution* factor must be considered.
(4) In summary, Optimal risk and fairness can be ensured with *response* and *request* features correspondingly. If reducing the number of DR requests is the only requirement, then *contribution index* should be used.

Feature combinations should be used while satisfying multiple requirements with α_1 * *consistency score* + α_2 * *contribution index* + α_3 * *response index* + α_4 * *request index*. α_1, α_2, α_3 and α_4 are weights given to different features based on their priority. For example, the risk on selection can be reduced by increasing the alpha values of consistency score and response index. Table 2 shows recommendations of features to be considered during DR consumer selection.

7 CONCLUSION AND FUTURE WORK

The imbalance between demand and supply leads to instability of the grid. Whenever the demand for electricity exceeds it's generation, it leads to blackouts or brownouts. So utilities look for opportunities for demand-side reduction to avoid such situations. Researchers have proposed numerous approaches for identification of customers for DR events.

This paper presented SmarDeR, a systematic smart approach to select consumers who meet utility requirements as well as are reliable. We introduced features that have to be considered while selecting consumers, and performance metrics for evaluating the selection mechanism. By using a right combination of features, we ensure a fair distribution of DR requests to all the consumers so that no segment of the population gets more benefits or burdens than the others. Hence, utilities can maintain reliable operation of the grid without creating demand fatigue among it's consumers. As a future work, we are working on how to distribute the DR requests to the potential consumers across different time slots in a day to avoid the payback effect using the algorithm mentioned in [10]. Also, we are developing an incentive structure to influence the consumer's participation in DR events.

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