Optimizing Customer Selection for Sustainable Demand Response

Sanmukh Kuppannagari, Rajagopal Kannan, Charalampos Chelmis, Arash Tehrani and Viktor K. Prasanna

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Ming Hsieh Department of Electrical Engineering – Systems
University of Southern California
Los Angeles, California 90089-2562

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Abstract

Demand Response (DR) is a widely used technique to minimize the peak to average consumption ratio during high demands. An effective DR scheduling algorithm should minimize the curtailment error - the difference between the targeted and achieved curtailment values to minimize the costs to the utility provider and maintain system reliability. Several polynomial time heuristics have been proposed in the literature to achieve this goal, however their accuracy can be extremely low. We argue that minimizing the error alone is not enough as peaks can be concentrated in some intervals while consumption being heavily curtailed in other intervals. In this paper, we leverage the availability of smart meters to provide fine grained data and customer control and formally develop the notion of Sustainable DR as a solution that distributes the curtailment evenly across the DR event. We formulate both Traditional DR and Sustainable DR problems as Integer Linear Programs. For both problems, we first provide a very fast $\sqrt{2}$-factor approximation algorithm. We also propose a Polynomial Time Approximation Scheme (PTAS) for approximating the curtailment error to within an arbitrarily small factor of the optimal. We develop a novel ILP formulation that solves the sustainable DR problem while explicitly accounting for strategy switching overhead as a constraint. We perform experiments using real data acquired from a university's smart grid and show that our sustainable DR model achieves near exact results (error in the order of 10^{-5}).

INTRODUCTION

Recent technological advances have transformed traditional power grids to complex cyber-physical systems [1], [2]. The widespread use of bi-directional smart meters, in addition to reporting energy consumption, allows remote monitoring and intelligent grid control. Utility providers now have several tools at their disposal to dynamically meet energy demand while ensuring the reliability of the power grid.

Reliable operation of a power grid requires utilities to constantly match (fluctuating) energy supply with (fluctuating) load. Demand levels of customers fluctuate with peak demands concentrated in some portions of the day. During such periods, the demand might exceed the generation capacity of the utility forcing them to buy energy from the spot market at high rates. Demand Response (DR) is a standard technique used by utilities to mitigate energy supply-demand mismatch. Customers are incentivised to enroll in the program and curtail their energy consumption during peak load times which is signaled by a DR event. Each customer is provided with various strategies to reduce consumption. e.g. a customer can reduce the air conditioning or turn off some number of lights. For each customer-strategy pair, the utility estimates the load curtailment. This information is then used to decide the optimal strategies that will achieve the desired curtailment value.

We observe that Demand Response can be implemented in two modes. Sometimes fine grained control of customer strategies may not be available, for example, due to a lack of smart meters for control and the necessity of manual intervention for adjusting strategies (such as manually turning on/off the AC). Under such circumstances, load curtailment during a DR event can be achieved by optimally selecting customer-strategy pairs to curtail demand by the desired amount for the entire peak demand period.

Conversely, when fine grained control is available, the entire peak period can be divided into smaller intervals where customer strategies can be micro-adjusted. Note that implementing the first approach (which we label *Traditional DR*) might produce customer strategy assignments which achieve the desired total curtailment value by aggressively curtailing demand over a few small intervals. This could create peaks and valleys of demand over intervals (while still technically achieving DR objectives). Such demand peaks could possibly exceed the instantaneous generation capacity, forcing the utility to pay for additional procurement of energy. This motivates our *Sustainable DR* approach: To leverage the availabilty of fine grained smart meter data and customer control by evenly distributing curtailment over the entire time period.

RELATED WORK

Significant literature exists addressing the challenges, solutions, implementations and estimation methodology for calculating the energy savings for Demand Response (DR) [3], [4], [5]. Early works focused on DR scheduling for individual residential cases [6] or household appliances [7]. These approaches are not scalable to smart grids.

Traditionally, DR algorithms have focused on targeting customers based on aggregate consumption data, relying on customer selection using billing data or surveys [8], [9], employing dynamic programming techniques for load management and minimizing peak load over a period [10], particle swarm optimization based techniques [11] and game theoretical solutions constrained by real time pricing [12] and customer comfort levels [13]. However, with data available from smart meters, work such as [14], [15] show that such approaches are very inaccurate. The actual consumption data over a period differs significantly from the data obtained from surveys or billing cycles. Moreover, the selection is done oblivious to the distribution of load throughout the day. Therefore such approaches contribute little to reducing the peak energy consumption and distributing it over other periods.

The authors in [16] propose a stochastic knapsack based algorithm for selecting customers to maximize reliability: the probability the desired curtailment value is achieved over the period of the entire DR event while limiting the utility's cost (one metric is the number of customers participating in the DR event). The algorithm relies on the central limit theorem to assume the joint customer response is normally distributed and thus is conditioned on the assumption that there are a large number of customers from whom a subset can be selected. For example, in order to achieve high reliability ($> 95\%$) for large curtailment targets, the algorithm requires around $N = 2000$ customers which increases the computation cost. Two heuristics are proposed but the approximation bounds are dependent on the ratio of customer demand response variances which could be arbitrarily large. Although fine grained data is available, the selection algorithm focuses on aggregating the curtailment over a time interval. However, as mentioned before, such an approach can aggressively curtail load in some intervals and concentrate peak in other intervals.

The notion of achieving sustainable DR over a peak period divided into subintervals was proposed in [17] using a change making heuristic to evenly distribute curtailment over intervals. The proposed definition, which includes several terms relating curtailment between adjacent intervals, the max and min curtailment values primarily attempts to achieve consistency between intervals without reference to the target. The customer-strategy pairs are also fixed across intervals. A detailed analysis of this heuristic (omitted due to space constraints) shows that it can lead to unbounded errors (deviation from the target). Our experimental results demonstrate this is indeed the case.

OUR CONTRIBUTIONS

In this paper, we leverage the availability of smart meters to provide fine grained data and customer control and formally develop the notion of Sustainable DR. A Sustainable DR solution minimizes the curtailment error - defined as the $\|l\|_1$ distance between achieved curtailment values and a smoothed target value per interval. We formulate both traditional DR and sustainable DR problems as Integer Linear Programs (ILP). For both problems, we first provide a very fast $\sqrt{2}$-factor approximation algorithm. By precomputing and storing results for a range of target values, our algorithm can return approximately optimal DR strategies in $O(1)$ time.

State-of-the-art works have a very low operation yield-the ratio of the actual energy curtailed vs the curtailment target, in the range of 10-30% [18]. In this paper, we also propose a Polynomial Time Approximation Scheme (PTAS) for approximating the ILP and substantially increasing the operation yield. Our proposed PTAS minimizes the curtailment error to within an arbitrarily small factor of the optimal. For sustainable DR an important practical consideration is the cost of switching between strategies. Even with smart meter control, it may be uneconomical to rapidly switch strategies between intervals. We develop a novel ILP formulation that explicitly accounts for switching overhead as a constraint and solves the sustainable DR problem. We perform experiments using real data acquired from a university's smart grid and show that our sustainable DR model achieves near exact results (error in the order of 10^{-4}).

TRADITIONAL DEMAND RESPONSE

Given the list of customers, the strategies they can adopt and the curtailments achieved by each customer-strategy pair, Traditional Demand Response (TDR) scheduling algorithms find the strategy to be adopted by each customer such that the difference between the targeted and achieved curtailment values is minimized. From the utility's point of view minimizing this difference is desirable for the following reasons:

1) Bounding the value by which the achieved curtailment overshoots the targeted curtailment ensures that the grid is not under utilized by trying to aggressively curtail the demand during the peak demand time.
2) Bounding the value by which the achieved curtailment undershoots the targeted curtailment ensures that lower costs are incurred to the utility to buy the additional required power to maintain grid stability.

A stochastic knapsack based heuristic for this problem is detailed in [16]. We solve the deterministic version of the same problem and measure its effectiveness in terms of the error.

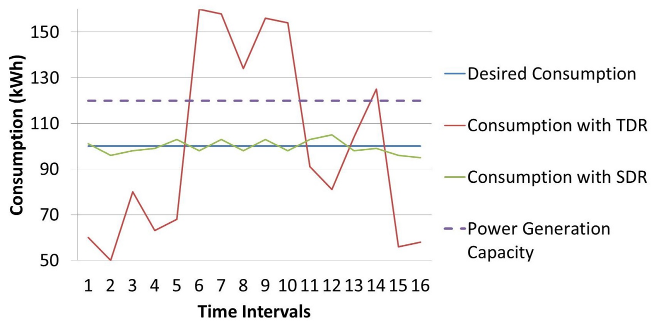

Fig. 1. SDR vs TDR

We are given a set of M customers, N strategies and a $\mathbf{C} \in \mathbf{R}^{M \times N}$ curtailment matrix with element c_{ij} denoting the curtailment value of customer i adopting strategy j. Let $\mathbf{A}$ denote the corresponding decision matrix. Let the desired curtailment value across the entire DR event be γ. The problem can be formulated as an ILP as follows:

$$\textbf{Minimize} : Error = \mid \sum_{i=1}^{M} \sum_{j=1}^{N} \mathbf{C}_{ij} * \mathbf{A}_{ij} - \gamma \mid \tag{1}$$

$$\textbf{Subject to} : \sum_{j=1}^{N} \mathbf{A}_{ij} = 1 \; \forall i \tag{2}$$

Equation 2 ensures that a customer adopts exactly one strategy in the DR event. This includes the default strategy with a curtailment value of 0. Experimental results for the Traditional DR problem are provided in a subsequent section.

Sustainable Demand Response

Motivation

The TDR algorithm proposed in the previous section will produce the desired result for the entire interval. However, it is possible that TDR will produce assignments which aggressively curtail the demand in some intervals while accumulating demands in other intervals. Such assignments will still have peaks in certain intervals of the DR event. These peaks can possibly exceed the generation capacity in those intervals forcing the utility to pay for additional procurement of energy.

An example scenario is shown in Figure 1. The traditional DR algorithm (error: 0.13 %) performs better in terms of error than the sustainable DR algorithm (error: 0.43%). However, at several intervals of the DR, the traditional DR exceeds the peak generation capacity which is undesirable.

We define the notion of Sustainable Demand Response (SDR) to address such cases. SDR attempts to evenly smooth the curtailment over the entire period of the DR event. Hence we define SDR as the customer-strategy assignment which minimizes the $\|l\|_1$ distance between achieved curtailment values and a smoothed target value per interval.

As before we are given a set of M customers, N strategies and a time varying $\mathbf{C(t)} \in \mathbf{R}^{M \times N}$ curtailment matrix with element $c_{ij}(t)$ denoting the curtailment value of customer i adopting strategy j at time interval t where $t \in \{1, \ldots, T\}$. Let $\mathbf{A}(t)$ denote the corresponding decision matrix at time t. Let the desired curtailment value across the entire DR event be γ.

We propose two novel ILP formulations for this problem. The formulations differ in the number of times the customers can change their strategies throughout the the DR event period.

ILP Formulation for Sustainable DR

We use the following ILP to model a Sustainable DR event.

$$\textbf{Minimize} : \sum_{t=1}^{T} \epsilon_t \tag{3}$$

Subject to:

$$\mid \sum_{i=1}^{M} \sum_{j=1}^{N} \mathbf{C}_{ij}(t) * \mathbf{A}_{ij}(t) - \frac{\gamma}{T} \mid \leq \epsilon_t \; \forall t \tag{4}$$

$$\sum_{j=1}^{N} \mathbf{A}_{ij}(t) = 1 \; \forall i, t \tag{5}$$

The objective is the minimize the $\|l\|_1$ norm (Equation 3). As before, Equation 5 ensures that at any given interval, each customer adopts exactly one strategy.

Algorithm 1: Fast $\sqrt{2}$-factor Sustainable DR Approximation

Preprocessing: Non-decreasing sorted lists $\{C^{(i)}(t)\}$ of customer-strategies for each customer $i \in S$ and each interval t

1 **for** *intervals* $t = 1$ *to* T **do**
2   **if** $\exists(k \in S) \wedge (j \in C^{(i)}(t)) : C_{kj}(t) \in [\frac{\gamma}{T\sqrt{2}}, \frac{\sqrt{2}\gamma}{T}]$ **then**
3         $A_{kj}(t) \leftarrow 1$;
        `// Select customer` k `and curtailment strategy` $C_{kj}(t)$
4   **else**
5         $(p, q_p) \leftarrow \mathrm{argmin}_{i \in S, j \in C^{(i)}(t)}\{C_{ij}(t) | C_{ij}(t) \geq \gamma\sqrt{2}/T\}$;
6         $X_p \leftarrow C_{pq_p}(t)$;
7   For each customer $i \in S : k_i \leftarrow \mathrm{argmax}_k\{C_{ik}(t) \leq \gamma/(T\sqrt{2})\}$;
8   Let r denote the smallest index such that $X_r \leftarrow \sum_{i=1}^{r} C_{ik_i}(t); X_r \geq \gamma/(T\sqrt{2})$;
9         $r \leftarrow M$ if $\sum_{i=1}^{M} C_{ik_i}(t) < \gamma/(T\sqrt{2})$;
        `// Select Strategies for Activation as follows`
10   **if** $X_p - \gamma\sqrt{2}/T \leq \gamma/(T\sqrt{2}) - X_r$ **then**
11   Set $A_{pq_p}(t) = 1$;
12   **else**
13   **for** $i \leftarrow 1$ **to** r **do**
14   Set $A_{ik_i}(t) = 1$;

Output: Matrix $\{A(t)\}$ of selected customer-strategies during each interval t.

Fast $\sqrt{2}$-factor Approximation for Sustainable DR

We now describe a fast algorithm for computing approximately optimal sustainable DR strategies. Our algorithm provides a $\sqrt{2}$-factor approximation to the optimal target during each curtailment period.

Theorem 1. *Algorithm 1 is a $\sqrt{2}$-factor approximation to the optimal sustainable DR solution.*

Proof: Let X_t denote the curtailment value for period t returned by Algorithm 1. We show that either $X_t \in [\frac{\gamma}{T\sqrt{2}}, \frac{\gamma\sqrt{2}}{T}]$ or X_t is the optimal curtailment value achievable for that period. If line 2 of the algorithm is satisfied, then this is trivially true. Assume line 2 is not satisfied. From line 8, we must have $\gamma/(T\sqrt{2}) \leq X_r = \sum_{i=1}^{r-1} C_{ik_i} + C_{rk_r} \leq 2 \cdot \gamma/(T\sqrt{2}) = \gamma\sqrt{2}/T$.

Finally, consider the case when when $r = M$ and $X_M \leq \gamma/(\sqrt{2}T)$. Since k_i represents the strategy with the largest curtailment value $\leq \gamma/(\sqrt{2}T)$ for each customer i, by definition X_r is the largest achievable curtailment value $< X_p$ and so either X_p or X_r is the optimal strategy for this period. □

The following result follows from a straightforward analysis of the algorithm.

Theorem 2. *Algorithm 1 can be used to compute $\sqrt{2}$-approximate sustainable DR solutions in $O(TM \log N)$ time when strategies are preprocessed in advance for a given curtailment target. The one-time preprocessing cost assuming apriori knowledge of curtailment strategies is $O(TMN \log N)$.*

By precomputing and storing results for a range of target values, we can speed up the retrieval of approximately optimal strategies even further to $O(1)$ time.

A PTAS for Sustainable DR

While the approximation algorithm above can be used to very quickly compute sustainable DR solutions, the error due to the $\sqrt{2}$-factor approximation may be unacceptable in some cases. Therefore, we also develop a Polynomial Time Approximation Scheme (PTAS) that approximates the optimal solution provided by the ILP in Equation 3 to within an arbitrarily small ϵ-factor in time polynomial in MN/ϵ.

Theorem 3. *Algorithm 2 is a PTAS for the ILP in Equation 3.*

Proof Sketch: The number of intervals $l \approx \log_{\frac{1}{1-\epsilon}}(\gamma/T)$ is polynomial in $\frac{\ln(\gamma/T)}{\epsilon}$. Line 9, if a curtailment value is already marked feasible (i.e $Q_s^{(k-1)}(t)$ is 0), then customer k does not contribute to the feasible solution. The total number of iterations is $O(lNM)$. From line 7, using induction, we can show $V_{j+1} \geq \sum_{C_{qr} \in B_j^{(M)}(t)} C_{qr} \geq (1-\delta)^M V_{j+1} \geq (1-\epsilon)V_{j+1} = V_j$. and hence $\sum_{C_{qr} \in B_j^{(M)}(t)} C_{qr} \in [V_j, V_{j+1}]$. Thus the algorithm outputs an ϵ approximation to the optimal achievable target and is therefore a PTAS.

ILP formulation for Sustainable DR with Strategy Overheads

Switching rapidly from one strategy to another during a DR event may be impractical and lead to the utility or the customer incurring additional overheads. We model this constraint by imposing a limit τ on the number of times a customer can switch strategies in between intervals. We formulate this modified SDR problem as an ILP with an additional novel strategy switching constraint. Since τ is fixed, a customer is likely to have contiguous strategies across intervals. We express this as a constraint in the ILP using an additional state transition variable.

$$\textbf{Minimize} : \sum_{t=1}^{T} \epsilon_t \tag{6}$$

Subject to:

$$\left| \sum_{i=1}^{M} \sum_{j=1}^{N} \mathbf{C}_{ij}(t) * \mathbf{A}_{ij}(t) - \frac{\gamma}{T} \right| \leq \epsilon_t \ \forall t \tag{7}$$

$$\sum_{j=1}^{N} \mathbf{A}_{ij}(t) = 1 \ \forall i, t \tag{8}$$

$$S_{ij}(t) = \mid \mathbf{A}_{ij}(t) - \mathbf{A}_{ij}(t-1) \mid \tag{9}$$

$$A_{ij}(0) = 0 \ \forall i, j \tag{10}$$

$$\sum_{t=1}^{T} \sum_{j=1}^{N} S_{ij}(t) \leq \tau \ \forall i, j \tag{11}$$

The new constraints to limit the strategy switching are introduced using Equations 9, 10 and 11. Equation 9 calculates the number of times customer i switches a particular strategy. Equation 11 bounds the total number of times a customer can switch strategies. In our experiments, we fix the value of $\tau = 6$.

Algorithm 2: PTAS for Sustainable DR during each interval t

1 $V_0 \leftarrow \min_{i,j} C_{ij}(t)$;
2 $X \leftarrow \min_{i,j} C_{ij}(t) \geq \gamma/T$;
3 Divide $[V_0, X]$ into l intervals $\{[V_i, V_{i+1}]\}$, $V_i = (1-\delta)V_{i+1}$, $0 \leq i \leq l-2$, $V_l = X$, $\delta = \epsilon/M$;
4 $\forall k \in S : Y_{kj} \leftarrow V_i$ if $C_{kj} \in [V_i, V_{i+1}]$;
5 $B_i^{(0)}(t) \leftarrow \emptyset$; $Q_i^{(0)}(t) \leftarrow 0$; $i = 0, 1, \ldots, l-1$;
// $B_i^{(k)}(t)$ is a subset of the first k customers, each with a non-zero strategy selection, that add up to a curtailment value $\in [V_i, V_{i+1}]$.
6 **for** *Customers* $k = 1$ *to* M **do**
7   **for** *all intervals* i*, all strategies* r **do**
8         $X_{ir} \leftarrow Q_i^{(k-1)}(t) + Y_{kr}$;
9   Let $X_{ir} \in [V_s, V_{s+1}]$;
10   **if** $\neg Q_s^{(k-1)}(t)$ **then**
11             $Q_s^{(k)}(t) \leftarrow V_s$ // Making $Q_s^{(k)}(t)$ a feasible curtailment value
12             $B_s^{(k)}(t) \leftarrow B_i^{(k-1)}(t) \bigcup C_{kr}(t)$;
            // Adding customer k strategy r pair to the feasible strategy set

Output: $B_j^{(M)}(t)$: Selection of customer-strategy pairs, where j is the closest interval to DR target γ/T with $Q_j^{(M)}(t) > 0$

TABLE 1
Comparison of demand curtailment values achieved in each interval for SDR and TDR for the targeted curtailment value of 1000 kWh

Time Interval of DR Event	Achieved Curtailment by TDR (kWh)	Achieved Curtailment by SDR (kWh)	Desired Curtailment per Interval (kWh)
1	48.2751	62.4999	62.5
2	48.6096	62.5000	62.5
3	52.2919	62.5000	62.5
4	51.6158	62.4999	62.5
5	46.8347	62.5000	62.5
6	53.4670	62.4999	62.5
7	55.4195	62.5000	62.5
8	56.2443	62.4999	62.5
9	58.4918	62.4999	62.5
10	65.8869	62.5000	62.5
11	64.5838	62.5000	62.5
12	71.5662	62.5001	62.5
13	75.1756	62.5000	62.5
14	78.3424	62.5000	62.5
15	84.1755	62.4999	62.5
16	91.5856	62.5000	62.5

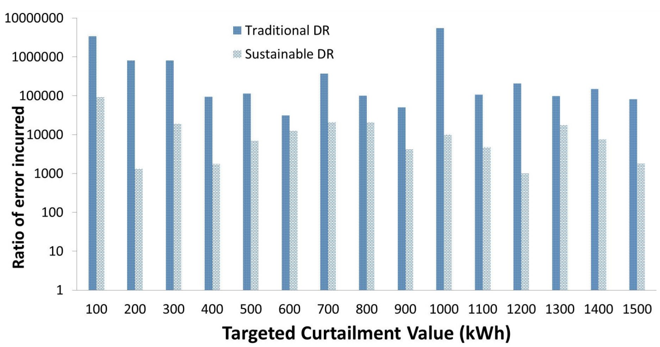

Fig. 2. Ratio of error incurred by State-of-the-art Heuristics to ILPs developed in this work vs Targeted Curtailment Values (logarithmic scale)

EXPERIMENTS AND RESULTS

Experimental Setup

We use the Optimization Programming Language (OPL) [19] to define the Integer Linear Programming (ILP) formulations developed in this work. The OPL definition is input to the IBM ILOG CPLEX Optimization Studio software (CPLEX) [20] which is an optimization software package for mathematical programming. CPLEX produces the optimal assignment and reports the value of the objective function. We use real data collected from the smart grid of an *Anonymous* university. The data is collected over 15 minutes intervals for a period of 4 hours during 1 to 5 pm which is when the system load was found to be the heaviest. 20 buildings are enrolled in the DR program and each building can adopt 1 out of 6 strategies. For each customer-strategy pair at a given time interval, the curtailment value is available in kWh.

Traditional DR

For Traditional DR we use the overall curtailment value for each customer-strategy pair in our experiments. For comparative purposes we look at the curtailment errors of the state-of-the-art change making heuristic [17].

Figure 2 shows the ratio of the %-error incurred by the two methods on a logarithmic scale. The absolute error of our ILP is $5.0 \times 10^{-7} - 7.0 \times 10^{-4}$ which are within the range of numerical precision error. Thus our ILP produces almost exact solutions.

In [16], the error is unbounded for smaller number of customers. As described in their paper the minimum number of customers required to achieve the targeted curtailment value with more than 95% probability is a quadratic function of the targeted curtailment value. However, as shown by the results, the error incurred in our approach is bounded irrespective of the number of customers.

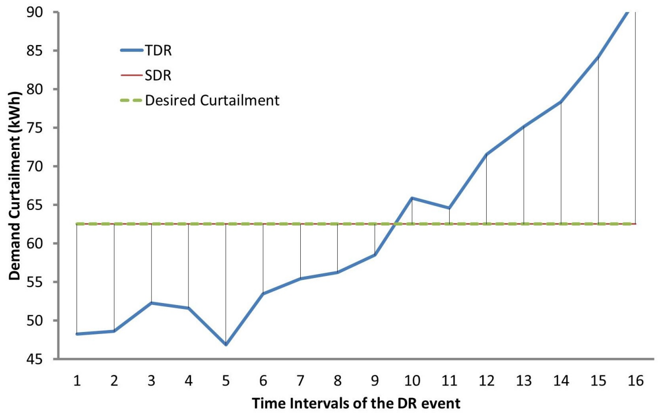

Fig. 3. Comparison of demand curtailment values achieved in each interval for SDR and TDR for the targeted curtailment value of 1000 kWh

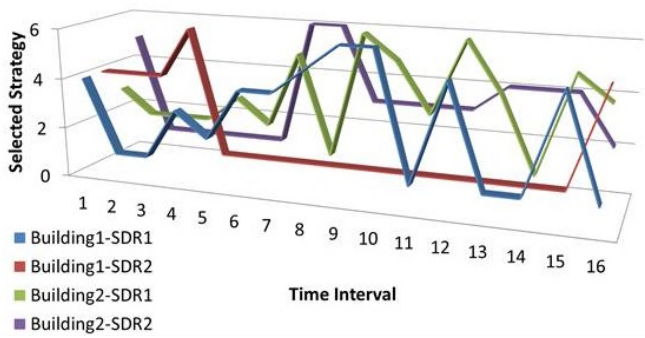

Fig. 4. Selected Strategies using SDR (SDR-1) and SDR with Strategy Overheads (SDR-2)

Sustainable DR

For Sustainable DR, we use the fine grained data available for each 15 minute interval for the duration of 4 hours. The curtailment value for each customer-strategy pair for each time interval is available. We compare the values of the $\|l\|_1$ obtained after customer selection with the state-of-the-art change making problem based heuristic [17].

In Figure 2 we show the ratio of the %-error incurred using the state-of-art heuristic and our SDR ILP on a logarithmic scale. We perform $10^3 - 10^5$ times better than the state-of-the-art heuristic. Our ILP produces solutions with error in the range $1.54 \times 10^{-4} - 1.67 \times 10^{-3}$. We found that the error of the change making heuristic became extremely large (around 60%) for some curtailment values. We believe this is because the heuristic focuses more on smoothing between intervals than on achieving the target and so one bad interval can lead to overall bad performance. Our fast $\sqrt{2}$-factor approximation algorithm with an error bound of 40% has a better error performance than the change making heuristic.

To emphasize the significance of Sustainable DR over Traditional DR, we compare the demand curtailment values achieved in each interval for the DR event for the targeted curtailment value of 1000 kWh. Traditional DR gives one strategy per building for the entire period. Using this information and the available fine grained data, we calculate the achieved curtailment in each interval for Traditional DR. The Traditional DR provides an almost exact solution with error 1×10^{-6} whereas the error for the Sustainable DR is 5.28×10^{-4}. Although the SDR error is larger than Traditional DR, it is still close to zero over each interval. Thus we show the results with precision in Table 1. Note that as shown in Figure 3 Traditional DR has peaks and valleys.

Sustainable DR with Strategy Overheads

The motivation behind using Sustainable DR with Strategy Overheads is to reduce the number of times each building switches its strategy in the DR interval. We limit the number of times building i can switch strategies. Figure 4 compares the strategies adopted by two buildings in the DR event using Sustainable DR approach and Sustainable DR with strategy overhead approach. Note that the line for the latter approach has less number of transitions as compared with the line for the former approach which is zig zag. Figure 5 compares the number of strategy switches for some of the buildings. Figure 6 shows the ratio of the error incurred by using the ILP for SDR with strategy overheads and SDR. Clearly there is a trade off between the increased error vs the cost savings offered by the SDR approach with constrained strategy switching.

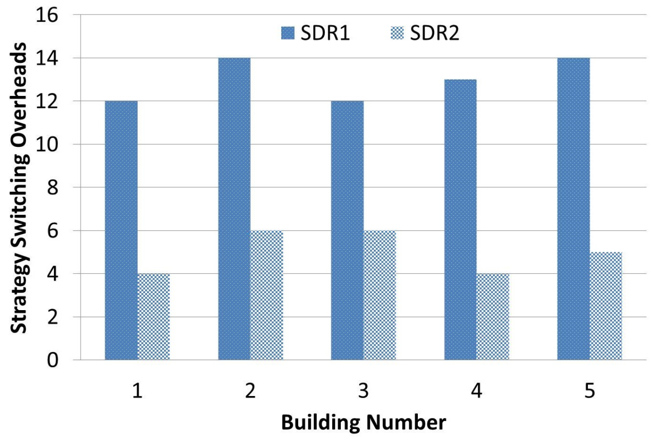

Fig. 5. Number of Strategy Switching Overheads using SDR (SDR-1) and SDR with Strategy Overhead (SDR-2)

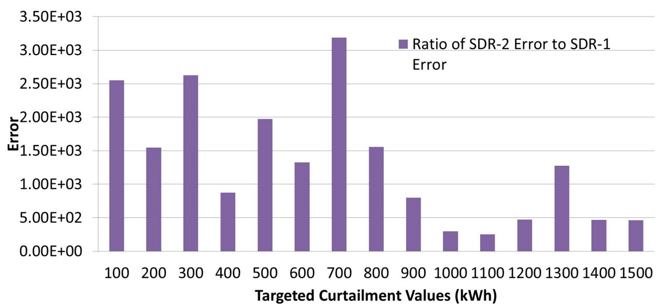

Fig. 6. Ratio of Error Incurred by SDR with Strategy Overheads and SDR

ILP is a computationally intensive process. To converge to the error rates shown in the results, the IBM CPLEX required 15-20 minutes of processing time. Since DR programs are based on predictive data [21] which are available in advance, the time required can be perceived as reasonable. For larger problem sets, accuracy can be traded off with the fast bounded approximate heuristics proposed in this paper.

CONCLUSION

In this work, we formulated the problem of customer selection for Demand Response as Integer Linear Programs (ILP). We motived the need for the Sustainable Demand Response by experimentally showing the cases where Traditional Demand Response produces peaks in the consumption potentially exceeding the generation capacity of the utility, and how the problem could be mitigated using Sustainable Demand Response. We showed that our ILP provides near exact solutions even in the cases where the existing heuristics produce unbounded errors. We also provided fast $\sqrt{2}$-factor approximation algorithm which returns approximately optimal DR strategies in $O(1)$ time and a Polynomial Time Approximation Algorithm for approximating the ILP. We developed a novel ILP formulation that explicitly accounts for switching overhead and solves the sustainable DR problem.

In future work, we will focus on associating cost functions to strategy switching. We will also incorporate a strategy transition matrix in our formulation which determines what strategy transitions are possible for a customer at any given interval of time.

REFERENCES

[1] A. Z. Faza, S. Sedigh, and B. M. McMillin, *Reliability modeling for the advanced electric power grid*. Springer, 2007.

[2] K. Moslehi and R. Kumar, "A reliability perspective of the smart grid," *Smart Grid, IEEE Transactions on*, vol. 1, no. 1, pp. 57–64, 2010.

[3] M. H. Albadi and E. El-Saadany, "Demand response in electricity markets: An overview," in *IEEE power engineering society general meeting*, vol. 2007, 2007, pp. 1–5.

[4] S. Borenstein, M. Jaske, and A. Rosenfeld, "Dynamic pricing, advanced metering, and demand response in electricity markets," 2002.

[5] F. Rahimi and A. Ipakchi, "Demand response as a market resource under the smart grid paradigm," *Smart Grid, IEEE Transactions on*, vol. 1, no. 1, pp. 82–88, 2010.

[6] F. Mangiatordi, E. Pallotti, P. D. Vecchio, and F. Leccese, "Power consumption scheduling for residential buildings," in *Environment and Electrical Engineering (EEEIC), 2012 11th International Conference on*. IEEE, 2012, pp. 926–930.

[7] N. Gatsis and G. B. Giannakis, "Cooperative multi-residence demand response scheduling," in *Information Sciences and Systems (CISS), 2011 45th Annual Conference on*. IEEE, 2011, pp. 1–6.

[8] L. Lutzenhiser, L. Cesafsky, H. Chappells, M. Gossard, M. Moezzi, D. Moran, J. Peters, M. Spahic, P. Stern, E. Simmons *et al.*, "Behavioral assumptions underlying california residential sector energy efficiency programs," *Prepared for the California Institute for Energy and Environment Behavior and Energy Program*, 2009.

[9] S. J. Moss, M. Cubed, and K. Fleisher, "Market segmentation and energy efficiency program design," *Berkeley, California Institute for Energy and Environment*, 2008.

[10] A. I. Cohen and C. C. Wang, "An optimization method for load management scheduling," *IEEE Trans. Power Syst.;(United States)*, vol. 3, no. 2, 1988.

[11] A. Sepulveda, L. Paull, W. G. Morsi, H. Li, C. Diduch, and L. Chang, "A novel demand side management program using water heaters and particle swarm optimization," in *Electric Power and Energy Conference (EPEC), 2010 IEEE*. IEEE, 2010, pp. 1–5.

[12] J. Chen, B. Yang, and X. Guan, "Optimal demand response scheduling with stackelberg game approach under load uncertainty for smart grid," in *Smart Grid Communications (SmartGridComm), 2012 IEEE Third International Conference on*. IEEE, 2012, pp. 546–551.

[13] A. Barbato, A. Capone, L. Chen, F. Martignon, and S. Paris, "A power scheduling game for reducing the peak demand of residential users," in *Online Conference on Green Communications (GreenCom), 2013 IEEE*. IEEE, 2013, pp. 137–142.

[14] J. Kwac, J. Flora, and R. Rajagopal, "Household energy consumption segmentation using hourly data," *Smart Grid, IEEE Transactions on*, vol. 5, no. 1, pp. 420–430, 2014.

[15] B. A. Smith, J. Wong, and R. Rajagopal, "A simple way to use interval data to segment residential customers for energy efficiency and demand response program targeting," in *ACEEE Summer Study on Energy Efficiency in Buildings*, 2012.

[16] J. Kwac and R. Rajagopal, "Demand response targeting using big data analytics," in *Big Data, 2013 IEEE International Conference on*. IEEE, 2013, pp. 683–690.

[17] V. Zois, M. Frincu, C. Chelmis, M. R. Saeed, and V. Prasanna, "Efficient customer selection for sustainable demand response in smart grids," in *Green Computing Conference (IGCC), 2014 International*. IEEE, 2014, pp. 1–6.

[18] J. Kwac and R. Rajagopal, "Targeting customers for demand response based on big data," *arXiv preprint arXiv:1409.4119*, 2014.

[19] Ibm ilog cplex optimization studio opl language reference manual. Online. [Online]. Available: http://www-01.ibm.com/support/knowledgecenter/SSSA5P_12.6.1/ilog.odms.studio.help/pdf/opl_langref.pdf

[20] Ilog cplex optimization studio welcome page. Online. [Online]. Available: http://www-01.ibm.com/support/knowledgecenter/SSSA5P/welcome

[21] S. Aman, C. Chelmis, and V. K. Prasanna, "Influence-driven model for time series prediction from partial observations," in *Twenty-Ninth AAAI Conference on Artificial Intelligence*, 2015.