Optimal Customer Targeting for Sustainable Demand Response in Smart Grids *

Sanmukh R. Kuppannagari, Rajgopal Kannan, Charalampos Chelmis, Arash S. Tehrani, and Viktor K. Prasanna

Ming Hsieh Department of Electrical Engineering,
University of Southern California, Los Angeles, California
{kuppanna,rajgopak,chelmis,saberteh,prasanna}@usc.edu

Abstract

Demand Response (DR) is a widely used technique to minimize the peak to average consumption ratio during high demand periods. We consider the DR problem of achieving a given curtailment target for a set of consumers equipped with a set of discrete curtailment strategies over a given duration. An effective DR scheduling algorithm should minimize the curtailment error - the difference between the targeted and achieved curtailment values - to minimize costs to the utility provider and maintain system reliability. The availability of smart meters with fine-grained customer control capability can be leveraged to offer customers a dynamic range of curtailment strategies that are feasible for small durations within the overall DR event. Both the availability and achievable curtailment values of these strategies can vary dynamically through the DR event and thus the problem of achieving a target curtailment over the entire DR interval can be modeled as a dynamic strategy selection problem over multiple discrete sub-intervals. We argue that DR curtailment error minimizing algorithms should not be oblivious to customer curtailment behavior during sub-intervals as (expensive) demand peaks can be concentrated in a few sub-intervals while consumption is heavily curtailed during others in order to achieve the given target, which makes such solutions expensive for the utility. Thus in this paper, we formally develop the notion of Sustainable DR (SDR) as a solution that attempts to distribute the curtailment evenly across sub-intervals in the DR event. We formulate the SDR problem as an Integer Linear Program and provide a very fast $\sqrt{2}$-factor approximation algorithm. We then propose a Polynomial Time Approximation Scheme (PTAS) for approximating the SDR curtailment error to within an arbitrarily small factor of the optimal. We then develop a novel ILP formulation that solves the SDR problem while explicitly accounting for customer strategy switching overhead as a constraint. We perform experiments using real data acquired from the University of Southern Californias smart grid and show that our sustainable DR model achieves results with a very low absolute error of 0.001-0.05 kWh range.

*This work has been funded by the U. S. Department of Energy under Award Number DE-OE0000192, the Los Angeles Department of Water and Power (LADWP) and the U.S. National Science Foundation under grant number ACI 1339756.

Keywords: Demand Response, Smart Grids, ILP, Customer Selection

1 Introduction

Recent technological advances have transformed traditional power grids into complex cyber-physical systems [7]. 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 reliability of their power grids.

Reliable operation of a power grid requires the utilities to constantly match (fluctuating) energy supply with (fluctuating) load. If demand exceeds the generation capacity of the utility, it becomes imperative for the utility to buy extra power from the spot market at higher rates thereby increasing its expenditure. Typically, peak power consumptions of several customers overlap during certain periods of a day. We refer to such periods as *peak demand periods*. During peak demand periods, the cumulative demand from customers in the grid might exceed the generation capacity of the utility. Therefore, utilities require sophisticated techniques to shift the consumption away from the peak demand period in order to avoid or minimize the expenditure of buying extra power.

Demand Response (DR) is a technique widely used by the utilities to curtail consumption during peak periods. Utilities enroll customers into DR programs. Enrollment in the DR can be voluntary: customers can be incentivised to curtail their demands, or it can be involuntary: customers can be penalized by increasing the tariffs. By reducing the consumption during peak periods, expenditure of the utility is minimized without compromising the system reliability.

A customer can adopt one of the several available strategies to curtail consumption. Strategies are actions such as turning down the air conditioner, dimming the lights which lead to reduction in power consumption. Using the data available from smart meters for each customer and using the state-of-the-art prediction techniques [3], utility can accurately predict the consumption of the customers during the peak periods. It can also predict the curtailment in consumption for each strategy a customer can adopt.

Selecting the right set of customer-strategy pairs to achieve a targeted curtailment value is critical for the success of a DR Event. The availability of smart controllers and meters with fine-grained customer control capability can be leveraged to offer customers a dynamic range of curtailment strategies that are feasible for small durations within the overall DR event. The objective function is defined such that it minimizes the aggregate deviation from the target as well as the maximum deviation from the smoothed average target. We refer to such a Demand Response event as *Sustainable Demand Response*. Sustainable Demand Response ensures that the DR-event is sustainable over the entire period.

The notion of Sustainable Demand Response is different from the existing works such as [11] which target the entire period to achieve the curtailment target. The limitation of such a Demand Response is that it tries to achieve an aggregate curtailment target over a period of time which may lead to aggressively curtailing demands in some intervals while accumulating demands in other intervals of the DR event. This could be unsustainable to the utility as certain intervals in which demands accumulate might exhibit a demand value which exceeds the generation capacity. We had previously formulated an Integer Linear Program(ILP) [10] for the problem of Demand Response targeting the entire DR period to bound the curtailment error: the difference between the achieved curtailment value and the targeted curtailment value which in some cases can be as high as 70% in the existing heuristics [12].

The contributions of this work are as follows:

- Formally define the notion of Sustainable Demand Response and empirically evaluate its advantages over the Demand Response which targets the entire period.
- Develop Integer Linear Programming formulation for Sustainable Demand Response to achieve

optimal minimum curtailment error: the difference between the achieved curtailment value and the targeted curtailment value.

- A Fast $\sqrt{2}$-factor approximation algorithm and a PTAS for the ILP formulations.
- Develop the notion of strategy overheads and formulate a novel ILP for Sustainable Demand Response with strategy overheads. This formulation takes into account that it may be uneconomical to rapidly switch strategies between intervals and thus limits the number of strategy switches by a customer during the DR event.

2 Related Work

Significant literature exists addressing the challenges, solutions, implementations and estimation methodology for calculating the energy savings for Demand Response (DR) [2, 16]. Early works focused on DR scheduling for individual residential cases [14] or household appliances [8]. 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 [13, 15], employing dynamic programming techniques for load management and minimizing peak load over a period [6], particle swarm optimization based techniques [17] and game theoretical solutions constrained by real time pricing [5] and customer comfort levels [4]. However, with data available from smart meters, work such as [18] 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 [19] develop a quadratic programming formulation for Demand Response which is then reduced into a distributed algorithm. The paper assumes the availability of continuous curtailment values. However, the practical DR implementation in USC's smartgrid allows only discrete curtailment values which forms the basis of modeling them as such in our work. This constraint makes the problem more complicated as the linear/quadratic program gets converted into an integer linear/quadratic program.

The authors in [11] propose a stochastic knapsack based algorithm for selecting customers to maximize the probability the desired curtailment value is achieved over the period of the entire DR event while limiting the utility's cost. 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.

The notion of achieving sustainable DR over a peak period divided into subintervals was proposed in [20] using a change making heuristic to evenly distribute curtailment over intervals. However, a detailed analysis (omitted due to space constraints) shows that it achieves consistency between intervals without reference to the target leading to unbounded errors which is also demonstrated by our experimental results.

3 Demand Response Formulation

We have discussed the problem of optimal customer selection for minimizing the curtailment error during the entire period of Demand Response extensively in one of our previous works [10]. We summarize the discussion for completeness.

We are given a set S 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 x_{ij} denote the corresponding decision variable. Let the achievable curtailment value across the entire DR event be γ. The problem can be formulated as an ILP as follows:

$$Minimize: \quad |\sum_{i=1}^{M}\sum_{j=1}^{N} c_{ij}x_{ij} - \gamma \,| \tag{1}$$

$$Subject\ to: \sum_{j=1}^{N} x_{ij} = \ 1 \qquad \forall i\ \{1,\ldots,M\} \tag{2}$$

$$x_{ij} \in \{0,1\}, \qquad \forall i,j$$

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 are provided in [10].

4 Sustainable Demand Response

4.1 Motivation

The algorithm mentioned in the previous section might aggressively curtail the demand in some intervals while accumulating demands in other intervals. Such assignments have peaks in certain intervals, which can possibly exceed the generation capacity forcing the utility to pay for additional procurement of energy.

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 S of M customers, N strategies. The entire DR period is divided into discrete time intervals. Dynamic customer strategies are represented by a time varying curtailment matrix $\mathbf{C}(\mathbf{t}) \in \mathbf{R}^{M\times N}$ with element $c_{ij}(t)$ denoting the discrete curtailment value of customer i adopting strategy j at time interval t where $t \in \{1,\ldots,T\}$. Let $\mathbf{X}(\mathbf{t})$ be the decision matrix with element $x_{ij}(t)$ denoting the corresponding decision variable at time t with γ denoting the achievable curtailment value across the entire DR event.

4.2 ILP Formulation for Sustainable DR

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

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

$$Subject\ to: |\sum_{i=1}^{M}\sum_{j=1}^{N} c_{ij}(t)x_{ij}(t) - \frac{\gamma}{T}\ | \leq \epsilon_t \qquad \forall t \tag{4}$$

$$\sum_{j=1}^{N} x_{ij}(t) = 1 \qquad \forall i,t \tag{5}$$

$$\forall x_{ij}(t) \in \{0,1\} \qquad \forall i,j,t$$

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. The various intervals in the ILP above are independent. This makes it trivial to parallelize by solving each interval as a separate optimization problem on a single node in a high performance cluster.

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

for *intervals* $t = 1$ *to* T **do**
- **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**
  - $X_{kj}(t) \leftarrow 1$;
  - `// Select customer` k `and curtailment strategy` $C_{kj}(t)$
- **else**
  - $(p, q_p) \leftarrow \text{argmin}_{i \in S, j \in C^{(i)}(t)} \{C_{ij}(t) | C_{ij}(t) \geq \gamma\sqrt{2}/T\}$;
  - `//` p `and` q_p `represent the customer and strategy indices of the customer with the smallest curtailment value` $\geq \gamma\sqrt{2}/T$
  - $Y_p \leftarrow C_{pq_p}(t)$;
  - For each customer $i \in S : k_i \leftarrow \text{argmax}_k \{C_{ik}(t) \leq \gamma/(T\sqrt{2})\}$;
  - Let r denote the smallest index such that $Y_r \leftarrow \sum_{i=1}^{r} C_{ik_i}(t); Y_r \geq \gamma/(T\sqrt{2})$;
  - $r \leftarrow M$ if $\sum_{i=1}^{M} C_{ik_i}(t) < \gamma/(T\sqrt{2})$;
  - `// Select Strategies for Activation as follows`
  - **if** $Y_p - \gamma\sqrt{2}/T \leq \gamma/(T\sqrt{2}) - Y_r$ **then**
    - Set $X_{pq_p}(t) = 1$;
  - **else**
    - **for** $i \leftarrow 1$ **to** r **do**
      - Set $X_{ik_i}(t) = 1$;

Output: Matrix $\{X(t)\}$ of selected customer-strategies $\forall t$. Bounded curtailment values $\widehat{\epsilon}_t \in [\frac{\tilde{\epsilon}_t}{\sqrt{2}}, \sqrt{2}\tilde{\epsilon}_t]$, where $\tilde{\epsilon}_t = \max(\epsilon_t^*, \gamma/T), \epsilon_t^*$ is the optimal solution to ILP.

4.3 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 and therefore for the entire DR event.

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

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.

4.4 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 unacceptably large in some cases. Therefore, using ideas from the subset sum problem [9] we 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.*

The proofs for the theorems have been omitted due to space constraints.

5 Sustainable DR with Strategy Overheads

5.1 Motivation

Driven by our experience with existing DR implementations on the USC smartgrid, we observe that it is impractical for customers to switch between too many strategies during the DR event as this leads to additonal overhead costs. We model this as an additional constraint in the ILP by using a new state transition variable that bounds τ, the number of times a customer can switch strategies between intervals. Note that under this formulation, a customer is likely to have contiguous strategies across intervals. In our experimental work section, we solve this ILP exactly for reasonable problem sizes (representing the USC microgrid) using the IBM CPLEX Solver. For very large problem sizes, the time required for an exact solution might be large. In such cases, one can use randomized rounding heuristics based on the LP-relaxation of the ILP to obtain approximate solution

5.2 ILP formulation for Sustainable DR with Strategy Overheads

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

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

$$Subject\ to: \mid \sum_{i=1}^{M}\sum_{j=1}^{N} c_{ij}(t)x_{ij}(t) - \frac{\gamma}{T} \mid \leq \epsilon_t \qquad \forall t \tag{7}$$

$$\sum_{j=1}^{N} x_{ij}(t) = 1 \qquad \forall i,t \tag{8}$$

$$x_{ij}(t) \in \{0,1\} \qquad \forall i,j$$

$$S_{ij}(t) = \mid x_{ij}(t) - x_{ij}(t-1) \mid \qquad \forall i,j,t \in \{2,\ldots,T\} \tag{9}$$

$$\sum_{t=2}^{T}\sum_{j=1}^{N} S_{ij}(t) \leq 2\tau \qquad \forall i \tag{10}$$

The new constraints to limit the strategy switching are introduced using 9 and 10 where 9 calculates the number of times customer i switches a particular strategy. Equation 10 bounds the total number of times a customer can switch strategies. Since the state variable $S_{ij}(t)$ counts both switching into and switching out from strategy j, equation 10 uses 2τ as the bound. In our experiments, we fix the value of $\tau = 2$.

Algorithm 2: PTAS for Sustainable DR during each interval t

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

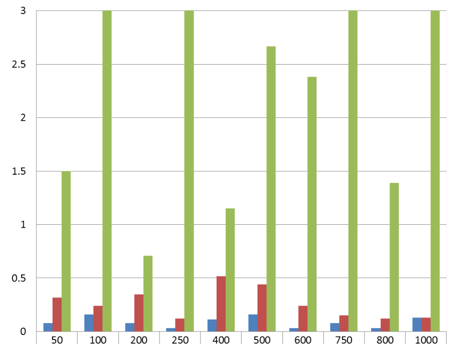
6 Experiments and Results

6.1 Evaluation Methodology

The objective of the ILPs formulated in this work is to minimize the curtailment error: difference between the targeted and achieved curtailment value. Since the ILPs are solved exactly, the respective errors are optimal. We compare the optimal minimal errors with the actual errors achieved by the state-of-the-art heuristic [20].

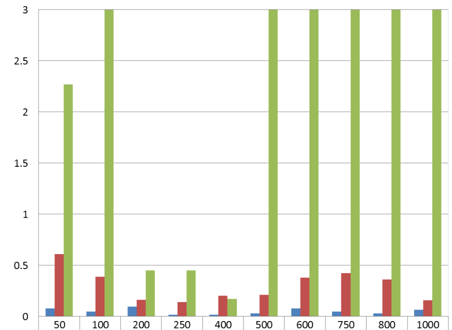
6.2 Experimental Setup

The model used for experimental setup is based on an existing DR implementation on the University of Southern California's (USC) smartgrid. The USC's smartgrid has over 50,000 smart meters which provide power consumption data for every 15 minute interval. 27 buildings are enrolled in the DR program and each building can adopt 1 out of 7 strategies. Demand Response events occur for 4 hours on weekdays from 1 pm to 5 pm. Using state-of-the-art prediction algorithms, the power consumption is predicted for each of the 27 buildings for the 4 hour horizon with very high accuracy. Moreover, the demand curtailment value for each customer-strategy pair is predicted for each time interval of the DR event. We use the Optimization Programming Language (OPL) to define the ILP formulations developed in this work in the IBM ILOG CPLEX software [1]. CPLEX produces the optimal assignment and reports the value of the objective function.



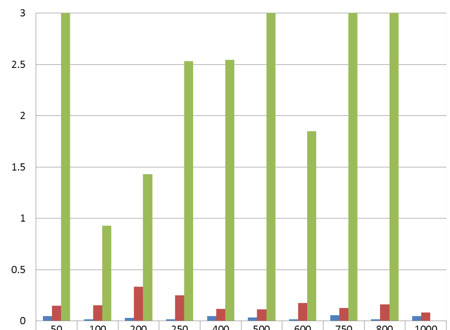
	50	100	200	250	400	500	600	750	800	1000
SDR	0.08	0.16	0.08	0.032	0.112	0.16	0.032	0.08	0.032	0.128
SDR with switch limit	0.317	0.24	0.346	0.122	0.516	0.44	0.241	0.15	0.121	0.13
State-of-the-art	1.499	3.101	0.709	8.056	1.15	2.665	2.382	8.426	1.391	3.528

(a) Absolute errors in kWh incurred for DR event on Monday 1-5 pm



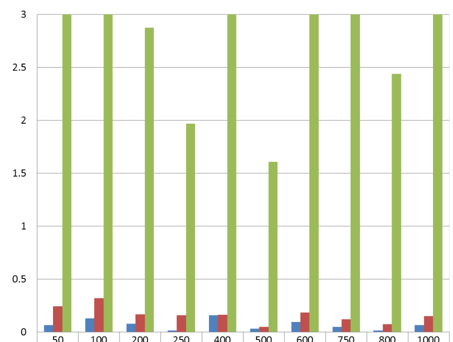
	50	100	200	250	400	500	600	750	800	1000
SDR	0.08	0.048	0.096	0.016	0.016	0.032	0.08	0.048	0.032	0.064
SDR with switch limit	0.608	0.389	0.164	0.142	0.203	0.211	0.381	0.423	0.364	0.159
State-of-the-art	2.27	8.896	0.45	0.452	0.172	7.859	6.342	3.189	6.649	5.241

(b) Absolute errors in kWh incurred for DR event on Tuesday 1-5 pm



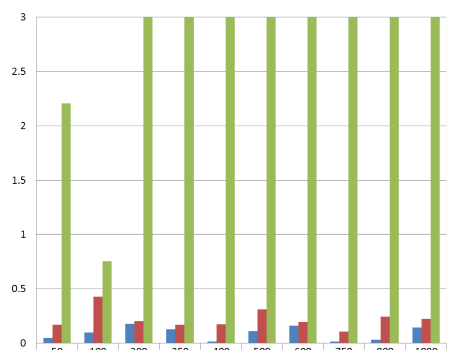
	50	100	200	250	400	500	600	750	800	1000
SDR	0.048	0.016	0.032	0.016	0.048	0.035	0.016	0.055	0.016	0.048
SDR with switch limit	0.148	0.153	0.333	0.249	0.119	0.116	0.175	0.128	0.161	0.083
State-of-the-art	4.388	0.929	1.431	2.533	2.547	4.302	1.85	9.225	3.673	0.001

(c) Absolute errors in kWh incurred for DR event on Wednesday 1-5 pm



	50	100	200	250	400	500	600	750	800	1000
SDR	0.064	0.128	0.08	0.016	0.16	0.032	0.096	0.048	0.016	0.064
SDR with switch limit	0.242	0.32	0.166	0.157	0.164	0.049	0.186	0.12	0.073	0.15
State-of-the-art	4.325	3.191	2.874	1.969	4.298	1.607	31.068	3.576	2.441	4.117

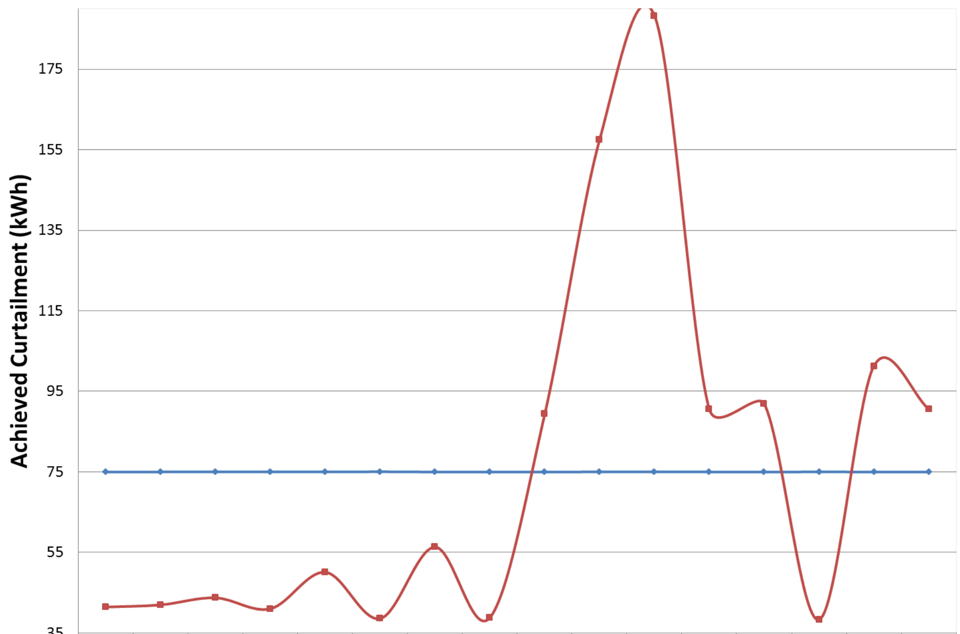
(d) Absolute errors in kWh incurred for DR event on Thursday 1-5 pm



	50	100	200	250	400	500	600	750	800	1000
SDR	0.048	0.096	0.176	0.128	0.016	0.112	0.16	0.016	0.032	0.144
SDR with switch limit	0.168	0.426	0.204	0.17	0.175	0.309	0.195	0.106	0.242	0.223
State-of-the-art	2.206	0.755	7.168	9.007	10.426	6.443	6.002	7.031	5.465	5.894

(e) Absolute errors in kWh incurred for DR event on Friday 1-5 pm

Figure 1: Absolute Error (kWh) incurred for Target values 50-1000 kWh in DR Events



	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
SDR	74.98	75	75	75.03	75	75.05	74.98	74.98	74.96	75.03	75	75	74.96	75.03	74.98	75
TDR	41.45	42	43.75	41.03	50.12	38.59	56.35	38.82	89.4	157.5	188.3	90.57	91.93	38.34	101.3	90.6

(a) Comparison of demand curtailment values achieved in each interval for SDR and TDR for the targeted curtailment value of 1200 kWh

6.3 Sustainable DR

In Figures 1a-1e, we compare the absolute errors in kWh incurred by the Sustainable Demand Response (SDR) ILP formulation and the state-of-the-art heuristic for Targeted curtailment values ranging from 50-1000 kWh. The vertical axis is limited to a maximum error of 3.0 kWh to ensure the readability of the graph. The actual error values are given in the table below the graphs.

Our SDR ILP is more restrictive as it ensures that the curtailment is distributed evenly across the intervals which is not a constraint in the state-of-the-art heuristic. Despite this restriction, our SDR ILP perform 4-2000 times better than the heuristic. The only time the heuristic performs better than our ILP is on Wednesday for a Target of 1000 kWh where the error of our SDR ILP is 0.048 kWh while that of the heuristic is 0.001 kWh.

To emphasize the significance of Sustainable DR over a DR targeting the entire interval, we compare the demand curtailment values achieved in each interval for the DR event for the targeted curtailment value of 1200 kWh. The DR ILP targeting the entire interval (TDR) incurs an error of 0.002 kWh which is far lower that the 0.031 kWh error incurred by the Sustainable DR ILP. However, most of the curtailment is achieved in intervals 10 and 11 and the rest of the intervals have lower curtailment values. The Sustainable DR achieves a curtailment value of around 75 kWh in each interval.

6.4 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 to $\tau = 2$. In Figures 1a-1e, we compare the absolute errors in kWh incurred by the Sustainable Demand Response with limits on strategy switching (SDR with switch limit) ILP formulation and the state-of-the-art heuristic for Targeted curtailment values ranging from 50-1000 kWh. The vertical axis is limited to a maximum error of 3.0 kWh to ensure the readability of the graph. The actual error values are given in the table below the graphs.

The SDR with strategy overheads is even more restrictive than the SDR ILP. This is reflected in the errors incurred which are an order higher than the SDR ILP. However, SDR with strategy overheads still performs 2-700 times better than the state-of-the-art heuristic. The only times the heuristic performs better than our ILP is on Wednesday for a Target of 1000 kWh where the errors 0.083 kWh and 0.001 kWh respectively and on Tuesday for a Target of 400 kWh where the errors are 0.203 kWh and 0.172 kWh respectively for our ILP and the heuristic. The maximum relative error incurred by our ILPs is 1% whereas for the heuristic we observed relative errors as high as 12 %.

ILP is a computationally intensive process. To converge to the error rates shown in the results, the IBM CPLEX required 5-10 minutes of processing time. Since DR programs are based on predictive data [3] 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.

7 Conclusion

In this work, we formulated the problem of customer selection for Demand Response as Integer Linear Programs (ILP). We motivated the need for the Sustainable Demand Response by experimentally showing the cases where the Demand Response which targets the entire period 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 solutions with low errors even in the cases where the existing heuristics produce unbounded errors. We also provided a 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] Ilog cplex optimization studio. Online: http://www-01.ibm.com/support/knowledgecenter/SSSA5P/welcome.

[2] Mohamed H Albadi and EF El-Saadany. Demand response in electricity markets: An overview. In *IEEE power engineering society general meeting*, volume 2007, pages 1–5, 2007.

[3] Saima Aman, Charalampos Chelmis, and Viktor K Prasanna. Influence-driven model for time series prediction from partial observations. In *Twenty-Ninth AAAI Conference on Artificial Intelligence*, 2015.

[4] Antimo Barbato, Antonio Capone, Lin Chen, Fabio Martignon, and Stefano Paris. A power scheduling game for reducing the peak demand of residential users. In *Online Conference on Green Communications (GreenCom), 2013 IEEE*, pages 137–142. IEEE, 2013.

[5] Jiang Chen, Bo Yang, and Xinping 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*, pages 546–551. IEEE, 2012.

[6] Arthur I Cohen and Connie C Wang. An optimization method for load management scheduling. *IEEE Trans. Power Syst.;(United States)*, 3(2), 1988.

[7] Ayman Z Faza, Sahra Sedigh, and Bruce M McMillin. *Reliability modeling for the advanced electric power grid*. Springer, 2007.

[8] Nikolaos Gatsis and Georgios B Giannakis. Cooperative multi-residence demand response scheduling. In *Information Sciences and Systems (CISS), 2011 45th Annual Conference on*, pages 1–6. IEEE, 2011.

[9] Oscar H Ibarra and Chul E Kim. Fast approximation algorithms for the knapsack and sum of subset problems. *Journal of the ACM (JACM)*, 22(4):463–468, 1975.

[10] Sanmukh R Kuppannagari, Rajgopal Kannan, and Viktor K Prasanna. An ilp based algorithm for optimal customer selection for demand response in smartgrids. In *The 2015 International Conference on Computational Science and Computational Intelligence (CSCI)*, 2015.

[11] Jungsuk Kwac and Ram Rajagopal. Demand response targeting using big data analytics. In *Big Data, 2013 IEEE International Conference on*, pages 683–690. IEEE, 2013.

[12] Jungsuk Kwac and Ram Rajagopal. Targeting customers for demand response based on big data. *arXiv preprint arXiv:1409.4119*, 2014.

[13] Loren Lutzenhiser, Laura Cesafsky, Heather Chappells, Marcia Gossard, Mithra Moezzi, Dulane Moran, Jane Peters, Mersiha Spahic, Paul Stern, Elizabeth 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.

[14] Federica Mangiatordi, Emiliano Pallotti, Paolo Del Vecchio, and Fabio Leccese. Power consumption scheduling for residential buildings. In *Environment and Electrical Engineering (EEEIC), 2012 11th International Conference on*, pages 926–930. IEEE, 2012.

[15] Steven J Moss, M Cubed, and Kerry Fleisher. Market segmentation and energy efficiency program design. *Berkeley, California Institute for Energy and Environment*, 2008.

[16] Farrokh Rahimi and Ali Ipakchi. Demand response as a market resource under the smart grid paradigm. *Smart Grid, IEEE Transactions on*, 1(1):82–88, 2010.

[17] Arnaldo Sepulveda, Liam Paull, Walid G Morsi, Howard Li, CP Diduch, and Liuchen Chang. A novel demand side management program using water heaters and particle swarm optimization. In *Electric Power and Energy Conference (EPEC), 2010 IEEE*, pages 1–5. IEEE, 2010.

[18] Brian Artur Smith, Jeffrey Wong, and Ram 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.

[19] Pirathayini Srikantha and Deepa Kundur. Distributed demand curtailment via water-filling. In *IEEE International Conference on Smart Grid Communications*, 2015.

[20] Vasileios Zois, Marc Frincu, Charalampos Chelmis, Muhammad Rizwan Saeed, and Viktor Prasanna. Efficient customer selection for sustainable demand response in smart grids. In *IGCC*, pages 1–6. IEEE, 2014.