An ILP based Algorithm for Optimal Customer Selection for Demand Response in SmartGrids

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***Abstract*—Demand Response (DR) events are initiated by utilities during peak demand periods to curtail consumption. They ensure system reliability and minimize the utility's expenditure. Selection of the right customers and strategies is critical for a DR event. An effective DR scheduling algorithm minimizes the curtailment error which is the absolute difference between the achieved curtailment value and the target. State-of-the-art heuristics exist for customer selection, however their curtailment errors are unbounded and can be as high as 70%. In this work, we develop an Integer Linear Programming (ILP) formulation for optimally selecting customers and curtailment strategies that minimize the curtailment error during DR events in SmartGrids. We perform experiments on real world data obtained from the University of Southern California's SmartGrid and show that our algorithm achieves near exact curtailment values with errors in the range of 10^{-7} to 10^{-5}, which are within the range of numerical errors. We compare our results against the state-of-the-art heuristic being deployed in practice in the USC SmartGrid. We show that for the same set of available customer-strategy pairs our algorithm performs 10^3 to 10^7 times better in terms of the curtailment errors incurred.**

Keywords: Demand Response, SmartGrid, Integer Linear Programming

CSCI-ISOT: Late Breaking Papers

I. Introduction

With the advent of advanced metering technologies such as smart meters, the traditional power grids have transformed into complex interconnection systems. Smart meters allow fine grained control and monitoring of customer consumption by utilities [1], [2]. By employing various data processing tools such as time series prediction [3], complex event processing [4] etc., the information collected from smart meters can be used to improve grid efficiency and reliability.

Utilities have to ensure reliable power supply while minimizing their expenditure. For system reliability, it is absolutely critical that power demand from customers is met. If demand exceeds the generation capacity of the utility, extra power needs to be bought from the spot market at higher rates, which increases the expenditure of the utility.

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Typically, peak power consumption of several customers in the grid overlap during certain periods of the day, for example, afternoon on a hot summer day. Such periods are referred to as *peak demand periods*. During peak demand periods, the power demand might exceed the generation capacity. To avoid buying extra power from the market, utilities require techniques that shift the consumption away from the peak periods.

Demand Response is a widely used technique by the utilities to reduce power consumption during peak periods. It is defined by the Federal Energy Regulatory Commission as, "Changes in electric usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity over time, or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized" [5]. Utilities roll out Demand-Response programs and enroll customers into it. The participation can be voluntary, the customers can be incentivised to curtail their consumption during the peak periods or it can be involuntary, the electricity rates of the peak periods can be increased to discourage customers from consuming a lot of power. In either case, by reducing the power consumption during peak periods, the expenditure of the utility is minimized while ensuring system reliability.

Now imagine that an apartment owner is contacted by the utility company asking her to curtail the power consumption from 1 to 5 pm everyday by 20 kWh. Given that her daily power consumption would not exceed that amount, it is infeasible for her to comply. Therefore for managing DR events, utilities assign each customer with a set of strategies corresponding to a range of curtailment values within their abilities. These strategies could include actions such as turning off the AC or switching off some of the lights. Meeting the overall curtailment target requires the utilities to carefully select customers and their corresponding strategies using this information.

State-of-the-art heuristics exist to address the problem of customer selection for Demand Response. However, the errors of such heuristics are unbounded and can be as high as 70% as mentioned in [6]. In this work, we define an Integer Linear Programming (ILP) formulation for the problem of optimal customer selection for Demand Response. The customer selection is optimal as it minimizes the curtailment error which is the difference between targeted curtailment and the achieved curtailment. We run experiments on real world data obtained by the University of Southern California SmartGrid and show that the curtailment errors are in the range of 10^{-7} to 10^{-5}. Compared with the state-of-the-art heuristic being deployed in practice, for the same set of customer strategy pairs, we perform 10^3 to 10^7 times better in terms of the curtailment errors incurred.

The rest of the paper is organized as follows: Section II details the work done in the research community related to Demand Response in SmartGrids. Section III defines the problem and also provides motivation for the same. Section IV demonstrates our experimental results on USC SmartGrid and Section V concludes our work with some details about the future plans.

II. Related Work

A survey of Demand Response including its definition; benefits and costs; and its measurement is provided in [7]. Other works such as [8] and [9] study the challenges involved in Demand Response, and develop estimation methodologies to calculate the energy savings.

Several works have focused on optimizing Demand Response scheduling from a customer perspective. Authors in [10] focus on scheduling consumption for individual residential buildings. In [11], authors focus on scheduling consumption for a multi-residential cooperative. In [12], authors use Artificial Intelligence to model customer response to dynamic pricing for Demand Response events. Experts system theory is employed in [13] for determining suitable customer response. However, these works focus on Demand Response from a customer perspective and hence are unsuitable for performing grid level global optimization.

Traditionally, customers were targeted based on the aggregate data obtained by their billing data or customer surveys [14], [15]. However, with the availability of smart meters, a more accurate means to measure customer consumption has become available [16], [17].

Authors in [18] consider a game theoretical approach constrained by real time pricing. In [19], authors apply particle swarm optimization based technique for customer scheduling. Customer comfort level is considered in works such as [20].

Several dynamic programming and heuristic based algorithms have also been developed for the problem of optimal customer selection. Authors in [21] use dynamic programming algorithm for minimizing peak load over a period. In [22], authors formulate the problem as an Integer Quadratic Programming and develop a heuristic for the same. A stochastic knapsack based approach is proposed by authors in [23]. A change making scheduler based algorithm is proposed in [24].

The problem with heuristic based approaches is that their errors are unbounded. For instance, in [23], the error is unbounded for smaller number of customers. 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. Using Integer Linear Programming based algorithm allows us to provide solutions with bounded errors.

III. Customer Selection for Demand Response

A. Motivation

A SmartGrid is typically operated by a utility. The utility is responsible for providing power, controlling and monitoring the SmartGrid. The utility provider has a fixed power generation capacity. Typically, this capacity is sufficient to fulfill the power requirements of the customers. However, when there is a surge in the demand from the customers, the utility needs to ensure that the demand is met by either adding generators or purchasing extra power from the spot market, both of which increase expenditure. Failure to do so compromises the system reliability and leads to blackouts.

Power consumption profile of a customer varies throughout the day with periods of high demand interspersed with periods of low power consumption. Certain periods of the day observe an overlap between the high demands of several customers. We denote such periods with the power requirement of the grid substantially higher than the rest of the day as peak demand period. The demand in a peak period can exceed the power generation capacity.

To minimize or avoid the expenditure of purchasing extra power during peak demand periods, utilities adopt the technique of Demand Response. Customers are either incentivised to reduce their consumption during a Demand Response Event (DR-Event) or they are penalized by increasing the cost of power during these periods. This reduces the peak power consumption which is now expected to be met by the available generation capacity.

Using smart meters, utilities have the power consumption data of each customer. The granularity of the data can be as small as 15 minutes. The power consumption profile of a customer does not change rapidly from day to day, so it is straightforward to predict future pattern. By employing prediction techniques, utilities determine the peak demand periods. They also determine the targeted curtailment required for a DR-Event which should be scheduled during this period. Discussion on the prediction techniques is beyond the scope of this paper. Readers can refer to [3] for further knowledge on this topic.

Utilities roll out a program to implement Demand Reponse and enroll customers into it. A customer is provided with a list of strategies to be followed each of which leads to a certain amount of curtailment in power consumption. Strategies can include procedures such as increasing the temperature of the AC systems by 2 degrees or turning off every other light in the hallways, etc. which reduce power consumption. During a DR-Event, the utility signals each customer to follow a particular strategy. A customer may be penalized if it fails to comply. For instance, the University of Southern California SmartGrid consists of 50,000 sensors across the 170 buildings to monitor electricity usage. Each building can adopt any one of seven available strategies during DR events which occur on Weekdays 1-5 pm [25].

Careful selection of customers is required to ensure that the targeted curtailment value is met. A good customer selection algorithm determines the subset of customers along with the strategies they should follow during the DR-Event such that the achieved curtailment value is as close as possible to the target. The reasons are as follows:

1) Limiting the amount by which the achieved curtailment value *overshoots* the target ensures that the grid is not underutilized. This avoids any loss of revenues to the utility due to underutilization of grid by aggressive curtailment.
2) Limiting the amount by which the achieved curtailment value *undershoots* the target ensures that the utility can avoid purchasing power from external sources by bounding the peak demand of the customers.

B. Problem Definition

We formally define the problem of optimal customer selection for Demand Response using the parameters defined in Table I. We are given a list of M customers and N strategies. Each customer can adopt exactly one strategy in the DR event. The decision variable x_{ij} is 1 if customer i adopts strategy j. We are also given the curtailment in power consumption c_{ij} obtained by customer i adopting strategy j. A default strategy with a curtailment value of 0 is also included in the curtailment matrix $\mathbf{C}$. A customer adopting a default strategy essentially means that it is not participating in the DR event.

A targeted curtailment value γ for the DR event is provided. The objective it to achieve a curtailment value as close to γ as possible. The ILP formulation for this problem is as follows:

$$Minimize: \mid \sum_{i=1}^{M} \sum_{j=1}^{N} c_{ij} * x_{ij} - \gamma \mid \qquad (1)$$

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

$$x_{ij} \in \{0, 1\}, \qquad \forall i, j \qquad (3)$$

Equation 1 minimizes the absolute curtailment error. Equation 2 ensures that a customer cannot adopt more than one strategy in the DR event. Detailed experimental results for customer selection using the above ILP is shown in Section IV.

IV. Experimental Results

A. Experimental Setup

The USC SmartGrid has over 50,000 sensors to monitor electricity usage and equipment status in real time [25]. Demand Response Events occur on weekdays between 1 and 5 pm. We use the data collected by the software developed to support data-driven demand response optimization in USC smartgrid [26]. The software provides us the curtailment values for each strategy that can be adopted by any building (customer) in USC for the queried time interval. For our experiments we use the data from 27 buildings each of which can adopt one of seven strategies. The data is collected for the time intervals 1-3 pm and 3-5 pm for each day from Monday to Friday. We run our experiments for Targeted Curtailment values ranging from 100 kWh to 1400 kWh.

TABLE I: Problem Parameters

Parameter Name	Description
M	Number of customers
N	Number of strategies for each customer
$\mathbf{C}$	$M \times N$ matrix. Element $c_{ij} \in \mathbf{R}$ is curtailment value of a customer i strategy j pair for the DR event.
$\mathbf{X}$	Decision variable for the DR event. Element $x_{ij} \in \{0, 1\}$ is the decision variable for customer i adopting strategy j.
γ	Desired Curtailment value across the entire DR event.

We use the Optimization Programming Language [27] to define the Integer Linear Programming formulation developed in this paper. IBM ILOG CPLEX optimization software [28] is used to solve the ILP and produce the set of customers and the strategies they should adopt.

We compare our results with the state-of-the-art heuristic [24]. Authors in [24] develop a change making problem based algorithm for customer selection. The change making problem determines how to make a given amount of money using the least amount of coins. The coins in the algorithm are the available customer-strategy pairs and their values the predicted curtailment values. The amount to be made is the targeted curtailment value. Customers are grouped into bins differentiated by their values. A greedy algorithm is used to pick customers from the bins with highest values. We choose this heuristic for comparison as it is used in practice by the USC SmartGrid to schedule customers and their strategies for the DR events.

B. Results and Analysis

The power consumption profile of a building is similar for the same day of a week across different weeks. So by running our experiments on data collected from DR events over a week, we are able to demonstrate our algorithm on a wide range of power consumption profiles. Moreover, a typical DR-event in the USC SmartGrid starts with the selection procedure at 1 pm and then another selection occurs typically around 3 pm. Therefore, we consider them as two separate DR events for our experiments.

Figure 1a and 1b show the errors incurred by our ILP based customer selection algorithm and the State-of-the-art heuristic [24] for every DR event from Monday to Friday for various curtailment target values. As shown in Figure 1a, the highest error incurred by our ILP based algorithm is around 0.0002 kWh during the DR-events on Tuesday 1-3 pm for a targeted curtailment of 600 kWh and Friday 3-5 pm for a targeted curtailment of 800 kWh. For the State-of-the-art heuristic, the highest error incurred is around 8 kWh during the DR event on Tuesday 3-5 pm for the targeted curtailment of 400 kWh as shown in Figure 1b.

One may note that the errors between the state-of-the-art heuristic and our approach differ by multiple orders of magnitude. so we take the ratio of the error for comparison. A higher value of ratio implies better performance by our approach. In Figures 2a-6b we compare the errors incurred by the two algorithms for various targeted curtailment value for each DR event

The customer selection problem can be visualized as a packing problem. We are trying to pack the targeted curtailment with values obtained from the customer-strategy pairs. The ILP produces the best possible packing. Any error is due to the nature of the data. Similarly, the heuristic based approach tries to provide best packing in each of the bins. Error incurred in packing each bin accumulates throughout the algorithm and may lead to very large errors. Since we are using real world data, as seen in the Figures 2a-6b the peaks in the ratio of errors for various DR events varies with the targeted curtailment values with no discernible pattern. The highest ratio observed is around 3×10^7 which occurs during the DR event on Thursday 1-3 pm.

Although solving an ILP is computationally intensive, optimal customer selection for each target was obtained in less than 5 seconds on a standard workstation. This time can be significantly reduced by using sophisticated computational platforms. Note that in a typical DR Event, the utility determines the curtailment target well in advance. Thus even a 5 second delay in computing the optimal customer-strategy pairs and signaling the customers is tolerable.

V. Conclusion

Optimal customer selection is critical for maintaining system reliability and minimizing utility expenditure in a SmartGrid. The heuristic based algorithms developed so far to address this problem may lead to unbounded errors in some cases which is unacceptable. By developing an Integer Linear Programming (ILP) based algorithm, we guarantee that the error is minimized. In practice, the error is close to zero which we have substantiated quantitatively by running experiments on real data from USC SmartGrid.

Our future work will focus on developing techniques to scale the ILP based algorithm for larger grid sizes. Several other objectives such as customer comfort level, strategy switching overhead will also be incorporated.

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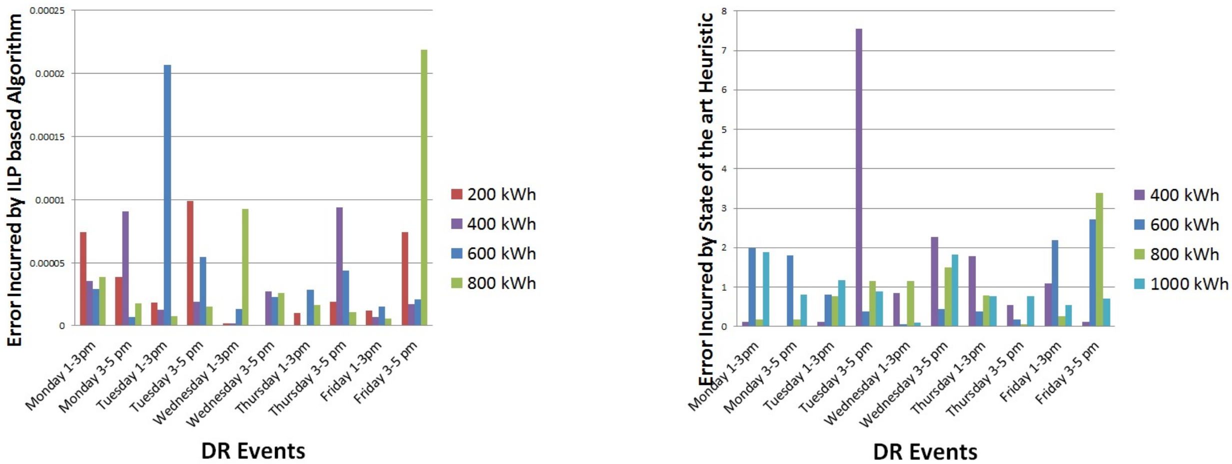
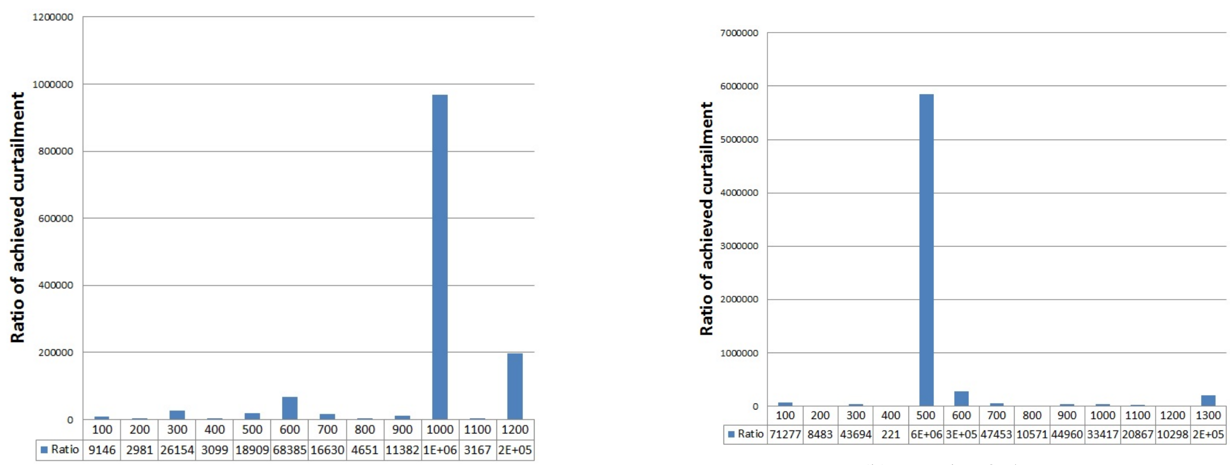


(a) ILP based Algorithm

(b) State-of-the-Art Algorithm

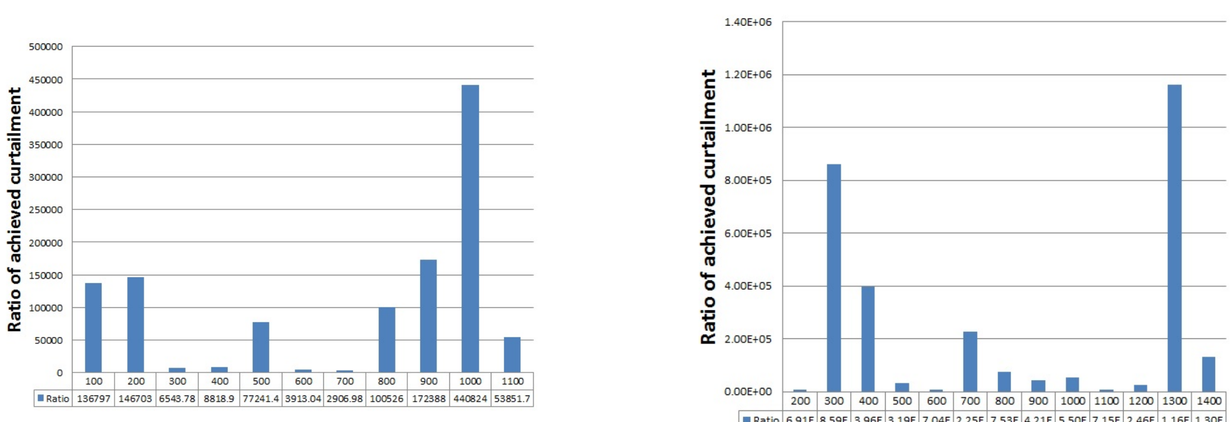
Fig. 1: Error incurred by ILP based Algorithm and State-of-the-art Algorithm for various targeted Curtailment Values for Different DR Event



(a) Monday 1-3 pm

(b) Monday 3-5 pm

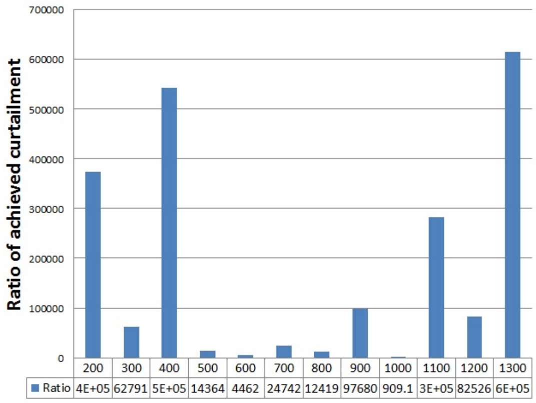
Fig. 2: Ratio of error of State-of-the-art Heuristic and ILP algorithm for DR events on Monday



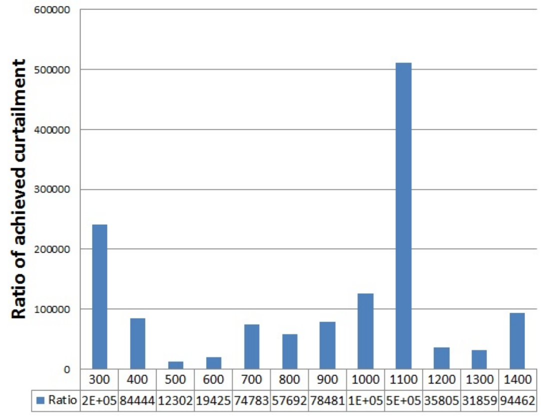
(a) Tuesday 1-3 pm

(b) Tuesday 3-5 pm

Fig. 3: Ratio of error of State-of-the-art Heuristic and ILP algorithm for DR events on Tuesday

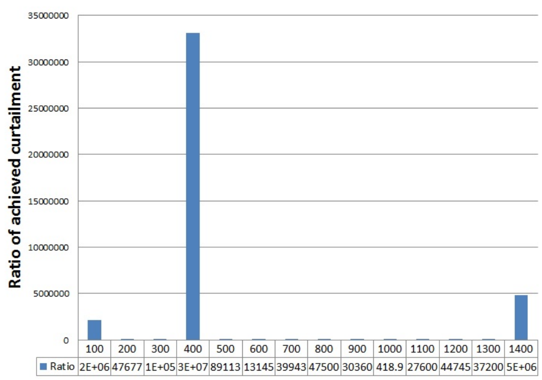


(a) Wednesday 1-3 pm

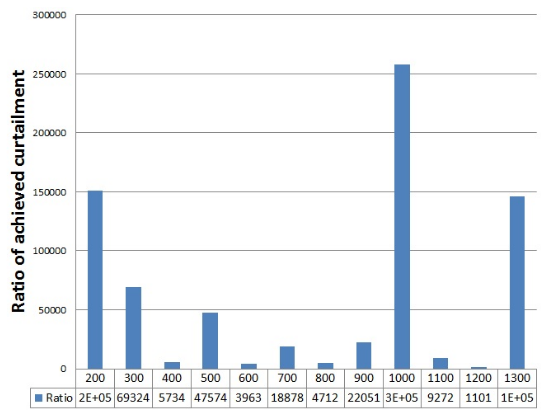


(b) Wednesday 3-5 pm

Fig. 4: Ratio of error of State-of-the-art Heuristic and ILP algorithm for DR events on Wednesday

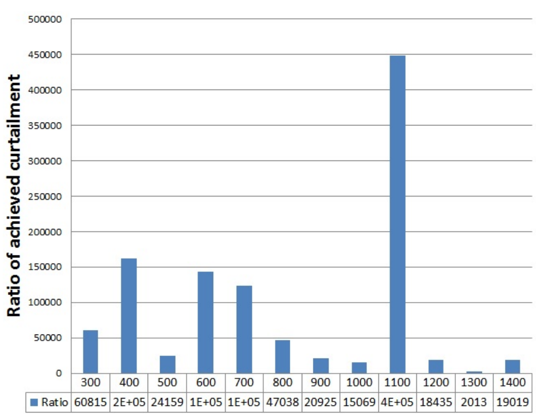


(a) Thursday 1-3 pm

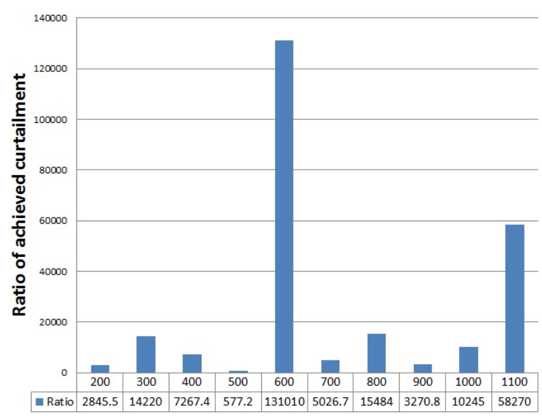


(b) Thursday 3-5 pm

Fig. 5: Ratio of error of State-of-the-art Heuristic and ILP algorithm for DR events on Thursday



(a) Friday 1-3 pm



(b) Friday 3-5 pm

Fig. 6: Ratio of error of State-of-the-art Heuristic and ILP algorithm for DR events on Friday