Scheduling Schedulable Energy in Smart Grid

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Abstract. Real-time pricing's total cost minimization problem is studied in this paper at a neighborhood area network level in smart grid. We propose a mathematical energy scheduling model for real-time pricing demand response, and based on which, a distributed energy consumption scheduling algorithm for total cost minimization is proposed.

Keywords: Demand response, real-time pricing, energy consumption scheduling, total cost minimization, neighborhood area network

1 Introduction

One of the most popular and promising areas within smart grid is the field of demand response [1]. This research area hides the potential key to the next stage of a more efficient smart grid. It also offers possibilities for the customers to receive a smaller and more manageable bill, which in return will further encourage current and potential customers to utilize their smart-grid-compatible appliances [2]. Along with the development of smart meter and two-way communication schemes are also developed methods for near real-time energy consumption scheduling [3]. Regardless of the mentioned achievements, there are still problems and challenges remain yet to be solved. Among them the main problem that requires a timely solution in demand response is the real-time demand response issue [4]. Demand response issue has a couple of challenges to it, with the first being customers' participation [5, 6]. The improvements on real-time demand response, in return, concern the customers as well. With the introduction of the Plug-in Hybrid Electric Vehicle (PHEV) into smart grid [7], a regular customer can now be both a power consumer and/or a power supplier. The second challenge of the demand response issue is real-time pricing (RTP). Schemes, such as Time-of-Use Pricing (TOUP) scheme [8], Critical Peak Pricing (CPP) scheme [9], [10], and Day-Ahead Pricing (DAP) scheme [11] that perform parts of RTP's function have enabled the customers to lower their power costs and have more flexibility with their power usage. But the challenge of RTP, that is the fact the customers might not be able to know the future power price, remains [12]. In real-time demand response system, price prediction challenges are preventing the system from minimizing customers' bills using the RTP scheme [5].

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In a scenario where the customer can manage its smart appliances energy consumption using smart home console while the demand response program is transparent to it, instead of having the customer worry about how to optimize the load management to reduce the bill payment, the demand response program will provide the automatic energy scheduling functionality to it. In this scenario, the customer wants to do laundry and tells the washer to wash using real-time demand response program. Then the washer communicates with the smart home automation console with a desired task schedule based on the customer's predefined settings on the washer and the smart home console.

All the appliances are controlled by the energy consumption scheduling console system. This is the system that assists the customers with their scheduling for energy consumption. A good schedule of energy consumption will not only save the customer a lot of dollars, but also reduce possible pressure that the power grid receives during peak hours [13].

Here we assume that only the schedulable energy is considered in this paper. This scenario assumes the energy consumption scheduling system has the ability to pause or resume. This paper proposes a real-time demand response system and its matching distribution energy consumption scheduling algorithms that aim at solving the total cost minimization problem. Forthcoming discussion about the problem and its solutions will also be hosted in the above-mentioned energy consumption scheduling system setup.

The reset of the paper was organized as follows. Section 2 discussed related works that have been done previously in the field of energy scheduling. Section 3 presents the system model. Section 4 provides the problem statement and the proposed solutions to the problems. Simulations and analysis will be found in Section 5. Finally, Section 6 will conclude this paper.

2 Related Work

Traditional demand response is achieved through Supervisory Control and Data Acquisition (SCADA) infrastructure [14], but it is not as real-time as in smart grid environment. Real-time demand response requires the power provider to update retail power price at each timeslot level for all the customers. Furthermore, it also obliges each customer to report load consumption to the power provider at each timeslot.

In most researches, the methods of achieving demand response through energy consumption scheduling can be grouped into two categories: task scheduling and energy-based scheduling [5]. A task scheduling method focuses on scheduling the fixed load requests throughout the timeline, while an energy-based scheduling method focuses on scheduling flexible load requests throughout the timeline [5]. The flexible load requests mean that load requests can be partially consumed and rescheduled throughout the timeline. It gives more flexibility to the customers on the energy consumption scheduling. For example, the paper [15] proposes an autonomous Demand-Side Management (DSM) framework to solve the optimization problem of reducing the utility's operational cost with an energy consumption scheduling algorithm. But in reality, sometimes customers do not fully trust each other, especially those within the same network, due to potential privacy leaking issues [16, 17, 18]. Moreover, it is important to realize that in their study, incentives are offered to the participants as the proposed pricing scheme to encourage the use of the energy consumption scheduling devices. However, this pricing scheme is linearly proportional to the load that each customer uses, but in reality the power price is not always proportional to the customers load consumption, especially during the peak-time of the utility. In addition, the work in [15] focuses on energy consumption scheduling of the appliances within a household instead of that of the whole neighborhood area network.

The paper [19] also introduces an energy consumption scheduling framework with optimal solutions to reduce the total cost and the peak-to-average-ratio (PAR) of the system when all the customers share their complete load profile. On the other hand, they also took the customers' concern about privacy into consideration and come up with distributed stochastic strategies that will extract partially enough information to improve the overall load profile. The strategies in [19] are considering how to minimize the power provider's cost and PAR without trying to motivate the customers. Their schemes may have some insights into modeling of customers autonomous energy consumption scheduling within neighborhood area network distribution network and it has the optimal goal of minimizing the utility's operational cost. But if one considers how the customers, instead of the power grid, are playing the center role of successful demand response, the challenges would be the lack of methods focusing on reducing customers' cost.

3 System Model

3.1 Customer Model

Assume that there are N customers in a Neighbor Area Network (NAN), denoted as $1, 2, ..., i, ...N$. Assume that time is divided into timeslots, and therefore let timeslot j denote the time period $[(j-1)\Delta t, j\Delta t)$, where $j = 1, 2, ...,$ and Δt is a unit time per timeslot. Assume that all the load demands from customers are schedulable power loads and they are known at the beginning of each timeslot. For customer i, its *demand of power load* at timeslot j is defined as $l_i(j)$ where $j = 1, 2, ...$ and $0 \le l_i(j) < l_i^{\max}(j)$, where $l_i^{\max}(j)$ denotes the *maximum load capacity* that the customer i can handle, which is normally a constant defined by each customer's setup of its own power system.

At each timeslot, all the customers send their load demand requests to the power provider. Then they wait for the power provider's response of the current power price. In the real-time price (RTP) scheme, each customer has the opportunities to dynamically schedule its load at each timeslot. The energy consumption scheduling algorithm exists and it uses load demand $l_i(j)$ and RTP power price as inputs and how much load they consume as outputs.

Let $o_i(j)$ denote the *actual energy consumption* of customer i at time slot j, and we have either $0 \le o_i(j) \le l_i(j)$ or $o_i(j) > l_i(j)$. if customer i consumes the energy within the *load demand* of j timeslot $l_i(j)$, then $0 \le o_i(j) \le l_i(j)$ holds. On the other hand, if customer i actually consumes not only all the *load demand* of j timeslot $l_i(j)$, but also the delayed load demand from previous timeslots, then $o_i(j) > l_i(j)$ holds. Let $b_i(j)$ denote the *instantaneous bill payment* for customer i at time slot j, and it is calculated as follows.

$$b_i(j) = o_i(j) \cdot p(j). \tag{1}$$

Let $B_i(j)$ denote the *normalized bill payment* of customer i during time period $[0, j\Delta t)$ and it is calculated as follows,

$$B_i(j) = \sum_{k=1}^{j} o_i(k) \cdot p(k). \tag{2}$$

3.2 Power Provider Model

Assume that there is only one power provider within the power distribution system. For the power provider, it receives the *load requests* $l_1(j), l_2(j), ..., l_N(j)$ from all the customers at timeslot j. Let the $a(j)$ denote *instantaneous aggregate load* of the power provider and is defined as

$$a(j) = \sum_{i=1}^{N} o_i(j). \tag{3}$$

Let $A(j)$ denote the *accumulative* agg*regated power load* of the power provider at time slot j and it is defined as

$$A(j) = \sum_{k=1}^{j} a(k) = \sum_{k=1}^{j} \sum_{i=1}^{N} o_i(k). \tag{4}$$

The above is the actually consumed aggregated load $A(j)$, but the aggregated original load demand also needs to be defined. Let $e(j)$ denote the *instantaneous aggregated load demand* of the power provider requested by all the customers $\{1, 2, ..., i, ...N\}$ at timeslot j. It can be calculated as

$$e(j) = \sum_{i=1}^{N} l_i(j). \tag{5}$$

Let $E(j)$ denote the *accumulative aggregated load demand* for the duration from timeslot 1 to timeslot j. It can be calculated as

$$E(j) = \sum_{k=1}^{j} e(k) = \sum_{k=1}^{j} \sum_{i=1}^{N} l_i(k). \tag{6}$$

Let $\gamma(j)$ denote the *Peak-Average load Ratio (PAR)* of the power provider at time slot j, and is defined as follows,

$$\gamma(j) = \frac{\max_{k\in\{1,2,\ldots,j\}}\{a(k)\}}{\frac{A(j)}{j}}, \tag{7}$$

where $\max_{k\in\{1,2,\ldots,j\}}\{a(k)\}$ is the *peak instantaneous aggregate load* during the time duration $[0, j\Delta t)$ and $\frac{A(j)}{j}$ is the *average load* during the same time period. Note that the paper [20] also defines this ratio, but the definition of this ratio is not exactly the same due to different load representation. The paper [19] defines a two-step conservation rate model for calculating the *accumulative cost function* for the utility of a 6-hour time duration, which was adopted by the BC Hydro company [21]. The time variable in [19] is a continuous variable instead of a discrete variable.

Let $\omega(j)$ denote the *instantaneous cost* of the power provider. Based on [19], $\omega(j)$ can be calculated as

$$\omega(j) = \begin{cases} K_1 \cdot a(j) + \varphi_1, & if \;\; a(j) < l^{peak}; \\ K_2 \cdot a^2(j) + \varphi_2, & if \;\; a(j) \geq l^{peak}. \end{cases} \tag{8}$$

where l^{peak} is the instantaneous peak load threshold of a specific power provider, which is the constant known to the power provider. K_1, K_2, φ_1, and φ_2 are the power provider's *preset constant parameters* based on its own situation measured in \$/kW, \$/kW, \$, and \$, respectively. This equation shows that the *instantaneous operational cost* $\omega(j)$ for the power provider will be a linear function of *the instantaneous aggregate* load $a(j)$, if $a(j)$ is lower than the *peak load* threshold l^{peak}, and $\omega(j)$ will be an increasing quadratic function of the $a(j)$, if $a(j)$ is higher than the *peak load* threshold l^{peak}. Then let $\Omega(j)$ denote the *accumulative cost* of power provider at time slot j and is defined as [19]

$$\Omega(j) = \begin{cases} \Omega(j-1) + \omega(j), & if \;\; j = 2, 3, \ldots; \\ \omega(j), & if \;\; j = 1. \end{cases} \tag{9}$$

4 Total Cost Minimization Problem in RTP demand response

4.1 Problem Statement

In a demand response system, the power provider always seeks to lower its load demand during peak time stage. In terms of measurement, the power provider seeks to minimize its *PAR* $\gamma(j)$ in (7). To achieve that, the power provider tries to persuade its customers to decrease their load consumption from the peak time or shift the load to non-peak time. But to incentivize the customers to lower the load consumption during peak time, the power provider employs the RTP scheme so that every customer uses the provider's real-time power price to adjust the load consumption accordingly.

Assume that all the *load demand* $l_i(j)$ for each customer i at timeslot j may be schedulable. Assume that at timeslot j, the customer i has the ability to automatically assign certain tasks to its household's appliances. Then all the appliances can automatically schedule the appliances' load based on the tasks that customer has assigned them to accomplish. Then the smart home console will have a load demand $l_i(j)$ known before the beginning of timeslot j for each customer.

In order for the power provider to measure the performance of energy consumption scheduling algorithm in terms of reducing the bill of the customers, we introduce the following metric to measure the performance. Let $B_{Avg}(j)$ denote the average bill of N customers over j timeslots. It is calculates as

$$B_{Avg}(j) = \frac{\sum_{i=1}^{N} B_i(j)}{N \cdot j} \quad (10)$$

Since $B_{Avg}(j)$ is the accumulative value of the average bill of N customers over j timeslots, the above normalization makes more sense than just an accumulative bill over j timeslots.

We assume that the energy consumption scheduling algorithm exists, and that it can help the customers to make decisions on how to consume the energy request at each timeslot. Assume that at each timeslot, the energy consumption scheduling makes decision on $o_i(j)$. If the load demand $l_i(j)$ is partially consumed as $o_i(j)$, there will be an instantaneous load remainder $l_i(j) - o_i(j)$ delayed for the later consumption scheduling. At j^{th} timeslot, customer i may have multiple previously accumulated delayed remainders and they are all waiting for consumption scheduling. Let $r_i(j)$ be the accumulated delayed remainders for customer i at j^{th} timeslot. Then $r_i(j)$ can be calculated as

$$r_i(j) = \begin{cases} r_i(j-1) + [l_i(j-1) - o_i(j-1)], \\ \quad if \ o_i(j-1) \le l_i(j-1), \ j = 2,3,...; \\ r_i(j-1) + [o_i(j-1) - l_i(j-1)], \\ \quad if \ o_i(j-1) > l_i(j-1), \ j = 2,3,...; \\ l_i(j) - o_i(j), \quad if \ j = 1. \end{cases} \quad (11)$$

Based on this accumulative load remainder, there is a case that the customers want to avoid. That is, some of their load requests are kept in the remainder for such relatively long time that they don't get used. Besides, for the power provider, if the customers putting too much load requests in the load remainder, it makes it difficult for the power provider to calculate and announce the real-time power price. Therefore, the unused part of load request stored in the load remainders means some cost for the customers. Let $c_i(j)$ denote the *remainder load cost* at timeslot j for customer i, and it can be calculated as

$$c_i(j) = \rho[r_i(j)], \tag{12}$$

where ρ is a function of $r_i(j)$ in terms of $\$/kWh$. It means the price function for unused load requests. Let $c_{Avg}(j)$ denote the average remainder cost of N customers over j timeslots, and it is calculated as

$$c_{Avg}(j) = \frac{\sum_{i=1}^{N} c_i(j)}{N \cdot j} \tag{13}$$

In order to measure the performance of using the energy consumption scheduling algorithm to schedule the power consumption, a weighted performance is needed. Let $c_{Tot}(j)$ denote the accumulative total cost for customer i at j^{th} timeslot. It can be calculated as

$$c_{Tot}(j) = \alpha \cdot B_{Avg}(j) + (1-\alpha) \cdot c_{Avg}(j). \tag{14}$$

Customer's Total Cost Minimization Problem: $\min c_{Tot}(j)$ (15)

4.2 Real-time Pricing Scheme

Let $p(j)$ denote the *retail power price* at timeslot j. According to [19], $p(j)$ is defined by the power provider, either based on the wholesale power market price [20], or based on the aggregated load [19]. In practice, the paper [20] adopts the power price prediction methods for the customers to make decisions on scheduling energy consumption. On the other hand, instead of using price prediction, the paper [22] points out that for power prediction, no matter it is off-peak or peak hour, estimation accuracy is very poor, especially for the off-peak with its accurate rate lower than 30% in most months. Therefore, a non-prediction-dependent RTP scheme is required for the customers in the demand response program. Based on the paper [23], a practical and polynomial real-time power price, $p(j)$ can be calculated as a function of the *instantaneous aggregated load demand*,

$$p(j) = \eta \cdot e(j)^{\varepsilon} \tag{16}$$

where η and ε are the parameters that defined by the power provider. In general, η is a constant and $\varepsilon \geq 1$, $e(j)$ is the *instantaneous aggregated load demand* in (5). To enable the power provider to persuade customers to use less power during the peak time, ε can be calculated as

$$\varepsilon = \begin{cases} 1, & if \;\; e(j) \leq l^{peak}; \\ \dfrac{e(j)}{l^{peak}}, & if \;\; e(j) > l^{peak}. \end{cases} \tag{17}$$

Now that the power price is calculated by the power provider based on (16), and then RTP price information is broadcasted to all the customers at the beginning of each timeslot.

4.3 Distributed Energy Consumption Scheduling on Cost Minimization

On the customer side, energy consumption scheduling is responsible for making the decision of its own energy consumption at each timeslot. The decision result will impact its *bill payment* individually. Thus all the customer's decisions at each timeslot will impact the whole distribution system's performance.

Solving the problem of minimizing customer's bill is an optimal process of decision making on choosing $o_i(j)$ over the j timeslots for customer i. Meanwhile, flattening the system's overall load demand is a byproduct of this optimal process.

For each timeslot, the decision of choosing $o_i(j)$ is made by the customer i based on the real-time power price and a power price threshold. The threshold is dynamically calculated at each timeslot based on the RTP, so that it will help the customer to minimize its bill payment. In a real-time demand response power system, each customer optimally consumes or schedules its *load demands* $o_i(j)$ based on the power price of each timeslot using the energy consumption scheduling. Each customer minimizes its *bill payment* calculated in (1).

In order to let the customer's energy consumption scheduling to make decisions that will benefit the customers' bill minimization, we introduce the power price threshold as the following to assist the customers to make decisions on $o_i(j)$.

$$p_i^{threshold}(j) = p_i^{avg}(j) \qquad (18)$$

- $p_i^{threshold}(j)$ is the threshold of power price that the customer i's energy consumption scheduling will use to manage all their appliances.
- $p_i^{avg}(j)$ is the average power price that customer i has been observed over the j timeslots, and it is a customized parameter for customer i.

We develop a strategy based on the threshold defined in (18). The idea behind the strategy is, if the RTP price is not expensive, each customer seeks to schedule more energy for consumption, and if the RTP price is expensive, each customer tends to schedule less energy for consumption. Thus the strategy is each customer uses a stationary policy y to decide how much remainder to consume if the $p(j) > p_i^{threshold}(j)$. Each customer uses a stationary policy x to decide how much remainder to consume if the $p(j) > p_i^{threshold}(j)$. Therefore, the decision of actually consumed energy at j^{th} timeslot $o_i(j)$ can be calculated as

$$o_i(j) = \begin{cases} x \cdot l_i(j), & if \;\; p(j) > p_i^{threshold}(j); \\ l_i(j) + y \cdot r_i\,(j), & if \;\; p(j) \le p_i^{threshold}(j). \end{cases} \qquad (19)$$

where $0 \le x < 1$ and $0 \le y \le 1$.

From (19), the solution to problem in (15) is now to find the optimal stationary policy (x, y) in (19) that will give the customer the minimized total cost in (15). Here we use simulation to find out the optimal policies for all the customers.

5 Simulation

Average load requests fluctuate within [0, peak load] following Gaussian distribution with a mean value of half of the peak load.

5.1 Simulation Setup

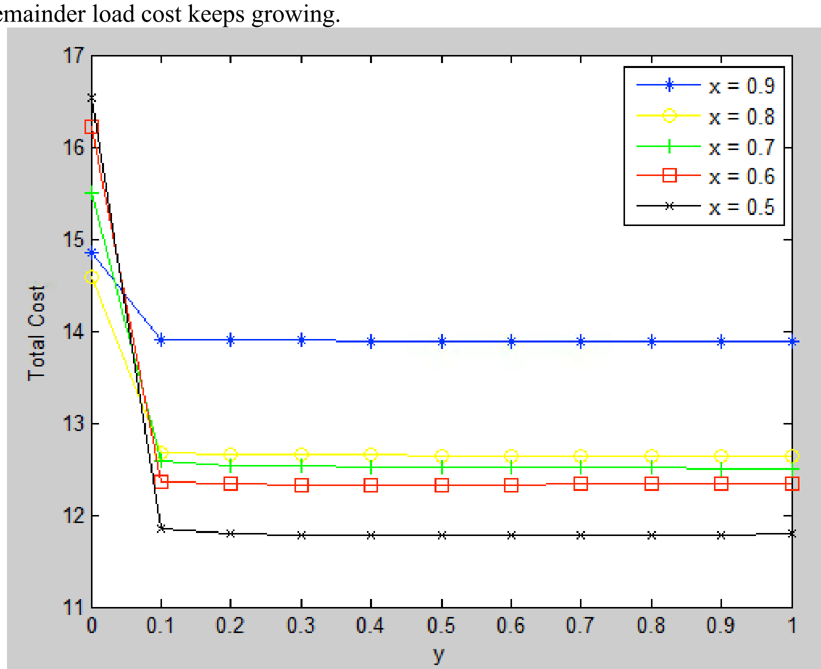
Assume that the amount of each customer's load demand follows the same normal distribution. Assume that the communication overhead and delay between all the customers and the power provider are ignored. Let μ denote the peak load defined by the power provider, let the normal distribution $(\mu, \sigma^2) = (\mu/N, (\mu/3N)^2)$, and this will guarantee the values of 99.7% of observations fall in the interval $[0, 2\mu/N]$ [24]. Even though the possibility of generating negative number is small, this design still eliminates them by regenerating another normal distribution number when it happens. To make the aggregated input load request less intense, we setup a dynamic way of generating normal distribution load request for each customer at each timeslot. If setting up input as letting each customer follow a normal distribution of $(\mu/N, (\mu/3N)^2)$, it will make the $e(j)$ in equation (5) stable as high as μ. But in order for the $e(j)$ to fluctuate within $[0, \mu]$, we let the aggregate load requests follow the normal distribution of $\left(\mu/2, (\mu/(2*3))^2\right)$. In this way, a random aggregated load requests is generated at current timeslot j, which is denoted as e_j^{rand}. Then, the aggregate load requests follow the normal distribution means that $e_j^{rand} \sim \left(\mu/2, (\mu/(2*3))^2\right)$.

Let each customer generate the load requests based on this random aggregated load request. We still use the normal distribution to let each customer generates its load request at each timeslot. But the normal distribution (μ, σ^2) follows $(e_j^{rand}/N, (e_j^{rand}/3N)^2)$. Since e_j^{rand} is a random value of the range $[0, \mu]$, each customer follows a varying normal distribution to generate its own load request at different timeslot. In this way, both the aggregated load request and the individual load request follow the normal distribution to generate load request at each timeslot. Let Load Peak=1000kWh, N=100, and η=1E-2 for the rest of the simulation.

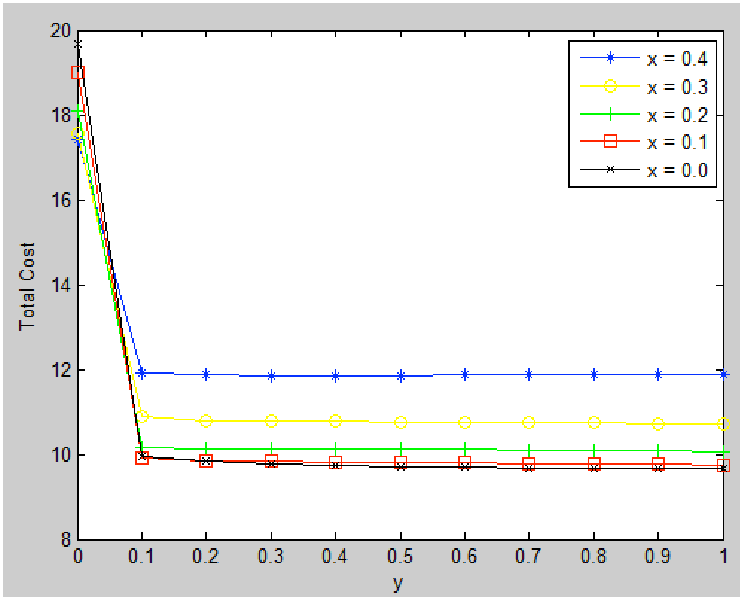
The following experiments are based on values of α (value in equation (14), which is the weight value to determine the total cost for the customer) and vales of μ. Also, we assume that $\rho[r_i(j)] = 10 \cdot r_i(j)$ in equation (12), which is linear.

5.2 Simulation Results

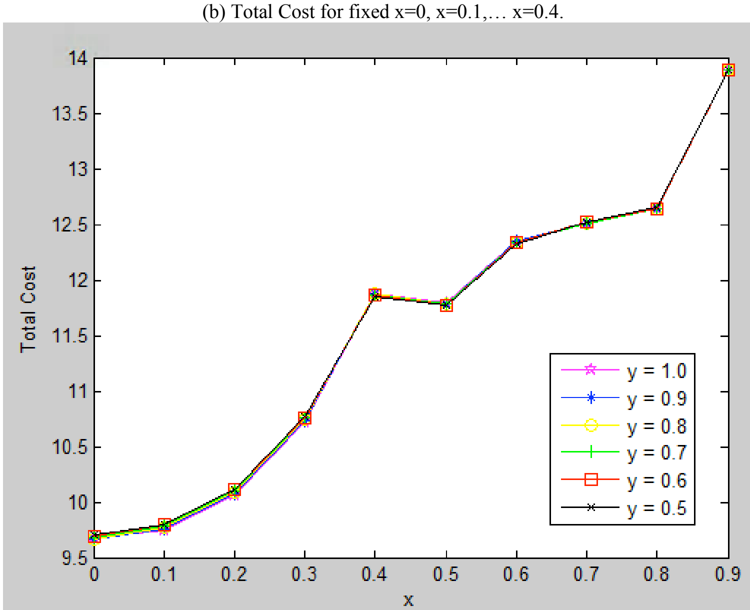
In the simulations, we have α=0.5 and μ=500kWh. Fig. 1(a) and Fig. 1(b) show the total costs over y based on different x values, and we observe that the lowest total cost is when x=0 or x=0.1, and y is approximately in [0.8, 1.0]. Fig. 1(c) and Fig. 1(d) show the total costs over x based on different y values, and we observe that the lowest total cost is when y is approximately in [0.5,1.0] and x=0.0. Also in Fig. 1(d), when y = 0.0, the total cost has the largest values. This means if the load requests are delayed, they will never be used even when the real-time price is cheap. Therefore, the remainder load cost keeps growing.



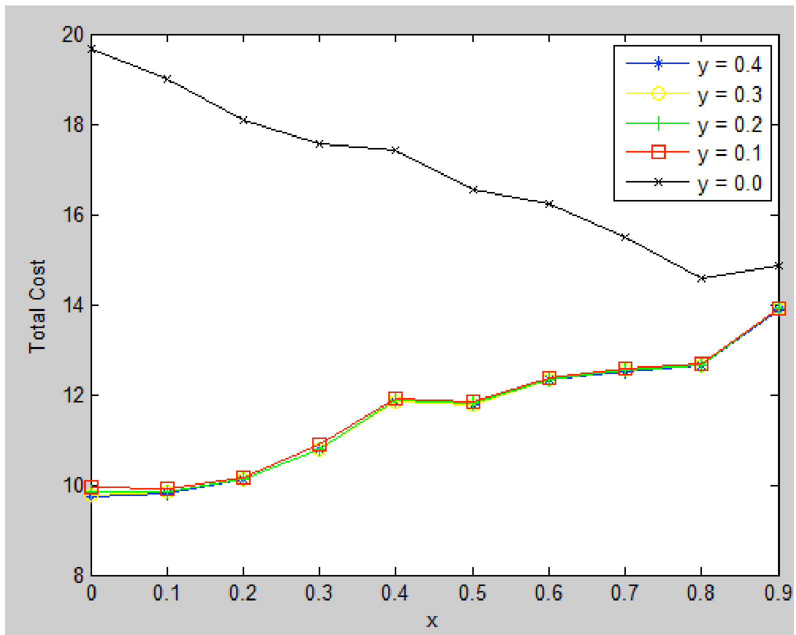
(a) Total Cost for fixed x=0.5, x=0.6,… x=0.9.



(b) Total Cost for fixed x=0, x=0.1,… x=0.4.



(c) Total Cost for fixed y=0.5, y=0.9, …, and y=1.



(d) Total Cost for fixed y=0.0, y=0.1,… ,and y=0.4.

Fig. 1. Total Cost

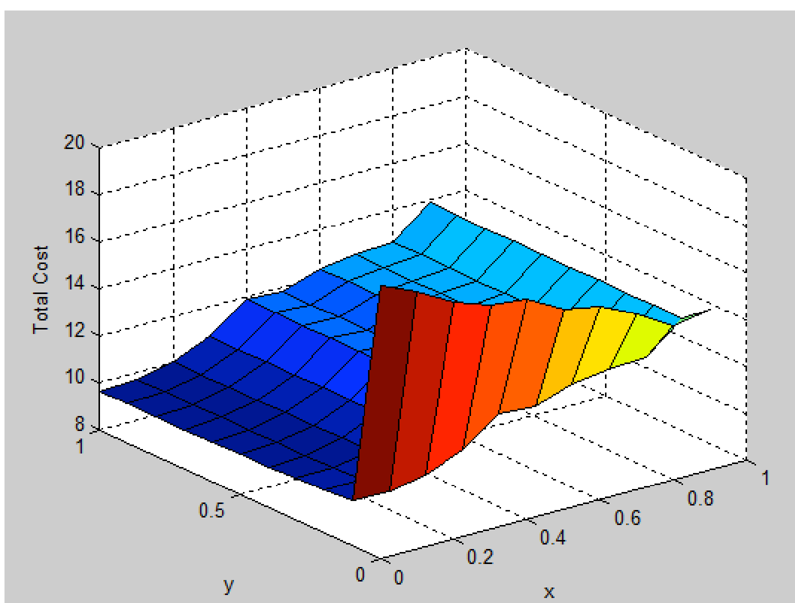


Fig. 2. Total Cost

As seen in Fig. 2, it is seen that the total cost has the largest value when x = 0 and y = 0; this is because that there is no load requests consumed that the large cost incurred by the customers waiting has dominate the total cost. For the smallest value of the total cost is when x = 0 and y = 1. This means that the best policy for customers is not to consume at all when the real-time price is expensive and delay them to the next timeslot as a load remainder, and then try to consume more of the remainder in the next possible cheap timeslot.

6 Conclusion

In this paper, we propose a problem of how to minimize the total cost for customers who participate in the operation of smart grid by using demand response and real-time pricing. To solve the problem, a new real-time price scheme is proposed, and based on which, the algorithm to find total cost minimization is proposed.

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