Indirect Demand Side Management Program Under Real-Time Pricing in Smart Grids Using Oligopoly Market Model

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***Abstract*—The rise in electricity demand, environmental concerns, and economic issues have increased the importance of demand response in recent years. Among different incentive methods of demand side management (DSM) programs, real-time pricing (RTP) can adaptively control the electricity consumption while giving the decision authority to customers and satisfying the power system constraints. Although the existing RTP methods require a complicated computational process to determine the equilibrium point, this paper proposes a heuristic two-stage iterative method to quickly find the market equilibrium using the Cournot oligopoly competition model in a smart grid. The proposed method minimizes the cost for each customer by running a simple computational algorithm on each customer's smart meter while also satisfying the power system constraints. The effectiveness and feasibility of the proposed method is demonstrated by conducting simulations in the IEEE 37-bus test system with about 1500 customers using real data sets of loads. The results show that the proposed technique can better manage the elastic loads in terms of power and cost in comparison with the existing methods and is quick enough to run in real-time.**

Keywords-Demand side management; Imperfect competition market; Indirect control; Real-time pricing; Smart grid; Smart meter.

I. INTRODUCTION

Demand response (DR) can be defined as any change in electric usage of end-use customers from their normal consumption patterns in response to incentive payments designed to induce lower electricity use at times of high cost of electricity supply [1]. Under this definition, the demand side management (DSM) programs include all activities that alters the consumer's demand profile to match the supply profile [2]. The idea of DSM is not new and it emerged in electrical systems in the 1970s and has evolved over the past four decades. The smart grid (SG), infrastructures such as two-way communication system are attracting more researchers to DSM concepts in recent years.

Implementing DSM leads to technical and economic benefits for utilities and customers, if the number of participants is large enough. Customer motivation methods in DSM have a major role in the customers' participation. The different motivation methods in DSM are surveyed into [3]. Generally, the motivation methods can be divided in two main categories: incentive based methods and time based methods. The incentive based programs offer payments to customers who reduce their electricity usage during periods of system need or stress [4]. However, in order to determine the amount of reduction, a baseline load threshold must be calculated for each customer, which is a complicated and imprecise procedure [5].

In the time based programs, the price of consumption is varied based on the time of usage and can lead customers to transfer consumption to the off-peak period [6]. The time based program has two different subcategories. Some programs offer varying prices for different time periods but do not change prices based on customers' decisions, e.g., the time of use (TOU) method. Some other programs consider the effects of customers' decisions and change the price in real-time manner, e.g., real-time pricing (RTP) method.

The TOU method has a critical drawback; since the price of each time period is independent from customers' behavior and each customer decides individually, it is possible that all customers decide to simultaneously use in off peak period , causing a new "rebound" peak [7,8]. In order to solve this problem, retailers must determine the price of each time period based on the real-time consumption. Implementation of RTP method requires two-way real-time communication and complicated computational process for determining the optimum price [3]. This complication causes most of researchers employ direct methods to control demand, and minimize the total cost of the distribution grid by a central optimization technique [9,10]. However, using a direct control method takes away the decision authority from customers and produces adverse effects in the popularity and security of participants [11]. In addition, most of DSM methods do not pay attention to each customer's profit, and as a result, customers tend to contribute less in DSM. In order to solve this problem, the authors of [12] propose a multi-agent framework to minimize the electricity bill of each household while considering the piecewise linear function for each customer's cost. Still, the method neglects the correlation of loads with each other and cannot prevent rebounding peak.

Implementing the RTP-based indirect DSM program involves the electrical market models with an oligopoly competition instead of the perfect competition model. Typically, there are two competitive market models: the perfect competition and the imperfect competition

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(oligopoly) model. The perfect competition model, which assumes that the decision of each participant in market has no effect in the market price, is relatively simpler and so it has gained popularity in the power market. Although in the power system, the consumption of each customer alone has negligible effect in the whole network; in indirect controlling, due to customers sometimes making similar decisions, it may have a big effect on the power system. In this case, the power market cannot be modeled by a perfect competition, and in order to consider the effect of real-time behavior of customers, an imperfect competition or oligopoly model is more suitable. The implementation of an imperfect competition is much more complicated than a perfect one. For modeling oligopoly energy productions, the Cournot competition model is widely used [13]. However, using this model on the customer side, with many participants, has more complexity. Since customers cannot neglect their energy consumption, they can only shift it to another time period; therefore, the energy consumption of each time depends on the consumption of other time periods. On the other hand, the energy price of different time periods depends on the total network consumption and loss in that time period. Consequently, in the Cournot model, the energy price of each time interval depends on the consumption of all customers in the present and the future time periods. The authors of [14] employ a Cournot competition to model a dynamic price for an intelligent building but they make some simplifying assumptions, such as linear inverse demand curve or having exclusive energy storage device to solve the problem, which limits the implementation of their technique.

Another weak point of existing research in DSM is that most of them do not consider the power system limits such as the electrical lines' overloading, power stability, power loss, and so on. A game-theoretic real-time price market to maximize the profit of each participant is proposed in [15]. However, their method does not have the ability to consider nonlinear power flow equations.

In this paper, we propose a new heuristic two-stage technique to implement indirect DSM program under RTP method. This technique can quickly find the optimum power of each customer in a decentralize manner to minimize their own cost while satisfying the technical constraints of the power system. The main contributions of this paper are summarized as follows:

- Proposes a dynamic RTP-based DSM program using a Cournot imperfect competition market model preventing rebound peak.
- Implements an indirect charging technique that gives the decision authority to all customers.
- Minimizes the cost of each customer individually instead of considering whole the network cost (all customers together).
- Proposes a heuristic two-stage iterative method to quickly find the market equilibrium point.
- Considers the power issues such as power loss or lines overload using nonlinear power flow equations.
- Solves systems with nonlinear constraints and non-convex cost function.

The rest of this paper is organized as follows. The mathematical modeling of the RTP-based indirect DSM is presented in Section II. A proposed heuristic method is explained in Section III. The simulation network and the simulation results are detailed in Section IV. Finally, we conclude in Section V.

II. RTP-BASED INDIRECT DSM MODEL

In this RTP-based indirect DSM program, each customer wants to schedule its appliances to minimize its cost by considering the influence of other customers based on the Cournot oligopoly model. It is assumed that each customer has two types of loads: inelastic loads, which cannot be shifted, such as lightings, and elastic loads, such as wet appliances, which can shift during a defined time period. When one appliance starts to operate it should continue its operation until the given task is done. In this case, each customer should determine the optimum time of turning elastic loads on, while satisfying the network and its own constraints. The objective function of this optimization problem is defined as follows:

$$\underset{t_{0,k}}{\text{Min}}\ Obj = \sum_{k=1}^{n_{e,i}} \sum_{t=t_{0,ik}}^{t_{0,k}+t_{d,ik}} P_{e,ik}(t).\pi(t) \tag{1}$$

where $P_{e,ik}(t)$ is the active power of the *i-th* customer's *k-th* elastic appliance in time t; $t_{0,ik}$ is the starting time of the *k-th* appliance; $t_{d,ik}$ is the time duration that the appliance need to finish its task; $n_{e,i}$ is the number of *i-th* customer's elastic appliances; $\pi(t)$ is the market price and it is updated based on the total real-time power consumption of the network in each time interval as follows:

$$\pi(t) = S\left(\sum_{i=1}^{n}\left(P_{ie,i}(t) + \sum_{k=1}^{n_{e,i}} P_{e,ik}(t)\right) + P_{loss}(t)\right), \tag{2}$$

where n is the number of customers, $P_{ie,i}(t)$ is the inelastic power of *i-th* customer; P_{loss} is the power loss of the electrical grid; and S is the power grid supply function calculated from supply side management (SSM) program or the supply curve giving the cost of the supplied energy for the power grid. The power loss of the network can be calculated as follows [16]:

$$P_{loss} = \sum_{i=1}^{m}\sum_{k=1}^{m} |V_i||V_k||Y_{ik}|\cos(\delta_i - \delta_k - \theta_{ik}), \tag{3}$$

where $|V_i|$ and δ_i are the magnitude and phase of *i-th* bus voltage, $|V_k|$ and δ_k are the magnitude and phase of *k-th* bus voltage, respectively; m is the number of network buses; and $|Y_{ik}|$ and θ_{ik} are the magnitude and phase of the grid admittance matrix, respectively. The voltage of all buses can be calculated from nonlinear power flow equations as described in many literatures. In this paper, a backward/forward sweep method, which considered to be the best appropriate method for distribution electrical networks, is implemented [17]. Since these equations are nonlinear, many DSM programs optimize the system neglecting the power loss and power constraints. However, in practice, the DSM program should consider the power network constraints in addition to each customer constraints. The overload of power lines and voltage bus regulation constraints are as follows:

$$I_k(t) < I_{k,\max} \quad \forall t, \tag{4}$$

$$V_{\min} < V_j(t) < V_{\max} \quad \forall t, \tag{5}$$

where $I_k(t)$ is the magnitude of k-th branch current in time t; $I_{k,max}$ is the k-th branch capacity; V_{min} and V_{max} are the minimum and maximum levels of voltage of the network, respectively. Furthermore, each customer has some individual constrains. First, their task should be finished before the desired time, so the starting time should be selected as follows:

$$t \le t_{0,ik} < t_{end,ik} - t_{d,ik} \quad \forall k, \tag{6}$$

where t is the present time interval, and $t_{end,ik}$ is the desired finishing time of i-th customer's k-th appliance. Second, each customer has a specific maximum allowable demand. Therefore, the total consumption of i-th customer in each time interval should satisfy the following constraint:

$$\left(p_{ie,i}(t) + \sum_{k=1}^{n_{e,i}} p_{e,ik}(t)\right)^2 + \left(Q_{ie,i}(t) + \sum_{k=1}^{n_{e,i}} Q_{e,ik}(t)\right)^2 \le S_{\max,i}{}^2 \quad \forall t, \tag{7}$$

where $Q_{ie,i}(t)$ is the inelastic reactive power of the i-th customer in time t; $Q_{e,ik}(t)$ is the reactive power of the i-th customer's k-th elastic appliance in time t; and $S_{max,i}$ is the maximum allowable apparent power of i-th customer. Consequently, the mathematical model of the RTP-based indirect DSM program using the Cournot oligopoly competition model is as follows:

$$\begin{aligned}
&\underset{t_{0,ik}}{\text{Min}}\ Obj = \sum_{k=1}^{n_{e,i}} P_{e,ik}(t).S\left(\sum_{i=1}^{n}\left(P_{ie,i}(t) + \sum_{k=1}^{n_{e,i}} P_{e,ik}(t)\right) + P_{loss}(t)\right) \\
&\qquad\qquad + \sum_{k=1}^{n_{e,i}} \sum_{\text{if } t=t_{0,ik},\, \tau=t+1}^{t_{0,k}+t_{d,ik}} P_{e,ik}(\tau).\pi^P(\tau) \\
&s.t. \\
&\quad P_{loss}{}^{pe} = \sum_{i=1}^{m}\sum_{k=1}^{m} \left|V_i^e\right|.\left|V_k^e\right|.\left|Y_{ik}\right|.\cos(\delta_j - \delta_k - \theta_{ik}), \\
&\quad \text{Power Flow equations [21]}, \\
&\quad I_k{}^e(t) < I_{k,\max} \qquad \forall k, \forall t, \\
&\quad V_{\min} < V_j{}^e(t) < V_{\max} \qquad \forall k, \forall t, \\
&\quad t \le t_{0,ik} < t_{end,ik} - t_{d,ik}, \qquad \forall k, \forall t, \\
&\quad \left(p_{ie,i}(t) + \sum_{k=1}^{n_{e,i}} p_{e,ik}(t)\right)^2 + \left(Q_{ie,i}(t) + \sum_{k=1}^{n_{e,i}} Q_{e,ik}(t)\right)^2 \le S_{\max,i}{}^2 \quad \forall t.
\end{aligned} \tag{8}$$

where $\pi^P(\tau)$ is the predicted energy price for future times. The equilibrium point (real-time price) of the network can be calculated from solving the above optimization problem by each customer, simultaneously. In order to solve this optimization problem, each customer should predict its own consumption for the future times and estimate other customers' consumptions in the present time and future times. Furthermore, this is a nonlinear non-convex multi-objective optimization problem with many variables, and it cannot be solved in this form. In the next Section, a heuristic two-stage iterative method to quickly calculate the Nash equilibrium point of the network is proposed.

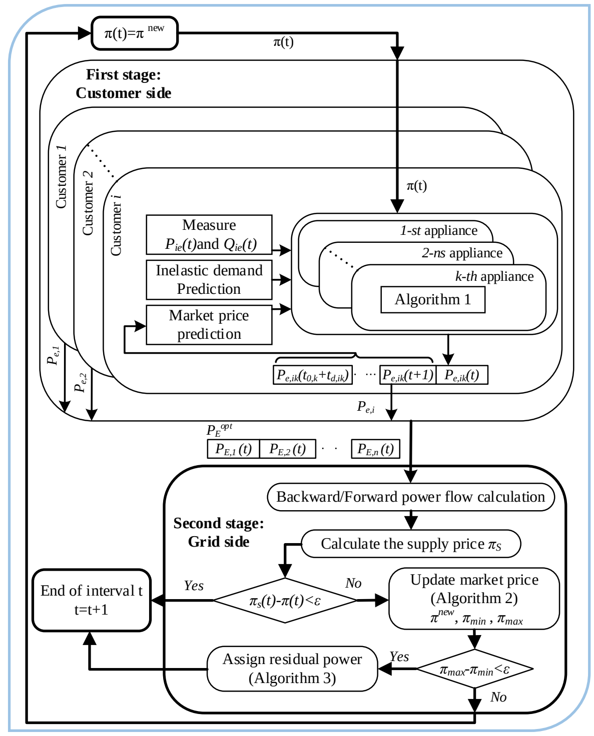

Figure 1. The proposed method to solve the RTP-based indirect DSM

III. THE TWO-STAGE HEURISTIC METHOD

This Section presents a heuristic two-stage iterative method to solve the RTP-based indirect DSM program optimizing problem in (8). In this method, a modified optimization problem, which neglects the network constraints and the dependency of price to other customers' decisions, is solved in the first stage by each customer. The second stage calculates the whole network states and compensates the modification of the first stage using an iterative algorithm to approach the equilibrium. Figure 1 illustrates the mechanism of the proposed method.

A. First Stage: Customer Side

In the first stage, customers minimize their cost regarding the local constraints in a given price. In this case, the optimization problem of (8) converts to (9) as follows:

$$\begin{aligned}
&\underset{t_{0,ik}}{\text{Min}}\ Obj = \sum_{k=1}^{n_{e,i}} \sum_{t=t_{0,ik}}^{t_{0,k}+t_{d,ik}} P_{e,ik}(t).\pi_d(t) \\
&s.t. \\
&\quad t \le t_{0,ik} < t_{end,ik} - t_{d,ik}, \qquad \forall k, \\
&\quad \left(p_{ie,i}(t) + \sum_{k=1}^{n_{e,i}} p_{e,ik}(t)\right)^2 + \left(Q_{ie,i}(t) + \sum_{k=1}^{n_{e,i}} Q_{e,ik}(t)\right)^2 \le S_{\max,i}{}^2.
\end{aligned} \tag{9}$$

where π_d (t) is a given market price, which is updated for time interval t by the second stage to consider the dependency of each customer to other customers and network constraints. Although, the optimization problem of (9) is much easier to solve than (8) and some of the existing optimization methods can be used to solve this problem, this paper propose a heuristic method to quickly find the optimum solution of (9). As our method only use the simple mathematical operation, it can be implemented in simple computing devices such as smart meters.

In order to accelerate the calculation process, the proposed technique schedules each appliance separately. The algorithm orders the plugged elastic appliances of *i-th* customer in time t from the appliance with the smallest to the largest desired finishing time, and then the starting time of each appliance is selected sequentially so that the cost becomes minimum. In other words, the algorithm gives a higher priority to the appliance that should finish its task sooner than others and has fewer options. In order to determine the starting time ($t_{0,ik}$), the electricity cost of the task for different starting times are calculated and the cheapest one that satisfies (7) is selected. Algorithm 1 details the first stage of the proposed heuristic method to solve (9).

B. *Second Stage: Grid Side*

In the first stage, the optimum consumption of each customer in the given demand price (π_d) is calculated. In the second stage, the supply price (π_s) for the total power of the network is calculated and if the prices are not same, the price of the first stage is updated to approach the equilibrium point.

Generally, in a rational power market, a supply curve is a non-decreasing function and a demand curve is a non-increasing function; and the Nash equilibrium point is the intersection of these two curves (as shown in Figure 2.a). In this case, if π_s is greater than π, the price of the equilibrium point (π^*) is also greater than π, and vice versa.

The proposed algorithm uses this idea and bisects the difference between these two prices (π_s - π_d) to find the equilibrium point. Algorithm 2 details the process of finding the new price (π^{new}) for the next iteration. In this algorithm, π_{min} and π_{max} are the upper and lower limits of the equilibrium price, respectively. In order to satisfy the network constraints, a controlling price is added into π^{new} to control the consumption of each bus.

In the indirect method, since each customer wants to minimize its own cost, they may make a similar decision and

Algorithm 1: First stage – Minimizing customer cost (9)

1: Order the *i-th* customers' elastic appliances from the smallest $t_{end,ik}$ - $t_{d,ik}$ ($k=1$) to the largest $t_{end,ik}$ - $t_{d,ik}$ ($k=n_{e,i}$).

2: For $k=1$ to $n_{e,i}$ **do**

3: Calculate cost $\sum_{t=t_{0,ik}}^{t_{0,k}+t_{d,ik}} P_{e,ik}(t).\pi(t)$ for $t_{0,ik} \in (t, t_{end,ik} - t_{d,ik})$.

4: Check constraint: $(P_{ie,i}(t)+\sum_{l=1}^{k}P_{e,il}(t))^2+(Q_{ie,i}(t)+\sum_{l=1}^{k}Q_{e,il}(t))^2 \le S_{\max,i}{}^2$

for all t.

5: Select the cheapest costs that satisfy the constraint.

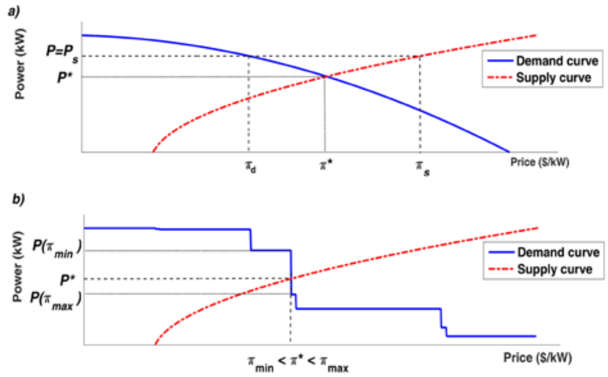

Figure 2. The demand and supply curve in a rational power market; a) a general form; b) when customers decide similar

Algorithm 2: Second stage - part 1, calculating π^{new}, π_{min}, π_{max}

1: If $\pi_d < \pi_s$ **then** $\pi_{min} = \max(\pi_{min}, \pi_d)$ **else** $\pi_{max} = \min(\pi_{max}, \pi_d)$

2: $\pi^{new} = (\pi_{min} + \pi_{max})/2$.

collectively cause sudden changes in the demand curve as shown in Figure 2.b. In this case, although the proposed bisectional method converges to the equilibrium price ($\pi_{min} \approx \pi_{max}$), the consumption power cannot be calculated from the demand curve due to the sudden changes in this curve. The algorithm calculates the consumption power from inverse supply curve and assigns the difference between P^* and $P(\pi_{max})$, called the residual power, to some random customers by changing their price from π_{max} to π_{min}. This little change has no effect on the market price but changes their power consumption. In a real system with different appliances and different consumption behavior of customers, the occurrence probability of this problem is very low. Still, the proposed algorithm can be used to handle the problem. Algorithm 3 details the proposed method to handle this problem.

IV. CASE STUDY

A. *Simulation Setup*

For our simulation, the IEEE-37 bus test system is selected. Figure 3 shows the single line diagram of this system and the line data and the maximum power of each bus is taken from [18]. We generate the load profiles based on homes with different appliances and customer behavior modeled in [19]. For this purpose, a group of different home profiles (without wet appliances) are created by the simulator given in [20] as inelastic loads; then the adequate number of them, randomly, is assigned to each bus to consume the same maximum power reported as in [18]. This procedure results in 1491 customers connected to the different buses consuming about 14.5 MWh in each day. This high-consumption inelastic profile helps us to show the effectiveness of the proposed method in a power system under stressed.

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Algorithm 3: Second stage-part 2, allocating residual power

1: Select π_{max} as π^*.
2: Calculate $P\ (\pi_{max})$ from Algorithm 1.
3: Calculate P^* from supply curve.
4: $P_{res} = P^* - P\ (\pi_{max})$
3: While $P_{res} > 0$ **do**
4: Select a customer randomly, change its price to π_{min}, and calculate $\sum P_{e,ik}(\pi_{min})$.
5: $P_{res} = P_{res} - (\sum P_{e,ik}(\pi_{min}) - \sum P_{e,ik}(\pi_{max}))$

We consider two different elastic appliances: dish washer and clothes washer with tumble dryer. The average consumption profiles of them is shown in Figure 4. These profiles are the hardest profiles to handle for the proposed algorithm due to a long time consumption period and a high difference of energy consumption during the period. When these appliances start to operate, they should operate until the task is completed. However, the price may change in future time intervals and this can become a source of error in the proposed method. Still, the simulation results in the next Section show that the proposed method can still manage this problem well.

It is assumed that customers use the dish washer with the probability of 50 % in each day and they turn it on between 8 and 10 am and the task needs to be done before 6 to 9 am of the next day with the uniform distribution. The clothes washer is plugged into the network between 10 and 12 am with probability of 50% and the task needs to be done before 10 to 12 am of the next day with the uniform distribution. These elastic appliances add about 5.5 MWh to total energy consumption of the network.

As shown below in (10), the supply function is calculated so that the average price for off-peak and on-peak time of inelastic loads equal to 4 and 17 ¢/kW according to [21].

$$S(P_{total}) = 3.77E-7.P_{total}{}^2 + 1.41E-4.P_{total} + 5.32E-2, \qquad (10)$$

where P_{total} is the total input power of the network including power loss. In this simulation the error of inelastic power prediction and price forecasting is modeled by a normal distribution with standard deviation equals to three per cent.

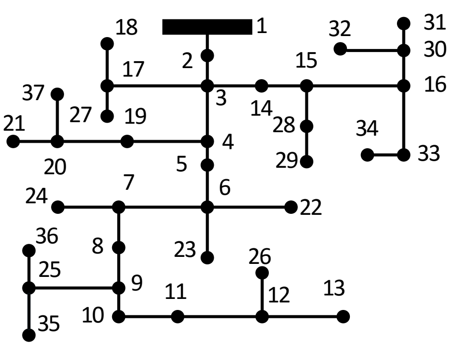

Figure 3. The IEEE-37 bus test system

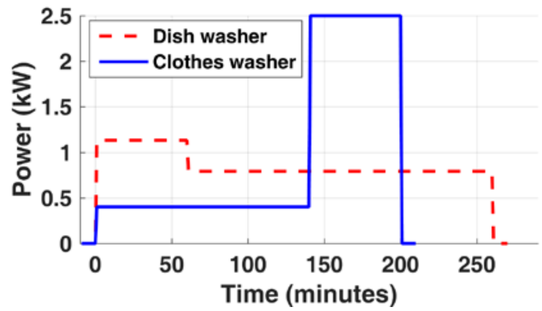

Figure 4. The average consumption profile of elastic appliances

B. *Simulation Results*

The proposed two-stage method solving the RTP based indirect DSM program is implemented in MATLAB platform using a computer with an 8-core 2.3 GHz CPU and 8 GB RAM. We consider different cases as listed below:

- Case 1: The network without elastic loads.
- Case 2: The network with the elastic loads and without DSM program (i.e., flat rating program).
- Case 3: The network with the elastic loads and with TOU based DSM program [21].
- Case 4: The network with the elastic loads and with the proposed RTP based indirect DSM program.

Figure 5 shows the total active power and the marginal cost of energy production in different cases. The system without elastic loads is shown in case 1 (details are shown in Figure 6). In this case, the demand peak is equal to 1045 kW and the maximum marginal cost is equal to 0.32 $/kW. Without DSM program (case 2), each appliance consumes the power as soon as it connects to the network. In this case, a demand peak (1908 kW), which is much higher than the inelastic demand peak is created around noon and increases the maximum marginal cost to 1.16 $/kW. The TOU based DSM program (case 3) has low energy tariff during off-peak periods, which attracts the elastic loads to consume power in these periods. In this case, a new rebound peak is generated as shown in Figure 5. The rebound peak in this case is equal to 1654 kW and the maximum marginal cost is 0.85$/kW. Table I compares the peak power, the energy loss during each day, the maximum marginal cost, the total energy cost, and the minimum bus voltage in different cases.

Figure 6 shows the total active power of elastic appliances in the proposed method. Customers, in order to avoid expensive electricity price, schedule their elastic loads when the real-time price is low. As a result, none of the elastic loads consumes energy between the hours of 17 and 23. This strategy leads the peak power of network and the maximum marginal cost of the production to remain constant although the energy consumption increased by 38%. Table I shows that the total cost of energy supplied in the proposed method (2849 $) is about half of the total cost of energy supplied in the flat rate (5617 $) or TOU based (5250 $) program.

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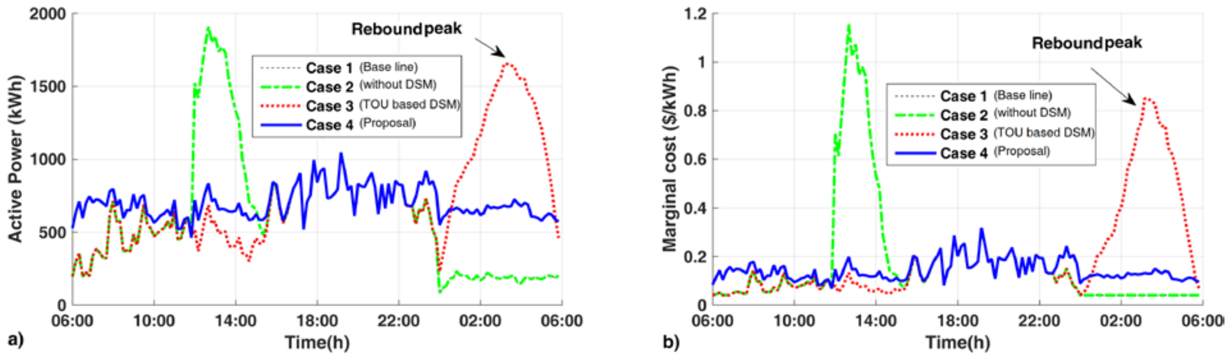

Figure 5. Comparison between cases 1-4: (a) total active power, b) marginal cost

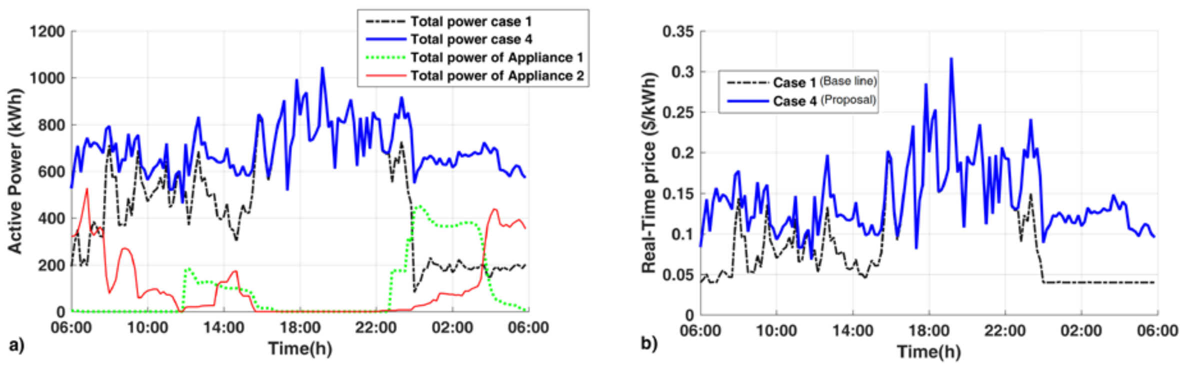

Figure 6. Comparation between the proposed method (case 4) and inealstic loads (case 1): a) total active power, b) the real time price

TABLE I. PERFORMANCE COMPARISON OF DIFFERENT CASES

	Peak power (kW)	Energy loss (kWh)	Maxi price ($/kW)	Total energy cost ($)	Mini voltage (%)
Case 1 (Base line)	1045	262	0.317	1710	95.1
Case 2 (Without DSM)	1908	583	1.156	5617	90.2
Case 3 (TOU based DSM)	1654	559	0.850	5250	91.3
Case 4 (Proposed)	1045	443	0.317	2849	95.1

The results show that the total elastic power consumption has some small local peak. These local peaks are happen because the method is an indirect one and each customer decides independently, and we consider the worst load profiles, which have a large operating period. Using load profiles, which has less dependency during time, such as water heaters or electrical vehicles, can improve the results even more.

Figure 7 shows the worst voltage profiles of different cases. In cases 2 and 3, because system has a high peak demand, the voltage of some buses drop lower than 95%, while the proposed method (case 4), has voltage profile exactly same as case 1 due to the peak load control. In cases 1 and 4, the worst voltage drop occurs on bus 26 at 19:20'.

The number of iterations and the calculation time for each time interval are shown in Figure 8. As each customer optimizes its consumption, the proposed method can quickly find the equilibrium point. In this implementation, each time interval is assumed equal to 10 minutes long, which is a practical assumption in SGs. However, the proposed algorithm can be employed for time intervals less than one minute due to fast calculation.

V. CONCLUSION

The environmental concern and shortage in fossil fuel is increasing the penetration level of renewable energy sources in the electrical grids. The uncontrollable nature of output power produced by renewable source makes a DSM program more imperative in the modern power grid. In this paper, a new RTP-based indirect DSM program using an imperfect competition market in smart grids is proposed. The indirect DSM program gives the decision authority to customers and can attract more customers to participate in the program, while the imperfect competition market model prevents the rebounding peak and satisfies the power system constraints. Although, the indirect demand control in an imperfect competition market leads to a complicated nonlinear non-convex multi-objective optimization problem, this paper proposes a heuristic two-stage iterative method to quickly solve the problem. The method is implemented in MATLAB on the IEEE 37-bus test system to analyze the effectiveness of the method. The test system includes about 1500 customers with actual load profiles and different elastic appliances. The results show that the proposed method solves the problem quickly enough for real-time application and it decreases energy cost of individual customers and

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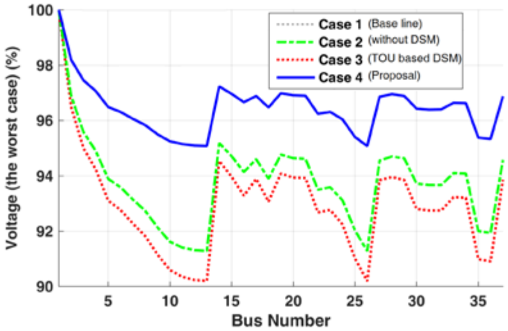

Figure 7. The worst voltage profiles

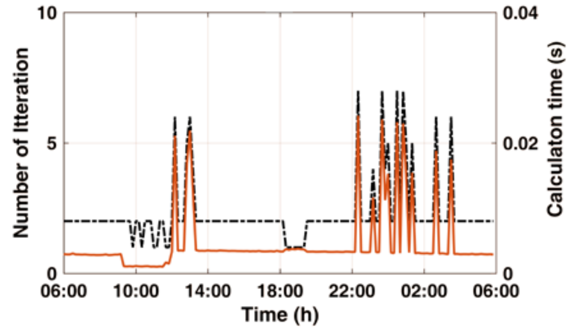

Figure 8. The numebr of itterations and the calculation time for each time interval

power loss, and also maintain power system constraints, such as voltage regulation, within their limits.

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