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Gaming Behavior in Wholesale Electricity Markets with Active Demand Response

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Abstract— **Consumers can become more active players in wholesale electricity market with demand response (DR) programs. This paper focuses on the gaming behavior analysis both on supply side and demand side when dynamic pricing introduced in wholesale electricity markets. To highlight the different demand flexibility and response ability of different customers, the optimal response strategies of three kinds of demand response programs are modeled separately. The optimal bidding strategies of supply side are formulated as linear supply function (LSF) bidding. Then this paper presents the market clearing model by a minimum cost unit commitment method and equilibrium results of supply and demand side real-time response to dynamic pricing by a repeated gaming framework. Finally, the gaming behaviors of different types of consumers and different capacities of generators are discussed by study cases.**

I. Introduction

Nowadays, it is widely accepted that most current electricity markets cannot be modelled under the perfect competition assumption due to the special features of the electricity supply industry such as, large investment size which limits number of producers, transmission constraints which isolate consumers from effective reach of many generators, transmission losses which discourage consumers from purchasing power from distant generators[1-3]. Furthermore, the lack of dynamic price signals on demand side is considered as a trigger leading to price spike by suppliers' "opportunistic tacit collusion"[4] and one of the primary factors contributing to the major power crisis in California's unregulated wholesale markets during 2000 and 2001[5, 6]. Since that time, improving the interactive between supply side and demand side through demand response (DR) and dynamic pricing (DP) under conditions within the electricity system and electricity market has become very important issues for system operators, market designers, terminal users and governments.

When electric demand is at or near its peak level, less efficient or higher cost generating units must be utilized to meet the higher peak demand. DR programs[7] are designed to encourage consumers response to this less efficient or high price status by modifying their demand level or pattern of load profile. Experiences of DR programs in the wholesale market are taking place all over the world. There has been 117% increase in the number of entities offering DR programs in the United States from 2006 to 2008[8]. The level of DR in European countries in 2008 is estimated at on average 2.9% of peak load[9]. DR program is also used as a popular load management tool to prevent power shortage in China[10].

According to the marginal cost pricing principles to the design of rate structures for regulated electricity markets[11], dynamic pricing offer a time-based pricing mechanism which is expected or observed change of the supply and demand balance and wholesale market costs during time[12, 13]. Some empirical evidences show that DP is an efficient tool to achieve demand response in the electricity systems[14-16]. Some others also showed that the consumption patterns are not influenced by dynamic pricing tariff choice significantly[17, 18], partly because of the lack of easy-to-use demand response strategies and price signal alert tools integrated in the energy management system of the retailers.

Smart grid technology enables bidirectional communication between power suppliers and demanders. Such bidirectional communication can be used by a conscious consumer to get the price signal and improve their demand response strategies. Some projects[19] have committed to provide a communications framework and price alert tools to make the price signals be published and delivered more easily to retailer users in near real time through advanced metering infrastructure (AMI). And a number of demand response models and strategies under smart grid technology, such as responses in real-time[20], response in commercial building[21], response with distributed renewable generation and storage [22], are also presented in recent years.

Demand response resource potential could range from 3 to 9% of a region's summer peak demand in most regions of U.S[8]. In some analysis, the amount even lies in the 27-44% range[14]. If as the Energy Policy Act (EPACT) of 2005 looked forward, unnecessary barriers to wholesale market demand response participation in electricity markets at either the retail or wholesale level have been eliminate by policy or technology approaches, the behaviors of demand side and supply side in wholesale electricity market will entirely change in the new competition environment. On the one hand, the demand side can schedule loads and distributed generations at the consumer level to response to the dynamic wholesale and retail electricity prices easily and actively. Demand side participation will directly influence market results. On the other hand, such response behaviors from demand side will lead to a new demand profile faced by supply side bidding. The optimal bidding strategies of suppliers need to be updated against response behaviors on

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demand side. If all potential demands respond to the dynamic market price in real-time optimally and all suppliers update their bidding strategies later, there are some questions such as what the market equilibrium will be? Do we still need so many on-peak capacities for reserve service? What the gaming behaviors of different demanders and suppliers are?

This paper presents a work try to answer the above questions through a pool-based marketplace simulation platform, in which generators offer their biddings in day-ahead and real time markets, and retail customers can respond to the price signal in real time pricing (RTP) mechanism. Bidding strategies of supply side and demand side are modelled in this paper. According to the profit maximization strategies of supply side bidding and demand side response, we describe the impact of the introduction of dynamic pricing to both supply side and demand side, when all of the participants can be involved in the RTP programs freely.

Rest of the paper is organized as follows. Section II and section III present the models of demand side response strategies and supply side bidding strategies respectively. Section IV describes the market clearing mechanism and an iterative process of interaction between supply side bidding and demand side response. Section V presents a case study concerning the optimal strategies of double side response to RTP. Finally, section VI concludes the gaming behaviors of different types of consumers and different capacities of generators are discussed by some study cases.

II. Demand Side Response Strategies

In current electricity markets, there are different kinds of DR programs designed to encourage consumers to reduce their power consumption or modify their load profile for reducing volatility in wholesale electricity prices, mitigating exercise of market power and improving reliability of the grid. On the view of demand side, customers that want to take advantage of these programs and tariffs can achieve DR through three kinds of strategies [23]: load curtailment, load shifting and fuel substitution. In this section, these different DP strategies are formulated respectively.

A. Load curtailment

Load curtailment is the reduction of electrical demand during a given time period without causing demand to increase during another period or using other substitutable power systems. Load curtailment is widely used in both incentive-based and price-based DR programs.

In this paper, load curtailment strategy are defined as the program participants are eligible to receive full spot price value for curtailment during hours when spot price is above certain price level as the case in NYISO[24]. Here, price elasticity rate is used to evaluate the demand response to a change in its price:

$$\Delta d_t = \varepsilon \frac{\Delta \lambda_t}{\lambda_t} d_t \tag{1}$$

where λ_t is spot price at time period t. $\Delta\lambda_t$ is the change of spot price. d_t and Δd_t are initial demand and demand response at time period t respectively. And ε is the price elasticity rate.

B. Load shifting

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Load shifting is a load management technique that aims to move demand from the peak hours to off-peak hours of the day. Under TOU or RTP tariff, the consumers can achieve significant benefits just through shifting load from high price time to low price time by energy storages[25, 26].

Assuming the load shifting works in peak hours and off-peak hours of a single day, the optimal load shifting strategy of a consumer can be formulated as:

$$\min_{p_t^G} \sum_{t=1}^{T} \lambda_t p_t^G \tag{2}$$

$$\text{s.t.} \quad V_t = (1-e)V_{t-1} + p_t^G - d_t \tag{3}$$

$$V^{Min} \le V_t \le V^{Max} \tag{4}$$

$$P^{Min} \le P_t^G \le P^{Max} \tag{5}$$

where λ_t is spot price at time period t. p^G_t and d_t are feed-in power from the grid and load demand at time period t respectively. V_t is volume of the energy storage at time period t. V^{Min} and V^{Max} are lower bound and upper bound of the energy storage respectively. P^{Min} and P^{Max} are lower bound and upper bound of the feed-in power flow respectively. And e is the losses in conversion and storage.

B. Fuel substitution

When electricity prices are higher than distributed generation cost, substitutable generation can be used to partly replace the feed-in power from the grid. Such DR strategy is fuel substitution. CHP (Combined heating and power) technology is probably the best known example of this DR strategy[27]. By generating electricity locally and utilizing the coproduced heat, CHP systems can substantially improve the efficiency of energy use in terminal consumers. Because of the coupling constraint of thermal output and power output in CHP system, the additional generation for DR will be limited by heating demand and decrease the efficiency of fuel conversion.

In this paper, CHP system is used to illustrate this DR strategy. Then the optimal fuel substitution strategy of a consumer is formulated as:

$$\min_{p_t^G, p_t^S} \sum_{t=1}^{T} [\lambda_t p_t^G - C(p_t^S - p_t^H)] \tag{6}$$

$$\text{s.t.} \quad p_t^G + p_t^S = d_t \tag{7}$$

$$\gamma^{Min} p_t^H \le p_t^S \le \gamma^{Max} p_t^H \tag{8}$$

where p^S_t and p^H_t are substitutable generation for DR and scheduled generation for heating at time period t respectively. $C(\cdot)$ represents the additional cost in this DR strategy. γ^{Min} and

γ^{Max} are lower bound and upper bound of the coupling constraint of thermal output and power output respectively.

III. Supply Side Bidding Strategies

In deregulated electricity markets, the suppliers (GENCOs) profits depend on the implementation of a successful bidding strategy. A good bidding strategy in electricity markets should involve unique features of electricity markets, such as operating constraints, price volatile, and oligopoly competition. Furthermore, bidding decisions are coupled with generation resource scheduling or unit commitment since generator characteristics and how they will be used to meet the accepted bids in the future have to be considered before bids are submitted. For example, if starting up a thermal unit is expected, the associated start-up cost should somehow be configured in the bid curves. The decisions, however, can be quite subtle since generally start-up costs usually are not part of a bid. GENCO's resource scheduling and bidding decisions should be integrated in its bidding strategies

In this paper, suppose the power supplier considered in this paper is a price-taker. That is, the generation capacity allocated to the wholesale market would not affect its market clearing prices. The wholesale market is considered as a power pool model with uniform clearing price. The suppliers submit hourly bid curves to ISO (Independent System Operator) each day. Based on these curves, ISO schedules the power generation of each unit to satisfy the system demand, reserve and other requirements, and sets the marginal bid price as the market clearing price, MCP.

A linear supply function (LSF) bidding[28] is assumed for supplier i:

$$o_i(p_{i,t},t) \equiv p_{i,t}(\lambda_t) = \beta_{i,t}(\lambda_t - \alpha_{i,t}) \tag{9}$$

Then the individual supplier's profit maximization model is used to obtain the optimal bidding strategies $\{\alpha_{i,t}, \beta_{i,t}\}$ in each hour based on the day-ahead market clearing price λ_t in last iteration. The optimal problem is formulated as:

$$\max_{\alpha_{i,t},\beta_{i,t},u_{i,t},x_{i,t}} \sum_{t=1}^{T} [\lambda_t p_{i,t} - C_i(p_{i,t}) - S_i(u_{i,t})] \tag{10}$$

s.t.

State transition:

$$x_{i,t+1} = x_{i,t} + u_{i,t} \quad \text{if } x_{i,t} \cdot u_{i,t} > 0 \tag{11}$$

$$x_{i,t+1} = u_{i,t} \quad \text{if } x_{i,t} \cdot u_{i,t} < 0 \tag{12}$$

Capacity:

$$\underline{P_i} \cdot u_{i,t} \le p_{i,t} \le \overline{P_i} \cdot u_{i,t} \tag{13}$$

Unit ramping:

$$| p^s_{i,t-1} - p^s_{i,t} | \le \Delta_i \text{ if } x_{i,t} \ge 1 \text{ and } x_{i,t+1} \ge 1 \tag{14}$$

Minimum up/down time:

$$u_{i,t} = 1 \quad \text{if } 1 \le x_{i,t} < \overline{\tau}_i \tag{15}$$

$$u_{i,t} = -1 \quad \text{if } -\underline{\tau}_i \le x_{i,t} < -1 \tag{16}$$

where $u_{i,t}$ is the discrete decision variable of generation i during time period t for up (1) or down (-1) of the generation at time t+1. $x_{i,t}$ represents the state of generation i during time period t, denoting number of hours that the generation has been on or off. Δ_i is the ramp rate of generation i. $\overline{P_i}$ and $\underline{P_i}$ are the maximum/minimum generation level of generation i, respectively. And $\overline{\tau}_i / \underline{\tau}_i$ represents minimum up/down time of generation i. Equ (11)-(16) are the operating constraints of an individual generator.

IV. Market Clearing and Simulation Design

In day-ahead wholesale market, the ISO is assumed to use a minimum bidding payment unit commitment algorithm[29] to clear the spot markets after receiving the forecasted load demand, offered demand response and bids from all suppliers.

This clearing mechanism can be formulated as the following mixed integer programming problem:

$$\min \sum_{t=1}^{T} \sum_{i=1}^{I} [o_i(p_{i,t},t) + S_i(u_{i,t})] \tag{17}$$

s.t.

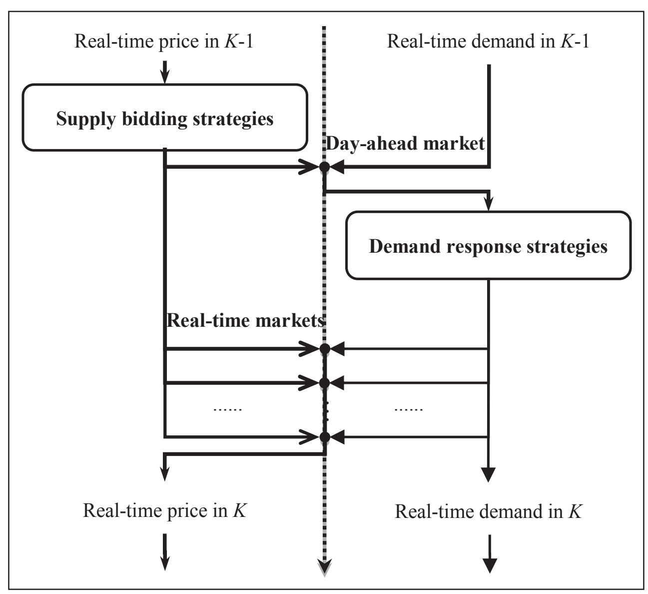
$$\sum_{i=1}^{I} p_{i,t} = D_t \tag{18}$$

and individual unit constraints (11)-(16).

Where D_t means the forecasted load demand minus offered demand response. S_i is the start-up cost of generator i. Equ. (18) represents the supplier-demand balance constraint in the whole system.

An iteration framework of supply and demand side real-time response to dynamic pricing is presented in this section.

Figure 1. Framework of the repeat game of supply and demand side real-time response to dynamic pricing



As shown in Fig. 1, suppliers and consumers update their decisions of bidding curve or load demand in a repeated game:

1) At stage K of the game, each generator updates his/her bids based on the real-time prices in last stage K-1 according to the profit maximization bidding strategies problem (10)-(16).

2) Then day-ahead market is cleared based on the updated bids and the demand profile in last stage by (11)-(16), (17), (18).

3) Consumers with different demand response programs types update their own response to the new day-ahead price through (1), (2)-(5) and (6)-(8).

4) Then the real-time price is cleared in each hour by supply side bidding strategies and demand side responses in stage K.

5) Go to the next stage K+1.

Under above framework, both supply and demand side participants keep updating their offers according to the clearing price and demand profile at last stage, until the repeated game is equilibrium. It should be clarified that although the best response strategy in most games can lead the game converging to iterative equilibrium as long as the gaming equilibrium is existing, there is still a lack of theoretical equilibrium conditions and convergence proof on iterative simulation algorithm for this game with nonlinear integer-constraint. However, the simulation algorithm in paper performs based on our numerical testing experience.

V. Case Study

This section presents a case study that illustrates the trends of bidding strategic behaviours in supply side and response strategic behaviours in demand side under dynamic pricing. A test system modified from the IEEE 10 units system is considered. The parameters of the generating units are given in Table I, II.

TABLE I. Units' Operating Constraints

Unit id	$\underline{p}$	$\overline{p}$	Δ	$\overline{\tau}$	$\underline{\tau}$	τ^c
1#	150MW	455 MW	Inf.	8h	8h	13h
2#	150 MW	455 MW	100MW/h	8h	8h	13h
3#	20 MW	130 MW	100MW/h	5h	5h	9h
4#	20 MW	130 MW	Inf.	5h	5h	9h
5#	25 MW	162 MW	Inf.	6h	6h	10h
6#	20 MW	80 MW	Inf.	3h	3h	5h
7#	25 MW	85 MW	Inf.	3h	3h	5h
8#	10 MW	55 MW	Inf.	1h	1h	1h
9#	10 MW	55 MW	Inf.	1h	1h	1h
10#	10 MW	55 MW	Inf.	1h	1h	1h

TABLE II. Units' Operating Costs (fuel cost and start-up cost)

Unit id	Fuel cost($) $C(p) = ap^2 + bp + c$			S^h	S^c
	a	b	c		
1#	0.00048	16.19	1000	$4500	$9000
2#	0.00031	17.26	970	$5000	$10000
3#	0.00200	16.6	700	$550	$1100
4#	0.00211	16.5	680	$560	$1120
5#	0.00398	19.7	450	$900	$1800
6#	0.00712	22.26	370	$170	$340
7#	0.00790	27.74	480	$260	$520
8#	0.00413	25.92	660	$30	$30
9#	0.00222	27.27	665	$30	$30
10#	0.00173	27.79	670	$30	$30

In this 10 units' system, unit 1# and 2#, which have lower generation cost and longer start-up time, are used as base load units. And unit 8# to 10# which has very short start-up time, are used as peaking units. The system demand and the unit commitment results of different types of units under marginal cost bidding are shown in Fig. 2.

Peaking units that generally run only when there is a high demand, known as peak hours. As shown in Table 2, the power supplied commands a much higher price than base load units, which leads to high real-time price in peak times. In these case, only two peaking units are started up in six peak hours.

The opposites of peaking units are base load units which have lower generation cost and longer start-up/shut-down time. They often stop only for maintenance or unexpected outages. As seen in Fig. 2, the base load units only curtail 20% their output on five night hours with low demand.

Figure 2. Generation of base load, middle load and peaking units under marginal cost bidding

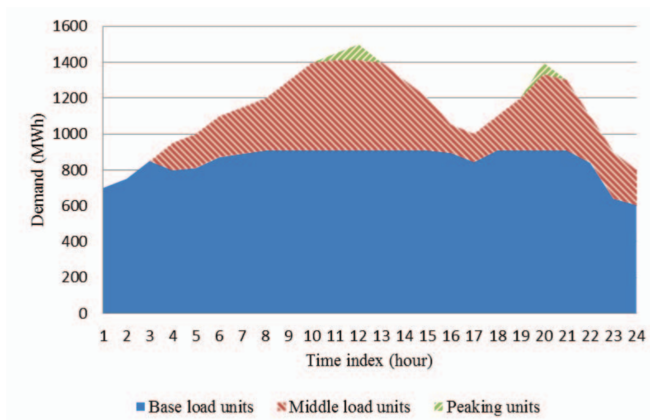
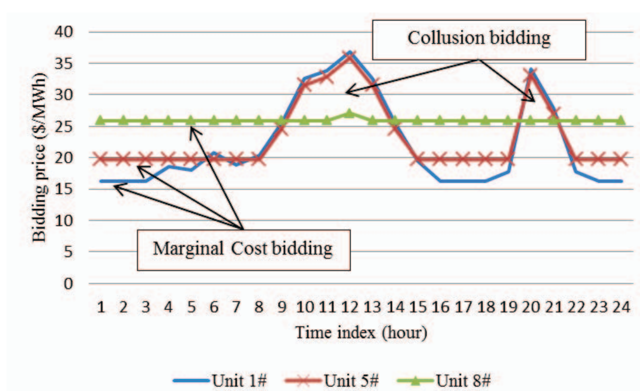


Figure 3. Strategic bidding offer of unit 1#(load load unit), unit 5#(middle load unit) and 8#(peaking unit)



As shown in Fig. 3, there are two peak time in a day: 12:00 and 20:00. If all the units bid as their marginal costs, base load units will keep on all the time and peaking units will be started up only on peak hours. The MCP (Market Clearing Price) is based on the marginal cost of base load units during 1:00~3:00, the marginal cost of peaking load units during

11:00, 12:00 and 20:00, and the marginal cost of middle load units during other hours. The collusion bidding still happens in some peak times (shown in Fig. 3).

VI. Conclusion

Under the assumption that all the retailer consumers have been involved in the demand response program with dynamic pricing and will respond to the price signal rationally, this paper discussion the market equilibrium considering both supply side and demand side gaming behaviors. Supply side is modeled as a pool-based marketplace with payment minimization auction and marginal cost pricing mechanisms. On the demand side, the particular demand profile and elasticity of consumers with three kinds of demand response programs are considered. The cost-efficient demand response strategies of the three kinds of consumers are modeled according to their load requirement features. An iteration based framework, which each stage includes supply side bidding, market clearing, demand side responding and dynamic price updating, is used to get the market equilibrium. Numerical testing results show that the demand response program with dynamic pricing does encourage the load shifting from on-peak time to off-peak time. The total demand profile can be lead to a more cost efficiency unit commitment schedule with less start-up operation and less peak unit requirement. But the collusion bidding still happens in some peak times.

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