A Game Theoretic Approach in Bidding Strategy in Iran Wholesale Electricity Market

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In this paper, we consider bidding behavior of producers in wholesale electricity market in Iran. Participating in a day ahead pay-as-bid electricity auctions for Generator Companies with purpose of profit maximization in spite of market regulation constraints is taken into account. Since bidding functions are restricted to be stepwise with maximum of ten steps per unit in each hour, we ask whether increasing steps will improve the Ex Ante profit of firms or not. Finally, in order to evaluate rationalities in bidding behavior of the market participants, our results are compared with outcomes of real bidding data.

Keywords: Bayesian Nash Equilibrium, residual demand, electricity day-ahead market, bidding strategy

INTRODUCTION

Following England and wales during 1990s many countries worldwide had run a deregulation program in their electricity market structures. Deregulation has caused some new issues to evolve mostly based on uncertainty in its essence e.g. load variations in different hours and distinct and unknown behavior of competitors in their bidding strategies.

A deregulated electricity market resembles an imperfect competition market or sometimes an oligopoly market. This is because of some intrinsic aspects of its structure: limited number of producers, so many obstacles for entrants, long period of installation of new plants and/or units, a huge amount of fixed cost, technical constricts of transmission lines and inevitable losses through all transformers and line cables (David and Wen, 2000). Limited number of suppliers in a specific geographical area will allow them to induce market power by their pricing behavior (David and Wen, 2000).

Electricity market can be modelled as a dynamic sophisticated environment with complicated interactions amongst players who confront different types of risks and try to optimize their profit as well as taking into account minimization of their risk. This kind of optimization is inspected in this paper.

PROBLEM DEFINITION

Market Conditions

Market structure have a significant impact on bidding strategy. One can categorize three structures known for deregulated electricity markets: Market Pools (PoolCo), Bilateral Contract (BC) Market and Hybrid Markets (Foley et al., 2010). In PoolCo all bids are accumulated regardless of to which buyer they are selling. In the other hand, in a BC market sellers and buyers can negotiate on the prices and independent system operator only controls for transmission line capacity and reliability of the network. Iran's newly established wholesale electricity market is Market Pool for supply side. There is no bidding for the demand side. The demand of the market is predicted for each hour by system operator and announced daily for 96 hours in future. Thus, demand is completely inelastic. Each GenCo bids accordingly three days ahead. In the following stages, congestions, and transmission capacity constraints will be taken into account and bids will be modified if necessary. In this paper, our focus is at the first stage in which players bid three days ahead. Auction takes place in pay-as-bid structure meaning that after clearing market, winners will be paid by their own bid price. More specifically, powers that had been bid lower than market clearing price will be sold at the price bid and all pairs bellow this power will be sold at their own bid price too.

In Iran electricity market power plants bid for each of their generating units in each hour. A bidding function in this context is constrained to be stepwise with maximum steps of ten stipulated by regulator. The price cap for each bidding function is determined too. Neither price tick size nor power tick size is defined for bidders.

We assume no supply shortage occurs. Hence, total power that had been bid is always more than total demand anticipated. The formidability of such assumption can be relieved by observing last periods of market clearings.

Time constraints for a generator to reach its stationary point and feeding the power network are neglected too. Start-up costs and shut down costs are not taken into account. As a newly founded market, no financial contracts such as forwards and futures are available nor reserve markets.

No unit is assumed to produce higher than its capacity. Hence, their supply function will be vertical for powers more than their potential capacity. Moreover, cost functions are assumed linear which held AVC constant enabling us to test our model through empirical data.

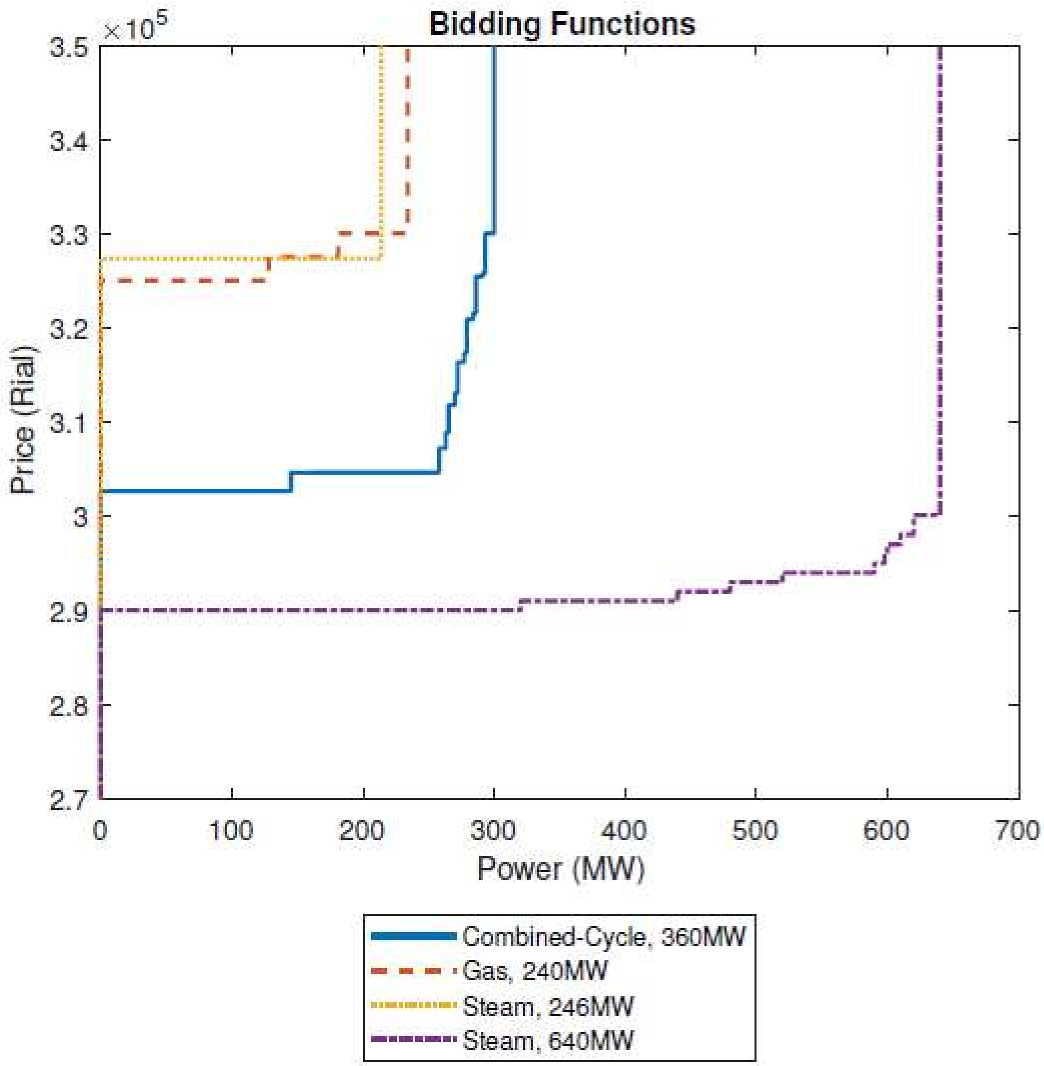
Data Description

Data includes a history of price-power bidding data for three-month period starting at 12th of August 2012 until 20th of November 2012. There are 636 generating units' bids from 121 power plants among which 404 units are gas generators, 121 are steam type, 90 Hydro, 4 Wind and 16 units are diesel type. Bidding data are sorted by codes for each power plant and no names are published for codes so it lacks maximum capacity and cost functions of generators but only its unit technology e.g. steam, combined, etc. Thus, we assume last steps of each unit had been bid for its maximum capacity, which can be observed by going through real time data in different days. We used another set of data containing average variable cost for various technologies of generators to make an estimation for AVCs of each unit. Ultimately, GenCos make bid for the power at the very beginning of the transmission line meaning that the cost of losses in transformations -for increasing voltage- is included in bidding prices since these costs are considered as production costs. In Figure 1 some bidding functions for power plants of different technologies are illustrated.

Problem Definition

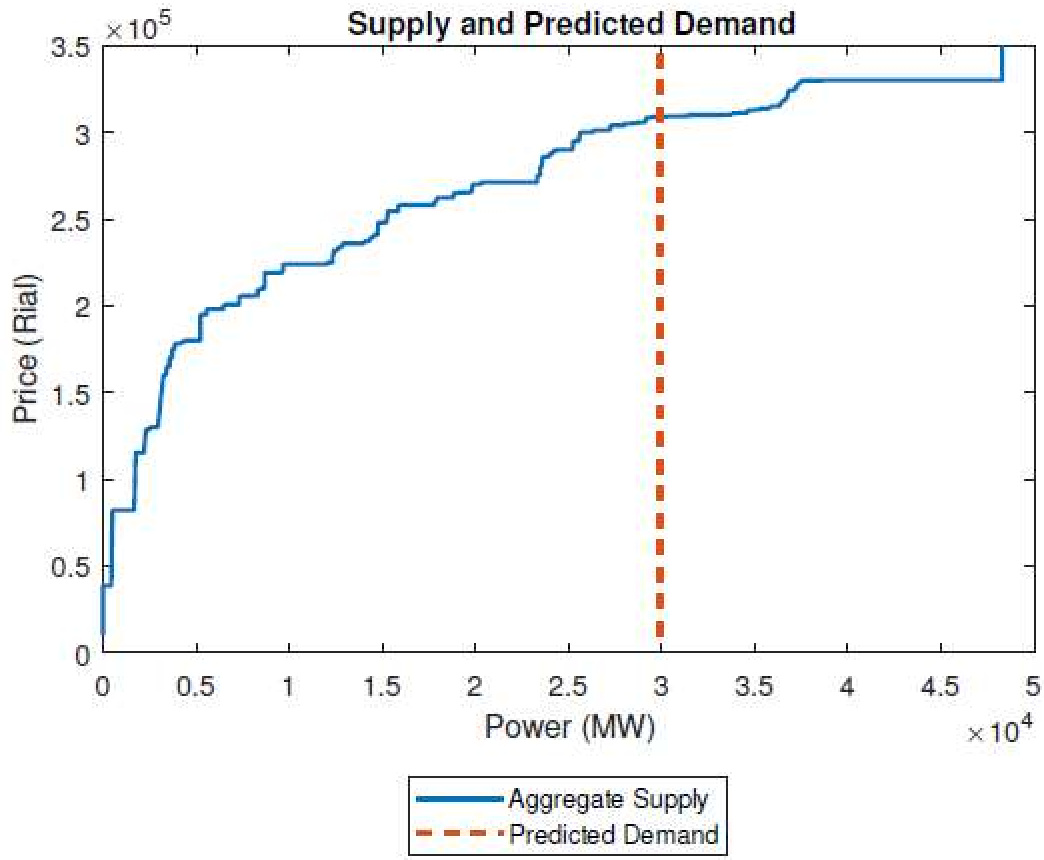
Each bidder must submit ten pairs of price-power for each of its generating units. Dispatching center will sum all the bidding functions horizontally and cross with total demand anticipated for that hour, as illustrated in Figure 2. and subsequently market-clearing price is determined.

FIGURE 1
BIDDING FUNCTIONS EXTRACTED FROM DATA SET



Suppose there are two identical independent firms, namely i and j, in this market, each allowed to bid at only two steps. One period has passed and market-clearing price has been determined. Firm i wants to maximize its profit for the next period. Had the firm i known the bidding function of firm j in last auction period it would have bid a single step, which would have maximized its profit given a certain residual demand and by residual demand we mean total demand minus supply of the other firm. However currently it has nothing but a residual demand of the last auction period. If it believes that firm j will repeat its last strategy so it has a certain residual demand for the next period, which leads to a single step. Here comes the uncertainty part. Suppose there were two auction periods in the past and it faced two distinct residual demand for each one. As our key assumption, it believes that firm j will repeat one of its strategies in the past. Should it bid in a single step or two step (two pairs of price-power each with different price)? By going from a single step into two distinct steps, it must confront some kind of risk. The reward is the more profit appointed to higher priced power, in case of winning. Our main interest is that by discriminating in the price of the two pairs in its bidding strategy will it obtain more profit in the next auction period.

FIGURE 2
INTERSECTION OF TOTAL DEMAND AND TOTAL SUPPLY EXTRACTED FROM DATA SET



To generalize this concept, suppose there are 90 days each with 24 hours that auction takes place. Bidding functions must be stepwise meaning that ten price-power pair must be submitted for generating units. A given power plant in such an environment faces many residual demands from last auction periods and wishes to maximize its profit for the next day hourly auctions. If we assume that, it assumes that its next day residual demand can be forecasted by using last residual demands' information, does increasing steps lead to a rise in its profit?

LITERATURE REVIEW

Deregulated electricity markets are not perfectly competitive and so producers can earn profit by strategic bidding and exercising market power (David and Wen, 2000). In Game Theory based approaches in bidding strategy there has been three main streams taken (Li et al., 2011). Cournot Competition, Bertrand Competition and Supply Function Equilibrium. In another study, by implementing Bertrand model, a strategic bidding was introduced for profit maximization by assuming that no deviation occurs in bidding of all other competitors period to period and marginal costs are constant (Ernst et al., 2004). In another paper, a Cournot model was used to simulate California electricity market and showed that power plants withhold part of their capacity to exercise market power and increase prices (Borenstein and Bushnell, 1999).

Supply Function Equilibrium, (firstly introduced in (Genc and Reynolds, 2011)), assumes players compete neither on prices (as in Bertrand) nor on quantities (as in Cournot) but on supply function. Later on, this model was extended and an empirical analysis on England electricity market (Green and Newbery, 1992). They showed that in an auction of a single homogeneous good under uncertainty of demand producers could earn more profit by bidding a supply function rather than a single pair of price-power.

In another research, a bidding strategy was introduced using SFE in which decision parameter of each player is slope of its supply function (Bompard et al., 2010). It was shown that capacity constraints of producers would make decision of high capacity units more influential allowing them to exercise market power and raise market prices. Some other noticeable works also examined the bidding strategy in different market structures (S. Y. Al-Agtash, 2010; S. Al-Agtash and Yamin, 2004; Genc and Reynolds, 2011; Haghighat et al., 2008; Hobbs et al., 2000; Li et al., 2011; Noghani and Noghanibehambari, 2019; Noghanibehambari and Rahnamamoghadam, 2020; Sioshansi and Oren, 2007).

Another study characterized a benchmark theory of static profit maximization and used firm-level data of Texas electricity market to compare firms' bidding strategy to the strategy induced by the model (Hortaçsu and Puller, 2008). They showed that firms with large stakes in the market performed closer to the theoretical benchmark than smaller firms.

There is also evidence that in a pay-as-bid auction it is ex-post optimal to bid in a single step if no shortages occurs at supply side regardless of any uncertainty in demand (Wang and Zender, 2002).

Our benchmark theory has been motivated by SFE and our work is close to what had been done in other similar research (e.g. (Hortaçsu and Puller, 2008)). However, our focus is to examine whether a firm can outperform by increasing steps of its bidding function.

EMPIRICAL APPROACH

We consider the problem as a Bayesian Nash Equilibrium. As our key assumption, each firm extracts a distribution function of its expected residual demand by using last residual demands, meaning that it believes that other firms take the same factors for their bidding strategy as they did for last periods. Thus, any of past residual demands resembles a state of the game to which a specific firm appoints a probability in accordance to its system of belief. Hence, the firm's objective function will be to maximize its expected net profit from all states of the game. Main constraints include power plant maximum capacity and price cap, which is determined by regulator. In calculating net profit, we use average variable costs since we assumed cost functions linear and hence marginal cost equals average variable cost in such cases. We must mention that profit function in equation 1 does not resemble real profit appointed to the firm for two reasons: fixed costs and other opportunity costs of fixed investments are not included. Secondly, labor costs are not taken into account. Since labor costs are estimated as a specific percentage of other production costs (which are included in AVC) and regarding the fact that we are about to compare profit values of the same firm in different cases, therefore neglecting these costs will not affect our results.

$$
\begin{aligned}
&\max \textstyle\sum_{i=1}^{i=T} F_i^f(p,P,t_i).\alpha(t_i) \\
&F_i^f(p,P,t_i) = \textstyle\sum_{j=1}^{j=L_i-1}\{p_j\,.P_j\} + p_{L_i}.\left(RD_i^f\left(p_{L_i},P_{L_i},t_i\right) - \textstyle\sum_{j=1}^{j=L_i-1} P_j\right) \\
&L_i \leq K; \qquad i = 1{:}T \\
&\textstyle\sum_{j=1}^{j=L_i} P_j^f \leq P_{max}^f \qquad i = 1{:}T \\
&RD_f(.,.,t_i) \leq P_{max} \qquad i = 1{:}T \\
&p^f(p,P) = p_k^f \qquad if \qquad \textstyle\sum_{j=1}^{k-1} P_j^f \leq P < \textstyle\sum_{j=1}^{k} P_j^f \\
&\quad for \qquad k = 1{:}K \qquad K \leq 10 \\
&\textstyle\sum_{j=1}^{k} P_j^f - \textstyle\sum_{j=1}^{k-1} P_j^f \geq \Delta P_{min}
\end{aligned}
\tag{1}
$$

$$p_k^f - p_{k-1}^f \geq \Delta p_{min}$$
$$RD_i^f(p, t_i) = D(p, t_i) - S_{-f}(p, t_i) \qquad , i = 1{:}T \qquad , f = 1,2, \dots, F$$
$$\alpha(t_i) = G(t_i) \qquad i = 1{:}T$$
$$\sum_{i=1}^{T} \alpha(t_i) = 1$$

In Equation 1 the profit function of firm f in auction period t_i for any price vector p and power vector P is introduced by $F_i^f(p, P, t_i)$ and $\alpha(t_i)$ is the probability function assigned to the residual demand of auction period t_i and subsequently to the profit function of firm derived from facing that residual demand. Any p_j resembles the price (height) of j^{th} step and every P_j is exactly the amount of power bid by j^{th} step meaning its width. $RD_i^f(p_j, P_j, t_i)$ is the residual demand curve facing firm f at such price and power level and in every auction period t_i and for every possible strategy that can be taken by firm in this auction period L_i is the number of distinctly-priced steps in its bidding function while K is the maximum number of such steps stipulated by market regulations. Totally, there are T auction periods. For each firm P_{max}^f represents its maximum capacity and we assume marginal cost will rise sharply after this capacity not allowing power plants to produce more than this level. $p^f(P, P)$ Shall be considered as firm's bidding function. ΔP_{min} And Δp_{min} are tick size of power and price. $S_{-f}(p, t_i)$ is the supply of all other firms except firm $f$and $D(p, t_i)$ represents total demand. $G(t_i)$ Is probability function representing a firm's system of beliefs that it assigns to residual demands.

One shall use above model to find optimum quantities for price-power, and then evaluate results by virtually participate in next day auction (day 21 of November). However to make a contribution of this model we used it for only two steps (meaning we assume $\mathrm{K} = 2$) and that all two power quantities are the same (meaning that $P_1 = P_2$) We used $MatLab2015$ in a $Corei3$ Laptop to run all simulations.

RESULTS

To run this model we shall specify and verify a system of belief (determining $G(.)$). With respect to the probability function, we choose different scenarios can be defined:

- ***Scenario*** $\boldsymbol{\theta_1}$: In order to run our model and optimize a firm strategy for any specific hour h, we opt residual demands of that hour in past data upon which our expected residual demand would be built. Actually, we assigned zero probability to all other residual demands but ones extracted for hour h. In this scenario, we use a uniform distribution function as introduced in Equation 2. Its rationale is because without any extra information, there is no superiority considered among residual demands and hence a uniform function seems to serve the best:

$$\alpha_t = \frac{1}{T} \tag{2}$$

It is worth noting that in case there are some residual demands very close to each other; one can expect that one of them have a higher probability to occur the next period than all the other residual demands. In this scenario, each residual demand has the same probability and suppose in an extreme case two of them overlap completely, and then we have one residual demand with a probability of twice all others.

- ***Scenario*** $\boldsymbol{\theta_2}$: like the previous scenario for every hour, we use residual demands of the same hour. By extracting market-clearing prices for the whole period, one can detect a (non-strict) decreasing trend, which matches the same trend in total demand. Therefore, the closer in time a residual demand is the higher probability we attach to it. In Equation 3, we introduced a smooth distribution function, which satisfies this condition:

$$\alpha_t = \frac{2t}{(T)(T+1)} \qquad 1 \le t \le T \tag{3}$$

where t represent an auction period.

- $\boldsymbol{Scenario\ \theta_3}$: residual demands differ from each other due to differing bidding strategies taken by firms; such as employing new analysts, deviation in market structure or regulation, deviation in expectations of firms, new entrants, deviation in anticipated demand, etc. in a short period of time, like three months in this case, most of these factors can be considered constant. We take into account deviations in forecasted demand. We assume bidding strategy of other firms is sensitive to level of predicted demand. Hence, we choose residual demands of all hours of all days in which the demand is in a 500 MW neighborhood of the demand announced by independent system operator for specific hour of next day. In different cases, we observed 400 to 800 residual demands that satisfy this condition. As expected by our assumption and shown in Figure 3 and Figure 4 residual demands in this case are much more concentrated and giving different weights to them does not change results significantly. Thus, we use equation 2 for probability distribution given to each residual demand.

Tables 1 through 8 illustrate a summary of the most important findings.

FIGURE 3
RESIDUAL DEMANDS IN SCENARIO θ_1, EXTRACTED FROM DATA SET

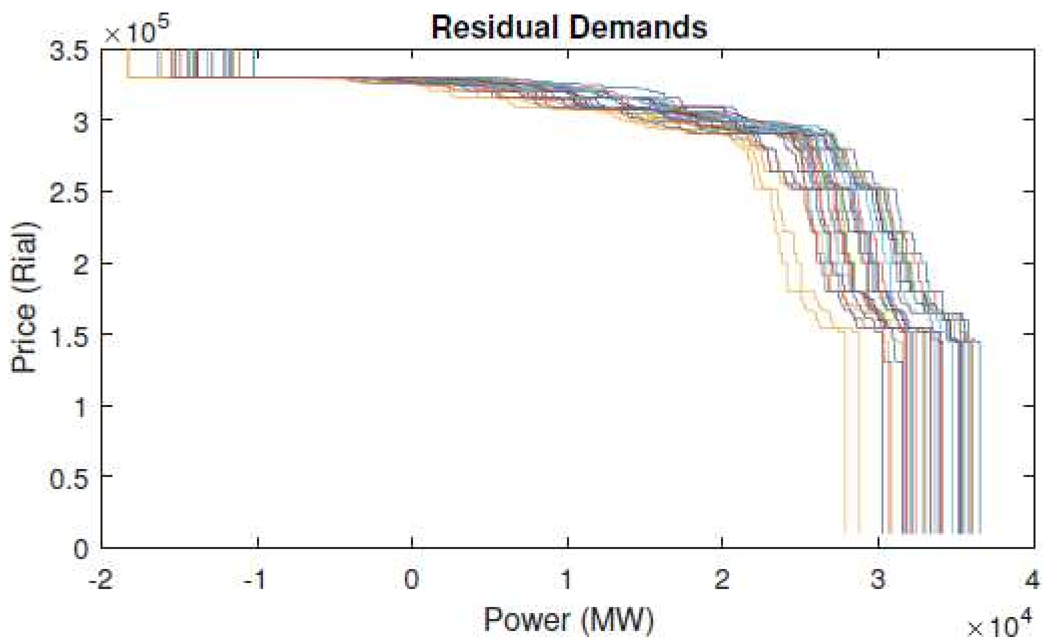


FIGURE 4
RESIDUAL DEMANDS IN θ_3, EXTRACTED FROM DATA SET

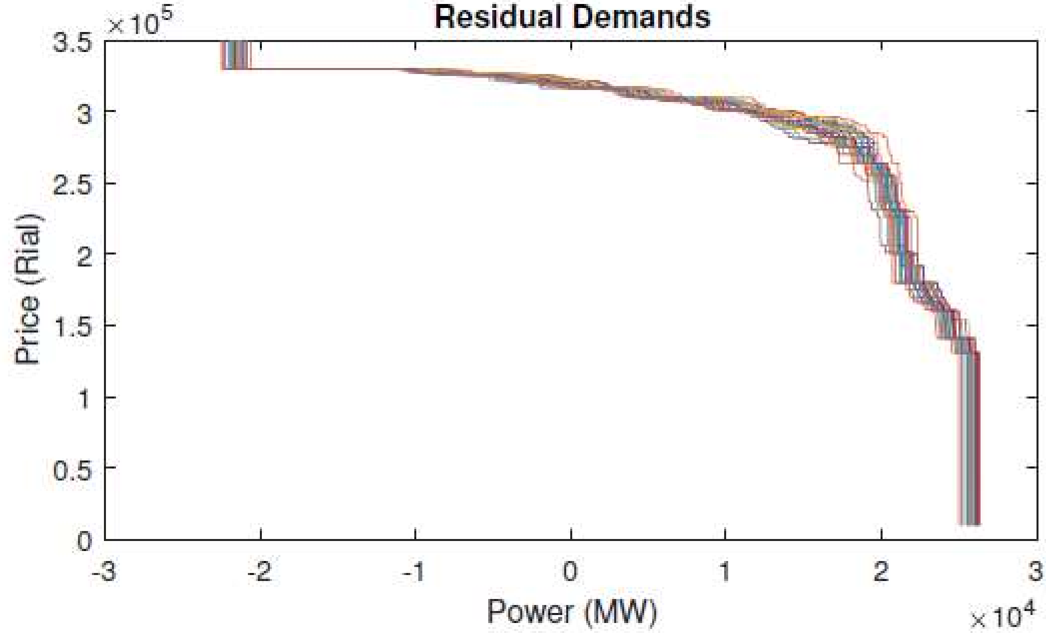


TABLE 1
RESULTS UNDER SCENARIO θ_1

No. of steps induced in our strategy	K=1	K=2	K=1	K=2	K=1	K=2
Power Plant Type and Capacity (MW)	Steam, 1600		954, gas		1600, Steam	
Hour (h)	4		1		2	
One- Step-Induced Strategy Pairs of Power (MW)- Price (Thousand Rials per MW)	(1600,283.5)	-	(954,271.5)	-	(1600,275.5)	-
Two- Step-Induced Strategy Pairs of Power (MW)- Price (Thousand Rials per MW)	-	(800,283.5) (1600,284.5)	-	(477,271.5) (954,272.5)	-	(800,275.5) (1600,276)
Profit under our Theoretical Benchmark for the Next Day (Million Rial)	28.758	28.762	62.569	63.046	74.221	74.620
Real Achieved Profit in the Next Day (Million Rial)	27.631		39.2741		60.963	

Profit under our Theoretical Benchmark for Last Days (Billion Rials)	6.3597	7.2733	6.0045	6.0236	9.1037	9.1281
Real Achieved Profit in Last Days (Billion Rials)	3.3561		3.2802		6.5713	

TABLE 2
RESULTS UNDER SCENARIO θ_1 CONTINUE

No. of steps induced in our strategy	K=1	K=2	K=1	K=2	K=1	K=2
Power Plant Capacity (MW)	1600, Steam		Steam, 1920		Gas, 37.6	
Hour (h)	7		4		4	
One- Step Induced Strategy Pairs of Power (MW)-Price (Thousand Rials per MW)	(1600, 254)	-	(1920, 269)	-	(37.6, 305.5)	-
Two- Step Induced Strategy Pairs of Power (MW)-Price (Thousand Rials per MW)	-	(800,254.5) (1600,257.5)	-	(960,269) (1920,270.5)	-	(18.8,305.5) (37.6,305.5)
Profit under our Theoretical Benchmark for the Next Day (Million Rial)	25.356	27.755	167.04	168.48	0	0
Real Achieved Profit in the Next Day (Million Rial)	22.042		16.166		0	
Profit under our Theoretical Benchmark for Last Days (Billion Rials)	5.0741	5.0968	8.989	9.0152	0.03895	0.03895
Real Achieved Profit in Last Days (Billion Rials)	2.1825		3.1438		0	

TABLE 3
RESULTS UNDER SCENARIO θ_1 CONTINUE

No. of steps induced in our strategy	K=1	K=2	K=1	K=2
Power Plant Capacity (MW)	Steam, 1600		Gas, 954	
Hour (h)	16		20	
One- Step-Induced Strategy Pairs of Power (MW)- Price (Thousand Rials per MW)	(1600,269)	-	(954,284)	-
Two- Step- Induced Strategy Pairs of Power (MW)- Price (Thousand Rials per MW)	-	(800,269) (1600,269)	-	(477,284) (954,284)
Profit under our Theoretical Benchmark for the Next Day (Million Rial)	120	120	68.688	68.688
Real Achieved Profit in the Next Day (Million Rial)	62.633		48.449	
Profit under our Theoretical Benchmark for Last Days (Billion Rials)	14.24	14.24	6.1819	6.1819
Real Achieved Profit in Last Days (Billion Rials)	9.1675		4.7004	

TABLE 4
RESULTS UNDER SCENARIO θ_2

No. of steps induced in our strategy	K=1	K=2	K=1	K=2	K=1	K=2
Power Plant Capacity (MW)	Combined, 1784		Steam, 1920		Combined, 2236	
Hour (h)	3		5		5	
One- Step Induced Strategy Pairs of Power (MW)- Price (Thousand Rials per MW)	(1784,233)	-	(1920,223)	-	(2236,217.5)	-
Two- Step Induced Strategy Pairs of Power (MW)- Price (Thousand Rials per MW)	-	(892,228) (1784,265)	-	(960,219) (1920,269)	-	(1118,216.5) (2236,280.5)
Profit under our Theoretical Benchmark for the Next Day (Million Rial)	58.872	72.291	78.72	35.52	74.906	36.335
Real Achieved Profit in the Next Day (Million Rial)	37.547		16.166		10.424	
Profit under our Theoretical Benchmark for Last Days (Billion Rials)	5.5242	7.4797	6.7347	7.816	6.5504	7.1534
Real Achieved Profit in Last Days (Billion Rials)	4.2364		3.8438		5.4646	

TABLE 5
RESULTS UNDER SCENARIO θ_2 - CONTINUE

No. of steps induced in our strategy	K=1	K=2	K=1	K=2	K=1	K=2
Power Plant Capacity (MW)	Combined, 2808		Gas, 37.6		Steam, 1600	
Hour (h)	7		12		7	
One- Step Induced Strategy Pairs of Power (MW)- Price (Thousand Rials per MW)	(2808,266.5)	-	(37.6,318)	-	(1600,255)	-
Two- Step Induced Strategy Pairs of Power (MW)- Price (Thousand Rials per MW)	-	(1404,224.5) (2808,236.5)	-	(18.18,318) (37.6,318)	-	(800,254) (1600,257.5)
Profit under our Theoretical Benchmark for the Next Day (Million Rial)	4.212	15.444	0	0	97.6	98.8
Real Achieved Profit in the Next Day (Million Rial)	0		0		22.042	
Profit under our Theoretical Benchmark for Last Days (Billion Rials)	7.0444	9.4549	0.13742	0.13742	5.08521	5.1225
Real Achieved Profit in Last Days (Billion Rials)	1.5002		0.00251		2.1825	

TABLE 6
RESULTS UNDER SCENARIO θ_2 - CONTINUE

No. of steps induced in our strategy	K=1	K=2	K=1	K=2
Power Plant Capacity (MW)	Steam, 1600		Gas, 954	
Hour (h)	2		20	
One- Step Induced Strategy Pairs of Power (MW)- Price (Thousand Rials per MW)	(1600,274)	-	(954,284)	-
Two- Step Induced Strategy Pairs of Power (MW)- Price (Thousand Rials per MW)	-	(800,274) (1600,275.5)	-	(477,284) (954,284)
Profit under our Theoretical Benchmark for the Next Day (Million Rial)	128	129.2	68.688	68.688
Real Achieved Profit in the Next Day (Million Rial)	60.963		48.429	
Profit under our Theoretical Benchmark for Last Days (Billion Rials)	9.4545	9.46289	6.2008	6.2008
Real Achieved Profit in Last Days (Billion Rials)	6.5713		4.7014	

TABLE 7
RESULTS UNDER SCENARIO θ_3

No. of steps induced in our strategy	K=1	K=2	K=1	K=2	K=1	K=2
Power Plant Capacity (MW)	Steam, 1600		Gas, 954		Gas, 954	
Hour (h)	4		16		7	
One- Step Induced Strategy Pairs of Power (MW)- Price (Thousand Rials per MW)	(1600,285)	-	(954,298.5)	-	(954,254.5)	-
Two- Step Induced Strategy Pairs of Power (MW)- Price (Thousand Rials per MW)	-	(800,283.5) (1600,288)	-	(477,298.5) (954,298.5)	-	(477,252) (954,253)
Profit under our Theoretical Benchmark for the Next Day (Million Rial)	145.6	146.8	82.521	82.521	40.545	38.637
Real Achieved Profit in the Next Day (Million Rial)	27.831		55.855		0	
Profit under our Theoretical Benchmark for Last Days (Billion Rials)	35.4825	37.844	26.1289	26.1289	11.2658	11.2948
Real Achieved Profit in Last Days (Billion Rials)	14.1622		18.0214		7.16741	

TABLE 8
RESULTS UNDER SCENARIO θ_3

No. of steps induced in our strategy	K=1	K=2
Power Plant Capacity (MW)	Gas, 96	
Hour (h)	4	
One- Step Induced Strategy Pairs of Power (MW)- Price (Thousand Rials per MW)	(96,305.5)	-
Two- Step Induced Strategy Pairs of Power (MW)- Price (Thousand Rials per MW)	-	(48,305.5) (96,305.5)
Profit under our Theoretical Benchmark for the Next Day (Million Rial)	0	0
Real Achieved Profit in the Next Day (Million Rial)	0	
Profit under our Theoretical Benchmark for Last Days (Billion Rials)	1.8049	1.8049
Real Achieved Profit in Last Days (Billion Rials)	0.38953	

CONCLUSION AND REMARKS

It is worth mentioning that if two distinctly priced pairs of price-power lead to an increase in profit in comparison with a single step strategy, ten distinctly priced step will surely contribute to more profit too. In addition, since our prices induced by our theoretical model tend to get close to price cap, they are far from firms' average variable costs. Therefore, for the firms with the same or even similar capacities our model induce the same strategy regardless of their technology. It does not mean that technology has not been taken into account because AVCs include this information.

Electricity market in a government-based country like Iran confront some basic structural problems, which may be troublesome for empirical analysis. We mention the main potential problem and argue that it shall not be our issue of concern.

Majority of power plants are –and with much more proportion had been, at 2012- public and owned by ministry of energy and has not been privatized yet. Ministry of energy is the lone buyer of power and in case any of these power plants gain, a profit by winning an auction it would not pay money since it is the owner too. However, at the end of fiscal year, the taxman look into booking profits and inquire for its pertinent taxes. That motivates these non-privatized firms to bid far below their AVC to avoid positive profits. The point is that their objective function is to gain a profit of zero and as long as their objective and accordingly their strategy does not change structurally any residual demand in the past contain this information regardless of what objective each firm is pursuing because those firm act rationally according to their objectives and utilities.

There are cases in which increasing steps will lead to a raise in profit of power plants. There has been detected two core complementary results. Firstly, firms with more capacity have more chance to increase their profit by increasing steps. This can be justified intuitively too. Residual demands are more concentrated around optimum prices for e.g. small gas power plants while for huge capacity plants they get more distant which let second step of bidding function raise and induce more profits. Secondly, off-pick times are more prone to be taken advantage of and increase profit by increasing steps. It means that taking the risk of implementing two distinctly priced pairs in off-peak hours is more justified by our data than peak hours. Vindication of such result is the same as the previous one.

Real bidding data has two aspects, which cannot be justified with our model. Although the model induces little differences between steps and bid prices are far above AVCs but a sample firm's real bid begins by prices very close to its AVC and bid powers of a huge proportionate of its capacity in order to guarantee its participation in the market and maybe avoid shut down and startup costs. It then bid its remaining capacity with prices that jump up to price cap in order to explore market prices. We did not consider these two aspects (guaranteeing participation in market and exploring the market) in our objective functions. Hence, our model is not supposed to explain them.

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