Multi-Agent Bidding and Contracting for Non-Storable Goods

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Abstract

We study electronic bidding and contracting for non-storable goods such as electric power using multi-GA agents and game theoretical approaches. In this framework, there is a long-term contract market as well as a back-stop spot market. Seller agents bid into an electronic bulletin board their contract offers in terms of price or capacity, while Buyer agents decide how much to contract with Sellers and how much to shop from the spot market. The problem is modeled as a von-Stackelberg game with Seller agents as leaders. We investigate if artificial agents will be able to discover equilibrium strategies if such an equilibrium exists; and if the agents can discover good and effective strategies when playing repeated non-linear games where there does not exist any equilibrium. This study is a companion of our earlier theoretical characterizations on optimal bidding and contracting strategies for non-storable goods, now adopting an agent-based approach.

1. Introduction

In recent years, we have seen a growing interest in the study of artificial agents [7, 9] and their applications in electronic commerce, such as buying and selling goods over the Internet, automated bargaining and negotiation [4, 20], dynamic pricing in agent-mediated knowledge marketplace [24], multi-agent supply chain management [3, 5, 23] and multi-agent enterprise modeling [6, 12, 13, 15 21], restructuring the electric power industry [2, 10, 11, 12, 13, 14, 22], and off-exchange trading [8]. This paper is in this "tradition". We study a general multi-agent bidding, auction and contracting support system (called "eBAC") and apply it to the selling and buying of non-storable goods such as electric power. eBAC is implemented using an earlier theoretical framework developed by Wu and his colleagues [2, 16, 17, 18, 19, thereafter WKZ for short]. In this framework, there is a long-term forward/contract market as well as a back-stop spot market. Seller agents bid into an electronic bulletin board their contract offers in terms of price or capacity, while Buyer agents decide how much to contract with Seller agents and how much to shop from the spot market. The problem is modeled as a von-Stackelberg game with Seller agents as leaders. Thus, our eBAC auction has some unique properties different from traditional auctions in the following ways: First, traditional bids are discrete choices while our agents' bids are continuous; Second, goods in traditional auctions are storable and those in ours are non-storable; Third, traditional auctions only consider a single Seller while ours considers multiple Sellers; Lastly, traditional auctions consist of only one source of procurement (the spot market), while ours consists of two sources: in addition to the back-stop spot market, we allow Buyers and Sellers sign long-term contracts in a forward market.

The goal of this study is as follows: First, we investigate if artificial agents will be able to discover equilibrium strategies if such an equilibrium exists; Second, we investigate if the agents can discover good and effective bidding, auction and contracting strategies when playing repeated non-linear games where there does not exist any equilibrium; Third, we explore the emergence of trust in the sense of what kind of mechanisms induce cooperation in the above setting. We test eBAC in the multi-Seller electronic marketplace. In this paper, we focus only on myopic bidding strategies, while in a separate study, we extend to non-myopic bidding with an extensive focus on the emergence of trust [20].

The rest of the paper is organized as the following. Section 2 provides a brief literature review. Section 3 describes our methodology and implementation. Section 4 experiments on multi-agent price or capacity bidding. Section 5 reports results of further experiments. Section 6 summarizes our findings.

2. Literature Review

In this section, we briefly review the auction of non-storable goods in WKZ papers and explain why an agent-based approach is interesting in this arena.

In the WKZ model (which might be thought of as the "month ahead" market), Sellers and Buyers interact through an electronic bulletin board, posting bids and offers until agreement has been reached. Capacity not committed through this contracting market is assumed to be offered on the spot market, but may go unused because of the risk of not finding customers or transportation capacity at the last minute. Buyers face another type of risk for demand not contracted for in the bilateral market, namely price volatility in the spot market. Such price volatility can be quite severe and has caused Buyers, say for example, in the electric power market to pay close attention to the proper balance in their supply portfolio between long-term contracting and spot purchases.

WKZ papers set up the theoretical framework for the optimal bidding and contracting for non-storable goods. The framework models the interaction of long-term contracting and spot market transactions between Sellers and Buyers for non-storable goods. Sellers and Buyers may either contract for delivery in advance (the "contracting" option) or they may sell and buy some or all of their output/input in a spot market. Contract pricing involves both a reservation fee per unit of capacity and an execution fee per unit of output if capacity is called. The key question addressed is the structure of the optimal portfolios of contracting and spot market transactions for these Sellers and Buyers, and the pricing thereof in market equilibrium if exists. WKZ papers show that when Sellers properly anticipate demands to their bids, bidding a contract execution fee equal to variable cost (b) dominates all other bidding strategies yielding the same contract output. The optimal capacity reservation fees are determined by Sellers to trade off the risk of underutilized capacity against unit capacity costs. Buyers' optimal portfolios are shown to follow a merit order (or greedy) shopping rule, under which contracts are signed following an index, denoted as *x*, which is an increasing function of the Sellers' reservation cost and execution cost. Existence conditions and structure of market equilibrium are characterized in WKZ papers for the associated competitive game between Sellers, under the assumption that they know Buyers' demand functions.

However, under some conditions, there does not seem to exist any equilibrium in the WKZ repeated bidding and auction game (as will further be shown below). We see in practice such conditions are violated frequently. When the real world is not as "clean" as required for WKZ theorems to go through, the literature is shy as to what should be a good or reasonable bidding strategy under realistic conditions. Maybe artificial agents are potential alternatives for business strategy discovering in such a complicated setting [10, 11, 12, 13, 14, 15, 21]. This is why we are interested in using agent-based approach to explore. In the next section, we describe our model in detail.

3. Models for Myopic Bidding

We begin our test of eBAC with Singe Seller (Single or Multi Buyers) environment, and then move to Multi-Seller electronic marketplace, where we test in detail both the path independent and path dependent repeated games of pure strategy bidding with the Seller agents act as leaders, along with a preliminary testing of mixed bidding strategies.

First, eBAC is used for a Single Seller, Single or Multi-Buyers market. As shown in Table 1, eBAC is able to discover the optimal bidding, auction and contracting strategies as predicted in the WKZ theoretical framework.

Table 1: Simulation results in a single Seller environment. Parameter are: b = 5, m = 0.1, â = 0.1, uniform distribution from 4 to 10, utility function U (x) = 10(1-e $^{-x}$).

	WKZ (Theory)	eBAC
s	1.50	1.50
g	5.00 = b	4.99 = b

Now we introduce our multi-Seller electronic marketplace in great detail. We consider two models in myopic bidding, the price bidding model and the capacity bidding model. We now describe the setting of each model in detail, with an emphasis on price bidding.

<u>Price Bidding Model.</u>

We first set up our price-bidding model for the multi-Seller case. There are *N* Sellers, which form a set $\Xi = \{1, \cdots, N\}$. Each Seller *i* maximizes its expected profit Ep_i by bidding a contract price x_i anticipating the Buyer's optimal contracting strategy Q_i. Each Seller has a capacity limit K_i and a minimum cost c_i for entering the forward contract market. In the following illustrative example, we assume as in standard economics literature, linear contract demand, however, eBAC is general in handling any demand functions, linear or non-linear. We assume the demand function as $D_i = (100 - x_i)^+$, where $y^+ = Max[y, 0]$. In case there is a bid tie, following WKZ [18, 19], we adopt the following bid-tie allocation mechanism: If there is a tie in bids among any subset of Sellers, then Buyers' total demand for that subset of Sellers is allocated to the Sellers in proportion to their respective bid capacities.

The following model describes the Seller's problem. $\forall k \in \Xi$, define the following sets:

$$M_k^1 = \{ i \in \Xi | x_i < x_k \};$$
$$M_k^2 = \{ i \in \Xi | x_i \le x_k \};$$
$$M_k^3 = \{ i \in \Xi | x_i = x_k \};$$
$$M_k^4 = \{ i \in \Xi | x_i > x_k \};$$

Seller's Model:

$$\underset{x_k}{Max} \; E p_k$$
$$p_k = [x_k - c_k] \cdot Q_k$$
$$D_k = (100 - x_k)^+$$

where according to WKZ [18, 19]

$$Q_k(x) = \begin{cases} K_k & D(x_k) > \sum_{i \in M_k^2} K_i \\ \frac{K_k}{\sum_{i \in M_k^3} K_i} (D(x_k) - \sum_{i \in M_k^1} K_i) & \sum_{i \in M_k^1} K_i < D(x_k) \le \sum_{i \in M_k^2} K_i \\ 0 & D(x_k) \le \sum_{i \in M_k^1} K_i \end{cases}$$

We define myopic bidding as the solution to the following optimization problem: $\underset{X_i(t)}{Maximize} \; E p_i (x_i(t) | x_{-i}(t-1))$.

Here, we assume each Seller can only memorize what happened last time, i.e., memory size is 1, forgetting previous strategies used by other players. We want to study the behavior of artificial agents when playing this repeated game.

The bidding system, as depicted in Figure 1, works as follows. There is a blackboard on the market. At time period *t*, each Seller observes other Sellers' last bids (during period *t – 1*) from the blackboard, then he privately chooses and posts on the blackboard a bid for the current time period (*t*).

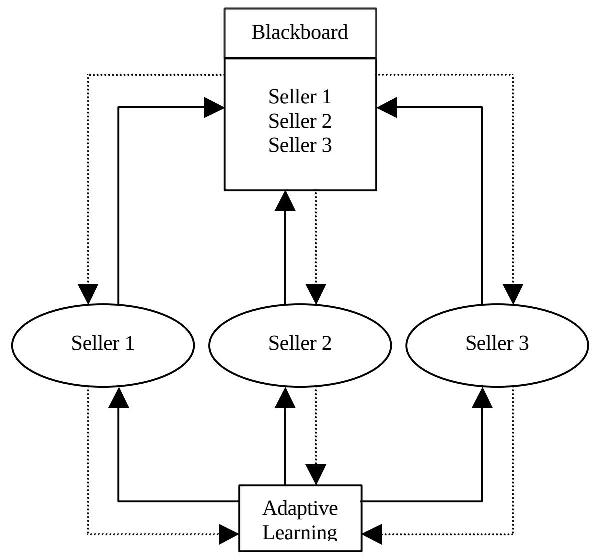


Figure 1: Myopic bidding system

Our agents learn their new bidding strategies via genetic algorithms [1]. The following is a description on the implementation of genetic algorithms in our system. (1) Representation: we employ floating-point implementation to represent agents' continuous strategy space. (2) Initial population: initial population is identical, we use the Seller's winning strategy from the latest time period. (3) Performance evaluation: the performance of winning strategy from last period will be re-evaluated according to current market condition. Figure 2 describes the flowchart of our myopic bidding system.

Now we consider a three-Seller repeated game to illustrate our approach. This three Seller example is already complicated enough in the sense that, we can only perform some analytical analysis under some assumptions/conditions [18, 19], and many times, when such conditions are violated, there does not exist any equilibrium for this rather simple setting. However, as common in industry practice, such conditions are frequently violated. For example, if the Sellers have the technology and capacity parameters as listed in Table 2, which seems to be trivial, then there does not exist any equilibrium in the WKZ repeated game. In the table, c_i is the technology index that indicates the minimum price requirement for Seller *i* to enter the forward contract market, and K_i is the Seller *i*'s total available capacity.

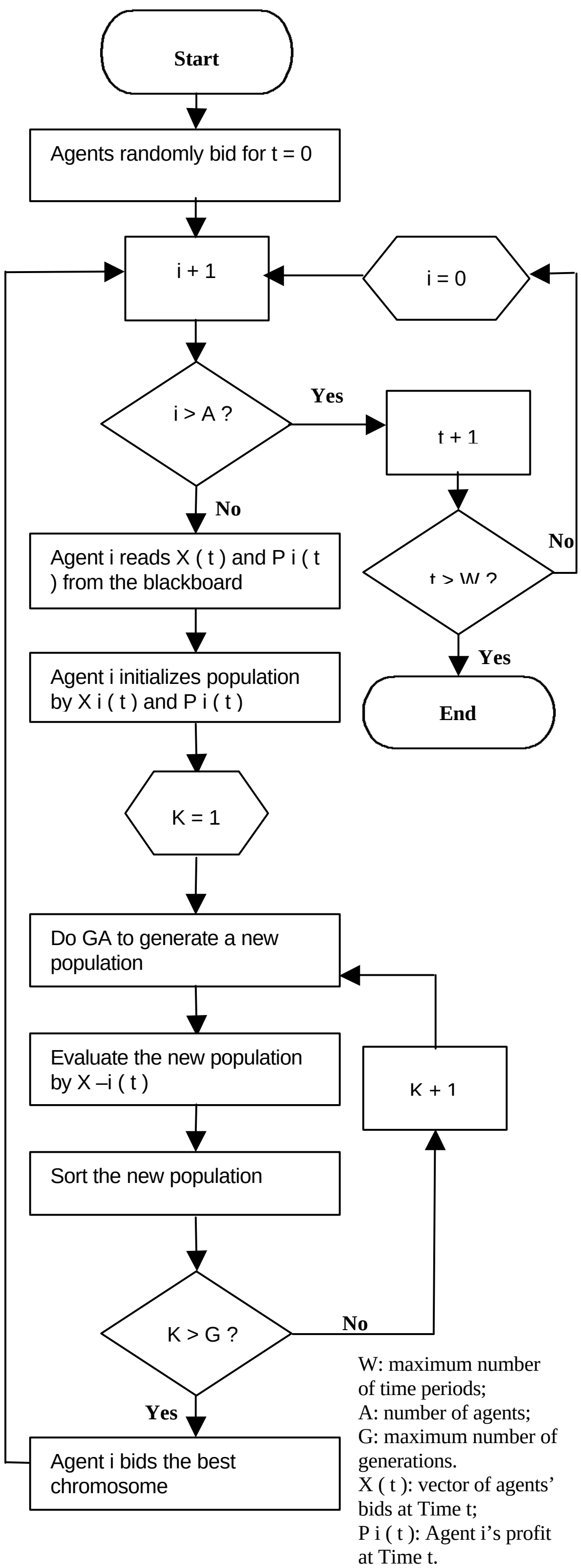


Figure 2: Flowchart of myopic bidding system.

Table 2: Technology and capacity parameters for the three-Seller contract market.

	i	1	2	3
Ex.1	c_i	10	10	18
	K_i	40	40	30

To get some insight of the game, we first consider a much simplified, static one-shot discrete bidding game. Assume Seller 1 and 2, can bid either 18 or 55, and Seller 3 can bid either 19 or 55. Table 3 shows the Nash equilibria, namely (18, 18, 19) and (55, 55, 55), for this normal form game. The game becomes interesting when it is played repeatedly and in continuous strategy space. Notice that the outcome of (55, 55, 55) Pareto dominates that of (18, 18, 19). When each Seller has a continuous bidding space, (55, 55, 55) is no longer the Nash equilibrium. For example, Seller 3 has an incentive to bid slightly less than the other players in order to contract all its capacity with the Buyers to profit more, indeed, there does not exist any equilibrium for this game in the continuous bid space under the above defined bid-tie allocation mechanism (which is mostly used in industry practice). We experiment eBAC to play this repeated bidding gaming, the goal is to see if artificial agents can discover the equilibrium strategy or are able to response optimally over time. We now describe agents bidding process.

Table 3: Nash equilibria for three-Seller price bidding normal form game.

		x_1			
		18		55	
		x_2		x_2	
		18	55	18	55
x_3	19	(328, 328, 1)	(320, 0, 30)	(0, 320, 30)	(338, 338, 30)
	55	(328, 328, 0)	(320, 129, 80)	(129, 320, 80)	(737, 737, 454)

Bidding Process. We start the game at Time 0, each Seller randomly selects its bidding price or, chooses a price based on some rules that serve his own interest. Then the game proceeds to Time 1, when each Seller observers others' previous bids, and find out whether his opponents are "nice" or "nasty" (defined below). The Seller then searches its new bidding strategy for Time 1 using GA and posts his new bid on the blackboard simultaneously with the other two players. The game goes on and on until a pre-specified stopping condition (such as the maximum number of rounds) has been reached.

Capacity bidding. Alternatively, Sellers can choose to bid capacity and let the forward contract market determine bid price p. Every Seller then sells his

$$\underset{L_i}{Max}\ Ep_i$$

$$p = \sum_{i=1}^{3} K_i - \sum_{i=1}^{3} L_i$$

$$p_i = [p - c_i] \cdot Q_i = [p - c_i] \cdot L_i$$

bid capacity by this same price. In the capacity auction mechanism, each Seller's model becomes the following:

In the dynamic capacity bidding game, similarly, each Seller chooses his current bidding strategy taking into account the other players' last bidding strategies,

$$\underset{L_i(t)}{Maximize}\ Ep_i(L_i(t) | L_{-i}(t-1)).$$

Again, agents learn new strategies via genetic algorithms.

4. Initial Experiments on Myopia Bidding

Based on the model described above, we test the multi Seller, single/multi Buyers electronic marketplace. We shall use the following three Sellers one Buyers market to illustrate some insightful discoveries, however, as noted above, eBAC is a general platform.

Table 4 summarized our experiment design and some initial results. While path independent strategy is defined earlier, path dependent strategy is defined as follows:

$$\underset{X_i(t)}{Maximize}\ Ep_i = \frac{\sum_{m=1}^{t} Ep_{i,m}(x_i(t) | x_{-i}(t-1))}{t}.$$

Table 4: eBAC results for example 1, c = (10, 10, 18), K = (40, 40, 30), "YES" means that there exists an equilibrium and eBAC can find it; "NO" means there is no equilibrium. "No co-op" means that agents are not cooperating with each other, and "Co-op" means agents are cooperating with each other.

	Bidding Price	Bidding Capacity
Path Independent	YES. No co-op. (18, 18, 19)	NO.
Path Dependent (Observed Average Profit)	YES. No co-op. (18, 18, 19)	YES. Co-op. (27, 28, 18)

Figure 3 shows the dynamics of profit (top) and agent price bidding (bottom) for a path dependent pure strategy *price* bidding game as specified in example 1. The agents quickly learn how to play "the price war" and find the non-cooperative Nash equilibrium.

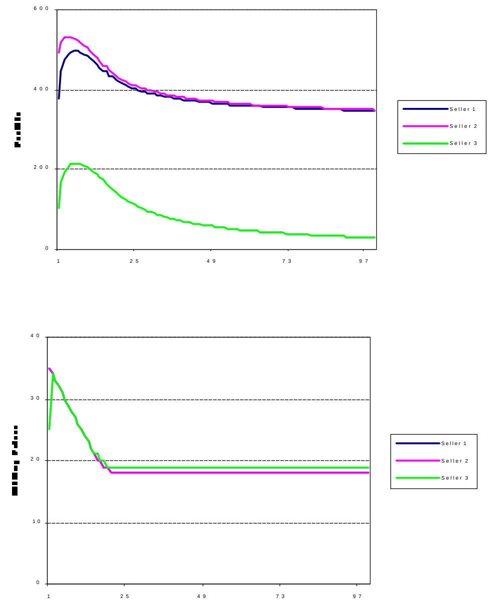
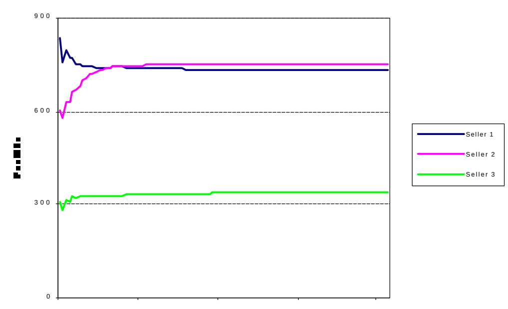


Figure 3: Dynamic pure strategy price bidding, path dependent: Profit and price over time for example 1.

However, under *capacity auction*, agents learn how to cooperate with each other. Figure 4 shows that in path dependent dynamic pure strategy *capacity* bidding games as specified in example 1, the agents learn to converge to a cooperative equilibrium.



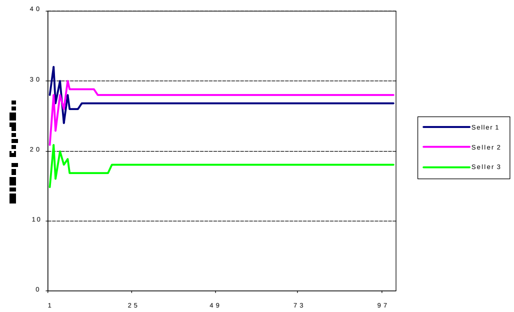
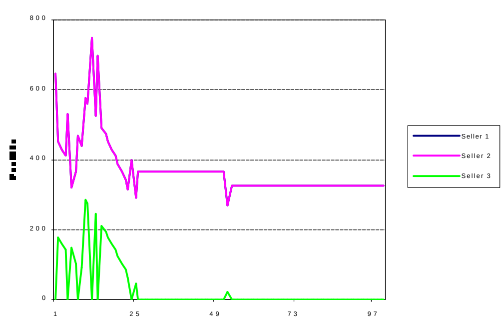
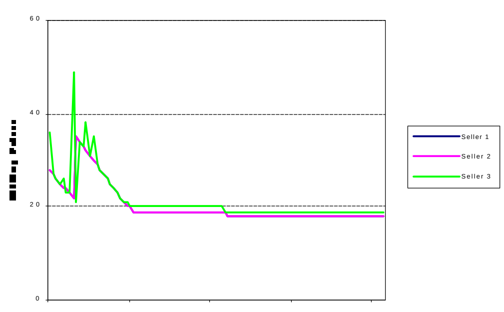


Figure 4: Path dependent dynamic capacity bidding: Profit and capacity over time for example 1.

Back to *price auction* mechanisms, if we allow the agents to use mixed strategies for their bidding, they can find optimal mixed strategies if such strategies exist, as shown in Figure 5. Each agent in this experiment can choose several feasible fixed integer prices: 10, 18 through 27, and 100 for Seller 1; 10, 18 through 27, and 100 for Seller 2; and 18 through 28 and 100 for Seller 3. Each agent bids mixed strategies to maximize path independent expected profit. We found that artificial agents quickly discover the equilibrium when using mixed bidding strategies. Figure 5 shows the learning procedure of artificial agent 2 to discover its optimal mixed bidding strategy.





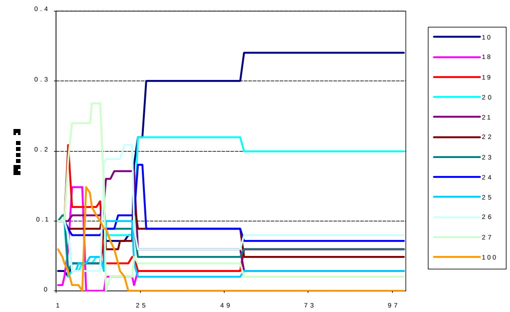


Figure 5: Dynamic mixed strategy price bidding, path independent (top to bottom): Profit, price and Sell 2's optimal strategy over time for example 1. It is interesting to notice the learning procedure for Sell 2 in discovering its optimal mixed strategy.

5. Further Experiments on Myopic Price Bidding

In order to test the stability and usability of our system, we design the following orthogonal experiment. We consider 2 factors: 1) the technology parameter c; and 2) the demand function D. We assume the overall capacity available from all Sellers is fixed, e.g., $\sum_{i=1}^{3} K_i$ = 90. We assume further all Sellers have the same total cost, so that K_i is inversely proportionally assigned to its cost parameter c_i.

Assume the demand function $D_i = (a - bx_i)^+$. The only possible cross-effect between c_i and D_i is that they form a strategy space $[c_i, \frac{a}{b}]$ for Seller i. Since D_i is the same for all the Sellers, we can view c as the factor that decides the relative size of Seller i's strategy space. Thus, there is no cross-effect between c_i and D_i, therefore we need not repeat the experiment on each level combination. There are four levels for c_i (see Table 5) due to different strategy space among the three Sellers. We randomly select each level from $(0,30]$, an interval of $\frac{\sum_{i=1}^{3} K_i}{3}$.

What the demand function matters is the relationship between the intercept a and total capacity supply $\sum_{i=1}^{3} K_i$. Since the strategy space of each Seller is determined by $\frac{a}{b}$, we can let b equal 1 and pick up a. Thus, there are only two levels for D_i (see Table 5), i.e. $a \geq \sum_{i=1}^{3} K_i$ and $a < \sum_{i=1}^{3} K_i$. We randomly select each level (in integer) from $[90,120]$ and $[60,90)$ respectively, left and right around 90 by a distance of $\frac{\sum_{i=1}^{3} K_i}{3}$.

We now in a position to set up the orthogonal experiment as shown in Table 5.

Table 5: Myopic repeated price bidding. PD: Path dependent; PI: Path independent; No: No equilibrium. No cooperation observed in all test cases.

		$D_i=(77-x_i)^+$	$D_i=(115-x_i)^+$	$*D_i=(100-x_i)^+$
c_i = 13, 13, 13 K_i = 30, 30, 30	PD	(16, 16, 16)	(30, 30, 30)	(21, 21, 21)
	PI	(16, 16, 16)	(30, 30, 30)	(21, 21, 21)
c_i = 11, 21, 21 K_i = 44, 23, 23	PD	(21, 22, 22)	(No, No, No)	(23, 24, 24)
	PI	(21, 22, 22)	(No, No, No)	(23, 24, 24)
c_i = 16, 16, 25 K_i = 34, 34, 22	PD	(No, No, 26)	(31, 31, 31)	(No, No, No)
	PI	(No, No, 26)	(31, 31, 31)	(No, No, No)
c_i = 7, 12, 17 K_i = 45, 26, 19	PD	(No, No, 19)	(No, No, No)	(No, No, No)
	PI	(No, No, 19)	(No, No, No)	(No, No, No)
* c_i =10, 10,18 K_i =40, 40,30	PD	(No, No, 19)	(No, No, No)	(18, 18, 19)
	PI	(No, No, 19)	(No, No, No)	(18, 18, 19)
* c_i =10, 12,14 K_i =40, 30,20	PD	(14, 14, 15)	(No, No, No)	(No, No, No)
	PI	(14, 14, 15)	(No, No, No)	(No, No, No)

As listed in Table 5, we find that: (1) no cooperation exists under any climate (for the given demand function), even in "friendly" environment, when the market is big enough to absorb all Seller's full capacity, Sellers do not cooperate with each other; (2) there is no statistical difference between path dependent and path independent strategies.

The result of cross point of Row 6 and Column 3 in Table 5, where c = (10, 12, 14), K = (40, 30, 20), shows an interesting phenomenon. As expected, when bidding prices, eBAC shows a bloody fight among agents over prices with no equilibrium strategies and no cooperation, as plotted in Figure 6. However, artificial agents are able to learn smart "dog-fighting" strategies that take advantage of other players' previous bids.

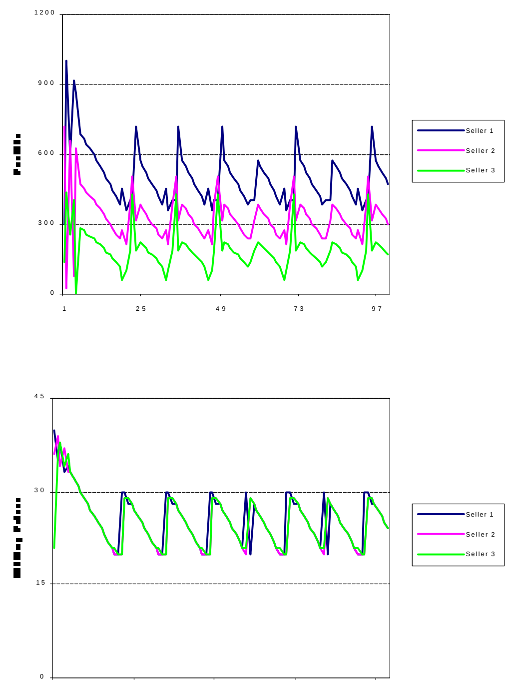


Figure 6: Dynamic pure strategy price bidding, path independent: Profit and price over time for example 2.

6. Summary

We now briefly summarize findings of various experiments conducted. First, and most importantly, we find that artificial agents are viable in automated marketplace: they can discover optimal bidding and contracting strategies in the equilibrium if exist. Second, they can find better strategies in a complex dynamic environment where equilibrium does not exist. Third, auction mechanism design plays a significant role to induce agent cooperation. Under myopic bidding, capacity-bidding mechanism induces cooperation, while pricing-bidding does not. In our orthogonal experiment, even when the market is big enough to buy each Seller's full capacity, i.e., the environment is "friendly", Sellers still would not cooperate with each other under our pure strategy pricing bidding mechanism. However, when agents are allowed to bid mixed strategies, they quickly learn how to discover the equilibrium strategies after several rounds of price war, the resulting equilibrium has some degree of cooperation. It is close-to the ideal full cooperation outcome. We have further extended the work here to non-myopic bidding with an extensive focus on the emergence of trust in part II of this work, see, [20].

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