COUNTERACTING SHILL BIDDING IN ONLINE ENGLISH AUCION

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ABSTRACT

Increasing popularity of online auctions and the associated frauds have drawn the attention of many researchers. It is found that most of the auction sites prefer English auction to other auction mechanisms. The ease of adopting multiple fake identities over the Internet nourishes shill bidding by fraudulent sellers in English auction. In this paper we derive an equilibrium bidding strategy to counteract shill bidding in online English auction. We develop an algorithm based on this strategy. An eBay like auction environment is simulated. Experiments are conducted in this environment to evaluate this strategy. Five more popular bidding strategies are compared with the proposed strategy. In the experiment, the bidders are randomly assigned a bidding strategy. All the bidders draw their valuation from the uniform distribution. The bidders compete to buy a product in the presence of a shill. The average expected utility of the agents with proposed strategy is found to be the highest when the auction continues for a longer duration.

Keywords: Online English auction, Shill bidding, equilibrium bidding strategy, bidder expected utility

INTRODUCTION

Online auctions account for a large volume of economic activities over the Internet. The auction sites rank high in both the number of visitors and the average time spent per visit. At any time, there are millions of auction listing in thousands of category on action sites such as eBay, Yahoo and uBid. Online auctions, however, has created a conducive environment for adopting unfair practices by bidders and auctioneers. Cheap pseudonyms [27], lack of personal contact [28] and the tolerance of bidders motivate the cheating. Harris survey [3] reports that 21% buyers take no action when they have problems in Internet transactions. Internet Fraud Complaint Center (IFCC) reports that Internet auction fraud comprises 64% and 46%of referred complaint in the years 2001 and 2002 respectively [1]. According to another source [4], Internet auction fraud accounts for 87% of all online crime. IFCC classifies auction frauds into six categories: Non-delivery of goods, miss representation of the items, triangulation, fee staking, selling of black-market goods, multiple bidding and shill bidding [2]. Shill bidding is prevalent in online English auctions. In this case a corrupt auctioneer appoints fake bidder(s) who place bids just to increase the price of the item without the intention of buying it. According to the most popular consumer-to-consumer auction Web site eBay shill bidding is the process of deliberate placing of bids to artificially drive up the price of the item.

There exist three broad categories of single sided action mechanisms: English auction, sealed-bid auction and Dutch auction. In the real world most of the important auctions are sealed-bid in nature. However, on the Internet English auctions are very popular. According to [29], about 88% Internet auctions are English auction and its variants. Dutch auction consists of 1% of Internet auction. Other forms of auctions, such as Vickery auction and double auction, account for the rest 11%. This may be due to the fact that English auction is well understood by all consumers, not just economists.

The popularity of online English auction and increased evidences of shill bidding motivates this research. In this paper we derive a bidding strategy that counteracts the shill bidding. A bidding algorithm is proposed based on this strategy. We conduct a simulation experiment in an eBay like environment to test the effectiveness of the proposed strategy.

The rest of the paper is organized as follows. In the next section, we discuss shill bidding in detail. The equilibrium bidding strategies for counteracting shill bidding is derived in the following section. In the subsequent section we discuss about the auction models and mechanisms at eBay [26] which sets the ground for our simulation environment. Next we present the simulation experiment where we compare the popular bidding strategies found on eBay with the proposed strategy. Before concluding the paper, a discussion on implementation aspects and a survey of the related works are presented.

SHILL BIDDING IN ONLINE ENGLISH AUCTION

Oxford English Dictionary online defines a shill is as a decoy or accomplice, especially one posing as an enthusiastic or successful customer to encourage other buyers, gamblers, etc. To shill is to boost for the auctioneer. Bid padding, phantom bidding, bidding of the wall, lift-lining, trotting, running, setting hidden reserve prices–these are examples of the seller's or auctioneer's activities that involve active participation in the bidding process. An excellent account of these practices can be found in [16]. Shill bidding is a modern composite term that includes these activities and much more. Shill bidding can take several forms: (1) The seller directly takes one or several buyer identities and places shill bid(s) for his own item. (2) The seller hires a buyer to bid up the seller's item. (3) The seller establishes a bidding ring composed of multiple buyers bidding on the seller's item, with or without the direct involvement of the seller. (4) The seller establishes a bidding ring composed of multiple sellers bidding on each other's items.

It has been identified that a shill follows few principles in practice [14] [11]. (1) The shills appear very frequently in the auction hosted by the seller. (2) They do not want to win the auction but want to drive up the winner. (3)Therefore, want to avoid bidding near the end of the auction where the chance of winning is greater. (4) Their bid increment is higher than average. More than once, shill bidding in eBay has become headline news [13]. An interesting empirical study is done by Kauffman and Wood [14] based on the data from 14, 528 rare coin auctions on eBay during May 1999 and February 2000. They found 10% of the auction buyers had shown questionable bidding behavior. They define questionable bidder behavior (QBB) as bidding on an item when the same or a lower bid could have been made on the exact same item in a concurrent auction ending before the bid-upon auction. Then, they identify questionable bidders (QB), those who exhibited QBB, and test the above four principles. They found support for all four: QBs had more bids per seller than other bidders (1.45 vs. 1.25), indicating that QBs are concentrating on specific sellers win only 26% while other bidders win 35% of the time; drop out on average 5.1 days before the auction ends compared with 1.8 day for the others; tend to bid 200% above the previous bid, if there is one, compared to 65% for the others. Shah *et al.* [11], applied data mining techniques on the data collected from eBay during October 2000 and May to July 2001. They discovered very strong relationships between some sellers and buyers. These relationships were often suspicious as the associated bidders seldom own the auction. These set of suspicious bidders often adopted unmasking strategy using eBay's proxy bidding (to be discussed) to discover the highest bid value. They suggested to uses these kinds of signals to detect shill bidding in English auction.

Occasionally the shill wins the auction if no other higher bid comes up. Under such circumstances, the item to be sold remains with the auctioneer. Such items are re-auctioned at a latter time. The sites charge a listing fee for all the items. Besides this, the site may also charge a commission fee on the winning auctions. If these fees are too low, it acts as an incentive to commit fraud. Increasing these fees however will not solve the problem in an auction site. Rather, the site may lose sellers to other sites with lower fees. Wang, Hidvegi, and Whinston [9] suggest a Shill Deterrent Fee Schedule (SDFS) for the auction sites to deter shill bidding. SDFS and its parameters are designed as an incentive mechanism to discourage sellers from submitting shill bids. Under SDFS, the auctioneer still charges the seller a listing and commission fee. However, SDFS is unique in the following: 1) a listing fee is a function of the seller's reserve; 2) a commission fee is a function of the commission rate and the difference between the final sale price and the seller's reserve; and 3) the commission rate is mathematically determined to ensure the non-profitability of shill bidding. The commission rate is a function of buyers' value distribution, which differs across auction markets.

AN EQUILIBRIUM BIDDING STRATEGY FOR COUNTERACTING SHILL BIDDING

The bidders may behave in an unanticipated way in a cheating environment. Game theoretic analysis can help to describe rational bidder's behavior in this scenario. For example, Porter and Shoham [4] have proposed the equilibrium bidding strategy to counteract cheating in sealed bid auctions. An equilibrium bidding strategy maximizes the bidders expected utility, holding the bidding strategies of all other bidders fixed. Motivated by their work we develop an equilibrium bidding strategy by an honest bidder for English auction when there is shilling. Our analysis is in a risk neutral setting, where the bidders opt to go out of the auction if he has to pay above their reservation value.

Problem Formulation

We consider the auction for a single indivisible object. The auction consists of *N* bidders: *N*-1 actual bidders and a shill. Each bidder associates two values with the product – the reservation value and the bid. The reservation value is the maximum price a bidder is willing to pay for the product based on his personal valuation. This information is private to each bidder. A bid on the other hand is the publicly declared price that a bidder is willing to pay for the product. Each bidder has a reservation value $\theta_i \, (i = 1,2,...N)$ for the object. Without the loss of generality we assume $\theta_i \in [0,1]$. Each agent's reservation value is independently drawn from a cumulative distribution function (*cdf*) *F* over [0,1], where *F*(0) = 0 and *F*(1) = 1. We assume *F*(.) is strictly increasing and differentiable in the interval [0,1]. The derivative of *cdf*, $f(\theta)$ is then the probability density function (*pdf*). Each bidder knows his reservation value and the distribution *F* of other agents. A bidding strategy $b_i : [0,1] \rightarrow [0,1]$ maps a bidder's reservation value to its bid. As we mention earlier $\theta = (\theta_1, \theta_2, ...\theta_n)$ is the vector of reservation values of all the agents and $b(\theta) = (b_1(\theta_1), b_2(\theta_2), ...b_n(\theta_n))$ is the vector of bids.

An honest bidder *i* can bid up to his reservation value, i.e. $\theta_i \geq b_i(\theta_i)$. On the other hand a dishonest bidder (shill) *j* can bid well above his reservation value in order to escalate the bid values of the honest bidders, i.e. $\theta_j \leq b_j(\theta_j)$. In this formulation we assume that the probability of a shill winning the auction is zero. Therefore, his bid value has to be less than that of the reservation value of the winner *i*, i.e. $b_j(\theta_j) \leq \theta_i$.

Bidder's Expected Gain (Utility)

The expected utility (gain) of a winner is the difference between his reservation value and his expected payment.

The expected gain of a buyer is defined by Riley and Samuelson [7] as follows:
Expected Buyers Gain = Probability of Winning *(Reservation Value – Bid)

$$= \text{Probability of Winning} *(\theta_i - b_i(\theta_i)) \quad (1)$$

As per the model an honest bidder can win this auction if his final bid is (1) higher than that of the reservation values of all other honest bidders and (2) bids of all the dishonest bidders (shills).This fact can be formalized as follows: Let the seller has a reservation value θ_s, which is a constant for a specific auction. The shill's bid can be greater than that of the seller's reservation value. It is also less than that of the reservation value of the winner (honest bidder). This makes the shill's probability of winning as zero. The probability that an honest bidder *i* beats a shill *j* is then $\Pr ob(\theta_s \leq b_j(\theta_j) \leq \theta_i) = F(\theta_i) - F(\theta_s)$. It is not profitable for a seller to accept any bid below his reservation value [11]. This implies $F(\theta_s) = 0$ .Thus, the probability that bidder *i* has a higher bid than a cheater can be represented by $F(\theta_i)$. Each honest bidder's reservation value has to be less than that of the bid value of the winner. So the probability that an honest bidder's bid is higher than that of another honest bidder is $F(b_i(\theta_i))$. Therefore, the probability that an honest agent's bid is higher than that of any other agent is the weighted average of these two probabilities, the weights being the probability of cheating (P^b) and non-cheating (1 - P^b) respectively. Probability that he wins the auction is therefore this probability raised to the power *N*-1 (His bid is higher than other *N*-1 agents). This can be represented as :

$$[P^b.F(\theta_i) + (1 - P^b).F(b_i(\theta_i))]^{N-1} \quad (2)$$

Thus, we can write bidder *i*'s expected utility as:

$$E_{\theta_{-i}} u_i(b(\theta), \mu^b, \theta_i) = (\theta_i - b_i(\theta_i)).[P^b.F(\theta_i) + (1-P^b).F(b_i(\theta_i))]^{N-1} \quad (3)$$

θ_{-i} is the vector of reservation values of all the agents except the agent *i*.

Equilibrium

It is assumed that the agents (bidders) are rational and maximizes their utility. The shill bids value higher than his reservation value. All the honest agents bid according to a symmetric bidding strategy. To find the equilibrium bidding strategy, we will maximize the expected utility function (Equation 3) by taking its derivatives with respect to $b_i(\theta_i)$ and setting it to zero. The equilibrium $b_i(\theta_i)$, derived from this equation is presented in theorem 1.

Theorem 1: In an English auction in which each bidder cheats with the probability P^b, it is a Bayes Nash equilibrium for each non-cheating bidder *i* to bid according to the strategy that is a fixed point in the following equation:

$$b_i(\theta_i) = \theta_i - \frac{\int_0^{\theta_i} (P^b.F(x) + (1-P^b).F(b_i(x)))^{N-1} dx}{(P^b.F(\theta_i).+(1-P^b).F(b_i(\theta_i)))^{N-1}} \quad (4)$$

Proof:

We define $\phi_i : [0, b_i(\theta_i)] \to [0,1]$ as the inverse function of $b_i(\theta_i)$. That is, it takes the bid of the agent *i* as the input and returns the reservation value θ_i that induces this bid. Thus, we can rewrite bidder *i*'s expected utility as:

$$E_{\theta_{-i}} u_i(b(\theta), \mu^b, \theta_i) = (\theta_i - b_i(\theta_i)).[P^b.F(\phi_i(b_i(\theta_i))) + (1-P^b).F(b_i(\theta_i))]^{N-1} \quad (5)$$

Finding the equilibrium

The agent *i*'s reservation value is private and is constant for him in the expected utility function. To find the equilibrium $b_i(\theta_i)$, we take the derivative and set it to zero.

$$0 = [(\theta_i - b_i(\theta_i)).(N-1).(P^b.F(\phi_i(b_i(\theta_i))) + (1-P^b).F(b_i(\theta_i)))^{N-2}.$$
$$(P^b.f(\phi_i(b_i(\theta_i))).\phi_i'(b_i(\theta_i)) + (1-P^b).f(b_i(\theta_i)))] -$$
$$(P^b.F(\phi_i(b_i(\theta_i))) + (1-P^b).F(b_i(\theta_i)))^{N-1}$$

To further simplify we use the formula $f'(x) = \frac{1}{g'(f(x))}$ where $g(x)$ is the inverse function of $f(x)$. Plugging in function from our setting gives us: $\phi_i'(b_i(\theta_i)) = \frac{1}{b_i'(\theta_i)}$ Applying both this equation and $\phi_i(b_i(\theta_i)) = \theta_i$ gives us:

$$0 = [(\theta_i - b_i(\theta_i)).(N-1).(P^b.f(\theta_i).\frac{1}{b_i'(\theta_i)} + (1-P^b).f(b_i(\theta_i)))] -$$
$$(P^b.F(\theta_i) + (1-P^b).F(b_i(\theta_i)))$$

Rearranging the terms yields:

$$b_i(\theta_i) = \theta_i - \frac{(P^b.F(\theta_i) + (1-P^b).F(b_i(\theta_i))).b_i'(\theta_i)}{(N-1).(P^b.f(\theta_i).+(1-P^b).f(b_i(\theta_i)).b_i'(\theta_i))} \tag{6}$$

In order to verify Equation 4, we first take its derivative:

$$b_i'(\theta_i) = 1 - [1 - \frac{(N-1).(P^b.F(\theta_i).+(1-P^b).F(b_i(\theta_i)))^{N-2}.(P^b.f(\theta_i).+(1-P^b).f(b_i(\theta_i)).b_i'(\theta_i)).\int_0^{\theta_i}(P^b.F(x)+(1-P^b).F(b_i(x))^{N-1}dx}{(P^b.F(\theta_i).+(1-P^b).F(b_i(\theta_i)))^{2(N-1)}}]$$

This equation simplifies to:

$$b_i'(\theta_i) = \frac{(N-1).(P^b.f(\theta_i).+(1-P^b).f(b_i(\theta_i)).b_i'(\theta_i)).\int_0^{\theta_i}(P^b.F(x)+(1-P^b).F(b_i(x))^{N-1}dx}{(P^b.F(\theta_i).+(1-P^b).F(b_i(\theta_i)))^{N}}$$

Plugging this equation in the numerator of Equation 6 yields Equation 4.

Special case*: *Uniform distribution

Here we consider uniform distribution as a special case. The result is found to be particularly robust for uniform distribution.

Corollary 1. In the English auction where the shill cheats with probability P^b, and $F(\theta_i) = \theta_i$, it is a Bayes-Nash equilibrium for each non cheating agent to bid according to the strategy

$$b_i(\theta_i) = \frac{N-1}{N}\theta_i \tag{7}$$

Proof: Putting $F(\theta_i) = \theta_i$ in equation 4 yields:

$$b_i(\theta_i) = \theta_i - \frac{\int_0^{\theta_i}(P^b.x + (1-P^b).b_i(x))^{N-1}dx}{(P^b.\theta_i + (1-P^b).b_i(\theta_i))^{N-1}}$$

Now plugging the strategy $b_i(\theta_i) = \frac{N-1}{N}\theta_i$, into this equation in order to verify this as a fixed point we get:

$$b_i(\theta_i) = \theta_i - \frac{\int_0^{\theta_i}(P^b.x + (1-P^b).\frac{N-1}{N}x)^{N-1}dx}{(P^b.\theta_i + (1-P^b).\frac{N-1}{N}\theta_i)^{N-1}} = \theta_i - \frac{\int_0^{\theta_i}x^{N-1}dx}{\theta_i^{N-1}} = \theta_i - \frac{(1/N)\theta_i^{N}}{\theta_i^{N-1}} = \frac{N-1}{N}\theta_i$$

Special Case: Probability of shill bidding is one

When the bidder is certain about the shill bidding, that is P^b equals to one, the equation 4 takes the form

$$b_i(\theta_i) = \theta_i - \frac{\int_0^{\theta_i} (F(x))^{N-1} dx}{(F(\theta_i))^{N-1}} \tag{8}$$

This is the equilibrium bidding strategy in an optimal auction as derived by Riley and Samuelson [7]. Therefore it can be concluded that if an honest bidder follows this strategy, he can counteract shill bidding in online English auction. This finding is also supported by [17].

Evaluating the bid value

The bidding strategies developed here can be used by an autonomous agent to bid on behalf of its user (bidder). According to the strategy a bidder can evaluate the optimal bids given three parameters: the bidder's private value θ_i, cumulative distribution function $F(\theta)$ and the probability of shill bidding P^b. When P^b is one, the calculation becomes fairly simple as equation 4 is reduced to 7. When P^b assumes any other value the fixed-point solution can be found by using a standard algorithm like Newton's method, or secant method or some hybrid algorithm [10][5]. However, every algorithm is not suitable for every type of functions. Moreover, the time complexities and improper choice of convergence criteria may be barriers to the online implementation of algorithms. Therefore, in the bidding algorithm we assume the probability of shill bidding is one for practical online implementations.

The proposed bidding algorithm

In online English auctions a new bid can come any time before the auction ends. Therefore, it is not possible to find number N of total bidders before the end of the auction. So for the purpose of our algorithms we consider current number of bidders as N and evaluate the bid value. Assuming the probability of shill bidding as 1, bid value can now be computed using Equation 7. The other unknown of this equation is the cumulative distribution function $F(\theta)$. This function can be constructed from the completed auction data for similar type of products from the auction site. For example, eBay keeps completed auction data for past thirty days in its site. A crawler can be used to collect these data [11][12]. We call the proposed algorithm as shill counteracting bidding strategy (SCBS).

AUCTIONS AT EBAY

We have conducted an experiment to compare the proposed bidding algorithm in an eBay like simulated environment. Therefore, we shall briefly discuss on (1) the actual models and mechanisms used in eBay and (2) the popular bidding strategies used in eBay [11]. Then we shall discuss the simulation environment and formally present all the bidding algorithms followed by the results of the simulation experiment.

Models

All eBay auctions use an ascending-bid (English) format with the important distinction that there is a fixed end time set by the seller. EBay provides a standard English auction and three variations:

Standard Auction: This is the most prominent type of listing. Here only one item (or group of items sold together) is being offered to the highest bidder.

Reserve Price Auction: The seller has a hidden reserve price that must be exceeded before the seller is required to sell. When a bidder's maximum bid is equal to or greater than the reserve price, the item's current price is raised to the reserve price amount.

Buy It Now Price: A variation of the standard auction in which a bidder can immediately win the item by choosing the Buy It Now option. A single item auction ends prematurely once a bidder exercises this option.

Dutch Auction: The seller offers more than one of the exact same items. The bidder enters the quantity of the items desired along with the price he is willing to pay per item. All winners pay the lowest winning bid price.

The Proxy Bidding

Regardless of the auction type, eBay uses a proxy mechanism for all submitted bids. The proxy mechanism allows a bidder to submit a maximum bid (i.e., maximum willingness to pay) with a guarantee that eBay will raise the bidder's active offer automatically until the bidder's maximum bid value is reached. The bid placed by the proxy system is referred as the bidder's proxy bid. In a reserve price auction, the seller's reserve price is treated like any other bid; if the buyer's offer meets or exceeds the reserve (secret) bid set by the seller, the buyer's bid would be raised to that price immediately. EBay enforces a minimum bid increment that, along with the current ask price, determines a lower bound on bids the server will accept. The bid increment table specified by eBay defines a schedule in which the increments increases as the current ask price increases.

Data available to a bidder

The data available to the bidders during the duration of the auction include: the item description, the number of bids, the ID of all the bidders, the time of their bid and the bid amount, the ID of the highest bidder, the time remaining until the end of the auction, whether or not the reserve price has been met, and the current ask price (list price). The list price is the second highest price plus a small increment as specified in the bid increment table of eBay. There reservation value submitted to the proxy bidder is made public only after they are out bid by some other bidder. The auction ends when time expires and the item goes to the highest bidder at the list price (second highest price with little increment).

Popular Bidding Strategies

It has been found [11] that the bidding strategies on eBay can be broadly classified into two categories based on the number of times a bidder bids during the life span of an auction: single bid engagement and multiple bid engagement. Three major strategies come under single bid engagement- *Evaluator, late bidder,* and *sniper*. Evaluators bids once and provide its reserve value to the proxy bidder. They can come any time during the span of auction. Late bidders bid towards the end of the auction. The snipers are also late bidders who submit their bids in the closing second of the auction. Their bid may sometimes be too late to be accepted. In multiple bid engagement strategy, a bidder bids more than once. Two major behaviors under this are: *skeptic* and *unmasking*. The skeptics submits the bids which have zero excess increment i.e., they submit a price just above the list price. Under unmasking behavior a bidder places a series of bids and tries to expose maximum bid or the current highest bidder. That is he continues unmasking behavior till he becomes the current highest bidder. A shill's behavior closely matches the unmasking behavior with the difference that he avoids winning. Therefore, shills stop bidding much before the auction ends.

THE EXPERIMENT

We have created an auction environment similar to eBay using Matlab to test the efficiency of the proposed strategy compared to the popular bidding strategies. We have considered only the reserve price auction model of eBay for the simulation purpose.

The Model and the Assumptions

Each auction has a duration T. This can be discretized in to T periods of equal length. Time t between the arrival of bids is represented by an exponential distribution with mean $(1/\lambda)$ and cumulative distribution function $1-e^{-\lambda t}$ where λ is the arrival rate of the bids. N bidders participate in the auction process. One of the bidders is a shill. Without the loss of generality we assume the N^{th} bidder is the shill. Each member of the bidder population draws its reservation value from the uniform distribution. The reservation value is private to the corresponding bidder bidder. Since a shill is appointed by the auctioneer we assume the valuation of the product by both the parties are same. Therefore, the reservation value or the shill can be used as the reserve price of the auctioneer. This value is declared as the initial listing price of the item. All other bidders are randomly assigned a bidding strategy.

A proxy system like that of eBay is implemented that accepted the highest declared price the bidder is willing to pay and increases the bid as least as possible in order to maintain him as the highest bidder. The price declared to the proxy may be less than or equal to the reservation value private to the bidder. The winner gets the item at the list price. The list price is the second highest bid plus a minimum increment. A bid is accepted in the system if it is greater than the list price. The identity of the highest bidder, list price, and minimum allowable bid increment are public to all the bidders.

A bidder is randomly selected from the population after *t* time units and submits a bid and submits a bid following the corresponding bidding algorithm (described below). A bidder may not bid at all in the total duration of the auction. This may be due to the fact that his bid value submitted to the proxy mechanism might be less than that of the list price at the time of its activation. The participation status (number of times participating in the auction) of each bidder in the population is maintained in the system. The number of effective bidders, who has participated at least once in the auction, is also a publicly known quantity. But for the shill all other type of the bidders can bid less than or equal to their reservation value. A shill is activated after a fixed interval and tries to escalate the price. The system minimizes the probability of shill winning the auction by stopping it few intervals before the auction ends. In spite of this if shill wins, he is allowed to withdraw his bid. The probability of shill bidding is assumed to be one. Different bidding strategies are simulated as follows. The evaluators, late bidders and the snipers are allowed to bid only once. The late bidders are allowed to bid only on or after (T-3) time slot. The snipers are restricted to bid in the last time slot. The probability that a bidder is a sniper in the last interval is fixed to be 0.8. The bidders with skeptic, unmasking, and SCBS bid multiple times.

Bidding Algorithms

Each honest bidder can adopt one of the 6 Strategies: Evaluator, late bidder, sniper, skeptic, unmasking or shill counteracting bidding strategy (SCBS). In this section we propose algorithms for each strategy as used in the simulation experiment. The variables used in the algorithms are as follows:

N: Size of the bidder population
T: Auction duration
t(*i*): i^{th} time instant
currentBidder : The id of the bidder randomly selected
bid : an array of dimension N to store the up-to-date bid values submitted by the bidders to the proxy system
theta: an array of dimension N to store the reservation values of all the bidders
listPrice: List Price
highBidder: Highest bidder's id
minIncrement: minimum increment allowed over the list price to make the bid acceptable by the proxy system
jumpIncrement: an increment much higher than the minimum increment

participants: number of effective bidders

theta is the reservation values of each bidder. It is a privately known quantity. *bid* is the value submitted by the agent to the proxy bidder. But for *theta*, all other variables defined above are publicly known. A bidder randomly checks the auction. If he is not the highest bidder then he executes the algorithm corresponding to the strategy.

1. Evaluator Strategy: A bidder with this strategy evaluates the product and bids only once. He declares his reservation value (private) to the proxy.

```
if (not participated earlier)
   bid(currentBidder) = theta(currentBidder);
end
```

2. Late bidder Strategy: Such a bidder bids once in the last few time slots. His bid value is much higher than the *leastPrice* and less than or equal to his reservation value (*theta*).

```
if (not participated earlier) and (t(i) is sufficiently close to T)
   bid(currentBidder) = min(theta(currentBidder),listPrice+jumpIncrement);
end
```

3. Sniper Strategy: This bidder bids in the last time slot, his bidding strategy is same as that of late bidder, but his bid is accepted with certain probability by the system.

```
if (not participated earlier) and (t(i) >= T-1)
  bid(currentBidder) = min(theta(currentBidder),listPrice+jumpIncrement);
end
```

4. Skeptic Strategy: A skeptic bids multiple times with minimal increment.

```
if (theta(currentBidder) >= listPrice+minIncrement)
   bid(currentBidder) = listPrice+minIncrement;
end
```

5. Unmasking Strategy: A bidder with this strategy bids multiple times within a short span of time with high bid increments till he becomes the highest bidder. In other words he unmasks the highest bidder and know the his bid value as submitted to the proxy bidder.

```
if (theta(currentBidder) >= listPrice+minIncrement)
   unmask the highBidder; /* by continuously placing a sequence of bids with a high increment value
   bid(currentBidder) = min(theta(currentBidder), bid(highBidder)+minIncrement);;
end
```

6. Shill counteracting bidding Strategy: In the experiment the bidder population draws its reservation values from the uniform distribution. Therefore the bid value is calculated using Equation 7.

```
if (((participants -1)/participants)*theta(currentBidder) >= listPrice+minIncrement)
   bid(currentBidder) = ((participants -1)/participants)*theta(currentBidder); /* Following equation 7 */
end
```

A framework for comparing the algorithms

The bidding algorithms are compared using the concept of the expected utility of a bidder defined in Equation 1. i.e.,

Expected utility = probability of winning (reservation value – bid)

The value of this function cannot be negative as a rational agent never bids above its reservation value. Since each agent is a utility maximizer, he tries to get the item is a price as low as possible and he is indifferent between not winning the auction and winning it in a price equals to its reservation value, i.e., the expected utility is zero if either of the terms in the multiplication are zero. In other words the buyers are risk neutral in nature. We calculate the probability of winning of the agent *i* as:

$$\frac{\text{(The number of effective bidders whose bid value is less than } i\text{)}}{\text{Total number of the effective bidders}}$$

Results

In this section we present the results of the experiment. There are *N* numbers of bidders in each experiment. Each bidder draws its reservation value from the uniform distribution. Each bidder other than the shill is randomly assigned with one of the 6 bidding strategy. The *N*th bidder is a shill. The bidders are randomly arrive and check the auction status and bids if necessary.

Each experiment consists of 1000 simulation runs repeated each time with different number of bidders in the system. Each experiment has different auction duration (*T*). Figure 1 to 4 present the results for four experiments with auction duration *T* equals to 1000, 100, 50 and 20 respectively. Six categories of bidders are formed based on their bidding strategy. Figures 1 to 4 show the average expected utility value of each category. For evaluators the average expected utility value is always zero. Therefore, we do not show the average expected utility plot for this category. Following observations can be made from the figures: (1) The SCBS algorithm shows better result when auction is continued for a longer duration of time i.e. $T = 1000$ (Figure 1), $T = 100$ (Figure 2), $T = 50$ (Figure 3). In figure 4, with $T = 20$, skeptic strategy out performs SCBS. However, in this figure when the number of bidders is less than ten SCBS is a better strategy. (2) With the exception of Figure 4, the average expected utility values of skeptic and unmasking strategies are almost same. These two strategies can be considered as the second best strategy. (3) It has been observer that in the real auction sites, the late bidding and snipping are two most popular strategies. The experiment shows that these two strategies perform the worst when there is shill bidding.

Table 1 shows the value of average expected utility and the percentage of winning by a particular category of agent in the simulation experiment when the auction duration is 100 time unit. SCBS strategy is developed in a risk neutral setting. Therefore the bidder with this strategy prefers to quit the auction instead of being cheated. This fact is evident in the table. Though the average expected utility increases, the winning percentage of SCBS agents decrease when the competition increases in the system the increased competition is characterized by the increase in the bidder population. The winning probability of the evaluators is always the highest. But his expected utility is always zero. This is due to the fact that the evaluator reveals his reservation value to the proxy bidder. Therefore, when shill escalates the price, the proxy system responds to this and goes up to the reservation value of the bidder. Hence, the agents wining probability increases at the cost of diminishing average expected utility.

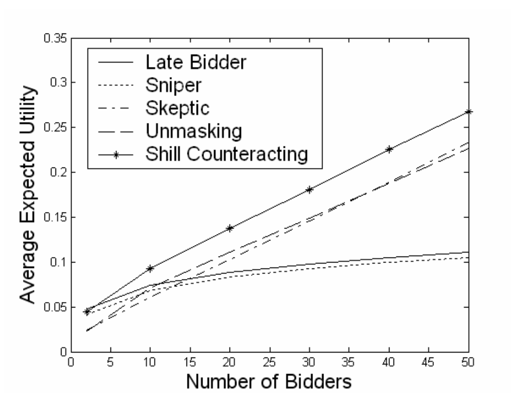

Figure 1: Average Expected utility of each bidder category when auction duration is 1000 time units.

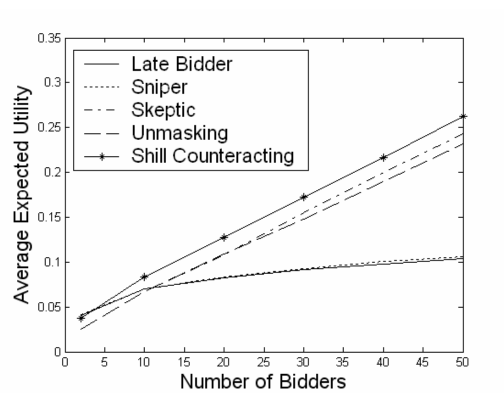

Figure 2: Average Expected utility of each bidder category when auction duration is 100 time units.

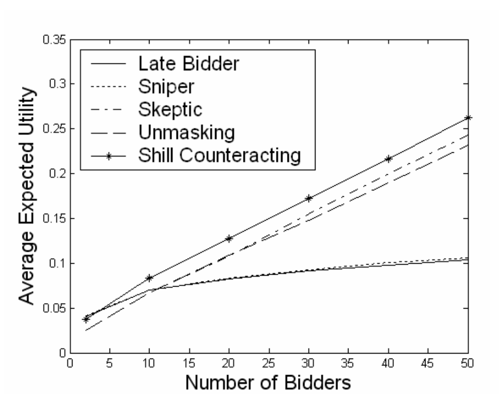

Figure 3: Average Expected utility of each bidder category when auction duration is 50 time units.

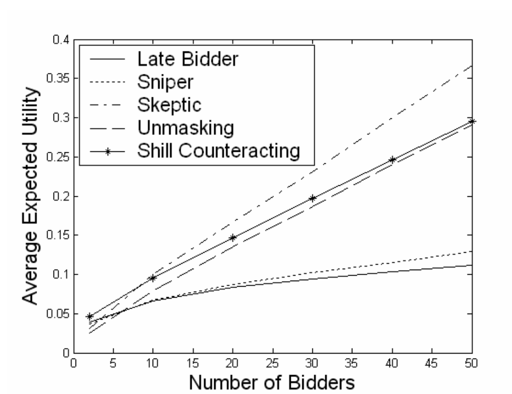

Figure 4: Average Expected utility of each bidder category when auction duration is 20 time units.

Table 1: Average expected utility vs. winning percentage

Strategy	N = 2		N = 10		N=20		N = 50	
	Average Expected Utility	Win %	Average Expected Utility	Win %	Average Expected Utility	Win %	Average Expected Utility	Win %
Evaluator	0	17.0000	0	27.3000	0	21.4000	0	23.4000
Late Bidder	0.0378	16.3000	0.0674	13.4000	0.0825	16.8000	0.1062	21.2000
Sniper	0.0394	15.9000	0.0666	10.9000	0.0826	17.3000	0.1062	24.1000
Skeptic	0.0252	17.8000	0.0673	20.8000	0.1127	17.9000	0.2477	12.3000
Unmasking	0.0252	16.5000	0.0639	19.1000	0.1086	20.1000	0.2299	14.1000
Shill Counteracting	0.0455	16.4000	0.0919	8.5000	0.1376	6.5000	0.2684	4.9000

IMPLEMENTATION ISSUES

The bidding algorithm can be implemented as an autonomous agent who bids on behalf of its owner. In this section we discuss some implementation issues considering eBay as the target auction site. The agent works over the proxy bidding system of eBay and executes the following steps:

1. Generating the real-life value distribution: EBay keeps the data from completed auctions of past 30 days available on its Web site. A crawler can conduct a search for a specified product category in eBay and collects all relevant pages. These pages can be cached locally and parsed to generate the price distribution. This distribution can be normalized to generate the probability density function and subsequently cumulative density function.
2. Getting the reservation value: The bidder can manually provide his reservation price to the agent. The probability distribution function may assist him to evaluate the expected price of the product.
3. Calculating the bid: The agent should access the action from time to time and find out the effective number of bidders in the system. Assuming that the probability of shill bidding is 1 the agent can use Equation 8 to evaluate the bid value.

RELATED WORK

A good introduction to auction theory can be found in [8]. Myerson [18] as well as Riley and Samuelson [7] have shown that if a certain regularity condition holds, the first and second price sealed-bid auctions and the English auction are optimal and give the same expected profit for the seller. Unfortunately, non-regular cases do occur in which these mechanisms are not optimal any more. A mechanism allowing shill bidding can give higher expected seller profit than the one against shill bidding [9].

Literature on auction fraud focuses mainly on buyer collusion and is quite limited. Klemperer [15] has cautioned of the danger of the thinness of the auction-theoretic literature on auction fraud. He states that most auction literature assumes a fixed number of buyers who behave non-cooperatively and auction surveys pay relatively little attention to collusion, which is reflected by the scant literature on this important topic [15]. Auctions with shill bidding and, in particular, revenue effects of shill bidding in English auctions have been analyzed before. The closest papers are from Graham, Marshall, and Richard [19][20]. They study English auctions where the seller's reserve price can be a function of the highest observed bid. These papers are the first to recognize that the optimal shill bid may be a function of the history when the bidders are heterogeneous and to show that shill bidding can enhance sellers' revenue. Their main emphasis is on modelling uncertainty a seller might have about identities of the bidders and its effects on the seller behavior. Wang, Hidvegi, and Whinston [9] consider a symmetric setup with non-monotone virtual valuations and with uncertain number of bidders. The optimal reserve price in this case depends on the number of bidders. They show that the English auction obtains the highest possible revenue since effectively the seller can observe the actual number of bidders and set her reserve price–shill bid–as a function of that number. Several papers study shill bidding in common values settings.

Use of agents in the electronic auction is emphasizing on the studies on automated auction and negotiation. Real-life [26] and simulation [21] environments for testing auction algorithms have been developed. Bidding strategies and algorithms for bid computation in simultaneous, multi-object and combinatorial auctions are proposed. The dynamic programming based bidding algorithms are found efficient both in single unit single action [12]and in sequences of overlapping English auctions [22]. Shehory [23] proposes two algorithms for an agent to visit multiple sites, with both auction and fixed price options, and to get that item in a price that maximizes the user's (owner of the agent) expected utility. Heuristics for solving multi-object combinatorial auctions are proposed [24][25] that are tractable and can be implemented online. Porter and Shoham [4] derive the equilibrium bidding strategies for an honest bidder who is aware of cheating in sealed-bid auctions. They consider two forms of cheating. In case of second price auction a seller inserts a fake bid to increase the payment of the winner. In case of first price auction a bidder examines the competing bids and submits a bid to win the auction with minimum payment. They also find the expected revenue loss for an honest seller due to the possibility of cheating.

CONCLUSIONS AND THE FUTURE WORK

The motivation behind our work is the popularity of online English auction and increased scope for shill bidding. In this paper we derive an equilibrium bidding strategy to counteract shill bidding in online English auction in a risk neutral setting. Based on this, we develop shill counteracting bidding strategy (SCBS) algorithm. An eBay like auction environment is simulated. Experiments are conducted in this environment to evaluate this strategy. Five more popular bidding strategies – evaluator, late bidder, sniper, skeptic and unmasking - are compared with the proposed strategy. In the experiment, the bidders are randomly assigned a bidding strategy. All the bidders draw their valuation from the uniform distribution. The bidders compete to buy a product in the presence of a shill. The average expected utility of the agents with proposed strategy is found to be the highest when the auction continues for a longer duration. We also have also observed that the winning probability decreases when the competition increases in the system.

Cheating in English auction can take place either in the form of shill bidding or multiple bidding. An auctioneer cheats in shill bidding. A bidder cheats in multiple bidding. In case of *multiple bidding* a cheating agent submits many bids adopting multiple identities. Some of these bids are higher than that of their personal valuation of the product. They drive the bid to such an extent that no other bidder dares to bid and withdraw themselves from the auction. At this point the cheater also withdraws all his bids except the one lowest value. So he acquires the product in a much cheaper price increasing his own gain. This kind of cheating is possible in the sites that allow bid withdrawal. In this paper we have considered counteracting cheating of the shill.

The result of multiple bidding can be studied in an environment where bid withdrawal is possible. A multistage gaming mode can be used to see the effect of bid withdrawal at certain stage. Our model assumes that the shill never wins the auction. But in real-life sometimes the shills win. So this model can be extended to accommodate this situation. The auction process over the internet involves three parties- the buyer (bidder), the seller (auctioneer) and the site that hosts the auctions. Much work has been done to see the reputation effect of sellers. Some work can be done to see reputation effect of the site that hosts the auction. Another interesting area of research could be establishing trust to prevent fraud in online markets.

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