A Simulation Study of Online Auctions: Analysis of Bidders' and Bid-takers' Strategies

Abstract

This paper examines factors which have been thought to influence the closing price on online auctions then illustrates how users can use data gathered from online auctions together with the identified factors to predict the closing price in a particular auction. We integrate literature from traditional auction theory with that of online auction theory, in order to construct a simulation model which captures the auction process in C2C electronic auctions, and can be used to analyze the impact of various bidder and bid-taker strategies.

Introduction

In recent years online auctions have emerged as a preferred venue for conducting a wide spectrum of business transactions both at the organizational and individual level (Pinker, Seidmann, & Vakrat, 2003). Online auctions are being used extensively by governments to buy and sell things such as treasury bills, oil-drilling rights, government contracts and foreign exchange (Klemperer, 1999; Wilcox, 2000), by businesses for the procurement of goods and services (Kwak, 2002; Snir & Hitt, 2003) and by individuals to buy and sell items ranging from books and CD's to valuable pieces of art and unique assets (Wilcox, 2000).

Electronic markets have been spurred and accelerated by advances in Information and Communication Technology (ICT).Unlike in traditional auctions potential buyers are not required to be physically present for the auctions and can bid over extended periods of time. Online auctions have benefited both buyers and sellers by increasing of the pool of potential bidders and decreasing the transaction cost of an auction (Bapna, Goes, & Gupta, 2000; Bapna, Goes, Gupta, & Jin, 2004; Wilcox, 2000). This has lead dramatic inroads into new markets such as those for relatively inexpensive and standardized consumer goods (Fox, 2002), which were previously untapped by traditional auctions .

It is important to note however that online auctions do pose a unique set of challenges for researchers (Ba, Whinston, & Zhang, 2003b; Bapna, Goes, & Gupta, 2001b; Bapna, Goes, Gupta, & Karuga, 2002) and practitioners alike. Traditional auctions have been studied in great detail with numerous theories being proposed and tested, however unique features of online auctions such as the ability of sellers to open or close their auctions any time during weekdays, weekends and even holidays, the availability of a vast quantities of information about the buyer(reputation, days active on the auction, number of items sold etc) and the product (pictures, prices of similar items on the auction, prices of similar items on other online stores etc) still need to be studied detail. Armed with such findings users of auctions can make more informed decisions for example if auction closing time affects selling price, seller could use this information to optimize their revenue by having their auctions close at a time when they are most likely to get the highest price.

The goal of this paper is to examine various factors which have been thought to influence the closing price on online auctions in detail and then illustrate how users can use information gathered from online auctions together with the factors identified to predict the closing price in a particular auction. We integrate literature from traditional auction theory with that of online auction theory, in order to construct a simulation model which captures the auction process in C2C electronic auctions. Data collected from real-world eBay online auctions are used to validate a simulation model then various factors are manipulated and their impact on the auctioneers' revenue is analyzed. Given such a model a seller can san their environment, input the conditions then determine how best to optimize his/her revenue.

The rest of the paper is presented as follows. In the next section we examine the literature paying attention to both conceptual and empirical contributions made to auction theory. Based on the literature we derive a set of variables for our model. The methodology section follows with a detailed description of the data collection procedure and the data collected. Statistical analyses are then conducted on the data. Thereafter, the simulation model and tool are presented, followed by sections on the analysis, results limitations and suggestions for future research.

Literature

Auctions

Traditionally, auctions were primarily of interest to economists, auctioneers and the socially affluent however, the emergence and explosive growth of on-line auctions has dramatically altered this paradigm with auctions expanding to millions of consumers' everyday purchase activity (Bazerman, 2001). As a platform that erases spatial and temporal constraints, online auctions have benefited both buyers and sellers by increasing the pool of potential bidders (Bapna, Goes, & Gupta, 2001), decreasing the transaction cost of an auction (Bapna, Goes, & Gupta, 2003; Wilcox, 2000), and matching demand and supply at the best price at one particular point in time (van Heck & Vervest, 1998) . With their unique advantages over traditional auctions, online auctions have quickly become a global billion-dollar industry where various activities such as companies liquidating unwanted inventory or individuals conducting "garage sales" occur (Ba, Whinston, & Zhang, 2003a; Bapna, Goes, & Gupta, 2001a).

Although literature on Economics and Marketing is replete with models, theories, and hypotheses on traditional forms of auctions, research on on-line auctions is relatively underdeveloped. Due to their unique rules and features, online auctions pose a unique set of challenges for researchers. For instance, online auction bid increments are usually much smaller than in most traditional auctions(Sinha & Greenleaf, 2000) and unlike in traditional auctions, bidders that participate in online auctions are not necessarily professional buyers (Wilcox, 2000). Hence, one may argue that online auctions are more transparent because both buyers and sellers can bypass the network of brokers and have equal easy access to pertinent information such as lot descriptions, asking price, last offer, and time remaining etc (Bapna et al., 2000) .Also, whereas the majority of traditional auctions are single-item auctions, on-line auctions are mostly multi-item in nature (Bapna et al., 2004). These and other differences between on-line auctions and traditional auctions have challenged the applicability of models and theories built on traditional auctions. For example, Rothkopf & Harstad (1994), argued that the results for single-item auctions do not apply to the multi-item situations while Bapna, Goes, & Gupta(2003), pointed out the difficulty and analytical untractability of applying game theory to on-line auctions where a large number of buyers are bidding for multiple items of goods. In addition, researchers have also noted that previous experimental and empirical work in auctions has not adequately addressed how the pervasive impact of advance electronic communication would influence the theory and practice of auctions .

Research on Online Auctions

The majority of studies on online auctions in the area of economics have been experimental in nature for instance Lucking-Reiley(1999) used an online field experiment to test the equivalences of the four types of auctions. In marketing, Sinha and Greenleaf (2000) theoretically investigated how discrete bidding and bidder aggressiveness in a model affect the optimal strategies for setting the lowest acceptable bid at which to sell the item. Two strategies were examined: setting a reserve price before the auction and covert shilling (sellers or sellers' agent act as legitimate bidders in an attempt to raise bids). Their finds reveal that both discrete bidding and aggressiveness affected the two strategies. Wilcox (2000) did an empirical study to explore the role experience plays on online bidding behavior and to examine whether experience leads to behavior that is consistent with theory on traditional auctions. They found that experience does lead to behavior that is in line with game-theoretical prediction in the traditional literature: more experienced bidders tend to follow Nash equilibrium bidding strategies and place their bids during the final minute of the auction; bidders learn successful bidding strategy from their experience; and nonprofessional bidders' behavior is not consistent with the normative prediction described in traditional theoretical literature. Finally, Dholakia, Basuroy, & Soltysinski (2002) investigated the effects of what they termed "herd behavior bias" on online auctions. "Herd behavior bias" refers to situations when bidders tend to bid for items with one or more bids and overlook comparable or even superior items with no bids during the same time period. Their findings reveal that the effects of the herd behavior bias decrease when the price of the item increases, but increase when quality is uncertain.

Online auctions have also begun to receive attention from other areas such as sociology, management and information systems. Brinkman & Siefert (2001) empirically tested the effects of trust on online auctions. They argued that the feedback systems offered by the online auction house mitigate risks associated with online transactions. Their results reveal that both the buyer and seller's chance of successfully participating in the auction community suffer when they get many negative feedbacks and lose trustworthiness. Ba et al. (2003a) proposed the utilization of information technology to help reduce fraud and build trust in online auction markets. They argued that the trusted third party helps trust building in the online auction communities by issuing digital certificates to each participant. They took a game theoretic approach and their analytical results supported their argument.

An integrative effort was made by Gilkeson & Reynolds (2003). The authors drew from traditional economic theories and theories from marketing and psychology and identified several key factors related to online auction success and closing price. They empirically examined the role of the identified factors on the success and closing price of online auctions. Their study finds that auction success positively correlates with the number of unexpected bids, but negatively correlates with opening price and a reserve price format. Also, there is a positive relationship between the average closing price and the number of unexpected bids, the opening price, and the reserve price format.

Auction mechanisms

Four basic types of auctions mechanisms are most commonly employed and analyzed: the English auction (also known as the oral, open, or ascending-bid auction), the Dutch auction (also called the descending-bid auction), the first-price sealed-bid auction, and the second-price sealed-bid auction (or Vickrey auction).
With the English auction, the seller announces prices, or bidders individually state their bids and the price is successively increased until only one winning bidder who bids the highest remains. This has been and still is the most popular type of auction mechanism. In a Dutch auction the auctioneer starts at an initial high price, and then lowers the price continuously until one bidder indicates that she will accept the current price. In the first-price sealed-bid auction, each potential bidder independently submits a single sealed bid and the highest bidder wins the item for the price she bids. The basic difference between the English auction and the first-price sealed-bid auction is that the English auction is open and the first-price sealed-bid auction is not. In other words, bidders can observe other bidders' bids and can revise their own bids based on their observation in English Auctions whereas they cannot do this in a first-price sealed-bid auction. Under the first-price sealed-bid auction, each bidder can only submit one single sealed bid and do not have access to information on other bidders' bids. The second-price sealed-bid auction (Vickrey Auction) works exactly like a first-price sealed-bid auction in that each potential buyer submits a single sealed bid and the highest bidder wins the item. The only difference is that in a second-price sealed-bid auction the winner only pays the second highest bidder's price for the item.

eBay's Auction Mechanism

Although several auction sites are currently operating on the internet, eBay has continuously remained dominant in this business. eBay's auction format is a hybrid of the English auctions and the Vickery (second-price sealed) auctions.
The seller designs her own item description and chooses a title, an opening price, a reserve price if desired, and an auction length (buy it now, 3, 5, 7, or 10 days). A reserved

price is the minimum amount the seller is willing accept for the item listed. If no buyers bid as much, or higher than the reserve price during the course of the auction, the seller will not sell the item and the auction is unsuccessful(Lucking-Reiley, 2000) .However, the seller has no control on bid increment. eBay specifies the bid increment and the rule is that the bid increment grows as the high bid grows. The following table shows how the increment is determined:

Current Price	Bid Increment
$ 0.01 -- $0.99	$0.05
$1.00 -- $4.99	$0.25
$5.00 -- $24.99	$0.50
$25.00 -- $99.99	$1.00
$100.00 -- $249.99	$2.5
$250.00 -- $499.99	$5.00
$500.00 -- $999.99	$10.00
$1000.00-- $2499.99	$25.00
$2500.00-- $4999.99	$50.00
$5000.00 and up	$100.00

To participate, a bidder summits a maximum bid amount which is hidden from other bidders and which must be equal or exceed the minimum bid. The minimum bid equals the opening price or the current highest bid plus an increment. The current highest bid is set to be the second highest bidder's bid. eBay automatically adjusts the current highest bid as the new bids enter and clearly the minimum bid grows as the amount of the current highest bid grows. For unreserved auctions, the bidder with the highest hidden maximum bid at the end of the auction wins the item but pays a price equal to the second highest bidder's maximum value plus the bid increment set the eBay. For auctions with a reserve price, eBay first checks the bidders' maximum bids against the hidden reserve price. If the reserve price is met or exceeded by the maximum bid, the reserve price becomes the current highest bid. If no maximum bids meet or exceed the reserve price at the end of the auction, no agreement is reached between the seller and the buyer and the auction is unsuccessful (Wilcox, 2000). In the situation of a tie, the current highest bidder wins (Gilkeson & Reynolds, 2003).In November 2000, eBay instituted a practice called "Buy it Now" which allows a bidder to instantly purchase the item at the listed Buy it Now price if no bids have been recorded(Wingfield, 2001). The complicated auction mechanism can be clearly explained by the following hypothetical example.

In this example, the open price and reserve price are set by the seller at $10 and $20 respectively. The bid increment is specified by the auction house as $1. Because the open price is $10, the minimum bid for bidder 1 to enter is $10+$1=11. Suppose that bidder 1 bid with a maximum amount of $15, the current highest bid is $15 and the minimum amount to enter the auction at this point in time is $15+ $1 = $16. Suppose that no more bids are submitted after bidder 1. Because $15 is less than the reserve price, the auction is unsuccessful. However, if bidder 2 enters a maximum bid of $28, since the reserve price is set at $20 which is less than $25, the current highest bid becomes $20 and minimum amount to enter becomes $20 + $1 = $21. Bidder 3, upon observing the current highest bid ($20), submits a maximum amount of $22. As the second highest bidder, bidder 3's bid ($22) becomes the current highest bid and minimum amount to enter becomes $22 + $1 = $23. Finally, bidder 4 enters with a maximum bid of $25. Although not the highest bidder, she moves the current highest bid up to $25 and minimum amount to enter up to $25 + $1 =$26. In the end, bidder 2 wins the auction and pays the second highest bid plus the bid increment ($26). The following table summarizes this hypothetical example.

Table 1: Hypothetical eBay Bid Example

Bid Number	Maximum Bi (Hidden)	Current Highest Bid	Minimum Amt to Enter	Open Price	Reserve Price	Bid Increment
0			$10+$1=$11	$10	$20	$1
1	$15	$15	$15+$1=$16			
2 (Win)	$28	$20(reserve price)	$20+$1=$21			
3	$22	$22	$22+$1=$23			
4	$25	$25	$25+$1=$26			

Theoretical Basis

In any auction mechanism, bidders have to determine how much to bid for the item. In the case of eBay bidders, they have to decide their hidden maximum bid. As previously noted, the auction mechanism adopted by eBay is a hybrid of the English auctions and the Vickery (second-price sealed) auctions. Nobel laureate William Vickrey (1961) showed that in a second-price sealed auction, each bidder has a dominant strategy, also known as unique Nash equilibrium strategy, of bidding his or her true valuation for the item under consideration. In short, bidding below the true valuation is not optimal because the bidder might lose the opportunity to win the item. On the other hand, there is not incentive to bid higher than the true valuation to because although it does raises the probability of winning the item, this increased probability of winning occurs at the cost of paying a price higher than the bidder's true valuation(Vickrey, 1961).

eBay allows sellers to list either single or multiple items for auction. The single item case can be regarded as a special case of multiple items because many single items are identical across different sellers and bidders have multiple choices on which one to bid on. So let N= {1, 2, …, N} be the set of the identical items available on eBay on a particular day. Let there be I bidders, each with a value of Vi for the product. Some bidders will choose to bid for item 1, some for item 2, etc. Let N_J denote the set of bidders bid for a particular item from N. In other words, 1_J $\{1_1, 1_2,\ldots,1_{(J-1)}, 1_J\}$ denote the bidders who bid for Item 1, 2_J {2_1, 2_2, …, $2_{(J-1)}$, 2_J} bid for item 2, and N_J {N_1, N_2, …, $N_{(J-1)}$, N_J} bid for Item N. Let bidder N_J {1_J, 2_J, …, N_J} be the set of the winners for each item and bidder $N_{(J-1)}$ {$1_{(J-1)}$, $2_{(J-1)}$, …, $N_{(J-1)}$} be the bidder who has the second highest bid for each item. Accordingly, set $V_{N(J-1)}$ {$V_{1(J-1)}$, $V_{2(J-1)}$, …, $V_{N(J-1)}$} denotes bidder $N_{(J-1)}$'s {$1_{(J-1)}$, $2_{(J-1)}$, …, $N_{(J-1)}$} true valuation for the item. Based on Vickrey's (1961) theory on Nash equilibrium strategy, every bidder will bid their true valuations. In other words, Bidder $N_{(J-1)}$'s bid, denoted by $B_{N(J-1)}$, is equal to his or her true valuation of the item, $V_{N(J-1)}$. Since in eBay the winner pays for the item at the second highest bidder's bid, theoretically the total revenue for item N on a particular day should be $\sum V_{N(J-1)}$(The second highest bid/true valuation for item1+ the second highest bid/true valuation for item 2+…+the second highest bid/true valuation for item N).

Hence, theoretically for a particular seller k who sells item k ($k \in N$) the question of maximizing his revenue on item k can be simplified as the question of how to maximize $V_{k(J-1)}$ ($V_{k(J-1)} \in V_{N(J-1)}$). Two conditions must be met to maximize $V_{k(J-1)}$. First, $\sum V_{N(J-1)}$ is the highest among the revenue of all the days. Second, $V_{k(J-1)}$ is the highest value in set $V_{N(J-1)}$.

To make $\sum V_{N(J-1)}$ the highest among the revenue of all the days, bidders' true valuation of the item on that particular day has to be higher than their true valuation of the item on other days. Under the assumption of independent private-value model, the bidder knows the value of the item to themselves with certainty, but does not know the valuation of the item to others. In this case, bidders' private valuation is statistically independent of other bidder's valuation and would not be affected by observing any other bidders' signals, behaviors, or preferences. However, as (Milgrom & Weber, 1982)noted, in reality bidder often may be uncertain about their private valuation. One reason of this uncertainty is because an item has a common value component whose value must be estimated by the bidder. To estimate the common value, bidders will scrutinize the demand and supply of the item and the bids from their competitors. When demand is much higher than the supply, bidders tend to price the item higher, which will give rise to higher valuations and higher bids. Similarly, their competitors tend to think the same way and bid higher. When they scrutinize each other's bids, they will bid even higher after the effect of demand and supply. So the demand and supply plays an important role.
Based on the literature review several factors might influence the winning price. These factors include the herd effect (the number of bids), the night and weekend effects, bidding signaling, feedback rating, length, opening price, night and day effect and shipping price.

Methodology for Data Collection

eBay auctions offering Kingston 256 DDR PC2100 Memory were selected for analysis in this study. This product was chosen for two reasons. First, it is standard in nature i.e. all pieces of Kingston 256 DDR PC2100 Memory are exactly the same. By randomly selecting a standard product such as this one we are better able to control for differences in final price arising from product attributes. Second, large volumes of this product are traded on e-bay thus allowing us to collect vast quantities of data for analysis. In total we were able to amass data on 249 distinct auctions for analysis.

eBay provides a feature that allows users to search for completed auctions by entering search key words for a particular item. eBay keeps a complete auction records for three weeks and thus after entering the search key words, a user can view the past three week's auction record of the item searched. Our data collection process was conducted as follows. First, the key words "Kingston PC2100 256MB DDR" were entered by using the completed-auctions search function. From this list auctions were randomly selected over a 30 day period. Of primary concern for the simulation were data related to bidders and items, arrival rates to the auction to the auction length/duration, number of bids, opening price, winning bid, day, feedback rating, and shipping cost. All these variables have been identified as having the potential to influence the final price of an online auction.

Statistical Analysis

Stepwise regression was used to determine which of the variables identified above influences closing price in the data set. The results are shown below.

Stepwise regression results

The goal of the study was to replicate the auction process on eBay as accurately as possible in order to gain an insightful working knowledge on which variables contribute to revenue generated in the auction. Correlation analysis was first conducted on the collected data to determine which of the variables identified in the literature correlate significantly with selling price. The results are shown in the table below:

The CORR Procedure

Pearson Correlation Coefficients Prob > |r| under H0: Rho=0

Selling Price	No of Bids	Feedback	Length	Opening Price	Night/Day Effect	Weekend Effect	Shipping Fee
Correlation Coefficient	0.51290	-0.22857	0.02466	-0.30007	0.15223	0.07142	-0.18710
P-Value	<.0001	0.0030	0.7517	<.0001	0.0495	0.3590	0.0155

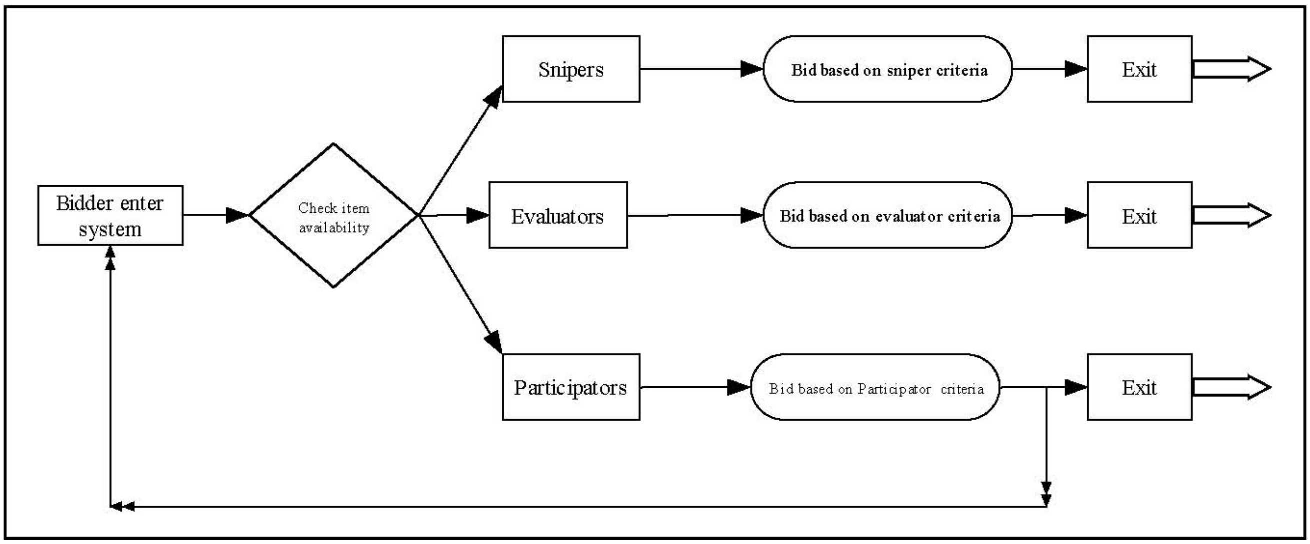
The number of bids (bids for item), feedback rating, opening price, night and day effect and Shipping are all significantly correlated to selling price at $\alpha = 0.05$. A note on feedback rating; negatively correlated to price: We strongly suspect that this is because the star used to calculate the final value entered into SAS may not be the one used by buyers. Typically bidders look at the seller's percentage rating rather than the star rating. This could explain the negative correlation found between selling price and feedback rating. All the other variables correlated with selling price as suggested by the literature.

The Simulation Model

General Description and Assumptions

The diagram below gives an overview of the general auction bidding process used in the simulation system.

Figure 1: General Auction Bidding Process



Bidders enter the system and check which items are available, then they branch off into various categories i.e. snipers, evaluators and participators.

Table 2 : Bidder Types and Characteristics

Type	**Characteristics**
Snipers:	Enter into the bidding process only towards the end of the auction.
Participators	Arrive at an auction throughout the duration of an auction.
Evaluators	These agents place just one bid that is equal to the highest feasible bid level below their valuation. Such agents do not participate in the auction on an ongoing basis and if there are enough bids above their bid,

Adapted from Buptna & Goes(2001)

Snipers will wait until the items have one day left on the auction. The others don't have to wait. All bidders check if their bid is higher than the minimum bid requirement. If their bid is lower than the minimum requirement for all items, they exit the system. If their bid is higher than the minimum requirement for some items they can bid for those items. Participators leave the system but they may return to bid again if they didn't win the item or the minimum requirement is lower than the price at which they are willing to bid. They usually bid the minimum requirement and an increment. If a bidder is qualified(their bid is higher than the minimum requirement) to bid for several items, they will bid for the one with the highest number of bids (herd effect).If all items have the same number of bids, we assume 50% of the bidders will bid for the items with the shortest number of days left, and 50% will bid for the items with the lowest minimum requirement.

Detailed Description of the Simulation Model

The full simulation model is shown below. For the purpose of this paper it has been divided into six parts. Subsequent paragraphs highlight and discuss each of the six portions in detail.

Figure 2: Complete Simulation Model

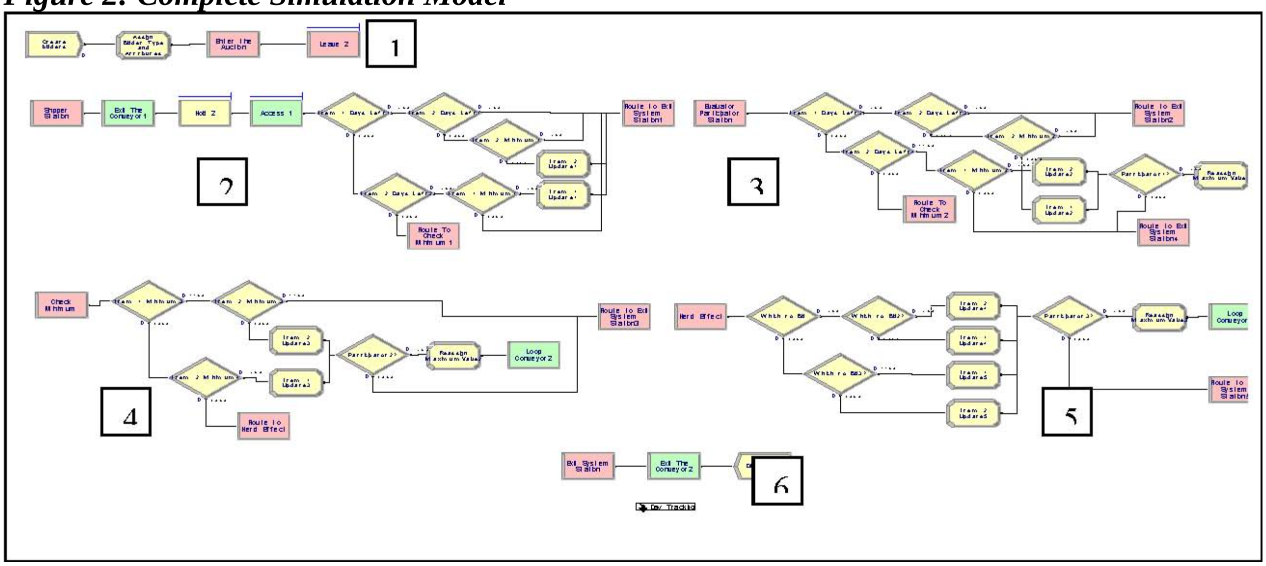
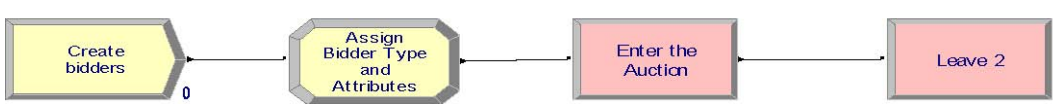


Figure 3: Bidder creation

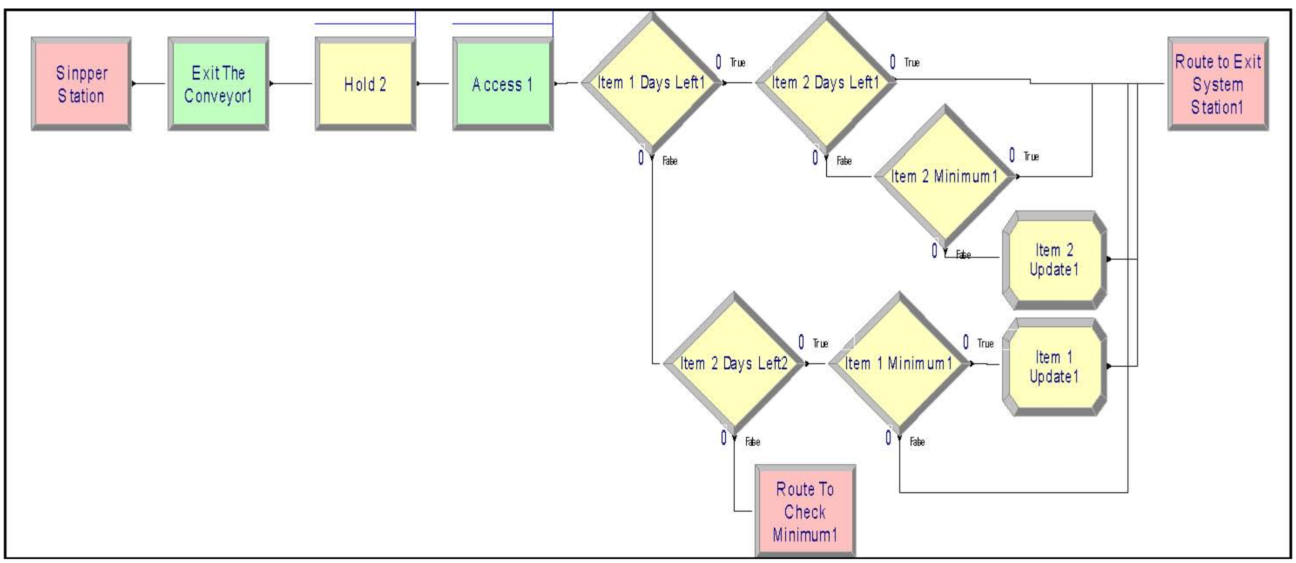


Bidders are created according to the arrival rate we obtained from the data. The bidders are then assigned certain attributes which include, bidder index, bidder types (sniper, evaluator, participator), bidding sequence, their bid and how may times they enter the system(at the initial stage this attribute is set as 1). Based on our data 40% of the bidders are snipers, 30% are evaluators and 30% are participators. Thereafter, bidders enter the auction. Since the participators may return to bid again we decide to use some Advanced Transfer constructs namely the Station Construct and the Conveyor Construct in order to allow participators to return to the auction and bid again. Enter the Auction station is the starting point of the conveyor. At Leave 2 the bidders access the conveyor and are routed to different stations according to the sequence they were assigned.

Snipers

1. Snipers are first sent to a sniper station. At this point they exit the conveyor and are held in a holding doc Hold 2 until an item has one day left for bidding. The day tracking module shown in figure 4 keeps track of the progression of the days and the days left for each item. When an item has one day left, this module will send out a signal to the snipers in the holding doc, and the snipers access the conveyor at Access 1 and begin the bidding process. Although the system created in this project is composed of two items, the basic logic will be the same if more items are added. Snipers enter and check which of the items has one day left.

Figure 4: Sniper



There are three possible scenarios:

1. Item 1 has 1 day left but item 2 either has more than 1 day or less than 1 day left. In this case snipers will only bid for item 1. Before they bid they will check if they are qualified. They compare their bid with the minimum requirement. If their bid is higher than the minimum requirement they place their bid and are then routed to the exit system station, if not they are automatically routed to the exit

system station. Additionally, item 1's attributes are updated. These attributes include the number of bids and the current bid.

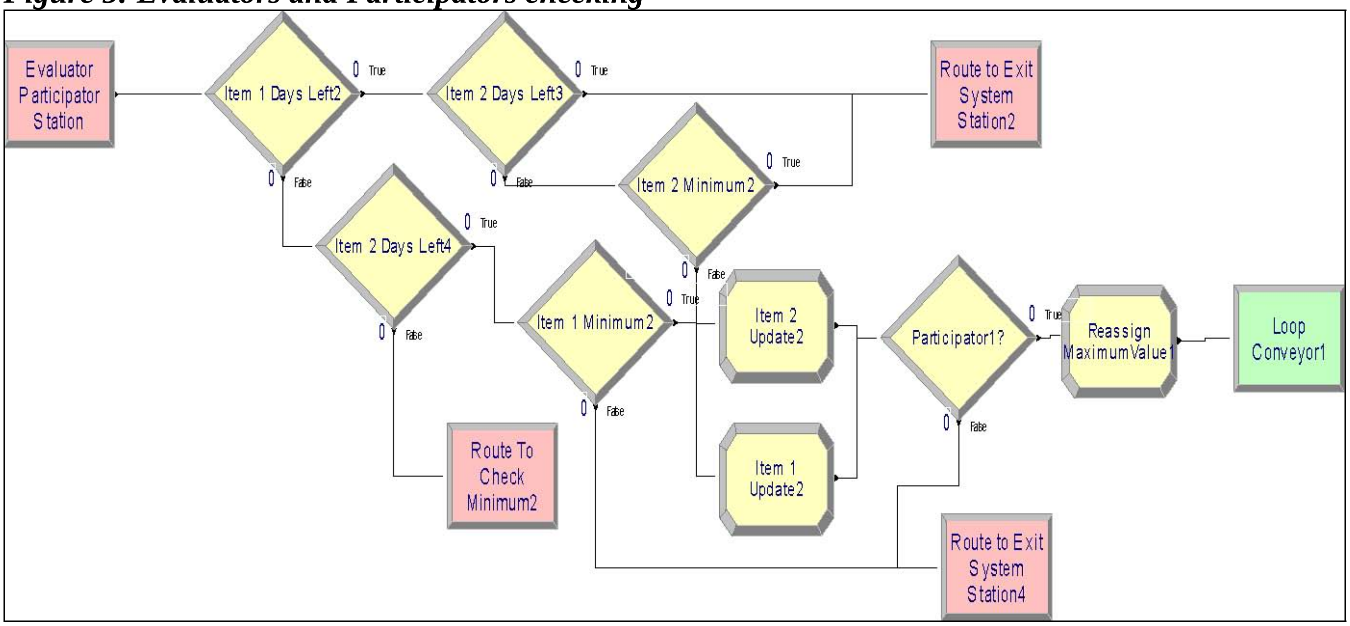
2. Item 2 has only 1 day left and item 1 has more than 1 day or les than 1 day left. In this case snipers will only bid for item 2. Before they bid they will check if they are qualified. So they compare their bid with the minimum requirement. If their bid is higher than the minimum requirement they place their bid then routed to the exit system station, otherwise they will be routed to the exit system station. Similarly, item 2's attributes are updated. These attributes include the number of bids and the current bid.

Both items have 1 day left. In this case they will be routed to a check minimum station(Check Minimum 1) where they check if they are qualified to bid on both items. If they are they will decide which item to bid on based on the herd effect. If they don't qualify to bid they exit the system.

Evaluators and Participators

Evaluators and participators will first be sent to a Evaluator and participator station. They will first check which items are available.

Figure 5: Evaluators and Participators checking



There are 4 possible scenarios:

1. Both items are not available. In this case all bidders are routed to the exit system station.
2. Only item 1 is available. In this case they check if they are qualified to bid . If not they will be routed to the exit system station. If yes they bid for item 1 and item 1 attributes(number of bids and current bid) will be updated. A decide construct is used to check if this bidder is an evaluator of participator. If they are a participator they will get onto the conveyor and be routed back and return to the auction for an

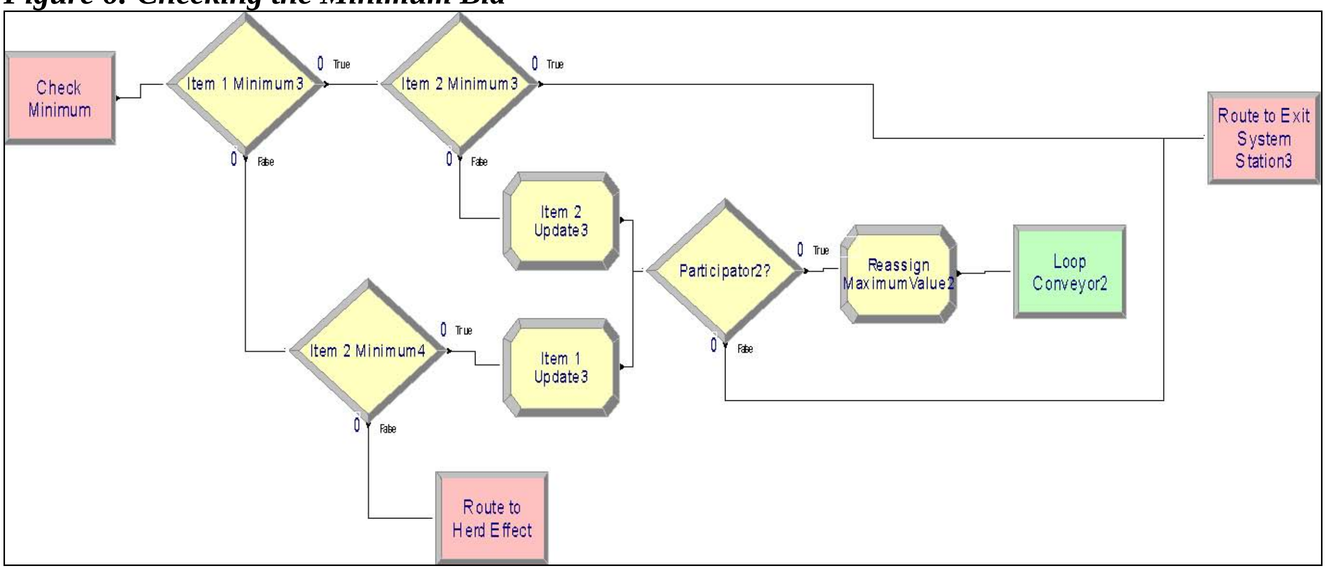
additional auction round. Before they are routed back an increment is added to their bid.

3. Only item 2 is available. In this scenario they check if they are qualified to bid . If not they will be routed to the exit system station. If yes they bid for item 2 and item 2 attributes(number of bids and current bid) will be updated. A decide construct is used to check if this bidder is an evaluator of participator. If they are a participator they will get onto the conveyor and be routed back and return to the auction for an additional auction round. Before they are routed back an increment is added to their bid.
4. Both items are available. In this case they will be routed to a check minimum station(Check Minimum 2) where they check if they are qualified to bid on both items. If they are they will decide which item to bid on based on the herd effect. If they don't qualify to bid they exit the system.

Check Minimum

Figure 6 illustrates how bidders check the minimum bid.

Figure 6: Checking the Minimum Bid



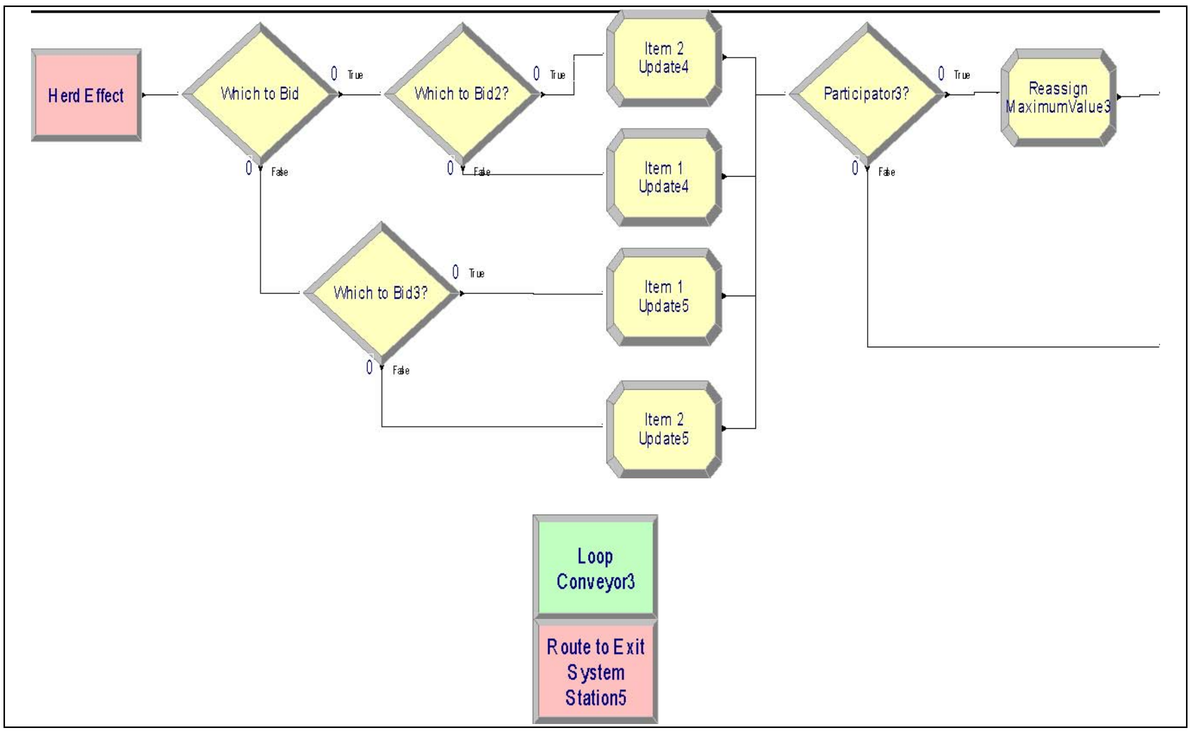
After bidders arrive at this station there are 4 scenarios;

1. They are not qualified to bid for either one of the items- In this case all bidders are routed to the exit system station.
2. They are qualified for only item 1 - They bid for item 1 and item 1 attributes (number of bids and current bid) will be updated. A decide construct is used to check if this bidder is an evaluator or participator. If they are a participator they will get onto the conveyor loop and return to the auction for an additional auction round. Before they are routed back an increment is added to their bid. If they are not a participator, they will be routed to the exit system station.
3. They are qualified for only item 2- In this case they bid for item 2 then item 2 attributes (number of bids and current bid) are updated. A decide construct is used to check if this bidder is an evaluator or participator. If they are a participator they will get onto the conveyor loop and return to the auction for an additional auction

round. Before they are routed back an increment is added to their bid. If they are not a participator, they will be routed to the exit system station.

4. They are qualified for both items- In this case they will be routed to a herd effect station where they check which item has a higher number of bids.

Figure 7:Capturing the Herd Effect



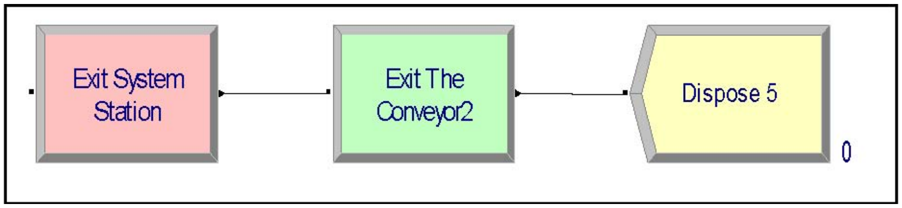
At this stage there are 3 scenarios:

1. Both items have the same number of bids- 50% of the bidders will bid for the item which as a lower current bid, and the other 50% will bid for the item with fewer days left. The attributes for the item on which the bidder bids are then updated.
2. Item 1 has a higher number of bids-Bidders will bid for item 1 and item 1's attributes will be updated.
3. Item 2 has a higher number of bids- Bidders will bid for item 2 and item 2's attributes will be updated.

For all three scenarios a decide construct will check if a bidder is a participator. If they are they will get onto the loop conveyor and return to the auction for an additional auction round. Before they are routed back an increment is added to their bid. If they are not a participator, they will be routed to the exit system station.

Exit

Figure 8: Exit the System

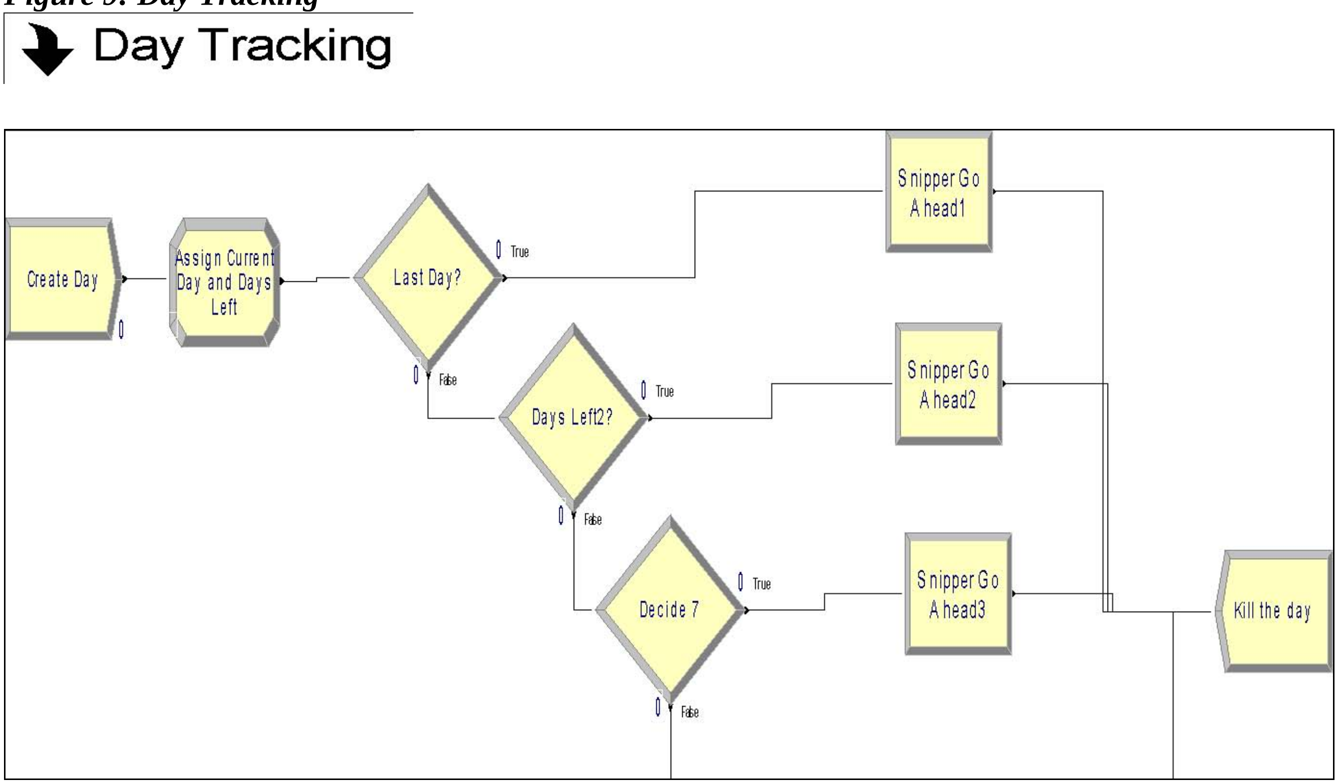


At the exist system station the bidders exit the conveyor then leave the auction.

Day Tracking Sub-module

The day tracking sub–module is a logic control sub-module which keeps track of the progression of day and days left for each auction item.

Figure 9: Day Tracking

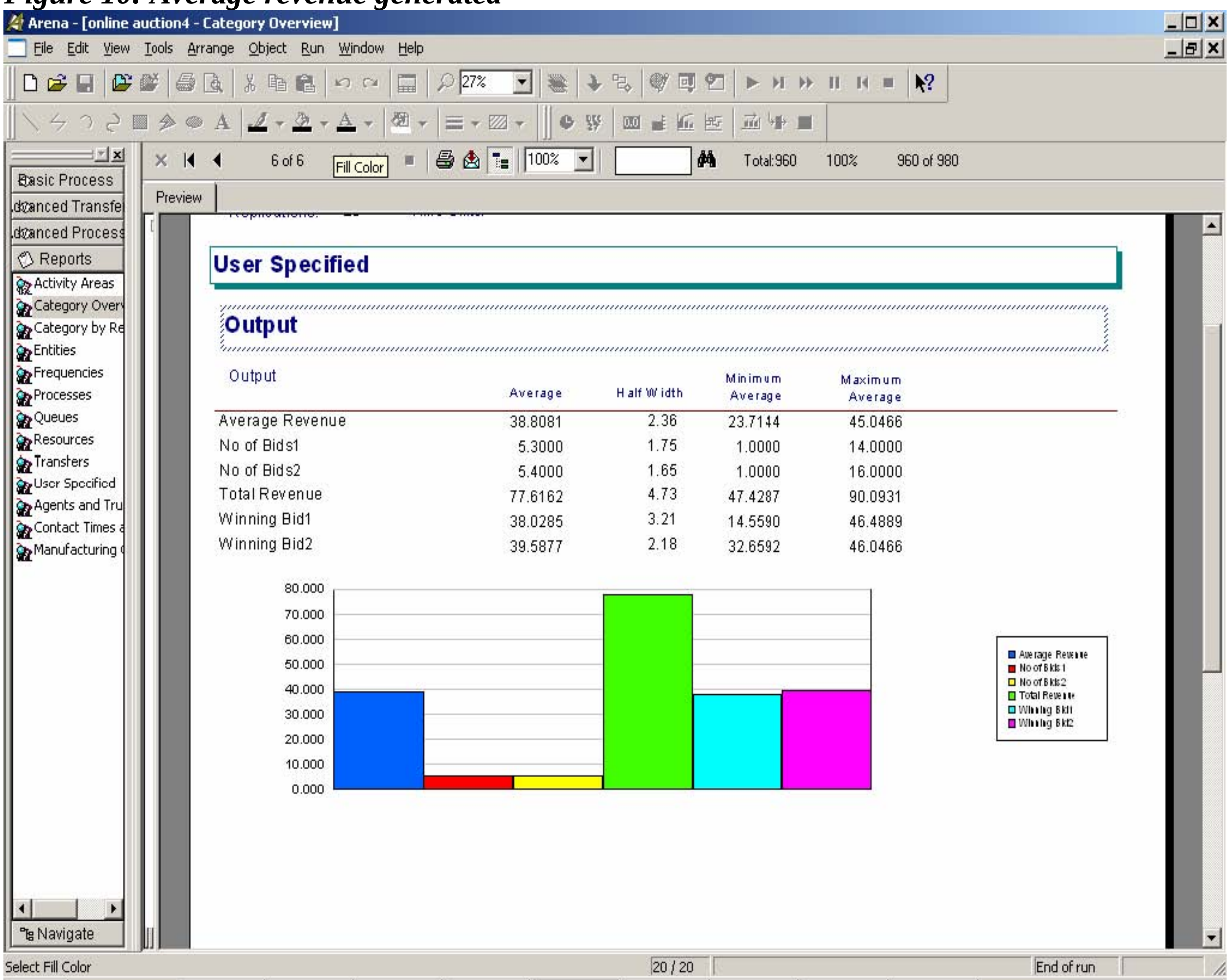


Every 24 hours the current day count will increase by 1 , and the days left for each item will decrease by 1. When either item only has 1 day left, this sub-module will send a signal to the snipers, so that snipers can go ahead and bid. When there are no items available a signal will be sent to snipers so that snipers won't pile up at holding doc 2.

Simulation Results

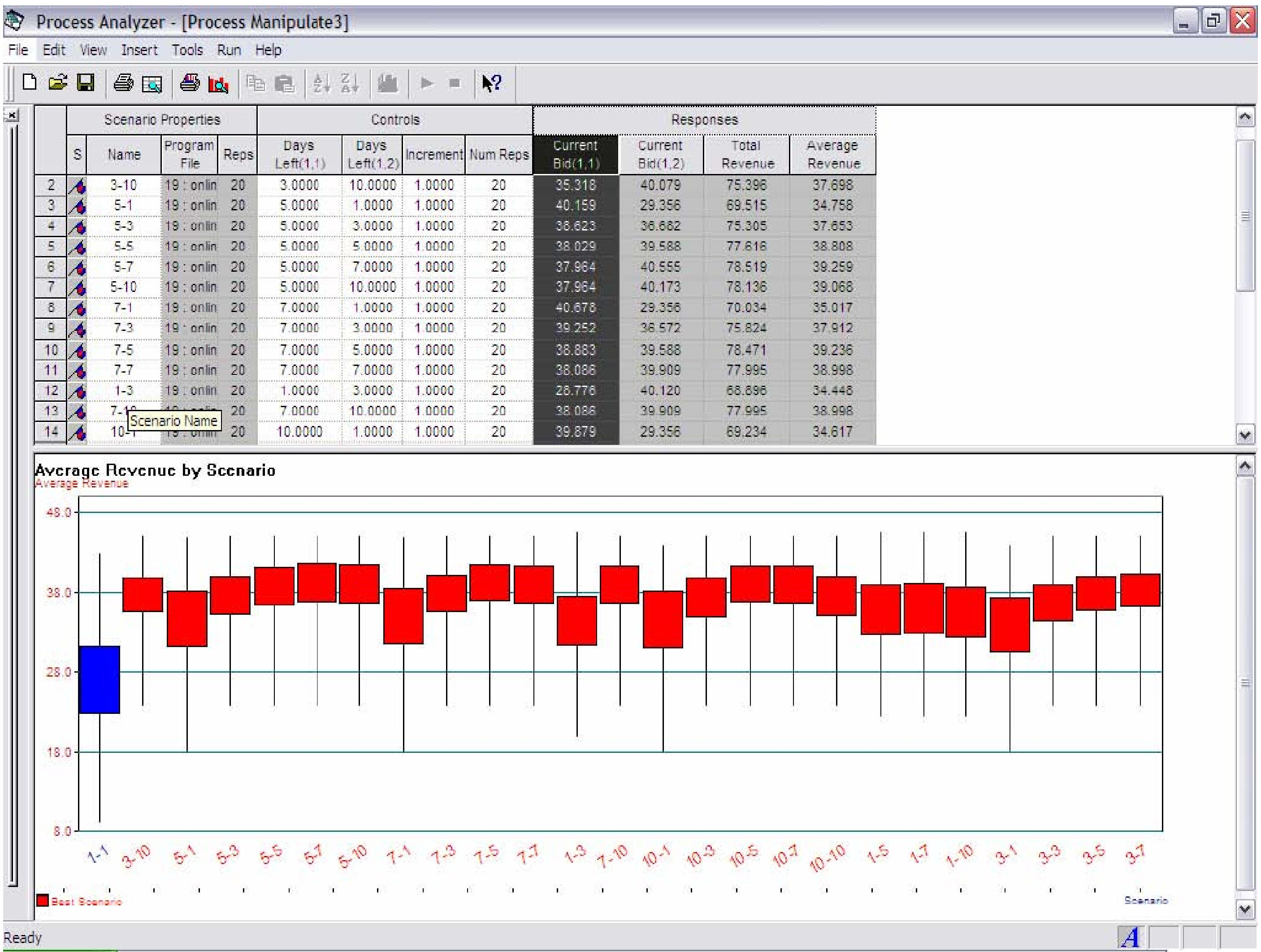
The subsequent paragraphs detail the major findings of the simulation study. It is important to note that Arena is not well suited to simulating scenarios such as online auctions, however we did manage to incorporate some of the essential elements of an online auction. The average revenue from the data collected from eBay was $37.66 and the average revenue generated by the simulation $38.80 with a half width of 2.36 (Figure 10).

Figure 10: Average revenue generated



We then manipulated auction length while holding all other things constant to see whether or not the number of days an item is placed on an auction makes a statistically significant difference to the average revenue generated. Figure 11 and 12 illustrate the 25 different scenarios developed for study and the average revenues for each seller.

Figure 11: Revenue Analysis

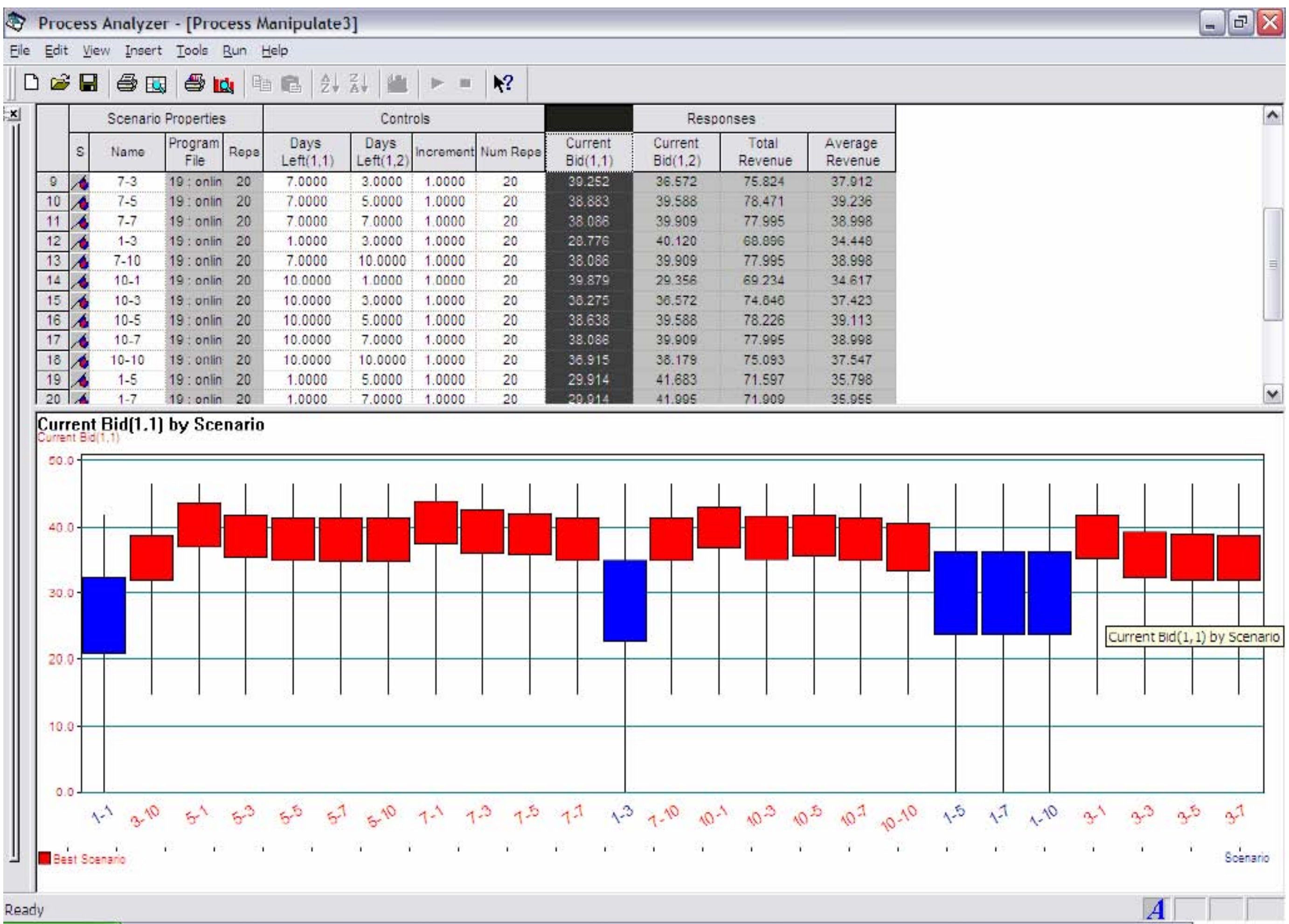


	Scenario Properties				Controls				Responses			
	S	Name	Program File	Reps	Days Left(1,1)	Days Left(1,2)	Increment	Num Reps	Current Bid(1,1)	Current Bid(1,2)	Total Revenue	Average Revenue
2		3-10	19 : onlin	20	3.0000	10.0000	1.0000	20	35.318	40.079	75.396	37.698
3		5-1	19 : onlin	20	5.0000	1.0000	1.0000	20	40.159	29.356	69.515	34.758
4		5-3	19 : onlin	20	5.0000	3.0000	1.0000	20	38.623	36.682	75.305	37.653
5		5-5	19 : onlin	20	5.0000	5.0000	1.0000	20	38.029	39.588	77.616	38.808
6		5-7	19 : onlin	20	5.0000	7.0000	1.0000	20	37.964	40.555	78.519	39.259
7		5-10	19 : onlin	20	5.0000	10.0000	1.0000	20	37.964	40.173	78.136	39.068
8		7-1	19 : onlin	20	7.0000	1.0000	1.0000	20	40.678	29.356	70.034	35.017
9		7-3	19 : onlin	20	7.0000	3.0000	1.0000	20	39.252	36.572	75.824	37.912
10		7-5	19 : onlin	20	7.0000	5.0000	1.0000	20	38.883	39.588	78.471	39.236
11		7-7	19 : onlin	20	7.0000	7.0000	1.0000	20	38.086	39.909	77.995	38.998
12		1-3	19 : onlin	20	1.0000	3.0000	1.0000	20	28.776	40.120	68.896	34.448
13		7-1 Scenario Name		20	7.0000	10.0000	1.0000	20	38.086	39.909	77.995	38.998
14		10-1		20	10.0000	1.0000	1.0000	20	39.879	29.356	69.234	34.617

When evaluating the average total revenue for item 1 and 2 it is interesting to note that at

$\alpha = 0.05$ or $\alpha = 0.1$ there is no statistically significant difference in revenue, for 24 out of the 25 different scenarios in terms of how items remains on the auction floor. For scenario 1-1 one plausible explanation for the difference in revenue is that items that remain for such a short period will not get much expose to many bidders, therefore for sellers it is not advisable to put items up for auction for only a single day unless they have a fixed price attached to them ("buy it now" items).
Figure 12 illustrates that from a seller's perspective there is no statistically significant difference between putting the items up for auction for 3, 5 7 or 10 days. This finding corresponds to our statistical analysis findings which indicated that there is no significant correlation between selling price and the number of days an item remains on the auction floor.

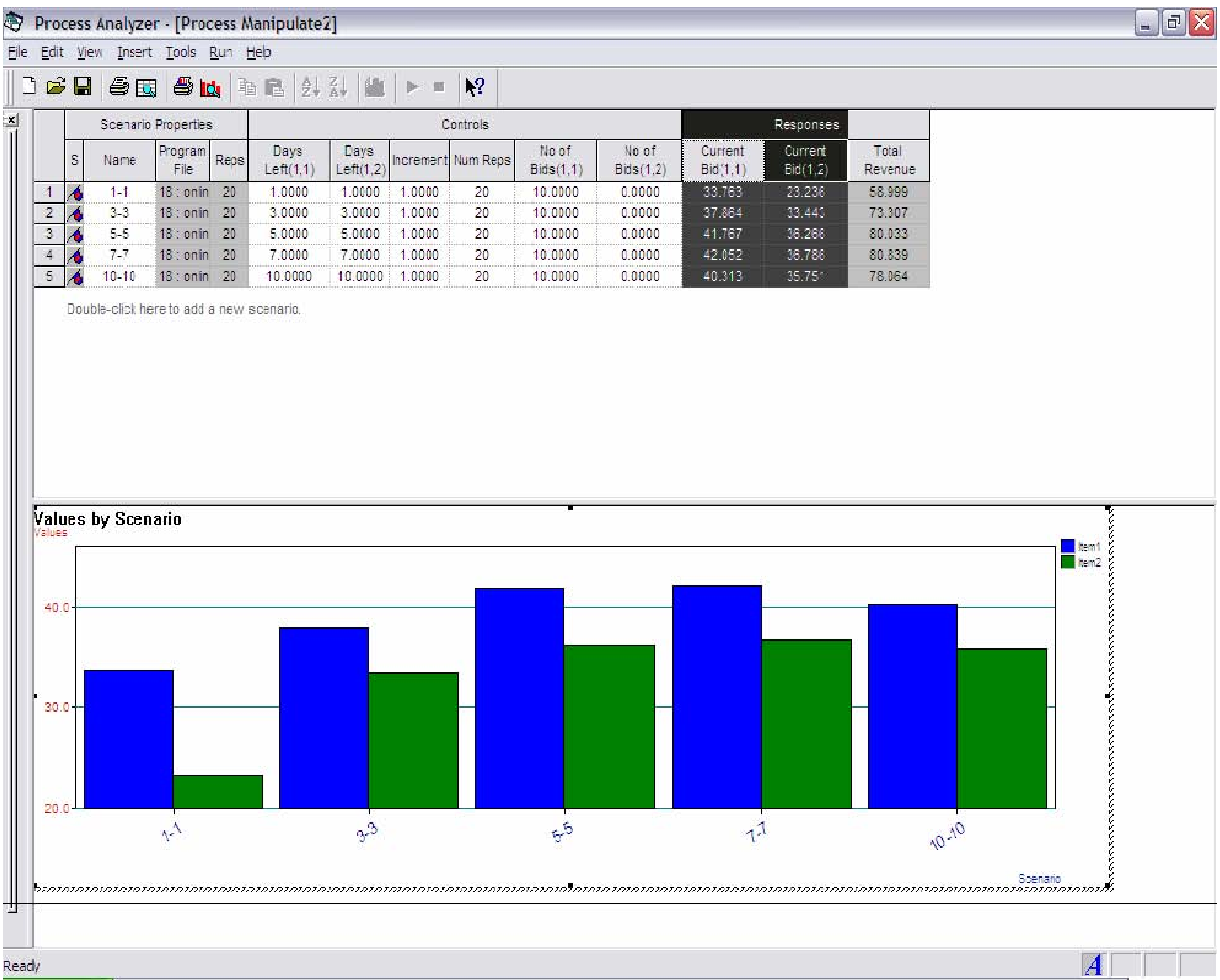
Figure 12: Revenue Analysis



	Scenario Properties				Controls					Responses		
	S	Name	Program File	Reps	Days Left(1,1)	Days Left(1,2)	Increment	Num Reps	Current Bid(1,1)	Current Bid(1,2)	Total Revenue	Average Revenue
9		7-3	19 : onlin	20	7.0000	3.0000	1.0000	20	39.252	36.572	75.824	37.912
10		7-5	19 : onlin	20	7.0000	5.0000	1.0000	20	38.883	39.588	78.471	39.236
11		7-7	19 : onlin	20	7.0000	7.0000	1.0000	20	38.086	39.909	77.995	38.998
12		1-3	19 : onlin	20	1.0000	3.0000	1.0000	20	28.776	40.120	68.896	34.448
13		7-10	19 : onlin	20	7.0000	10.0000	1.0000	20	38.086	39.909	77.995	38.998
14		10-1	19 : onlin	20	10.0000	1.0000	1.0000	20	39.879	29.356	69.234	34.617
15		10-3	19 : onlin	20	10.0000	3.0000	1.0000	20	38.275	36.572	74.846	37.423
16		10-5	19 : onlin	20	10.0000	5.0000	1.0000	20	38.638	39.588	78.226	39.113
17		10-7	19 : onlin	20	10.0000	7.0000	1.0000	20	38.086	39.909	77.995	38.998
18		10-10	19 : onlin	20	10.0000	10.0000	1.0000	20	36.915	38.179	75.093	37.547
19		1-5	19 : onlin	20	1.0000	5.0000	1.0000	20	29.914	41.683	71.597	35.798
20		1-7	19 : onlin	20	1.0000	7.0000	1.0000	20	29.914	41.995	71.909	35.955

Finally, we examined the herd effect. To do this we controlled all other variables and manipulated the number of existing bids that item 1 has. The initial number of bids on Item 1 was set at 10 for every combination of days the item are on auction. Figure 13 show that there is a difference in revenue for those items without pre-assigned values and those that do. Although bidders are not allowed to “manipulate” the number of bidders bidding for their item, it is interesting to note that the herd effect may play an important role in determining average revenue on an auction.

Figure 13:Herd Effect Analysis



	Scenario Properties				Controls						Responses		
	S	Name	Program File	Reps	Days Left(1,1)	Days Left(1,2)	Increment	Num Reps	No of Bids(1,1)	No of Bids(1,2)	Current Bid(1,1)	Current Bid(1,2)	Total Revenue
1		1-1	18 : onlin	20	1.0000	1.0000	1.0000	20	10.0000	0.0000	33.763	23.236	58.999
2		3-3	18 : onlin	20	3.0000	3.0000	1.0000	20	10.0000	0.0000	37.864	33.443	73.307
3		5-5	18 : onlin	20	5.0000	5.0000	1.0000	20	10.0000	0.0000	41.767	36.266	80.033
4		7-7	18 : onlin	20	7.0000	7.0000	1.0000	20	10.0000	0.0000	42.052	36.786	80.839
5		10-10	18 : onlin	20	10.0000	10.0000	1.0000	20	10.0000	0.0000	40.313	35.751	78.064

Limitations and Future Work

The work done here is only the beginning of a new and very exciting stream of research which involves collecting data from online auctions and using simulation tools to model these markets. Practioners and researchers can then use such models to make predictions on the performance of a particular auction given particular conditions. Although Arena worked for the present study, it may not the most suitable simulation tool for the replication of online auctions. Some of the features of eBay cannot be fully captured with Arena. Some limitation constrained our endeavors in replicating the eBay auction system fully, and subsequently, forced us to be innovative in using various constructs such as variable matrices, conveyors and stations just to name a few in an attempt to achieve our goals.

It is clear that simulation software that has the same level of power as Arena but more suited for replicating scenarios such as auctions is required. Recent work in Agent-Based Computational Economics (ACE), may provide clues as to how to go about modeling such scenarios using agent based technology. ACE is the computational study of economies or markets replicated as dynamic systems of interacting agents. However, because this field is relatively, young various unforeseen complications may arise. The results for the present study are interesting and we present a framework for future researchers to use when constructing simulation studies for electronic auctions. As more sophisticated technologies emerge future research would benefit from employing a similar approach to the one used in this paper to capture and model and analyze different types of auctions such as multi-attribute auctions , combinatory auctions or procurement auctions.

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