World Review of Business Research
Vol. 1. No. 4. September 2011. Pp.160-176

BDI Agent Based Final Price Prediction for English Auctions in Mobile E-Commerce

Nandini S. Sidnal * and Sunilkumar S. Manvi**

Bidding in e-auctions in mobile environment is a challenging task as the bidder is mobile that may cause disconnections and may not be acquainted with the e-market environment that hosts multiple concurrent e-auctions. One of the ways to ensure winning a bid is to predict the final price of considered relevant auctions to decide the bidding strategies. Final price prediction of an auction depends on market parameters and bidders behavior. This paper presents a cognitive agent based model based on Belief Desire Intention (BDI) architecture to predict the final price on behalf of the bidder on every round of an auction (English auctions). The model is simulated to test the performance measures. A common platform of bidding strategies are considered for comparing the proposed model with grey theory based final price prediction model. The results demonstrated that the proposed model performed better than the grey model.

Field of Research: Mobile E- Commerce

Keywords: Auctions, Final price prediction, BDI agent, Belief formulator, mobile bidders

1. Introduction

Mobile E-commerce is an extension of E-commerce that has the ability to conduct commerce using wireless mobile devices such as mobile phone, PDA, smart-phone, dash-top devices, etc. It is defined as buying and selling of services, information or goods irrespective of locations initiated and/or completed by using mobile access to computer-mediated networks with help of an electronic handheld device in wireless network environment. Some of the applications of mobile E-commerce are mobile ticketing, location-based services, mobile banking, mobile brokerage, auctions, mobile purchase, mobile marketing and advertisement, etc. With the advent of smart wireless hand held devices, the bidders can participate in e-auctions any time, any where and any place. Bidding in an e-auction is a challenging task as the bidder is mobile which may cause frequent disconnections and may not be acquainted with the e-market environment that hosts multiple concurrent e-auctions for required items. With the advent of smart wireless hand held devices, the bidders can participate in e-auctions any time, any where and any place. Bidding in an e-auction is a challenging task as the bidder is mobile which may cause frequent disconnections and may not be acquainted with the e-market environment that hosts

*Prof. Nandini S Sidnal, K.L.E.S College of Engineering, Belgaum, Karnataka, India.
Email: sidnal.nandini@gmail.com
**Dr.Sunilkumar S Manvi, Wireless Information Systems Research Laboratory, RITM, Bangalore, India.
Email:sunil.manvi@revainstitution.org

multiple concurrent e-auctions for required items. The mobility of user can be taken care of by using the mobile agents for bidding since they can communicate asynchronously without the need of permanent connectivity [1].

One of the techniques to ensure winning a bid is to predict the final price of considered set of relevant auctions. However, it is not trivial to predict the final price of an auction as it depends on the two dynamic factors such as e-market environment and bidder's behavior. The log of final prices do not bear much influence on the prediction, where as uncertainty caused due to the aforesaid factors have a higher influence on prediction. The factors that influence the variation in the e-auction environment are number of bidders, number of concurrent active auctions for the same product, reputation of the auction site and opening bid value. The bidding rate depicts the bidder behavior and will be able to identify if the bidder is either risk neutral or risk proclave.

Artificial intelligence provides many alternatives as far as nonlinear problems are considered. Some of them are mentioned in the related works (see section 1.1). Traditional prediction methods, such as time series, usually depends heavily on huge historical data and use statistical distribution to predict the final price as given in [2]. The next generation methods like the fuzzy approach, artificial neural networks, grey system, expert system and genetic algorithms require considerably less historical data for prediction compared to statistical prediction. These methods have their own limitations such as developing knowledge base, frequent appropriate training of the networks with the updated requisite information. The grey theory forecasting system has the inability to establish the social relationship among the variables that influence prediction of the final price.

In this paper, a set of relevant auctions identified as described in [3] are considered by the bidder to participate in bidding. This paper presents a cognitive agent based model (by using static and mobile agents) by employing Belief Desire Intention architecture to predict the final price of the identified relevant auctions on behalf of the bidder after every round of an auction (English auctions). The predicted value is used further to compute the bid value during the bidding process so as to increase the probability of winning an auction satisfactorily. The prediction method takes care of the nonlinear relationship between the final price and the factors that influence the prediction. The related works and contributions are discussed in this section. Section 2 describes the proposed model in terms of the network, market, bidder and auction environment, computational models and agencies. Simulation model along with simulation procedure and performance parameters are provided in section three, results are discussed in fourth section which is followed by conclusions in final section.

1.1 Related Works

Some of the works related to final price (or final price) prediction in auctions are given in this section. In [14], development of a predictor agent that utilizes Grey System Theory to predict the on-line auction final price in order to maximize the bidder's profit is presented. The performance of this agent is compared with an Artificial Neural Network Predictor Agent (using Feed-forward Back-propagation Prediction Model). The work claims to be better than fuzzy or artificial neural network model. It considers few final prices in the past but does not consider other factors like bid rate, number of bidders or concurrent auctions etc., that influence the final price. All auctions are assumed to have begun at the same time and all the bidders participate from the beginning. Hence it does not consider the real world situations of the on-line auctions. This work is considered for comparison with our proposed model for predicting final prices.

The work presented in [4] considers only the log of the final price and does not consider parameters like the number of bidders, bid rate etc., which may not lead to accurate prediction. Large amounts of historical exchange of data from possible auction sites are collected, and machine learning algorithms are used in combination with the traditional statistical methods to forecast the final prices of products. An attribute construction method to overcome the problem of dynamically changing bid list is used. In [5] the authors have presented a simulated environment to test the proposed algorithms. The simulated results are further used to decide the final prices. By mimicking the bidder's behavior, the prices are predicted by running the auctions in many iterations. The environment considered does not exactly mimic the real world situation as the bidder behavior and other changing factors are not considered. [6], the work proposes a bid calculation function based on forecasting of the next price in English and Dutch auctions. The forecasting is based on two linear adaptive filters for stochastic estimation, whose parameters are computed using a genetic algorithm. The work given in [7] presents an auction system based on mobile agents. By using a proxy server, a user can generate a mobile auction agent by giving the bidding information, including the maximum bidding price. The agent then moves to the required server to participate in an auction according to the user's requirements. A mathematical model is presented to analyze the commonly used proxy bidding method.

The study in [8] suggests and validates a forecasting model of winning bid prices. Especially, it explores the possibility of using the data mining approaches, such as neural network and Bayesian network in building a forecasting model. It considers only bid period and opening bid value to predict the final price. The goal of the work in [9] is to derive models for forecasting the final price of ongoing on-line auctions. A dynamic forecasting model is proposed to predict the auction price that can overcome the dynamic nature of the E-market and bidder behavior. The modern functional data analysis methods that take into account the price velocity and the price acceleration as the basis of forecasting model are presented. In [10], historical data is collected and machine learning algorithms are used to predict the final prices just before the auction commences. The input to the system is the data filled in by the seller, details of the seller, item, and attributes of the auction. It does not address concurrent auctions and number of bidders. In [11], an approach to develop bidding agents that participate in multiple alternative auctions with the goal of obtaining an item with a given probability is presented. In [12], a neuro fuzzy method is proposed to predict the final price in addition to exploring the complicated nonlinear relationship among the auction mechanisms and final price. The work given in [13] presents some important kind of e-auctions such as single seller English auction, nth price English auction and continues double auctions and is contemplated and a solution is provided for each of them.

A suite of heuristics [16] that were designed for bidding in the simultaneous auctions that characterize the Trading Agent Competition (TAC) Travel Game are given. At a high-level, the design of many successful TAC agents can be summarized as: (i) predict: build a model of the auctions' clearing prices, and (ii) optimize: solve for an (approximately) optimal set of bids, given this model.

Based on the analytical and related experimental results it is concluded that RoxyBot–2000's bidding heuristic is effective in that it performs well in a decision-theoretic setting when prices are given—equivalently, under the assumption of perfect price prediction—and it performs well in a game-theoretic setting where price predictions are imperfect. However, this bidding heuristic, which operates on (deterministic) price point estimates, does not explicitly plan for uncertainty in the auction dynamics. A heuristic that would be superior in this respect would optimize with respect to noisy (i.e., stochastic) models of estimated clearing prices. Indeed, embedded in RoxyBot–2006, the top-scoring agent in TAC– 2006, is such a bidding heuristic.

This paper[17] presents the design, implementation and evaluation of a novel bidding strategy for obtaining goods in multiple overlapping English auctions. The strategy uses fuzzy sets to express trade-offs between multi-attribute goods and exploits neuro-fuzzy techniques to predict the expected closing prices of the auctions and to adapt the agent's bidding strategy to reflect the type of environment in which it is situated. We show, through empirical evaluation against a number of methods proposed in the multiple auction literature, that our strategy performs effectively and robustly in a wide range of scenarios.

This paper developed a new algorithm that guides an agent's bidding behavior in multiple overlapping English auctions for a single item characterized by multiple attributes. The FNN strategy uses neuro-fuzzy techniques to predict the expected closing prices of the English auctions and to determine which auction the agent should bid in at what time. The use of a fuzzy Neural network also allows the agent's decision making criteria to be adapted to the situation in which it finds itself. Moreover, we benchmarked our algorithm against a number of common Alternatives available in the literature and showed the superior performance of our method. Our algorithm can also make trade-offs between the different attributes that characterize the desired good in order to maximize the user's satisfaction.

In an agent-based online auction system[18], a bidding agent can automatically place bids on behalf of a human user according to a user-specified bidding strategy. Current implementations of bidding agents only support a set of simple predefined bidding strategies. In this paper, a formal bidding strategy model is introduced that supports specification of complex bidding strategies for autonomous bidding agents. The formal model is defined as a layered bidding strategy model (LBSM), which can be represented using notations adapted from UML activity diagrams. For real-time and efficient reasoning, the formal model is converted into a rule-based bidding strategy model (RBSM) represented in bidding strategy language (BSL), which can be directly executed by a reasoning module of an autonomous bidding agent. We present an algorithm for converting an LBSM to a rule-based bidding strategy model, and an algorithm to drive the reasoning engine. Finally, a prototype agent-based online auction system using JADE is developed to demonstrate how layered bidding strategies can be precisely specified, and how our approach may support analysis of impacts on bidding histories by using different bidding strategies in agent-based online auctions.

The major significance of this work is to support model-based specification of flexible and complex bidding strategies by human users. Due to the layered bidding strategy model, our approach also supports reuse of bidding strategies including simple and complex strategies.

We observe from the literature survey that even though several models are available for predicting the final price in an auction, there have been always some limitations which provide the scope for rethinking of final price predictions. To overcome the limitations such as non-inclusion of some market parameters, absence of iterative predictions and bidder's behavior parameters, a combination of statistical and cognitive approach has been proposed in this paper.

1.2 Our Contributions

In this paper, we propose a model for prediction of final price based on the information collected from the relevant auction sites using BDI architecture. The model works in following phases. (1) The relevant auction services for the requested desire (product) are obtained from the work given in [3]. (2) From the relevant auction sites, information about the history of auctions conducted so far for the same requested product are fetched. The information (parameters) with respect to the average opening bids, average final value, number of bidders, reputation of the site and bid rate are obtained. (3) From the same relevant auction sites, current auction information for the parameters mentioned in step 2 is obtained. (4) Past and the current belief sets for the auctions are formulated based on past and current information. (5) The final price at the time of commencement of auction is predicted based on the information derived from past belief set where the historical data would be stored. (6) From the current belief set, the final price for the subsequent iterations are predicted, and (7) Prediction continues till the auction is completed or withdrawn.
Our contributions in the paper are as follows. (1) The work emphasizes on the influence of most of the e-market and bidder parameters to predict the final price. (2) Employs software agents (static as well as mobile) to perform final price prediction. (3) The key parameters considered are pragmatic rather than assuming the ideal conditions. (4) Predicts the final price on every round of auctions to facilitate bidding strategy using the computational Model. (5) The historical data required to predict is relatively lesser than other methods of prediction. (6) The computations used to predict are not complex and are based on cognitive reasoning.(7) The proposed model is compared with grey system forecasting logic (which is shown to be better than artificial Neural network and Fuzzy system) [14] by considering bidding strategy defined by authors of [15] (referred as NJ strategy in this work) and the random bidding. It is observed that proposed model performs better than grey theory model in terms of accuracy, winning probability and overheads.

2. Proposed Work

This section describes the proposed model in terms of the network, market, bidder and auction environment, computational models and agencies.

2.1 Network Environment

The network environment consists of clusters of auction servers in a fixed network, regional gateways, and mobile bidders in the wireless environment. Clusters are categorized based on their physical geographical locations where each cluster consists of auction servers hosting several auctions. The gateways are connected to the network based on the regions. Mobile bidders are in the vicinity of a wireless local area or in a cellular network. The mobile bidders in a particular region request its regional gateway for auction services. The gateway comprises of auction service directories, case base and the computational methodologies to identify the relevant auctions to participate in bidding process, computational methodologies to predict final price of relevant auctions. An agent platform exists in all the components of network environment to facilitate agent based activities. The agent platform supports persistence, security, communication and computing services.

2.2 Market Environment

The e-marketplace is flexible and can be configured to take up any number of English auctions at any discrete time. The auctions can run concurrently on various auction servers that are connected to the WWW. Each auction house located on a server conducts multiple auctions for various products and comprises of an agent platform that can host an agency to carry out the auctions and communicate with the bidders. The auctions start with a predefined opening bid value in case of English auction. The auctions have a defined start which varies from one auction to another and is completed when only one bidder remains. Thus there can be multiple auctions running in parallel for a product in the market at a given time with overlapping start and end times. Each active auction maintains an e-board to display information of active auctions. The service directory on the regional gateway provides the information of all active auctions for the products requested by the bidder’s.

2.3 Auction Environment

The auctioneer conducts the auctions and will follow ascending price model with finite number of discrete bid levels/iterations. They will have a fixed start time and a soft final time to avoid snipping. It permits bidders to bid for a common item starting from a defined opening bid. Each bidder is permitted to bid his value higher then the maximum bid value in the previous round. The maximum bid value at each iteration is announced on the e-board maintained by the auction site. The final price is the maximum bid announced by the bidder in the last iteration where only one bidder is left out in the bidding process. The auctioneer decision is final and notifies the participating bidders about final price and the winner details.

2.4 Bidder Environment

The mobile bidders register themselves in the registration desk of the regional gateway to participate in bidding. The bidders may use handheld devices to bid. A light weight agent platform that hosts an agency to carry out auctions and communicate with the bidders may be loaded on the handheld devices of the bidders. The agencies assist the bidder in fetching a set of relevant auctions based on their individual requirements and predict the final price in each relevant site so as to participate effectively in bidding so as to increase the winning chances. The participating bidders may be risk neutral, averse or proclave based on their aggressiveness to posses the product. A bidder can participate simultaneously in more than one auction to bid for either a single/multiple products. The bidders follow bidding strategies such as given in (Minghua et al. 2006) and random bid increments within the specified range.

2.5 Final Price Prediction Computational Model

This section describes the computations required to predict the final price and in turn assist to compute the bid increment at each iteration. The final price is predicted before the commencement of the auction and at every round to compute the bid increment till the completion of an auction. The factors considered for prediction are number of bidders, number of concurrent auctions, bid value, and reputation of the auction and bid rate. The average values of the aforesaid parameters are obtained from the recent past completed auctions to predict a final price for the first round (before commencement) of the relevant auction and for the subsequent rounds the values of the parameters are derived from the previous rounds. Predicted final price may be defined as a tuple χ (β, ψ, ζ) where β is a set of belief sets, ψ is the product name (desire) with specifications, ζ is the computations (plan) to predict final price. β is represented by the following set. β = { α_c, α_p, α_c α_h}. Where α_c is the belief set of the current round of relevant auction, α_p is the belief set of the previous round of the relevant auction and α_h is the belief set obtained by considering the average of the past closed auctions in the same auction site and are represented by following sets. $\alpha_p = \{\omega^i_1,\omega^i_2,\omega^i_3,\omega^i_4\}$. $\alpha_c = \{\Phi^i_1, \Phi^i_2, \Phi^i_3, \Phi^i_4\}$. $\alpha_h = \{\eta_1,\eta_2,\eta_3,\eta_4\}$. α_c and α_p are updated for every round of auctions for i = 1 to n, where *n* is the number of rounds. The four parameters in each of the sets correspond to number of bidders, number of concurrent auctions, bid values and bid rate. One more parameter called reputation of the auction site is also taken into account along with these parameters. While considering α_h, η_k is represented by equation **1** at the beginning of auction.

$$\eta_k = \sum_{j=1 \text{ to } m} \eta^j_k / m. \qquad (1)\alpha$$

where *k* =1 to 4 and *m* past closed auctions depending on bidders choice and/or availability of past history at the auction sites. The members of α_p are given by equation 2 for *k* = 1 to 4 for rounds of auction.

$$.\ \omega^I_k = \{ \eta_k \text{ for } i = 1\ \Phi^{i-1}{}_k \text{ for } i = 2 \text{ to } n\} \qquad (2)$$

The factors influencing the prediction of final price are computed as follows.

• **Number of bidders -** let Φ^i_1 be the number of bidders participating in the i^{th} round of the current relevant auction and ω*i*1 be represented by equation 2 for k=1. Thus ζ^i_1 in equation 3 represents the influence of number of bidders. If the number of bidders is many the demands for the product would be high: hence bidding becomes rigorous and in turn the final price may increase.

$$\zeta^i_1 = \Phi^i_1 - \omega^i_1\ ) / \omega^i_1 * 100 \qquad (3)$$

• **Number of concurrent auctions** - let Φ^i_2 be the number of concurrent auctions available at the i^{th} round of the relevant auction and ω^i_2 is given by equation 2 for k=2. Thus ζ^{i}_{2} in equation 4 represents the influence of number of concurrent auctions on the final price. If the product that is being auctioned is available to bid in many concurrent auctions then final price decreases as the options for bidders increase.

$$\zeta^{i}_{2} = (\Phi^{i}_{2} - \omega^{i}_{2}) / \omega^{i}_{2} * 100 \qquad (4)$$

• **Opening bid value** - the influence of the opening bid value on the final price of the considered relevant auction is given by τ^{i}_{3} in equation 5, where ω^{i}_{3} is given by equation 2 for k=3 and Φ^{i}_{3} is the bid value at i^{th} round of the considered relevant auction. Final price is directly proportional to the opening bid value since the opening bid value is evaluated based on the final price in the past.

$$\zeta^{i}_{3} = \{(\Phi^{i}_{3} - \omega^{i}_{3}) / \omega^{i}_{3} * 100 \text{ for } i = 1$$
$$0 \qquad \text{for } i = 2 \text{ to } n\} \qquad (5)$$

• **Bid rate** - is the rate at which the bid increment is changing at each round.
ω^{i}_{4} is the maximum bid value in the previous round given by equation 2 for k=4. Φ^{i}_{4} is the maximum bid value in the i^{th} round. This factor ζ^{i}_{4} is given in equation 6.

$$\zeta^{i}_{4} = \quad \{(\Phi^{i}_{4} - \Phi^{i}_{4}) / \Phi^{i}_{4} * 100 \text{ for } i = 2 \text{ to } n$$
$$0 \qquad \text{for } i = 1\} \qquad (6)$$

• **Reputation/Reliability of auction site** - final price depends on the reputation of the auction site. The reputation of the auction site is obtained from the feedback given by the participants/user-agents. It is represented by ζ_5 and is constant through out the auction process. ζ is the set of plans (computation of the aforesaid parameters) to predict the final price χ^{i} at i^{th} round. Plans are executed by first computing γ^{i} and then χ^{i}, where i is number of rounds. γ^{i} represents the average final price for the desired product in the recent past m closed similar auctions before the commencement of the auction (before the first round, i.e., i= 1) as well as predicted final price in subsequent rounds of auction (for i = 2 to n rounds). γ^{i} is given by equation **7**,

$$\gamma^{i} = \{ \quad \sum_{j=1 \text{ to } m} \gamma^{i} / m \quad \text{for } i = 1$$
$$\gamma^{i-1} = \quad \text{for } i= 2 \text{ to } n\} \qquad (7)$$

The final price of an auction for i^{th} round is computed as χ^{i} given in equation **8** using the aforesaid parameters, ζ^{i}_{1}, ζ^{i}_{2}, ζ^{i}_{3}, ζ^{i}_{4}, and ζ_5. Finally, the predicted final price χ^{if} is computed as given in equation 9 which can be used for bidding strategy.

$$\chi^{i} = \gamma^{j} + \zeta^{i}_{1} * \gamma^{j} - \zeta^{i}_{2} * \gamma^{j} + \zeta^{i}_{3} * \gamma^{j} + \zeta^{i}_{4} * \gamma^{j} + \zeta_{5} * \gamma^{j} \qquad (8)$$
$$\chi^{if} = \{\chi^{i} \qquad \text{for } i=1$$

$$(\chi^{i-1} + \chi^{i}) / 2 \quad \text{for } i=2 \text{ to } n\} \qquad (9)$$

2.6 Agency

In this section, we discuss the gateway agency used in the model. This agency located in the regional gateway consists of a BDI bidder agent that creates mobile agent clones to perform its task of predicting the final price of the relevant auctions.

Figure 1 shows the gateway agency and the relevant auction sites in various clusters. This agency predicts final price of the relevant auctions before the auction commences and also at each round of the auction. It consists of a static bidder agent based on BDI architecture. It creates mobile agent clones, controls and coordinates the activities of the clones and thus it is called as a master agent.

The BDI bidder agent dispatches a mobile agent clone to each relevant auction site to place bids and to fetch the context of the current environment to predict the final price. Before the commencement of an auction the clones communicate the history of the bidding information of past auctions from the respective auction sites for the products mentioned in the bidder's desires.

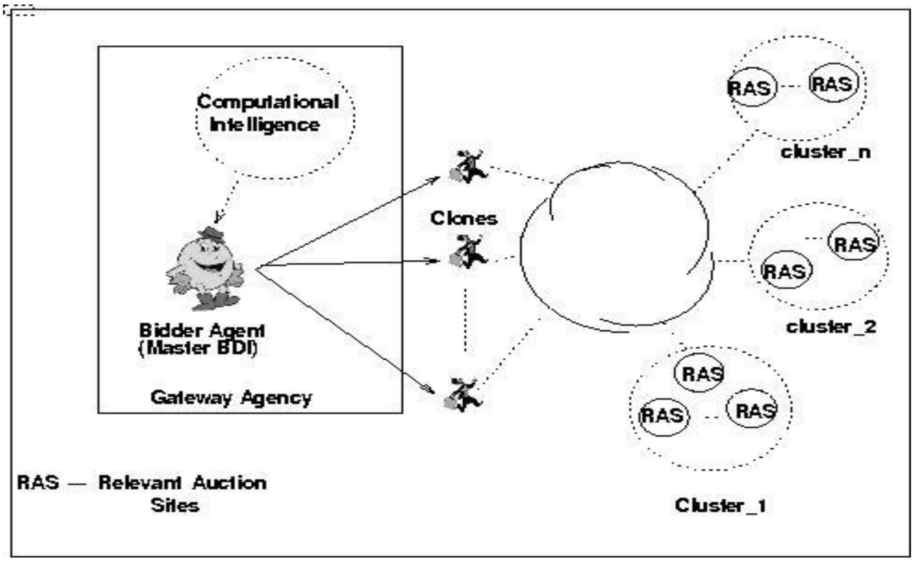

Fig. 1: Gate way Agency

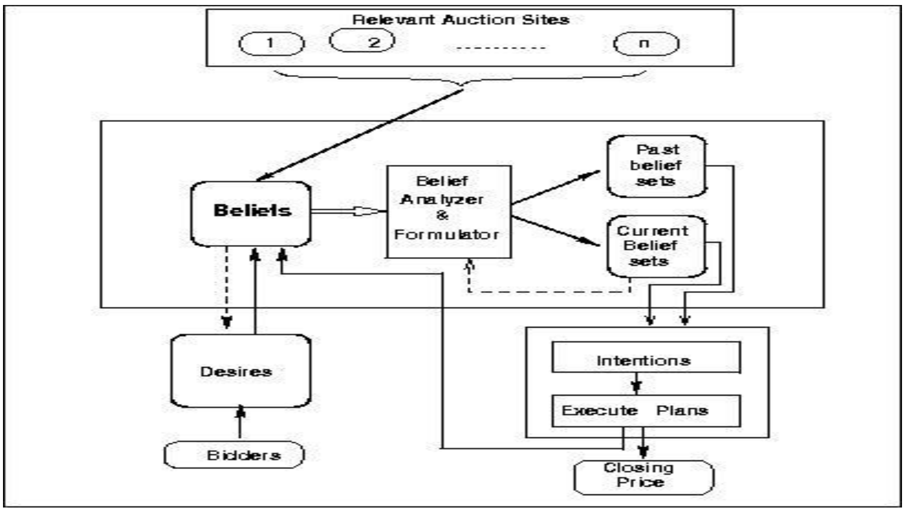

Fig. 2: BDI based Bidder Agent

The historical information such as average final prices, average opening bid value, number of rounds etc. are fetched. The master agent uses the aforesaid information provided by the clones to predict the final price of an auction that are due to commence using the computational model given in section 2.5. After every round, the clones communicate the current context environment such as number of bidders, current maximum bid, bid-rate, etc. to the master agent which in-turn predicts the final price and the bid increment after every round of auction. This communication continues either until the master wins or the auction closes or withdraws. Figure 2 depicts the architecture of the BDI bidder agent. The BDI bidder agent stores all the information about the relevant auctions in its beliefs. The belief analyzer classifies and formulates the beliefs into past and current belief sets. The past belief set consists of historical information while the current context environment is stored in the current belief set. After each round of bidding the contents of current belief set are transferred to past belief set.

The BDI bidder agent does not assume ideal conditions of the environment in which it is situated, rather it assess by using the updated belief sets and hence quickly and accurately determines the environment. It can predict even when the co-bidders are risk neutral, averse or proclave. The BDI bidder agent is guided by the norms defined by the bidder and auctioneer. It will simultaneously participate in only those relevant auctions identified by the bidder. It will not bid more than the allotted budget and will interact with the bidder after every round or whenever required. It will program the clones only to extract the announced information and will not intrude in accessing the auction sites secured information. The BDI bidder agent can as well sleep/skip few rounds to study the environment and then continue predicting. Thus the bidder agent is a normative BDI agent.

2.2.1. Advantages and limitations The advantages of the proposed model are as follows.

• Autonomy of predicting the final price is achieved.
• It can predict the final price at any point of time during the auction process.
• The prediction does not need huge historical data.
• The bidder agent can assess the type of environment in which it is situated rather than assuming the ideal conditions.
• The computations used to predict are simple.
•The prediction is tailored to each bidder’s requirements, preferences and priorities.
The limitations of the proposal are as follows.
• Suffers from more sophisticated mechanism that can be used for belief parsing, analysis and formulation.
• Does not consider a mechanism to infer the varied intentions.

3. Simulation Model

The proposed model has been simulated in various network scenarios. Simulation environment for the proposed work comprises of four models namely network,market, auction and bidder models. The models are described as follows.

Network model - the network considered for simulation is combination of both wired and wireless environment. It consists of *Nc* cluster, each cluster consisting of *Nk* servers hosting *Nu* auctions in the fixed network, *Rg* regional gateways hosting *Nm* service directories and *Np* BDI agents to bid on behalf of *Np* bidders. *Ns* servers, a subset of *Nk* are connected to the gateway within the region.

Market model - the simulated virtual market place consists of *Naa* number of active auctions offering *S* auction services in *Nk* auction servers. *Naa* is subset of *Nu* since at a given point of time *t*, all auctions are not active. *Nra*, a subset of *Naa* are relevant concurrent auctions auctioning the same product in a considered time window and personalized to each bidders requirements. The market place is flexible and can be configured to run any number of auctions. Each auction auctions *Pk* products. Every active auction maintains an E-board that maintains the details of current active auctions.

Bidder model - bidders may bid/ sleep/withdraw from the relevant auctions. Each bidder predicts the final price for the products that lie in the range units *x* to *y*. The bidder participates in all the relevant auctions (*Nra*) concurrently. The BDI agent bids the bid value *Bvi* in all the relevant auctions after interacting with the bidder after each round. Each bidder is allotted a budget of unit *Bu* within which the BDI agent has to bid and may be increased on request. The numbers of bidders in the relevant auction sites are *Nb*. The work in (Minghua, et al. 2006) is considered for simulating bidding strategies for one of the bidder participating in the auction. This is referred as NJ strategy in our work. For the remaining bidders random bidding strategy is used where the bid increments are randomly selected in a given range.

Auction model - all the relevant auctions fix the opening bid value unit *OB*. After each round the maximum bid value unit *Mb* is announced on the auction site E-board. Bidding is stopped when only one bidder is left-out. The data such as average final price *apcp*, average number of bidders *ANb*, average number of concurrent auction sites *ANca*, and average opening bids unit *AOB* from the past *n* completed auctions in the relevant auction sites are fetched.

3.1 Simulation Procedure

To illustrate some results the following data is considered. *Nc* = 1 to 4, *Nk* = 1 to 8, *Nu* = 50 to 80, *Rg* =1, *Nm* =1, *Np* = 2 to 30, *Ns* = 1 to 4, *Naa* = 5 to 500, *Nra* = 2 to 16, *Nb* = 20 to 40, *Pk* = 10 to 400, *Bvi* = 200 to 1000, *Bu* = 25000 to 30000, *OB* = 400 to 1000, *x* = 25000 to *y* 32000, *n* = 4, *apcp* = 28000 to 31000, *ANca* = 2 to 16, *ANb* = 20 to 40, *AOB* = 600 to 1000.

Begin
• From each identified relevant auction identified, fetch the current and past data about the relevant auctions.
• Formulate the belief sets.
• Apply the proposed computational model to predict the final price at every round.
• Apply the grey system forecasting logic to predict the final price before the commencement of the auction.
• Using the NJ bidding strategy and random bidding technique for bidders, compute the bid value at each round till the allotted time for auction is exhausted or some one wins.
• Compute the performance of the models.
End

3.2 Performance Measures

The following performance measures are considered in simulation. Final price (Actual/Predicted) – is defined as the predicted and actual final price at some relevant auctions sites after completion of auctions. Probability of winning - is defined as chances of winning in one of the relevant auction using the predicted final price. Agent Overhead - it is the additional code, data and state of the agent that utilizes the communication channel while migrating to the server. Computational overhead - it is the additional number of instructions executed to predict the final price and the related parameters.

4. Results

In this section, the results obtained with proposed work and grey model is discussed. The simulation is carried on core2duo machine using 'C' language. The analysis of the performance parameters are given in this section.

4.1 Bid Value and CP Prediction Convergence

Figures 3 and 4 depict the various scenarios of bidder behaviors while comparing the predictions of closing prices. The scenarios are of concurrent relevant auction sites where the same product is being auctioned. Figure 3 depicts that the bidders in relevant auction site 1 tend to show the combination behavior of bargaining and being risk neutral since the graph is linear. Figure 4 shows that the bidders in relevant auction site 2 are desperate in bidding. The bid values rise very steeply initially and then rises linearly until it reaches the closing time. The bidders in this site are risk proclave.

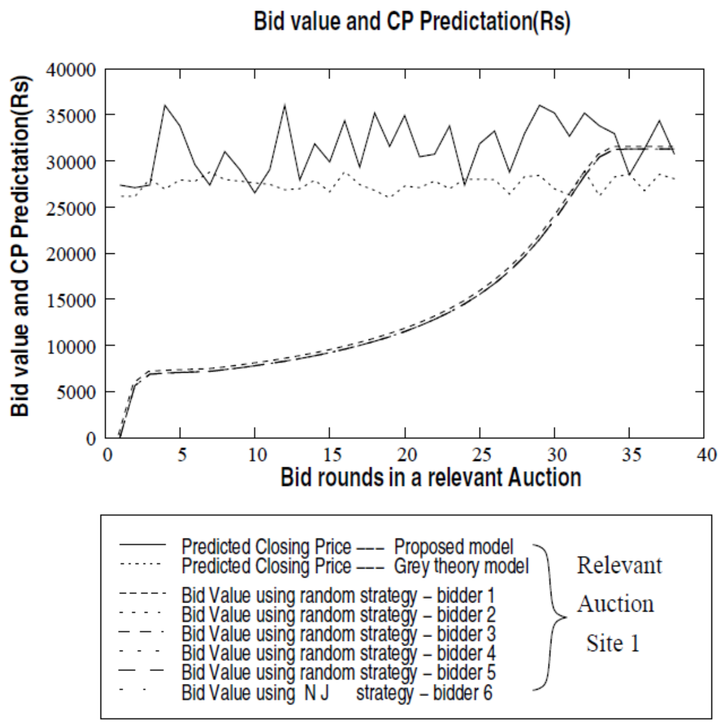

Figure 3: Bid Value and CP prediction vs. Predictions as auction progresses(in relevant auction site 1)

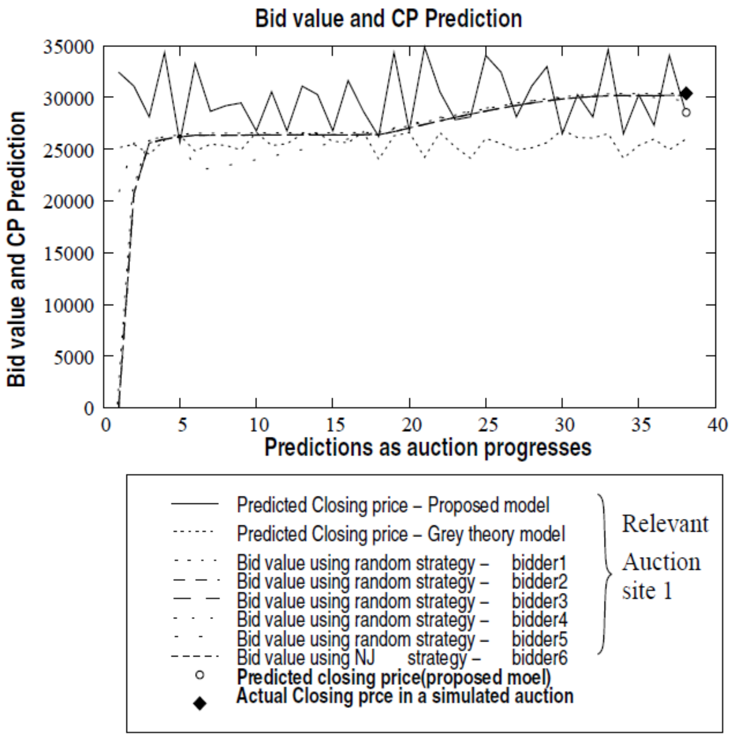

Figure 4: Bid Value and CP prediction vs.Predictions as auction progresses(in relevant auction site 2)

4.2 Final Price (Actual/Predicted)

Figure 3 shows the actual and predicted final prices. The predicted final prices using the proposed model and grey theory model are compared with the actual final prices for an item requested by a bidder following NJ strategy to bid in different relevant auctions that are concurrently running. It may be observed that in all relevant auction sites the predicted final price using proposed model is closer to the actual final price than the predicted final price using grey code theory.

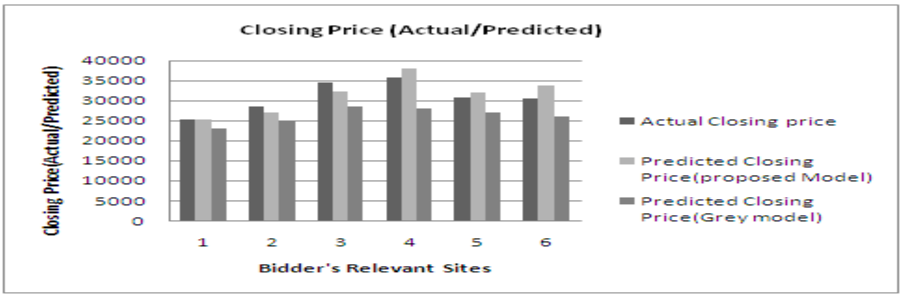

Fig. 3: Final price (Predicted/ actual) vs. Bidders Relevant Auction Sites

4.3 Probability of Winning

Figure 4 shows the probabilities of winning using both the prediction methods. The probability of winning is higher when the proposed model is used to predict the final price as it uses a combination of statistical methods and cognitive reasoning.

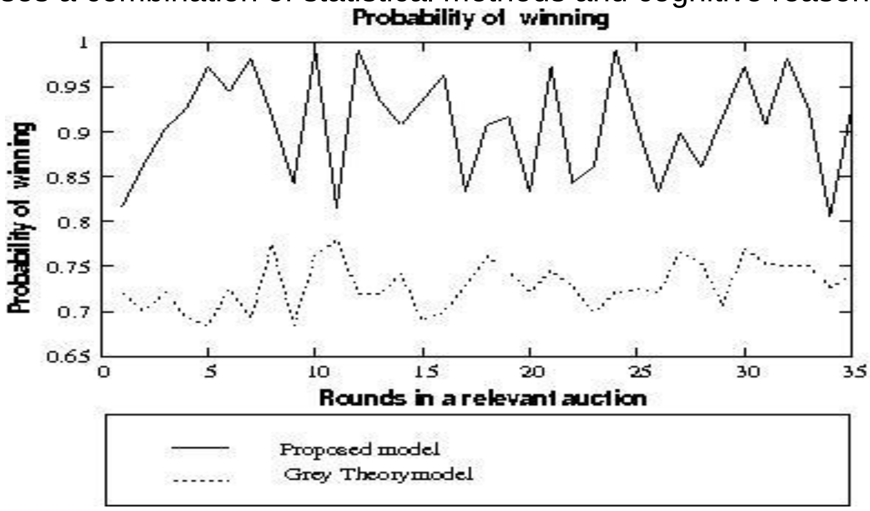

Fig. 4: Probability of winning vs. Rounds in a Relevant Auction site

4.4 Overhead Computations

Figure: 5 and 6 show the overhead in terms of bandwidth utilized and the number of computations to predict the final price. With the usage of BDI agent to predict final price, the bandwidth utilized for communications between the relevant auction sites is higher than without using agents for prediction such as grey theory model. The numbers of computations are to be performed to predict the final price after each round of auction. A trade-off has to be considered between the extra bandwidth utilized and the computations performed with that of the cognitive reasoning used to improve the probability of winning.

5. Conclusions and Future Scope

This paper elaborated on predicting the final price of the e-auctions in mobile environments using cognitive agents. The budget allotment may be planned based on the knowledge of predicted final price before the commencement of an auction. Thus, prediction may improve the probability of winning. This work brought out the cognitive reasoning used in combination with statistical methods for predicting final prices to decide the bidding incrementing strategy for every round of an auction. Proposed prediction model performed better than grey theory model on a common platform with the use of common bidding strategy in terms of accuracy. This is because the proposed model considers all the dynamic factors such as number of bidders, number of concurrent auctions, opening bid value, bid rate and reputation of the relevant auction that affect the final price and also employs cognitive capabilities in bidder agents. A mechanism based on machine learning for parsing and analyzing beliefs and formulating belief set may be adopted. Varied intentions can be inferred for execution of plans based on fuzzy or neuro fuzzy methodologies.

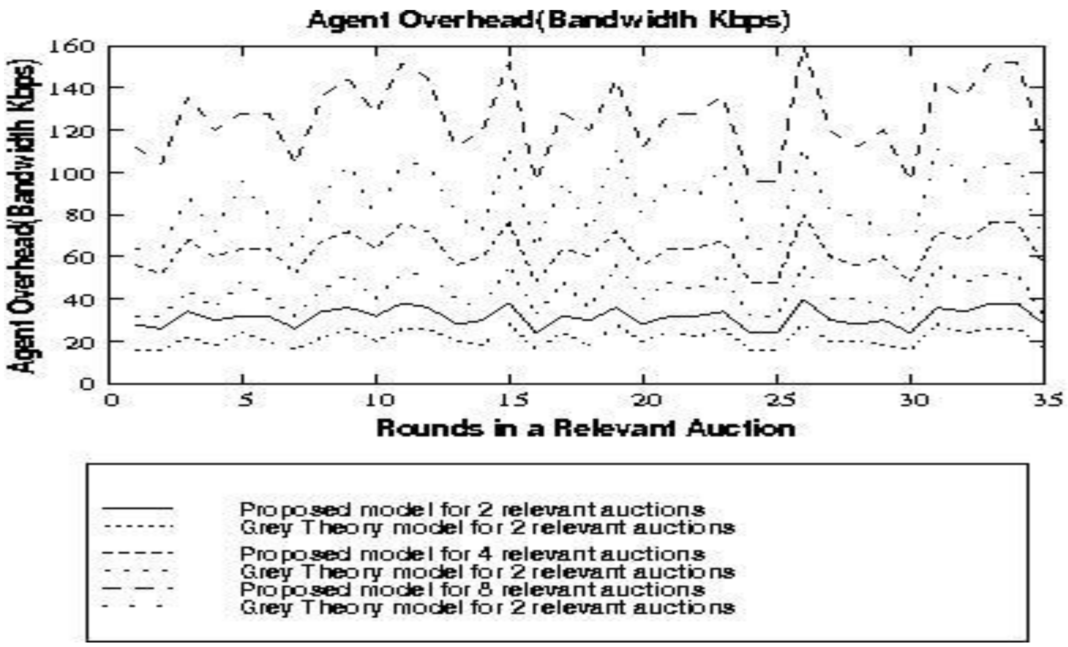

Figure 5: Agent overhead vs. Rounds in a Relevant Auction site

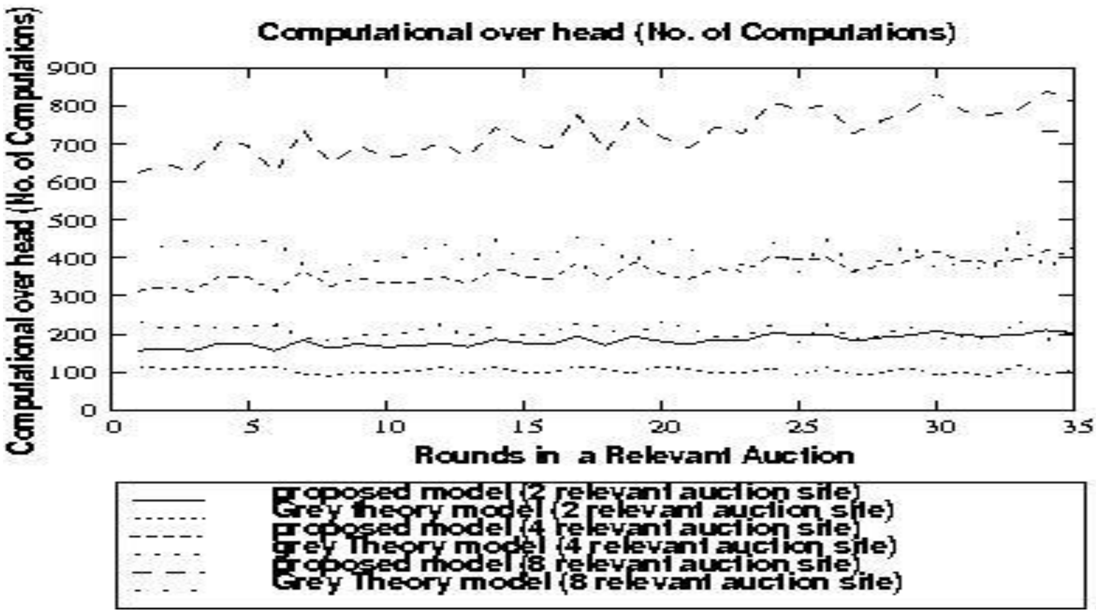

Figure 6: Computational overhead vs. Rounds in a Relevant Auction site

References

Nandini S and SunilKumar S M, 2006, *'Mobile Agents Suitable for Mobile Commerce'. In H.R.Mohan (ed.), Proceedings of the IEEE National Conference on Information and Communication Convergence (IEEEICC 2006), Chennai, India, December 21, IEEE press, Chennai, India, 2006,* pp 321-326.

Sayan M, Edgar O, and Federico G, 1997, *'Nonlinear Prediction of Chaotic Time Series using Support Vector Machines, In Gray(ed.)', Neural Networks for Signal Processing VII, Proceedings of the 1997 IEEE signal processing Society workshop Florida, USA, September 26, 1997, IEEE press, Florida,* pp 511-519.

Nandini Sidnal and Sunilkumar Manvi, 2011, *'Identification of User Relevant Auctions using Agents in Mobile E-commerce'. Relevant Auctions, G.S.Tomar and Venkatesh M (eds.), Proceedings of II International conference on e-auction, e-business, e-management and e-learning(IC4E 2011), Mumbai, India, Jan 8,2011 ,IEEE press, Mumbai, India,* pp 126-130.

Esther D, Alex R, Nicholas J and Micheal HR, 2007, *'Optimal Design of English Auctions with Discrete bid levels'. ACM Transactions on Internet Technology, 7, 2, May 2007, (34 pages).*

Shihyu C, Chin-Shien L, Chi-hong C, Tai-Ru H and Yu-Chen H, 2007, *'A Simulation-Based Model for Final Price Prediction in Online Auctions'. Journal of Economics and Management, 3, 1, 2007,* pp 1-16.

Dionisis K, and Pericles M, 2005, *'Adaptive pricing functions for open outcry Auctions'. In Andrzej S, Jean-paul B, Lakhmi Jain, Ron S, Pierre M, Jiming L, Ning Z.(eds.), Proceedings of International Conference on Intelligent Agent Technology(IAT05), Compiegne, France, September 19, 2005, IEEE computer society, France,* pp 653-656.

Jie Z, and Henry C, 2004, *'A Mathematical model for Analyzing the Proxy Bidding Method for Mobile Agent- Based Auction Services'. In Qin Xin(ed.), Proceedings of the 18th International Conference on Advanced Information networking and Applications(AINA-o4), Fukuoka, Japan, June 9, 2004, IEEE computer society, Washington.*

Kim H and Baek S, 2004, *'Forecasting Winning Bid Prices in an Online Auction Market', Journal of Electronic Science and Technology of China, 2, 3, September 2004,* pp 213-219.

Shanshan W, Wolfgang J, and Galit S, 2004, *'Forecasting eBay's Online Auction Prices using Functional Data Analysis',(December 10 2004), Available at www.citeseerx.ist.psu.edu.viewdoc. Last accessed on December 2, 2008.*

Rayid G, and Hillery S, 2009, *'Predicting the End Price of online auctions', (June 2004)Availableathttp://www.accenture.com/siteCollectionDocments/Last accessed on January 2, 2009.*

Marlon D, Lachlan A, Guido G, and Arthur HM, 2005, *'Probabilistic Automated bidding in multiple auctions'. Journal Electronic Commerce Research, 5, 1, January 2005,* pp 25-49.

Chin-Shien L, Shih-Yu C, Chi-Hong C, Tai-Ru H, and Yu-Chen H, 2010, *'A Final Price prediction model for online english auctions A Neuro Fuzzy Approach'. Available at www.atlantis-press.com/php/downloadpaper/. Last accessed on September 20, 2010.*

Mohammad A, Tabarzad L, Caro L, and Poorang H, 2006, *'Heuristic Price Prediction and Bidding Strategy for Internet Auctions'. International Journal of Computer Science and Network Security, 6,9A, September 2006,*pp 161-166.

Deborah L, Patricia A, Ho-Chong M and Ng-Kah W, 2008, *'Assessing the Accuracy of Grey System Theory against Artificial Neural Network in Predicting Online Auction Final Price' ,Available at www.iaeng.org/ publication/ IMECS2008. Last accessed on January 15, 2011.*

Minghua H, Nicholas J and Adam P, 2006, *'A heuristic bidding strategy for buying multiple goods in multiple english auctions'. ACM Transactions on Internet Technology, 6, 4, November 2006,* pp 465-496.

Amy Greenwald and Victor Naroditskiy, 2006, *'Heuristics for the Deterministic Bidding Problem', SIGecom Exchanges, 6(1), 2006,* pp 35-44.

Minghua H, Nicholas J and Adam P, 2006, *'A heuristic bidding strategy for buying multiple goods in multiple English auctions'. ACM Transactions on Internet Technology, 6, 4, November 2006,* pp 465-496.

Takayuki Ito, Hiromitsu Hattori and Toramatsu Shintani, 2002, *'Incentive Compatibility on Multiple Internet Auctions based on Bidding Support Agents'. Available from http://www2002.org/CDROM/poster/138.pdf.*