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DECISION SUPPORT STRATEGY FOR FUTURISTIC BIDDING IN PARALLEL AUCTIONS

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ABSTRACT

In this paper, we describe a scenario for a distributed marketplace where software agents makes decisions on behalf of the consumer and endeavors to guarantee the delivery of the item according to the user's preferences The agent monitors and collects information from the ongoing auctions and determines which auction it wishes to participate in. We propose a possible scheme to support this scenario, which is based on the emerging technologies and standards. We have presented various bidding strategies for agents participating in simultaneous auctions. Firstly we analyze the strategies ranges from no look a head to full look ahead and then present our theoretical approach to the problem of simultaneous bidding for single item.

1. INTRODUCTION

An auction is a bidding mechanism, described by a set of rules used for allocating goods, tasks and resources. There are two types of participants in auctions i.e. auctioneer and bidder. Auctioneer is the one who is willing to sell a commodity while the Bidder is the one who is willing to buy the commodity being sold by auctioneer. Auction enforces agreement between auctioneer and winning bidder. There is another kind of auction in which there are lot of sellers while only one buyer. Such an auction is called Reverse Auction. E.g. procurement. Auctions can be easily implement able over the Internet and several successful websites exist for buying and selling items using auction protocols. EBay[1] and Yahoo[2] are some of the most successful websites over the internet. E.g. the user can sell his used personal computer by auctioning it on ebay.

2. AUCTION TYPES

Literature in both books and research articles from contributors defines various types of auctions. This section gives a brief account of the various proposed auction types

2.1 Auctions By Value

There are three qualitatively different auction settings depending on how an agent's value of the item is formed. [4]

2.1.1 Private value Auctions [4]

In case of a PVA (private value auction) the actual worth of the commodity depends on your own preferences. For example auctioning off the cake that the winner bidder will eat. The key is that the winning bidder will not resell the item or get utility from showing it off to others. [4]

2.1.2Common value Auctions [4]

In case of CVA (common value auctions) the value of the commodity depends entirely on other persons view of the value of an item.

Correlated value Auctions [4]

In COVA(correlated value auctions) the value of the commodity depends partly on own preferences and partly on others' values for it.

2.2. Auctions by look ahead

There are again two different schemes defined in text of bidding when it comes to auctions and bidding for commodities

2.2.1 No Look Ahead[7]

The notion of no look ahead says that the decision of bidding should be make without looking into the future marketplace conditions. We pursues no strategy and only bids according to the current market price of the item. Moreover there is no way to indicate the user's constraints and preferences.

2.2.2. Look Ahead [7]

As we move towards look ahead, we always make the decision by considering the future market conditions. It follows some rational policy and bids according to the strategy which is based on future consideration of market price of the item. Moreover there are ways to indicate the user's constraints and preferences. The user may want to buy the good at the least price by analyzing the market over a long time[7]. It is also possible that the user want to buy good immediately with less consideration of the price. There are mechanism in look ahead to consider these references.

There are different strategies proposed which are explained below:

2.3 Auctions by Protocol

Wikipedia the worlds largest online resource of information divides the auctions protocols into two main categories namely Primary and secondary type of auctions having four and seven types of sub auctions each. These may again be subdivided into two types as seen in table 2.1

Primary Auctions	Secondary Auctions
The English Auction	All-pay auction
The Dutch Auction	Buyout auction
The First-Price, Sealed-Bid Auction	Combinatorial auction Lloyd's syndicate auction
The Vickrey Auction	No-reserve auction (NR)
	Reserve auction
	Silent auction
	Top-Up Auction
	Walrasian auction

Table 2.1 *Major types of auctions and their classifications (More can be read about them at http://en.wikipedia.org/wiki/Auction) [14]*

3. FUTURE BASED APPROACHES AS PROPOSED BY VARIOUS AUTHORS

In future based approaches [4] [5] [7] it is assumed that the agent has some expectation of the number of auctions selling a given item type in the near future. In addition, the agent has expectations of closing prices, or valuations of other bidders, of the items in those auctions. Based on previous auctions, one may design a probabilistic model for future auctions. This approach is for the buyers who want to obtain a certain number of a given item type over a given time period. It is possible that the buyers may not have an exact number of item to buy rather, they have a utility function which evaluate their own value of obtaining a given number of units of the item of interest[4]. `

4. CONSTRAINTS ON E-MARKETPLACE AUCTION SETTINGS

In our pre supposed e-marketplace, the auctions taking place are simultaneous, they have the same opening time, and they terminate when no buyer place a bid in any of the auctions. Each buyer can know how many bids are active in a given auction, and he has access to the current price. Thus, if there are more bids than he has at the same price, he cannot know whether his bids have been placed first or not.

5. FUTURISTIC BIDDING STRATEGIES

Apparently the goal of each buyer is to maximize the difference between the valuation function and the cost of obtaining the units[6]. To achieve this goal, each buyer may use the expectation of the closing price of auctions in the future. [4] proposes three different strategies corresponding to how far an agent looks ahead to the future are designed namely one-day *strategy,* two-days *strategy,* three-day *strategy etc* Similarly any of the adopted strategy is also heavily dependent on the time type of auctions as defined in respect of time.

6. DIFFERENCE FROM PRIOR WORK

The vision of our proposed strategy is to develop an intelligent agent bidding strategy working on user's behalf that monitors and collects information from the ongoing auctions, make decisions on behalf of the consumer and endeavor to guarantee the delivery of the item in maximum time allocated by the buyer. The agent must ensure that it never bids above the private valuation (the maximum amount that the consumer is willing to pay) and it tries to get the item in a manner that is consistent with the consumer's preferences (e.g., at the earliest time, at the lowest price, or with maximum chance of succeeding). It must be able to work on multiple auction types

The aims of carrying out this theoretical study is to evaluate and define that can a smart agent be created which has the following

- Final bidding plan generation and monitoring which is fully automated till the procurement process is completed.
- Capable of intelligent behavior
- Operate able in Fractal Environment (Peaks on the edges)
- Operate able in Quasi -Fractal Environment (Peaks dispersed though out)
- Capability to evolve its intelligence by continuous learning of not only environment but also social behavior patterns of other agents. (0→ 3 level) [0-> dumb 3-> Most Intelligent]
- Should always be able to achieve near optimal results
- Very high successful procurement rates
- Deal made must be globally optimal
- Proposed agent architecture should be Probabilistic Stochastic Rule Based Reactive

There have been several attempts **[8] [9] [10] [11] [12] [13] [15]** to design sophisticated and efficient bidding strategies for agents participating in online auctions summarized in the table on the next page. Some of them are discussed here in detail

[8] is broadly similar to the mechanism defined in this paper. However, there are several important differences between one-to-one negotiations and multiple auctions. Principal in the midst of these, are the type of the strategy that are considered relevant and the aspects of the sphere of influence that need to be reflected in the tactics. An extension to Faratin's model is given by [**9**] who analyzed the evolution of the negotiation strategies using Genetic Algorithms, and determined which of them are appropriate in which situations. The aim of his work was to perform an evaluation of the range of negotiation strategies by analyzing their relative success, and how these strategies evolve over time to become a fitter population. This approach is somewhat similar to our work, but the main difference is in the domain that we are dealing with (multiple auctions versus bilateral negotiations).

[10] is a multi-agent system that supports users in attending, monitoring and bidding in multiple auctions through a process called co-operative bidding [Ito et al. 2000]. This approach demonstrates how agents can cooperate and work together to do the bidding process in multiple auctions. It consists of one leader and several bidder agents, where the leader agent acts as the coordinator and the facilitator of the whole bidding process. Bidding is done by exchanging messages between the user, the leader agent and the bidder agents.

However, the main problem with this approach is that the agents do not actually make the bidding decision. This decision is left to the user. Thus, the agents do not have full autonomy and the decision-making process is slow since the agent needs to interact with the user from time to time.

The **trading agent competition (TAC) [10]** provided a platform for agent designers to develop autonomous agents that can compete with one another in multiple simultaneous auctions for complimentary and substitutable goods.

The key feature of TAC is that it required autonomous bidding agents to buy and sell multiple interrelated goods in auctions of different types **[11].** Each participating agent is a computer-generated travel agent with the goal of assembling a quantity of travel packages for its eight clients.

Each client is characterized by a random set of preferences for the possible arrival and departure dates, hotel rooms and entertainment tickets. The objective of a TAC agent is to maximize the total satisfaction of its customers (i.e., the sum of the customer's utilities). The competition attracted a number of alternative agent designs (e.g., ATTac-2000 [12], RoxyBot **[11]**, Aster **[11]** and SouthamptonTAC **[11]**).

Although there are clearly some similarities with our scenario, there are also a number of important differences. In particular, we concentrate on the bidding strategies to obtain a single item rather than worrying about the complementary goods that need to be bundled with the desired item.

Moreover our algorithm proposes a coordination mechanism to be used in an environment where all the auctions terminate simultaneously, and a learning method to tackle auctions that terminate at different times.

[11] also considers this environment, but utilizes stochastic dynamic programming to derive formal methods for optimal algorithm specification that can be used by an agent when participating in simultaneous auctions for a single private-value good.

Both of these works are designed specifically for purchasing items in the multiple English auctions and their algorithms are not applicable in a heterogeneous protocol context.

[12] presented another decision theoretic framework that an autonomous agent can use to bid effectively across multiple auctions with various protocols (namely, English, Dutch, first price sealed bid and Vickrey auctions).

In order to come up with the best bid value that guarantees the delivery of the item, an agent must always speculate about future events. **[15]**

No Known system up to date concerns with the issues of specific Agent Architecture, market payment protocols and development of bidding strategies via Probabilistic Scholastic approach and concerning the Quasi-Fractol landscape produced as a result of heterogeneous market protocols. Furthermore there is no known system which addresses the simultaneous use of large number of resource, dynamic resource requirements, complex communication structure and stringent performance requirements in e-commerce multi-agent systems.

To address these shortcomings, we believe it is necessary to develop an autonomous agent that can participate in multiple heterogeneous auctions, that is empowered with trading capabilities and that can make purchases autonomously.

7. PROPOSED APPROACH

The agent Architecture we have devised after studying various approaches in the e-commerce bidding society is a revamp of Belief Desire Intension Architecture retailored from the scratch to fit our requirement goals. The consequential Architecture is named as e-COMMBDI and is drastically different form the original approach. It employs user provided static Intentions (Deliberations) with attached priority, and the Beliefs and Desires are naturally inspired and judged by analysis on basis of Intensions(means end reasoning) for accomplishment of the goal.

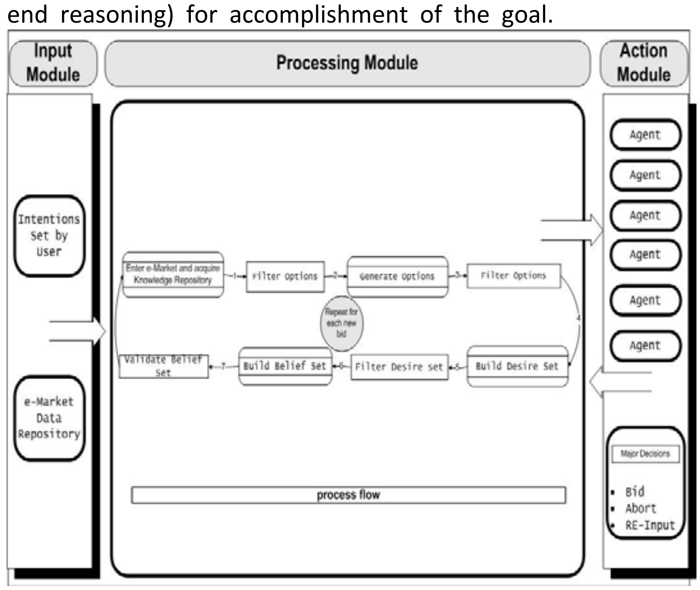

***Figure: 7.1** Proposed Abstract Diagram of Working and Agent Anatomy*

The details of the final concrete architecture will be provided in further papers as we are still working on the .

Since the BDI Architecture has its ancestry in the philosophical ritual of understanding *practical reasoning*—the process of deciding, moment by moment, which action to perform in the furtherance of our goals [15] we found it most convenient if it was molded to fulfill our requirements, but since the changes needed were drastic it resulted into a whole new style. We suggest that [18] should be consulted for anyone who wants further insight on BDI Architecture.

We have personalized the E-COMMBDI Architecture with static Intention Centric focal point, while the Desires and Beliefs are persistently updated according to the real-time input data. The theoretical aspects of the philosophical Intentions, Beliefs and Desires in E-COMMBDI Architecture are as follows

7.1 Intentions

These are options laid down by the user, and are unswervingly responsible for formulation of the outcome in the ongoing process according to user's requirements. Given that Intentions are equivalent to owner's guidelines, thus they not only impel the deliberation process but are utterly accountable for mean-ends reasoning by serving as means of legalization for Desires and Beliefs. The Intentions are answerable for the Agent's current focus.

7.2 Desires

These are the set of options generated during the progression of agent pre bid training. They comprise of the set former solutions by parties for the current problem being on hand, which in this case will be the values of preceding successful bids for procurement of the same item sought for by Agent.

7.3 Beliefs

The Desires if validated by matchmaking with the Intensions become Beliefs. For example if the Desire was to buy an item for 20$, and the Intention was to buy it for 40$ or less then a Belief is established that the item can be bought and the bidding will instigate on this Belief. Similarly the optimized Desire set gives augment to the Beliefs set which are consistent with the Intentions.

7.4 Static Intentions and their effect on mean ends-reasoning proposed approach

7.4.1 Non Varying Intentions

Intentions for a bidding cycle are constant and have precedence weights associated with them provided by the owner. Only the owner can withdraw the agent if no procurement has been made and the whole bidding cycle has to be restarted if Intentions or Intention weights are changed.

***7.4.2 Intentions impel means-ends reasoning*.**

If an Intention has been made to buy an item from the market place, then the agent will attempt to achieve the Intention, which involves, amongst other things, deciding *how* to achieve it, for example, by entering an auction and bidding for the desired item. Moreover, if one particular course of action fails to achieve an Intention, then IT will typically attempt others. Thus if it fail to gain an item in one auction, it might try another auctions selling the same commodity.

***7.4.3 Intentions constrain future deliberation*.**

If Intention is to buy a PC, then it will not entertain options that are incompatible with this Intention. Only those Intentions are entertained in the Agent which are mutually exclusive and the probability of achieving both simultaneously is no infinitesimal. For example bidding for and item at the lowest price ever, with desperation factor of a 100%.

***7.4.4 Intentions persist*.**

The Agent if intelligent will not typically give up on its Intentions without good reason—they will persist, typically until either it believe it has successfully achieved them, if it believes they cannot be achieved or are unrealistic, or else because the purpose for the Intention is no longer present.

***7.4.5 Intentions manipulate Beliefs upon which future realistic reasoning is based*.**

If the agent adopts the Intention to buy an item, then it can plan for the future on the assumption that it *will* bid for that item and acquire it. For if it intends to procure some item while simultaneously believing that it will never be able to procure one, then it is being irrational.

7.4.6 Re-evaluation of Belief and Desires

Beliefs and Desires are reevaluated if they are not according to the required criteria during the first training phase of the agent. They also determine if the Intentions are realistic or not. If the set of Beliefs B is an empty set then the Intentions are not realistic because no such Desires could be gathered or the Desires are inconsistent with the Intentions.

The Beliefs and Desires may be reevaluated in the initial or middle part once the bidding cycle commences if the critical e-market parameters like availability, supply demand etc change drastically or if the other agent's bidding strategies or prices start varying drastically.

8. PROPOSED ALGORITHMIC SOLUTION TO PROBLEM OF SIMULTANEOUS BIDDING

Given below is the proposed futuristic bidding strategy for bidding using look ahead in auctions using the proposed input, processing and Action Modules proposed by adopting the DBI architecture.

8.1 Fetch Intentions Algorithm

This function is responsible for formulation of priority based Intention hierarchy formation which is considered when the intelligent bidding strategy is formulated. For example giving a higher weight to the desperateness factor results in a more aggressive bidding strategy. While giving more time to bid evolves into a more mild approach towards procurement, thus increasing the probability for a better and cheaper procurement.

```
Input:          Intentions set by the user
Output:         Cumulative Weight Load

Procedure: START
Show dialog having intentios and weight options

FOR J=1…n
set each coefficient Wj to desired value
END FOR
Calculate Cumulative Weight Load = Σi=1….n Wj * Ij
END
```

8.2 Fetch Market Data

This function is responsible for keeping the data gathered from both internal (EBAE) and external (current and previous e-Market and other active agent monitoring etc.) sources. This organization obviously makes the job of scheduling tasks much easier because tons of relevant data is now in well organized clusters

```
Input :         Join Market and Request Data
Output:         Repository Data

Procedure: START
Set Connection =  Connection ϕ
/* Criterian → Fetch Acuction Data where the desired items were sold*/

FOR EACH Auctioni ϵ {Total Auctions}
FOR EACH Itemi ϵ {Auctioni}
Submit_Request(Auction_ID, Members_ID, Winnig_Bid)
WHERE
(Auction ϵ {Total Auctions} && time > Auction.End && Desired_Item)
END FOR EACH
END FOR EACH
/* For new and Upcoming Auctions data selling the item of interest*/

after interval i
FOR EACH Auctioni ϵ {Total Auctions}
WHERE (timestamp_Auction > timestamp_Local_Repository)
FOR EACH Item ϵ {Auctioni}
Submit_Request(Auction_ID, Members_ID, Winnig_Bid)
END FOR EACH
END FOR EACH
```

8.3 Auction Selection Function

This function simply selects a set of Auction from the ongoing Auction pool on basis of availability of Desired item or items. Furthermore it keeps track of new auctions and frequently updates the Filtered Auction set with new auctions of interest.

```
Input :         Join Market and Request Data
Output:         Selected Auctions
Procedure: START
Set Connection =  Connection ϕ
/* Criterian → Fetch Acuction Data where the desired items were sold*/
FOR EACH (Auctioni ϵ {Total Auctions} && Itemi ϵ {Auctioni})

Submit_Request(Auction_ID, Members_ID, Minimum_Bid)
WHERE
(Auction ϵ {Total Auctions} && time < Auction.End && Desired_Item)
END FOR EACH
```

8.4 Filtering Function

This function filters the Auction set which was produced as a result of Auction Selection Function. It screens out the target Auctions where the probability of success OR effective time utilization is maximum

Input: {Auction Set}
Output: {Optimized Auction Set}
Processing: START

FOR EACH Auction$_i$ ϵ {Selected Dutch Auctions || Selected English Auctions}

Submit_Request(Auction_ID, Members_ID, Winnig_Bid)
WHERE
(Auction ϵ { Selected Auctions } && time > Auction.End && Desired_Item) &&
$P_i^w(v) = (\sum_{P>v} P_i^c(P) + P_i^c(v)/2) \geq 50\%$

/* where $P_i^w(v) = \sum_{P>v} P_i^c(P) + P_i^c(v)/2$ is the winning probability of English and Dutch Auctions as indicated in [Reference] */
END FOR EACH

FOR EACH Auction$_i$ ϵ {Selected Vickery Auctions}

Submit_Request(Auction_ID, Members_ID, Winnig_Bid)
WHERE
(Auction ϵ { Selected Auctions } && time > Auction.End && Desired_Item) && $P_i^w(v) = (1/\sum n_i / x) \geq 50\%$

/* where $P_i^w(v) = (1/\sum n_i / x)$ is the winning probability of Vickery Auctions as indicated in [Reference] */

END FOR EACH

8.5 Desire Generation Function

The list of options is validated against the Intentions and only those options and Intentions which are mutually inclusive are adopted as Desires of Agent

Input: {Optimized Auction List}
Output: {Desire Set}

Procedure: START
Load the Cumulative Weight Structure

IF ($\Sigma_{i=1....n}$ W$_j$ * I$_j$)- W$_{BD}$ $\leq$ W$_{BD}$

/* if the weight of Bargain tactic W$_{BD}$ is higher or euqual in magnitude to the Desprateness tactic select the Early Start Late Finish (ESLF) and Late Start Late Finish (LSLF)Auctions*/

FOR i = 1…n
FOR EACH Auction$_i$ $\in \{ESLFAcutions \| LSLFAuctions\}$
FOR EACH Item$_i$ $\in \{ESLFAcution_i \| LSLFAuction_i\}$
Set Desire$_i$ = Price of Item$_i$

/* Get procurement price and place it in the Desire Set/*

END FIR EACH
END FOR EACH
END FOR
END IF

IF ($\Sigma_{i=1....n}$ W$_j$ * I$_j$)- W$_{DP}$ $<$ W$_{DP}$

/* if the weight of Desprateness to procure tactic W$_{DP}$ is higher or euqual in magnitude to the Desprateness tactic select the Early Start Early Finish (ESEF) and Late Start Early Finish (LSEF)Auctions*/

FOR i = 1…n
FOR EACH Auction$_i$ $\in \{ESEFAcutions \| LSEFAuctions\}$
FOR EACH Item$_i$ $\in \{ESEFAcution_i \| LSEFAuction_i\}$
Set Desire$_i$ = Price of Item$_i$
/* Get procurement price and place it in the Desire Set/*

END FIR EACH
END FOR EACH
END FOR
END IF
IF D$_{set}$ = = ϕ
Fetch Market Data( )
END IF

8.6 Desire Filtering Function

This Desire set though trimmed down can still be very large and diverse, thus if required, it is further optimized by the Revision Function

Input: {Desire Set}
Output: {Optimized Desire Set}

Procedure: START

/* Remove the desires with highest and lowest values if Desire Set is too large or the distribution in not even. Also Remove the Desire if its value is above the private value*/

FOR EACH $Desire_i \in \{DesireSet\}$
IF $Desire_i$ .value > Private Value
THEN
{DesireSet} = DesireSet - Desire$_i$
END IF

END FOR EACH

IF $Desire_i$ .count > Threshold
THEN
FOR EACH $Desire_i \in \{DesireSet\}$
Find $Desire_i$ where $Desire_i - Desire_{i-1} <$ Difference between two consecutive elements in case of even distribution
{DesireSet} = DesireSet - $Desire_i$
IF Desire.count $\leq$ Threshold
EXIT
END IF
END FOR EACH
ENF IF
/* Threshhold is the number of bid attempts we can make to procure the desired item within the allocated time frame, and is highly dependent on the variables like the number and type of auctions and their starting and ending times */

8.7 Belief Generation Function

This function now generates the Beliefs on which the bidding plan commences. This Belief set along with the prioritized Intentions take us gradually to the means-ends-reasoning process associated with the Agent.

FOR EACH $Auction_i \in \{EnslishAuctions\} || \{DuchAuctions\}$
FOR EACH $Desire_i \in \{OptimizedDesireSet\}$
IF

$$P_i^w(Desire_i) = (\sum_{P>v} P_i^c(P) + P_i^c(Desire_i)/2) \leq 50\%$$

THEN
{DesireSet} = DesireSet - $Desire_i$
END IF
END FOR EACH
END FOR EACH

FOR EACH $Auction_i \in \{SealedAuctions\}$
FOR EACH $Desire_i \in \{OptimizedDesireSet\}$
IF $P_i^w(Desire_i) = (1/\sum_{Desire_{i_{1...n}}} n_i / x) \leq 50\%$
THEN
{DesireSet} = DesireSet - $Desire_i$
END IF
END FOR EACH
END FOR EACH
{Belief Set} = {Optimized Desire Set}

8.8 Assigning Beliefs to Bids

This part of module is responsible for assigning beliefs to bids

Input: {Belief Set}
Output: {Bid}

Procedure: START

FOR EACH $Belief_i \in \{BelefSet\}$ with ASSIGN flag = = N
IF
(Belief.ASSIGN.count < Belief.total) && (Belief.slelect.cycle $\leq$ max.slelectcyle)
THEN
Set Belief.ASSIGN = Y
END IF
END FOR EACH

8.9 Means-ends Reasoning Function

This function takes perceptual input and the current set of Beliefs constructs the logic to proceed with the bidding plan.

For English Auctions 1…n in Selected Auction Set DO
CurrentAcution = $EnglishAuction_i$
IF
$Auction_i$ time < $Auction_{i+1}$ time AND
Auctioni current pice < $Auction_{i+1}$ current price
EnglishAuctionListj = Current Auction
J=J+1
END IF

For English Auctions 1…n in Selected Auction Set DO
CurrentAcution = $EnglishAuction_i$
IF
$Auction_i$ $(\sum_{P>v} P_i^c(P) + P_i^c(v)/2) >$
$Auction_{i+1}$ $(\sum_{P>v} P_i^c(P) + P_i^c(v)/2)$
EnglishAuctionListj = Current Auction
J=J+1
END IF

FOR Duch Auctinos 1…n in Selected Auction Set DO
CurrentAuction = $DuchAuction_i$
IF
$Auction_i$ time < $Auction_{i+1}$ time AND
$Auction_i$ current pice < $Auction_{i+1}$ current price
$DuchAuctionList_J$ = Current Auction
J=J+1
END IF

For Duch Auctions 1…n in Selected Auction Set DO
CurrentAcution = $DuchAuction_i$
IF
$Auction_i$ $(\sum_{P>v} P_i^c(P) + P_i^c(v)/2) >$
$Auction_{i+1}$ $(\sum_{P>v} P_i^c(P) + P_i^c(v)/2)$
DutchAuctionListj = Current Auction
J=J+1

END IF

FOR SealedBid Auctions 1…n in Selected Auction Set DO
CurrentAuction = SealedBidAuctioni
IF
$Auction_{i.}$endingtime < $Auction_{i+1.}$endingtime AND
$Auction_i$ current pice < $Auction_{i+1}$ current price
$SealedBidAuction_J$ = Current Auction
J=J+1
END IF

FOR SealedBid Auctions 1…n in Selected Auction Set DO
CurrentAuction = SealedBidAuctioni
IF
$Auction_{i.}(1/\sum n_i/x)$ > $Auction_{i+1.}(1/\sum n_i/x)$
$SealedBidAuction_J$ = Current Auction
J=J+1
END IF

Now as it can be clearly seen the Auctions are separated by protocol and are in a precedence hierarchy wr.t time price and probability of winning. The agent shall start Bidding in Auctions from lowest hierarchy in Non Sealed Bid Auctions. The Dutch Auctions have highest precedence followed by English and Sealed Bid Auctions. Get Private Value of other agents form current and previous Auctions. The Private Value of Auctions can be easily obtained form English Auctions by noticing their last bids in an auction. i.e. where they drop off. Leave auction where an agent is present whose private value > own Private Value(This option is only viable if we develop such a scheme where market data is public and is available for monitoring). IF not in a winning position in lower hierarchy auction AND Bid not pending in a sealed Bid Auction Allowed to bid in the upper hierarchy English and Dutch Auctions. Furthermore IF Auction remaining time in Sealed Bid Auctions < 1/99 of total time AND not in a winning position in any of the Auctions AND not bidding in any Sealed Auctions then Allowed to bid in the Sealed Bid Auction of highest priority. This ensures that we can scan and bid all possible auctions of interest and still be able to come out with only a single or desired number of items in case of a success.

9. CONCLUSION

This article proposes a future based approach for simultaneous e/m-auctions running arbitrary auction protocol. Our mechanism enhances the state of the art in a way that enables optimal bargain leverage to procure one to many desirable items generating the best possible deals at the given instant. Furthermore the scheme also ensures to keep track of desirable data about items of interest so that intelligent learning may be made possible or more efficient for procurement of desired item by using various machine learning techniques.

10. FUTURE WORK

Much work needs to be done for the mathematical conceptualization of proposed hypothesis to ensure time/ cost effectiveness and reasonable success rate in order to be a reality. Currently work is being on implementing a future based intelligent bidding plan by gathering stimulus from concerned environment (Marketplace simulator) regarding item of interest. This bidding action strategy will be statistically compared with several agent bidding strategies in active use by agent participation in a bidding agent competition game. The technique is also limited to basic auction set and it can be enhanced to cater for all types of auctions.

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