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A Multi-criteria Model for Electronic Auctions

Marie-Jo Bellosta Imène Brigui Sylvie Kornman Daniel Vanderpooten
LAMSADE, Université Paris Dauphine
Place du Maréchal De Lattre de Tassigny
75775 Paris Cedex 16, France
{bellosta,brigui,kornman,vdp}@lamsade.dauphine.fr

ABSTRACT

In this paper we present a multi-criteria model for electronic auctions, which is based on reference points. According to the model, the buyer must specify an aspiration point that expresses his desired values on the attributes of the item to be purchased and a reservation point that represents the minimal values required. Negotiation takes place between software agents that negotiate on behalf of their human owners. The multi-criteria model allows the buyer agent to control the negotiation process on each attribute of the deal. We illustrate the use of this model by providing an auction mechanism based on an English reverse auction protocol.

Categories and Subject Descriptors

J.8 [**Computer Applications**]: Internet Applications—*Electronic commerce*

Keywords

Electronic commerce, multi-attribute auction, software agents.

1. INTRODUCTION

Auction theory has caught tremendous interest from both the economic side as well as the Internet industry. An auction is a competitive mechanism to allocate resources to buyers based on predefined rules. These rules define the bidding process, how the winner is determined, and the final agreement. In electronic commerce transactions, auctions are conducted by software agents that negotiate on behalf of buyers and sellers [8, 9, 10, 11]. The various auction protocols include English, First-price Sealed Bid, Dutch, and Vickrey [18]. Besides price-only, single-item auctions that dominate the current landscape [4, 11, 14], other types of auctions have been defined and studied such as multi-item auctions [1], combinatorial auctions [6, 16] and multi-attribute auctions [2, 3, 5]. Multi-item auctions are auctions in which an auctioneer wants to sell a set of indivisible items which may be identical or not. Combinatorial auctions are multi-item auctions in which bidders can make bids for subsets of items. Multi-attribute auctions allow negotiating on multiple attributes, involving not only the price, but also other attributes such as quality, guarantee, delivery terms and conditions. Buyers reveal their preferences on the item to be purchased and sellers compete on both price and non-price attributes to win the contract. This paper is aimed at defining a buyer agent for multi-attribute auctions.

Multi-attribute auctions require several key components to automate the process:

- a preference model to let the buyer express his preferences,
- a multi-criteria aggregation model to let the buyer agent select the best offer,
- a decision making component to let the buyer agent formulate his asks.

Buyer's preferences are expressed by defining a set of relevant attributes, the domain of each attribute, and criteria which are evaluation functions that allocate a score for every possible values of a relevant attribute. Most multi-criteria aggregation models used in multi-attribute negotiations are scoring functions based on a weighted sum. It is well-known, however, that the weighted sum, which is the simplest multi-criteria aggregation model, suffers from several drawbacks. First, it requires the specification of weights which are difficult to obtain and to interpret. This is all the more important that slight variations on these weights may change dramatically the choice of the best bid. This is partly due to the fact that the weighted sum is a totally compensatory aggregation model. In our context, a very bad value on a criterion can be compensated by a series of good values on other criteria. Such a bid could obtain a weighted sum similar to a bid with rather good scores on all criteria, while in many cases, the latter would be preferred. This suggests the use of non-compensatory or partially compensatory aggregation models. Finally, it can be shown that some of the non-dominated solutions, called non-supported, cannot be obtained as the best proposal using the weighted sum for any possible choice of weights. This is a very severe drawback since these non-supported solutions, whose potential interest is the same as the other non-dominated solutions, are rejected only for technical reasons.

In order to address these shortcomings, we propose the use of an alternative multi-criteria model for the buyer's preferences, based on reference points. We also propose an English reverse auction mechanism based on this model where buyer's asks specify the values required on the attributes of the item at each step of the auction process. This mechanism provides more control to the buyer agent over the bidding process than with the weighted sum model. In this approach, preference information and relative importance of criteria is not expressed in terms of weights, but more directly in terms of required values on the criteria. Moreover, while in the weighted sum, any non-dominated solution can be obtained as the best proposal.

The remainder of this paper is structured as follows. Section 2 analyses related work on multi-attribute auctions. Section 3 presents the preference model and the multi-criteria aggregation model used by the buyer agent. Section 4 describes the auction mechanism used to formulate the buyer agent asks. Section 5 shows an illustrative example of our approach. Section 6 summarizes our contribution.

2. RELATED WORKS

Works on multi-attribute negotiations are generally based on the weighted sum aggregation model [2, 3, 12, 13]. Oliveira et al. define in [13] a multi-attribute peer-to-peer negotiation protocol, which is a modified version of the reverse English auction. Bids are evaluated by a scoring rule designed by the buyer. Negotiation starts when a buyer agent sends a request for an item to all the potentially interested sellers. The request defines the initial negotiable product together with information on the buyer's preferences and the minimum evaluation required for a bid. Sellers evaluate the request and send out acceptable bids or retire from the competition. Once the buyer has received all the replies, he selects the best bid and sends out its value as a counter-proposal. The negotiation process goes on until all but one seller quit and ends with a commitment to the last seller. Oliveira et al's protocol has been defined in order to take into account multi-attribute aspects of a deal. It can be adapted to any multi-criteria aggregation model, where bids evaluation is performed by some one-dimensional real-valued function. We have adopted it as the basis of our experiments.

Bichler et al. [2, 3] have implemented multi-attribute auctions in a market place, which support negotiation on multiple attributes. They introduce a virtual currency that expresses the overall utility of a bid. The buyer has to reveal at least a part of his utility function to suppliers in order to let them evaluate their bids. The bidding process can be conducted according to various auction schemes (English, Vickrey, First-Price, Sealed-Bid). Auction starts when the buyer specifies a Request For Bid (RFB) and submits it to the e-broker of the market place. The e-broker notifies suppliers with corresponding offers and collects their bids. After the auction closes, the e-broker computes the winning bid and compiles a contract. Some procedures are provided to help buyers to express their preferences on the purchase product and sellers to formulate their bids. In [2], Bichler claims that the utility scores achieved in multi-attribute auctions are significantly higher than those of single-attribute auctions. However, in [3] Bichler notes that the interpretation of the weights associated to each attribute is not always clear. The model that we propose is based on elements that are easy to interpret (reservation levels and aspiration levels) and simplifies the elicitation phase of the buyer's preferences.

Morris et al. [12] propose a multi-attribute aggregation model based on the definition of a weighted distance from a preferred point. They have developed the SARDINE system (System for Airline Reservations Demonstrating the Integration of Negotiation and Evaluation) that uses software agents to coordinate the preferences and interests of each party involved in purchasing a plane ticket. Negotiation is a non-binding arrangement allowing the buyer to make multiple bids on multiple offers. The buyer's preferences consist of a preferred value and a flexibility rating for each fly parameter. The flexibility rating is used to determine an acceptable range and a weight that mirrors the importance attached to the considered parameter. There are three possible values for the flexibility rating: "very flexible", "somewhat flexible" and "not flexible". Bids are ordered according to their distances from the preferred point. The buyer agent locates the best flights for the user by minimizing the distance function shown above:

$$\text{dist} = \sum_i \text{weight}_i \left(\frac{\text{preferred}_i - \text{actual}_i}{\text{range}_i} \right),$$

where actual denotes the value for a located airline fly.

As the weighted sum model, the present multi-attribute aggregation model is a compensatory model. Moreover, it presents other shortcomings. The most significant one is that both values (preferred_i - x) and (preferred_i + x) provide the same contribution to the overall distance. For instance, considering the attribute hour and assuming that a preferred level of 8.am is given, bids with 6.am and 10.am will be deemed equivalent, which is certainly not the case. The model presented here makes use of a reference point that expresses the preferred values on each criterion like the SARDINE system, however it is not a compensatory model and does not suffer from the above shortcoming.

3. THE MULTI-CRITERIA MODEL

In this section, we present the preference model that capture the buyer's preferences and the multi-criteria model used to select the best bid. Both models belong to the family of so-called reference point approaches [20, 21] which have been used in a large variety of contexts (see, e.g., [7, 15]) and make use of aspiration and reservation levels.

3.1 The preference model

The preference model is defined through the following concepts and notations:

- p, the number of attributes.
- $D = D_1 \times \ldots \times D_p$, the decision space where D_j is the domain of values for attribute j $(j = 1, \ldots, p)$.
- $C = C_1 \times \ldots \times C_p$ defines the criterion space.
- v_j, the value function defined from D_j to $C_j = [0, 100]$ that corresponds to attribute j.
- Let $x = (x_1, \ldots, x_p) \in D$ denote a bid, $b_j = v_j(x_j)$, $b = (b_1, \ldots, b_p) \in C$ denotes the bid evaluated on all criteria, $(j = 1, \ldots, p)$.

The preference model includes two reference points :

- the *aspiration point*, denoted by $a = (a_1, \ldots, a_p)$ where $a_j = v_j(dv_j)$ are aspiration levels and $dv_j \in D_j$ is the desired value of the buyer on criterion j.

- the *reservation point*, denoted by $r = (r_1, \ldots, r_p)$ where $r_j{=}v_j(mv_j)$ are reservation levels and $mv_j \in D_j$ is the minimal value required on criterion j.

We also recall the following classical concepts in multi-criteria decision analysis (see, e.g., [17, 19]):

- Δ, the dominance relation defined as follows :

$$b\Delta b' \Leftrightarrow \begin{array}{l} \forall j \in \{1,\ldots,p\}\ b_j \geq\ b_j' \\ \text{and } \exists l \in \{1,\ldots,p\} : b_l > b_l' \end{array}$$

- b is non-dominated iff there is no b' such that $b'\Delta b$.

- The *ideal point* over a given set of bids $B{\subset}C$ consists of the maximal scores separately reached on each criterion, denoted by

$$ideal = (ideal_1, \ldots, ideal_p)$$

where $ideal_j = \max_{b \in B}(b_j)$.

- The *anti-ideal point* over a given set of bids $B{\subset}C$ consists of the minimal scores separately reached in each criterion, denoted by

$$antiIdeal = (antiIdeal_1, \ldots, antiIdeal_p)$$

where $antiIdeal_j = \min_{b \in B}(b_j)$.

3.2 The multi-criteria aggregation model

The multi-criteria aggregation evaluates bids on the basis of a deviation from the aspiration levels that measures the maximum difference between the desired values and the bids values on each criterion. Considering aspiration point a and any bid b, this deviation is given by:

$$\text{deviation}(a, b) = \max_{j=1,\ldots,p}\{\lambda_j(a_j - b_j)\} \qquad (1)$$

where $\lambda_j = 1/(\text{ideal}_j - \text{antiIdeal}_j)$.

Note first that dividing $(a_j - b_j)$ by $(ideal_j - antiIdeal_j)$, $(j = 1, \ldots, p)$, reduces the scale differences on criteria. Second, note that the multi-criteria aggregation model is not a compensatory model. The model takes equally into account differences between the preferred value and the bid value on each criterion and retains the higher difference. Thus, a bad score on a criterion cannot be compensated by good scores on other criteria.

Using the deviation notion, we define a strict preference relation $\succ$ on $C \times C$ as follows :

$$b \succ b' \Leftrightarrow \text{deviation}(a, b) < \text{deviation}(a, b')$$

3.3 Choice of the best bid

Let *best* denote the best bid among a given set of bids B and $d = \text{deviation}(a, best)$. Let B^* denote the set of bids minimizing the deviation from the aspiration point a:

$$B^* = \{b \in B : \arg\min_{b \in B}\{\text{deviation}(a, b)\}\} \qquad (2)$$

If B^* contains only one bid, this bid *best* is non-dominated. If B^* contains more than one bid, the best bid is selected according to the following lexicographic algorithm: for each bid of set B^* compute the deviation from the aspiration point a without considering the criterion on which the deviation is reached and determine the new set B^{**} of bids whose criterion values minimize the deviation. Repeat the process until B^{**} contains only one bid which is recognized as the best one, or until all criteria are eliminated, in which case *best* is selected arbitrarily. The use of this lexicographic algorithm ensures that *best* is non-dominated.

4. THE AUCTION MECHANISM

In this section, we illustrate the use of the multi-criteria model presented in the last section on a multi-attribute reverse English auction. A multi-attribute reverse English auction involves n seller agents, which are the bidders competing together to sell an item characterized by p attributes to a unique buyer agent, which is the auctioneer.

First, we define the counterproposal rule according to the *beat-the-quote* rule introduced by Wurman [22] and we outline its properties. Then, we present the protocol used by the agents during the negotiation process. Finally, we detail the negotiation buyer agent's algorithm.

4.1 Definition of counterproposals

At each round t of an English auction, the buyer agent collects all the bids, selects the best one as the reference bid for the next round and formulates the counterproposal. The definition of counterproposals is based on the beat-the-quote rule. In an English auction, this rule specifies that any new bid must beat the best bid received at the previous round. When the bid evaluation process can be summarized by some one-dimensional real-valued function, this rule can be implemented by communicating to the sellers the evaluation of the best current bid augmented by an increment ε. Sellers are then asked to send new bids whose evaluation is at least as good as this augmented evaluation. Observe that this requires that sellers know and implement the buyer's evaluation model.

We show that our approach satisfies the beat-the-quote rule without revealing the buyer's evaluation model to the sellers. This is achieved through the use of a reservation point as indicated by the following result.

PROPOSITION 1. *Assuming that the bidding process is led using the reference point model described by relations (1) and (2). A sufficient condition for the bidding process to satisfy the beat-the-quote rule is to impose the following constraints on the reservation levels:*

$$r_j^{t+1} \geq a_j - (d^t - \varepsilon)/\lambda_j,\ \forall t \in \{1, \ldots, last{-}1\},\ \forall j \in \{1, \ldots, p\}$$

where ε denotes a specified increment and d^t denotes the minimal deviation from the aspiration point at round t.

PROOF. The beat-the-quote rule requires that any bid $b^{t+1} \in B^{t+1}$ provided at round $t + 1$ should be better than $best^t$. Thus, we have: $\text{deviation}(a, b^{t+1}) < \text{deviation}(a, best^t)$ and $\text{deviation}(a, best^t) = d^t\ \forall t \in \{1, \ldots, \text{last} - 1\}$, which is satisfied whenever $\text{deviation}(a, b^{t+1}) \leq d^t - \varepsilon$ $(\varepsilon > 0)$ i.e. when $\max_{j=1,\ldots,p}\{\lambda_j(a_j - b_j^{t+1})\} \leq d^t - \varepsilon$ which is equivalent to $\lambda_j(a_j - b^{t+1}) \leq d^t - \varepsilon,\ \forall j \in \{1, \ldots, p\}$, equivalent to $b_j^{t+1} \geq a_j - (d^t - \varepsilon)/\lambda_j$. $\square$

Given this result, and in order to meet the requirements of the initial reservation levels defined by the buyer, we propose to set reservation levels as follows:

$$r_j^{t+1} = \max\{a_j - (d^t - \varepsilon)/\lambda_j, r_j^1\} \quad \forall t \in \{1,\ldots,\text{last}-1\}, \forall j \in \{1,\ldots,p\} \tag{3}$$

Thus, at round $t+1$, the buyer agent sends out the reservation levels defined by (3) as a counterproposal to all the sellers which must provide a new bid.

4.2 Properties

The previous mechanism shows some interesting properties. We first state two lemmas which are useful to establish these properties.

LEMMA 1.

$$deviation(a, r^t) \leq d^t \qquad \forall t \in \{1,\ldots,last\} \tag{4}$$

PROOF. The definition of reservation levels implies that any bid must be greater than or equal to the reservation levels, which must hold in particular for the best bid. Thus we have: $best_j^t \geq r_j^t$, $\forall t \in \{1,\ldots,\text{last}-1\}$, $\forall j \in \{1,\ldots,p\}$ which is equivalent to $\lambda_j(a_j - best_j^t) \leq \lambda_j(a_j - r_j^t)$ which implies $\max_{j=\{1,\ldots,p\}} \lambda_j(a - best_j^t) \leq \max_{j=\{1,\ldots,p\}} \lambda_j(a - r_j^t)$, $\forall t \in \{1,\ldots,\text{last}-1\}$, hence $\text{deviation}(a, best^t) \leq \text{deviation}(a, r^t)$, corresponding to the result. □

LEMMA 2.

$$deviation(a, r^{t+1}) < d^t \qquad \forall t \in \{1,\ldots,last-1\} \tag{5}$$

PROOF. The definition of reservation levels at round $t+1$ given by (3) implies $r_j^{t+1} \geq a_j - (d^t - \varepsilon)/\lambda_j$, $\forall j \in \{1,\ldots,p\}$ hence $\lambda_j(a_j - r_j^{t+1}) \leq d^t - \varepsilon$. Thus, we have $\max_{j\in\{1,\ldots,p\}} \{\lambda_j(a_j - r_j^{t+1})\} \leq d^t - \varepsilon < d^t$. □

We give now four interesting properties.

PROPERTY 1. *The sequence of reservation points r^t is an increasing sequence for relation $\succ$, i.e. we have*

$$r^{t+1} \succ r^t \qquad \forall t \in \{1,\ldots,last-1\} \tag{6}$$

PROOF. From (4) and (5), we get $\text{deviation}(a, r^{t+1}) < \text{deviation}(a, r^t)$, $\forall t \in \{1,\ldots,\text{last}-1\}$. □

PROPERTY 2. *The sequence of best bids $best^t$ is an increasing sequence for relation $\succ$, i.e. we have*

$$best^{t+1} \succ best^t \qquad \forall t \in \{1,\ldots,last-1\} \tag{7}$$

PROOF. From (4) and (5), we get $d^{t+1} < d^t$, $\forall t \in \{1,\ldots,\text{last}-1\}$. □

PROPERTY 3. *The sequence of reservation points r^t, $t \in \{1,\ldots,last\}$, is an increasing sequence for the dominance relation, i.e. we have*

$$r^{t+1} \Delta r^t \qquad \forall t \in \{1,\ldots,last\text{-}1\} \tag{8}$$

This property ensures that reservation levels get higher on each criterion at each round of the auction.

PROOF. According to the definition of the dominance relation, we must prove $r_j^{t+1} \geq r_j^t$, $\forall j \in \{1,\ldots,p\}$ and $\exists k \in \{1,\ldots,p\}$ such that $r_k^{t+1} > r_k^t$. Let us prove that $r_j^{t+1} \geq r_j^t$, $\forall t \in \{1,\ldots,\text{last}-1\}$, $j \in \{1,\ldots,p\}$. For $t = 1$, we have according to relation (3)

$$r_j^2 = \max\{a_j - (d^t - \varepsilon)/\lambda_j, r_j^1\} \quad \forall t \in \{1,\ldots,\text{last}-1\}, \quad \forall j \in \{1,\ldots,p\}$$

which implies $r_j^2 \geq r_j^1$, $\forall j \in \{1,\ldots,last\}$. For $t > 1$, we have $r_j^{t+1} = \max\{a_j - (d^t - \varepsilon)/\lambda_j, r_j^1\}$ and $r_j^t = \max\{a_j - (d^{t-1} - \varepsilon)/\lambda_j, r_j^1\}$. According to (4) and (5) we have $d^t < d^{t-1}$, $\forall t \in \{2,\ldots,\text{last}-1\}$ which implies $a_j - (d^t - \varepsilon)/\lambda_j > a_j - (d^{t-1} - \varepsilon)/\lambda_j$. Hence $\max\{a_j - (d^t - \varepsilon)/\lambda_j, r_j^1\} \geq \max\{a_j - (d^{t-1} - \varepsilon)/\lambda_j, r_j^1\}$ and thus $r_j^{t+1} \geq r_j^t$. Let us prove that $\exists k \in \{1,\ldots,p\}$ such that $r_k^{t+1} > r_k^t$. According to (4) we get $d^1 \leq \text{deviation}(a, r^1) = \max_{j=\{1,\ldots,p\}} \lambda_j(a_j - r_j^1)$. We have $d^1 > d^1 - \varepsilon$, $\varepsilon > 0$, and hence $\max_{j=\{1,\ldots,p\}} \lambda_j(a_j - r_j^1) > d^1 - \varepsilon$. Hence, $\exists k \in \{1,\ldots,p\}$ such that $\lambda_k(a_k - r_k^1) > d^1 - \varepsilon$. Hence $r_k^1 < a_k - (d^1 - \varepsilon)/\lambda_k$. Hence $r_k^2 = \max\{a_k - (d^1 - \varepsilon)/\lambda_k, r_k^1\} = a_k - (d^1 - \varepsilon)/\lambda_k > r_k^1$. Thus, $\forall t \in \{1,\ldots,\text{last}-1\}$ $r_k^{t+1} = a_k - (d^t - \varepsilon)/\lambda_k$. Considering that $d^{t+1} < d^t$, we get $\forall t \in \{1,\ldots,\text{last}-1\}$ $r_k^{t+1} > r_k^t$. □

4.3 The multi-attribute reverse English auction protocol

The protocol specifies the actions agents should take during a negotiation process and the rules indicating what messages should be sent. In a reverse English auction, the protocol primitives are : `callForPropose`, `requestForPropose`, `propose`, `accept`, `reject`, and `abort`. Semantics of actions are defined in Table 1 where g refers to the group of seller agents, s refers to a seller agent and b refers to a buyer agent.

4.4 The negotiation buyer agent's algorithm

The negotiation buyer agent's algorithm is decomposed into four steps as follows. We assume that the auction starts with the name of the item to be purchased and the set of seller agents that provide the item.

Information collect The buyer agent collects the buyer's preferences (the value functions, the aspiration levels and the reservation levels) and the closing time of the auction.

Call for propose The buyer agent defines the reference points using the value functions, specifies the increment used to define counterproposals, the time duration of a negotiation round and sends to the n seller agents a `call for propose` message with the value functions, the reservation points and the closing time as arguments.

Lambda definition The buyer agent receives the first bids (receiving `propose` messages and/or `abort` messages). He defines the lambda values associated with each criterion, which are used in the bids evaluation during the whole auction process.

Auction loop The buyer agent repeat the following operations until the end of the auction, i.e the set of competitive sellers is empty or the closing time is reached:

1. he evaluates the received bids and selects the best one as the reference bid for the next round and states the corresponding seller as *active*;

action	semantic	context
`callForPropose(b, g, preference)`	b initiates the negotiation with the relevant seller agents g giving his preferences on the item	b believes that the group of sellers g sells the desired product
`propose(s, b, bid)`	s sends a bid to b	used in response to a `callForPropose` or a `requestForPropose` action
`requestForPropose (b, g, counter-proposal)`	b asks to the group of remaining sellers g to improve their previous proposal	used in response to a `propose` action
`accept(b, s)`	b accepts the last bid supplied by s	used in response to a `propose` action
`reject(b, s)`	b rejects s from the negotiation	used in response to a `propose` action
`abort(s, b)`	s leaves the negotiation	used in response to a `requestForPropose`, or a `callForPropose` action

Table 1: Protocol actions

Computer	**trademark**					**disk**		**guarantee**						**price**	
value	Eol	Yellow	Dino	Bimbo	Bremens	2	100	6	12	18	24	36	48	1000	5000
score	10	60	75	90	90	10	100	10	20	50	65	75	100	100	5

Table 2: Value Functions

2. he defines the next reservation levels;
3. he sends his new request to the remaining seller agents except for the active seller;
4. he waits for the seller bids (receiving `propose` messages and/or `abort` messages) and collects all the bids.

Auction end The auction fails if there is no seller in competition. Otherwise, the auction succeeds and the winner is chosen as follows: if the closing time is reached, then the buyer agent selects the best bid as the winning bid, sends an `accept` message to the winner and a `reject` message to the other sellers. Otherwise, the best bid of the previous round is the winning bid and the buyer agent sends an `accept` message to the corresponding seller.

5. AN ILLUSTRATIVE EXAMPLE

In this section, an application example is presented where the negotiation process is applied, explained and discussed. Then, the expected properties of the auction are outlined.

5.1 The buyer's preferences

The negotiation situation is an auction where one buyer agent negotiates with seven seller agents ($S_1, \ldots, S_7$) over a computer described by four attributes (trademark, disk capacity, guarantee conditions and price). Each seller identifies around twenty product references that match the buyer's requirements. The buyer agent starts the auction with the following buyer's preferences :

- the value functions defined in Table 2;
- the buyer aspiration is a computer from the Yellow trademark, with a capacity of 8 giga octets, a guarantee of 6 months and a price of 2200 €, which corresponds to the aspiration point $a = (60, 16, 10, 71.5)$.
- the initial reservation values correspond to the Yellow trademark, a minimum capacity of 7 giga octets, a minimum guarantee of 6 months and a maximum price of 4000 €, from which the reservation point $r^1 = (60, 15, 10, 29)$ is defined.

seller	**bids**	**evaluation**	**dev**
S_1	(Bremens,26,12,3905)	(90, 32, 20, 31)	1.82
S_2	(Bimbo, 47, 12, 3274)	(90, 51, 20, 46)	1.14
S_3	(Yellow, 14, 18, 3568)	(60, 21, 50, 39)	1.46
S_4	(Bremens, 44, 18, 4000)	(90, 49, 50, 29)	1.91
S_5	(Bimbo, 11, 18, 3063)	(90, 18, 50, 51)	0.91
S_6	(Bimbo, 14 , 18, 3653)	(90, 21, 50, 37)	1.55
S_7	(Dino, 17, 12, 3737)	(75, 24, 20, 35)	1.64

Table 3: Bids received at round 1

5.2 The first round

Table 3 presents the set of bids received at the first round. The lambda values are computed according to (1): $\lambda_1 = 1/(90-60) = 1/30$, $\lambda_2 = 1/(51-18) = 1/33$, $\lambda_3 = 1/(50-20) = 1/30$, $\lambda_4 = 1/(51-29) = 1/22$. S_5's bid b_5 =(90, 18, 50, 51) is the best bid with deviation$(a, b_5) = 0.91$. The reservation levels for round 2, denoted by r^2, are computed according to relation (3) with an increment ε set to 0.15: $r^2_1 = \max(r^1_1, 60 - (0.91-\varepsilon)/\lambda_1) = 60$; $r^2_2 = \max(r^1_2; 16 - (0.91-\varepsilon)/\lambda_2) = 15$; $r^2_3 = \max(r^1_3; 10 - (0.91-\varepsilon)/\lambda_3) = 10$; $r^2_4 = \max(r^1_4; 71.5 - (0.91-\varepsilon)/\lambda_4) = 54$. Note that only the reservation level for price has increased.

5.3 The auction process

The auction takes place in 9 rounds reported in Table 4. Counterproposals in the form of reservation levels allow the buyer agent to control the auction process on each attribute of the item. During the six first rounds, requirements over non-price attributes are invariant, while improvements over the price attribute are asked at each round and each price reservation level corresponds to the lower price required. From round 7, all reservation levels increase at each round. The growing of the successive non-price reservation levels do not lead to require improvements at each round but only

t	r^t	**deviation**(a, r^t)	**remaining sellers**	**active seller**	**best bid** best^t	d^t
1	(60, 15, 10, 29)	1.92	S_1 S_2 S_3 S_4 S_5 S_6 S_7	S_5	(90, 18, 50, 51)	0.91
2	(60,15, 10, 54)	0.77	S_1 S_2 S_3 S_4 S_5 S_6 S_7	S_7	(75, 32, 65, 54)	0.77
3	(60, 15, 10, 58)	0.62	S_1 S_2 S_3 S_4 S_5 S_6 S_7	S_6	(75, 60, 50, 58)	0.62
4	(60, 15, 10, 61)	0.47	S_1 S_2 S_3 S_4 S_5 S_6 S_7	S_1	(60, 93, 20, 62)	0.43
5	(60, 15, 10, 65)	0.27	S_1 S_2 S_3 S_4 S_5 S_6 S_7	S_6	(75, 49, 50, 65)	0.27
6	(60, 15, 10, 69)	0.13	S_1 S_3 S_4 S_5 S_6 S_7	S_7	(90, 32, 50, 69)	0.13
7	(61, 16, 11, 72)	-0.02	S_5 S_6 S_7	S_6	(75, 49, 50, 72)	-0.02
8	(65, 21, 15, 75)	-0.173	S_6 S_7	S_7	(90, 32, 50, 75)	-0.173
9	(70, 26, 20, 79)	-0.3	S_7	S_7		

Table 4: Auction process

seller	**best bid**	**evaluation**	**dev**
S_1	(Yellow, 14, 12, 1842)	(60, 21, 20, 80)	0.0
S_2	(Yellow, 97, 12, 2347)	(60, 97, 20, 68)	0.16
S_3	(Yellow, 90, 12, 2221)	(60, 91, 20, 71)	0.02
S_4	(Yellow, 92, 12, 1758)	(60, 93, 20, 82)	0.0
S_5	(Dino, 14, 18, 2010)	(75, 21, 50, 76)	-0.17
S_6	(Dino, 44, 18, 2053)	(75, 49, 50, 75)	-0.16
S_7	(Bremens, 26, 18, 2010)	(90, 32, 50, 76)	-0.2

Table 5: The best bids of each seller

after several rounds, when the reservation level gets over scores corresponding to values of the attributes. For example consider the trademark attribute, the growing of the successive reservation levels lead to ask improvements after several rounds: $r_1^7 = 61$, $r_1^8 = 65$, $r_1^9 = 70$ corresponds to a requirement of the Dino trademark. A new improvement would be required with a reservation level over 75 corresponding to the Bimbo or Bremens trademark. The auction ends with an agreement with Seller S_7. The winning bid (90, 32, 50, 75) corresponds to a computer from the Bremens trademark, with a capacity of 26 giga octets, a guarantee of 18 months and a price of 2040 €, which is over the aspiration point.

5.4 Interpretation

The auction process can be interpreted considering the best bids of the competitive sellers (see Table 5) and the sequence of values deviation(a, r^t), $t \in \{1, \dots, 9\}$, (see Table 4). Let $best(S)$ denote the best bid of Seller S.

1. At each round t, a seller S can provide a bid when his best bid is better than the active reservation levels r^t, i.e. when deviation$(a, best(S)) \leq$ deviation(a, r^t). At the first round, all the sellers can provide a bid. Seller S_2 withdraws at the sixth round when deviation$(a, r^t) = 0.13 < 0.16$. Sellers S_1, S_3 and S_4 withdraw at the seventh round, when deviation$(a, r^t) = -0,02$. They are followed at the last round by Seller S_5 and Seller S_6.

2. Seller S_7 that minimizes deviation$(a, best(S))$ wins the auction with a bid which is slightly better than the second best bid, which is proposed by Seller S_5.

Tables 4 and 5 validate all the properties stated in 4.2. The sequence of reservation points r^t, $t \in \{1, \dots, 9\}$, is an increasing sequence for relations $\succ$ and Δ. The sequence of best bids best^t, $t \in \{1, \dots, 9\}$, is an increasing sequence for relation $\succ$. Finally, efficiency is achieved in the sense that the seller with the best bid (Seller S_7) wins the contract.

6. CONCLUSIONS

This paper describes a multi-attribute auction mechanism based on reference points. As with the weighted sum model the buyer's preferences include value functions. However, weights associated with attributes are replaced by aspiration levels that represent the required values on the attributes of the item to be purchased. Auctions are conducted using reservation levels that express the minimum values acceptable on the attributes. This way of defining counterproposal enforces a successive refinement of the best bids in each round and also ensures the efficiency of the auction (i.e. the seller with the best bid wins the contract).

This mechanism addresses the shortcomings of the weighted sum model and provides a direct control on the bidding process. Moreover, the fact that the buyer broadcasts counterproposal as new reservation points, allows him to keep private his aggregation model.

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