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Design of Auctions for Electronic Business

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Summary

Auctions are important market mechanisms for the allocation of goods and services. Auction theory has caught tremendous interest from both the economic side as well as the Internet industry. The popularity of auctions and the requirements of e-business have led to growing interest in the development of complex trading models. Design of auctions is a multidisciplinary effort comprised of contributions from economics, operations research, informatics, and other disciplines. Combinatorial auctions have recently generated significant interest as an automated mechanism for buying and selling bundles of goods. They are proving to be extremely useful in numerous e-business applications. Important issues in the design of combinatorial auctions are presented. Iterative combinatorial auctions with multiple criteria are proposed complex trading models. The iterative procedure is composed of three key components: a preference model, an optimization model, and a negotiation model..

Key words

Auctions, e-business, combinatorial auctions, multicriteria auctions, iterative auctions, negotiations.

Introduction

Auctions are important market mechanisms for the allocation of goods and services. Auctions are often preferred to other common processes because they are open, quite fair, easy to understand by participants, and lead to economically efficient outcomes. Many modern markets are organized as auctions. Auction theory has caught tremendous interest from both the economic side as well as the Internet industry. Design of auctions is a multidisciplinary effort comprised of contributions from economics, operations research, informatics, and other disciplines. The popularity of auctions and the requirements of e-business have led to growing interest in the development of complex trading models (Bellosta, Brigui, Kornman, & Vanderpooten, 2004; Bichler, 2000; (Oliveira, Fonsesca, & Steiger-Garao, 1999). An auction is a competitive mechanism for allocating resources to buyers based on predefined rules. These rules define the bidding process, how the winner is determined, and the final agreement. In electronic business transactions, software agents negotiate on behalf of buyers and sellers to conduct auctions. Iterative combinatorial auctions with multiple criteria are proposed in the paper as complex trading models.

Combinatorial auctions are those auctions in which bidders can place bids on combinations of items, the so-called bundles. The advantage of combinatorial auctions is that the bidder can more fully express his preferences. This is particular important when items are complements. The auction designer also derives value from combinatorial auctions. Allowing bidders more fully to express preferences often leads to improved economic efficiency and greater auction revenues. However, alongside their advantages, combinatorial auctions raise a host of questions and challenges (Cramton, Shoham, & Steinberg, 2006; de Vries & Vohra, 2003).

In the iterative approach, there are multiple rounds of bidding and allocation and the problem is solved in an iterative and incremental way. Iterative combinatorial auctions are attractive to bidders because they learn about their rivals' valuations through the bidding process, which could help them to adjust their own bids.

Auctions with complex bid structures address multiple attributes of the items (price, quality, quantity, delivery time, and others) in the negotiation space. Multi-criteria approach can be helpful for detailed analysis of combinatorial auctions. Buyers can specify evaluations on the attributes of the items to be purchased.

The iterative procedure is composed of three key components to automate the process:

- a preference elicitation model,
- an optimization model,
- a negotiation model.

The preference elicitation model is used to let the buyer express his preferences. The optimization model selects the best offer for the seller's agent. The negotiation model helps participants in auctions to find a consensus.

1. Preference elicitation model

The key feature that makes combinatorial auctions most appealing is the ability for bidders to express complex preferences over bundles of items, involving complementarity and substitutability. Items are complements when a set of items has greater utility than the sum of the utilities for the individual items. Items are substitutes when a set of items has less utility than the sum of the utilities for the individual items.

Two items A and B are complementary, if it holds: v({A, B}) > v({A}) + v({B}).

Two items A and B are substitute, if it holds: v({A, B}) < v({A}) + v({B}).

Different elicitation algorithms may require different means of representing the information obtained by bidders. Sandholm & Boutilier (2006) describe a general method for representing an incompletely specified valuation functions. A constraint network is a labeled directed graph consisting of one node for each bundle b representing the elicitor's knowledge of the preferences of a bidder. A directed edge (a, b) indicates that bundle a is preferred to bundle b. Figure 1 represents an example of a constraint network for bundles of three items (A,B,C).

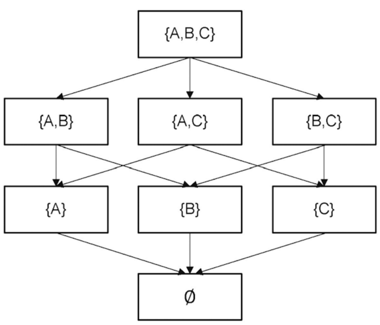

Figure 1 Constraint network

The constraint network representation is useful conceptually, and can be represented explicitly for use in various elicitation algorithms. But its explicit representation is generally tractable only for small problems, since it contains 2m nodes. In iterative auctions, bidders do not have to submit bids on all possible bundles at once, but can bid only on a small number of bundles in each round. The dynamic version of Analytic Network Process can be used for preference elicitation of bundles in a constraint network.

The Analytic Hierarchy Process (AHP) is the method for setting priorities (Saaty, 1996). A priority scale based on reference is the AHP way to standardize non-unique scales in order to combine multiple performance measures. The AHP derives ratio scale priorities by making paired comparisons of elements on a common hierarchy level by using a 1 to 9 scale of absolute numbers. The absolute number from the scale is an approximation to the ratio wj / wk and then it is possible to derive values of wj and wk. The AHP method uses the general model for synthesis of the performance measures in the hierarchical structure.

$$u_i = \sum_{j=1}^{n} v_j w_{jk}$$

The Analytic Network Process (ANP) is the method (Saaty, 2001) that makes it possible to deal systematically with all kinds of dependence and feedback in the performance system. The well-known AHP theory is a special case of the Analytic Network Process that can be very useful for incorporating linkages in the system.

The structure of the ANP model is described by clusters of elements connected by their dependence on one another. A cluster groups elements that share a set of attributes. At least one element in each of these clusters is connected to some element in another cluster. These connections indicate the flow of influence between the elements (see Figure 2).

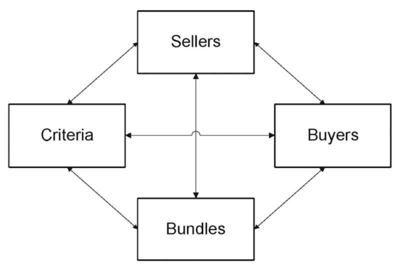

Figure 2 Clusters and connections in multicriteria combinatorial auctions

The clusters in multiobjective combinatorial auctions can be sellers, buyers, bundles of items, and evaluating criteria also. Paired comparisons are inputs for preference elicitation in combinatorial auctions. A supermatrix is a matrix of all elements by all elements. The weights from the paired comparisons are placed in the appropriate column of the supermatrix. The sum of each column corresponds to the number of comparison sets. The weights in the column corresponding to the cluster are multiplied by the weight of the cluster. Each column of the weighted supermatrix sums to one and the matrix is column stochastic. Its powers can stabilize after some iterations to limited supermatrix. The columns of each block of the matrix are identical in many cases, though not always, and we can read off the global priority of units.

The AHP and ANP have been static but for today's world analyzing is very important for time dependent decision making. The DHP/DNP (Dynamic Hierarchy Process/ Dynamic Network Process) methods were introduced (Saaty, 2003). There are two ways to study dynamic decisions: structural, by including scenarios, and functional, by explicitly involving time in the judgment process. For the functional dynamics, there are analytic or numerical solutions.

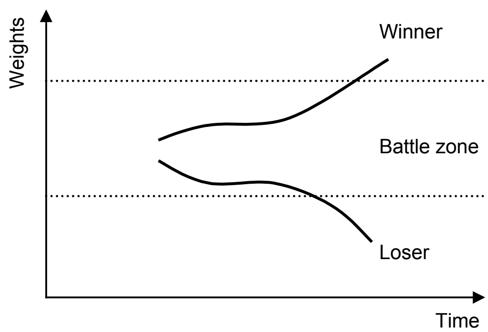

Figure 3 Time Dependent Weights

The Dynamic Network Process seems to be the appropriate instrument for analyzing dynamic effects (Fiala, 2006). The method is also appropriate for the specific features of multicriteria combinatorial auctions. The method computes time dependent weights for bundles of items for bidders (Figure 3).

In the multicriteria combinatorial auction model we take into account the auctioneer, bidders, criteria and bundles as clusters and different types of connections in the system. There are also some dependencies and feedback among elements and clusters.

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. The time dependent global priorities of bundles are used for the evaluations or the prices offered by buyers.

We used the alpha version of the ANP software Super Decisions developed by Creative Decisions Foundation (CDF) for some experiments for testing the possibilities of the expression and evaluation of the multicriteria combinatorial auction models (Figure 4).

2. The auction optimization problem

Many types of combinatorial auctions can be formulated as mathematical programming problems. From different types of combinatorial auctions we present an auction of indivisible items with one seller and several buyers. Let us suppose that one seller offers a set M of m items, $j = 1, 2, \ldots, m$, to n potential buyers. Items are available in single units. A bid made by buyer i, $i = 1, 2, \ldots, n$, is defined as

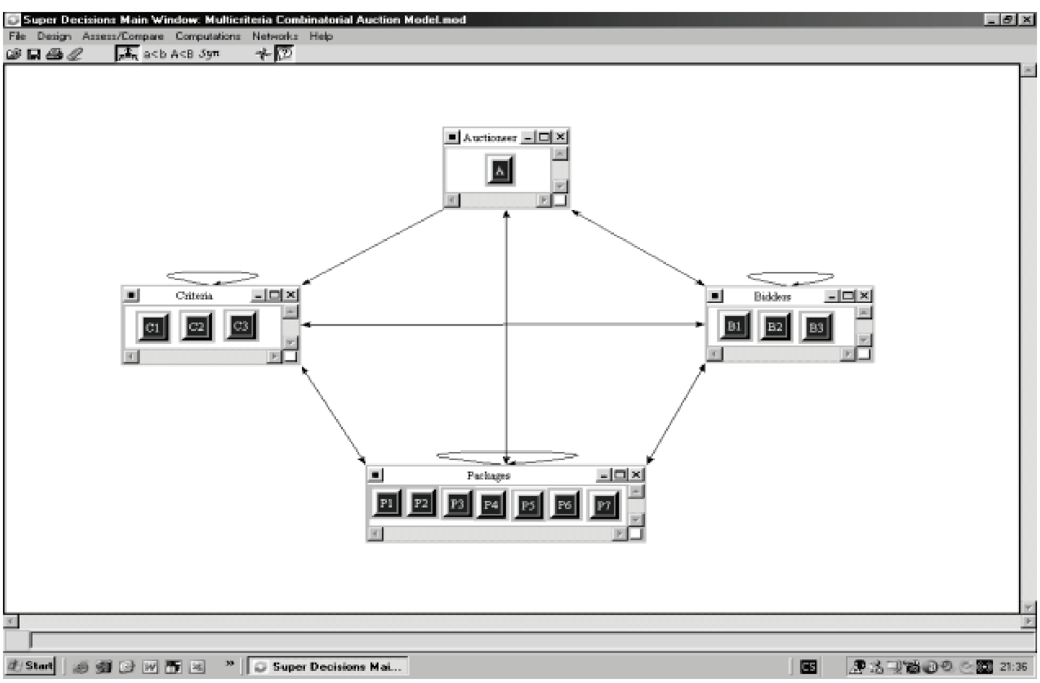

Figure 4 Multicriteria combinatorial auction model

$B_i = \{S, v_i(S)\}$,

where

$S \subseteq M$, is a combination of items,

$v_i(S)$, is the evaluation or the offered price by buyer i for the combination of items S.

The objective is to maximize the revenue of the seller given the bids made by buyers. Constraints establish that no single item is allocated to more than one buyer.

Problem formulation

Bivalent variables are introduced for model formulation:

$x_i(S)$ is a bivalent variable specifying if the combination S is assigned to buyer i ($x_i(S) = 1$).

The auction problem can be formulated as follows

$$\sum_{i=1}^{n} \sum_{S \subseteq M} v_i(S)\, x_i(S) \rightarrow \max$$

subject to

$$\sum_{i=1}^{n} \sum_{S \subseteq M} x_i(S) \leqq 1, \quad \forall j \in M, \tag{1}$$

$$x_i(S) \in \{0, 1\}, \ \forall\ S \subseteq M, \ \ \forall\, i,\ i = 1, 2, \ldots, n.$$

The objective function expresses the revenue. The constraint ensures that overlapping sets of items are never assigned.

Complexity is a fundamental question in combinatorial auction design. There are some types of complexity:

- computational complexity,
- valuation complexity,
- strategic complexity,
- communication complexity.

Computational complexity covers the problem of computation amounts expected of the mechanism to compute an outcome given the bid information of the bidders. This is an extremely important question because winner determination problem is an NP-complete optimization problem. Valuation complexity deals with computation amounts required to provide preference information within a mechanism. Estimating every possible bundle of items requires exponential space and hence exponential time. Strategic complexity concerns the best strategy for bidding. Communication complexity concerns communication exchange between bidders and the auctioneer until an equilibrium price is reached for the mechanism to compute an outcome.

3. The negotiation model

Auctions have emerged as a particularly interesting tool for negotiations. Combinatorial auctions provide a mechanism for negotiation between buyers and sellers. Various concepts of negotiation models can be used for modeling combinatorial auctions. We propose iterative approach for solving multicriteria combinatorial auctions. The approach is based on the primal-dual algorithm.

One way of reducing some of the computational burden in solving combinatorial auctions is to set up a fictitious market that will determine an allocation and prices in a decentralized way. In the iterative approach, there are multiple rounds of bidding and allocation, and the problem is solved in an iterative and incremental way. Iterative combinatorial auctions are attractive to bidders because they learn about their rivals' valuations through the bidding process, which could help them to adjust their own bids. There is a connection between efficient auctions for many items, and duality theory. The primal-dual algorithm can be taken as a decentralized and dynamic method of determining the pricing equilibrium. A primal-dual algorithm usually maintains a feasible dual solution and tries to compute a primal solution that is both feasible and satisfies the complementary slackness conditions. If such a solution is found, the algorithm terminates. Otherwise the dual solution is updated towards optimality and the algorithm continues with the next iteration.

In iterative auctions, bidders do not have to submit bids on all possible bundles at once, but can bid only on a small number of bundles in each round. One way of reducing some of the computational burden in solving the winner determination problem is to set up a fictitious market that will determine an allocation and prices in a decentralized way. In the iterative approach, there are multiple rounds of bidding and allocation, and the problem is solved in an iterative and incremental way (Parkes, 2001).

The fundamental work (Bikhchandani & Ostroy, 2002) demonstrates a strong interrelationship between the iterative auctions and the primal-dual linear programming algorithms. There is a connection between efficient auctions for many items, and duality theory. The Vickrey auction can be taken as an efficient pricing equilibrium, which corresponds to the optimal solution of a particular linear programming problem and its dual. The simplex algorithm can be taken as static approach to determining the Vickrey outcome. Alternatively, the primal-dual algorithm can be taken as a decentralized and dynamic method of determining the pricing equilibrium.

For the winner determination problem we will formulate the LP relaxation and its dual. Consider the LP relaxation of the winner determination problem (1):

$$\sum_{i=1}^{n} \sum_{S \subseteq M} v_i(S)\ x_i(S) \rightarrow \quad \max$$

subject to

$$\sum_{i=1}^{n} \sum_{S \subseteq M} x_i(S) \leq 1, \ \forall j \in M, \tag{2}$$

$$x_i(S) \geq 0, \ \forall \ S \subseteq M, \ \ \forall \ i, \ i = 1, 2, \ldots, n.$$

The corresponding dual to problem (2)

$$\sum_{j \in S} p(j) \rightarrow \quad \min$$

subject to

$$\sum_{j \in S} p(j) \geq v_i(S) \quad \forall \ i, \ S, \tag{3}$$

$$p(j) \geq 0, \qquad \forall \ j.$$

The dual variables $p(j)$ can be interpreted as anonymous linear prices of items, the term $\sum_{j \in S} p(j)$ is then the price of the bundle S.

The general scheme of iterative auction formats based on the primal-dual approach can be outlined as follows:

1. Choose minimal initial prices.
2. Announce current prices and collect bids. Bids have to be higher or equal than the prices.
3. Compute the current dual solution by interpreting the prices as dual variables. Try to find a feasible allocation, an integer primal solution that satisfies the stopping rule. If such solution is found, stop and use it as the final allocation. Otherwise update prices and go back to 2.

4. Conclusions

For electronic auctions we propose the use of multicriteria iterative combinatorial auctions. Combinatorial auction is the important subject of an intensive economic research. Iterative process helps the bidders express their preferences. Multicriteria approach can be helpful for detailed analysis of combinatorial auctions. The preference elicitation model is used to let the buyer express his preferences. The preferences are modelled by the dynamic version of Analytic Network Process. The optimization model selects the best offer for the seller. Auctions have emerged as a particularly interesting tool for negotiations. Auctions provide a mechanism for negotiation between buyers and sellers. The negotiation model helps to find a consensus for participants. We propose iterative approach for solving multicriteria combinatorial auctions. The approach is based on the primal-dual algorithm. The combination of such approaches can give more complex views on electronic auctions. A possible flexible approach is presented.

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