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A Roadmap to Auction-based Negotiation Protocols for Electronic Commerce

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Abstract

Economic mechanisms are used to determine the flow of resources in a supply chain and to achieve an efficient allocation of goods and services in networked economies. In order to choose the "right" allocation mechanism for a certain situation it is important to know about the characteristics of different negotiation situations and the set of available mechanisms suitable in these situations. Over the past few years there has been an enormous interest of researchers in economics, computer science and game theory to develop advanced economic mechanisms for the creation of new types of electronic exchanges. Combinatorial auctions, multi-attribute auctions and multi-stage auctions are some of the approaches to extend the framework of mechanism design theory. In this paper we develop a classification scheme for negotiation situations in electronic commerce based on microeconomic theory. We describe classic mechanism design and auction theory, and classify old and new approaches in this field.

1. Introduction

Negotiation is a crucial part of commercial activities in physical as well as in electronic markets. Current human-based negotiation, is relatively slow, does not always uncover the best solution, and is furthermore constrained by issues of culture, ego, and pride [1]. In order to support new business practices on the Internet, electronic commerce systems need the ability to negotiate. New interoperability standards like the Open Trading Protocol (OTP) [2] or OMG's Negotiation Facility [3] try to model the negotiation process during an electronic market transaction in a more or less sophisticated way and illustrate the importance of the topic for electronic commerce. In this paper we develop a classification scheme of negotiation situations in electronic commerce and give an overview of old and new negotiation protocols.

1.1. Negotiations in Electronic Commerce

Negotiation is a process by which a joint decision is made by two or more parties. The parties first verbalize contradictory demands and then move towards agreement by a process of concession making or search for new alternatives [4]. Negotiation in electronic commerce can be defined as the process by which two or more parties multilaterally bargain resources for mutual intended gain, using the tools and techniques of electronic commerce [1]. Although, researchers in economics, game theory and behavioral sciences investigated negotiation processes for a long time, a solid and comprehensive theoretical framework is still missing. "Over forty years of intense theoretical research has failed to produce an adequate general, computational theory of bargaining and negotiation [5]." A basic finding of negotiation sciences is that there is not a single negotiation protocol for all possible negotiation situations. Different negotiation protocols are appropriate in different situations, and so any generic mediation service should support a range of options [6]. In the following we describe some of the factors influencing commercial negotiations.

First of all it is important to find out if the negotiation is a *cooperative or a competitive negotiation*. Competitive negotiation assumes that there is at least some conflict of interest. No pre-game agreements (i.e. coalitions) are allowed and hence the rules of the game completely define the players' moves and payoffs. Cooperative situations are described as non-zero-sum game where parties are resolving a conflict over multiple interdependent, but non-mutually exclusive goals. The degree of goal incongruency, and the methods for managing the conflict which arises determine the best strategies for players to adopt in the different circumstances.

Of course also the *number of participants* on each side plays a crucial role in a negotiation and serves as a proxy for bargaining power. The bargaining power of each participant will clearly affect the outcome. As in the physical world, a monopolist can drive a different deal from a vendor who is one of a hundred possible sellers. Of course, one-to-one negotiations are again quite different. Also the type of participants can play a role for the information system used to support the negotiation. Professionals like market makers on a stock exchange or purchasing managers in business-to-business electronic commerce have a better knowledge about market conditions and products traded on a market than customers in a retail market and thus need a very different form of IT support. Guttman et al. [7] give a good overview of the requirements for negotiations in retail electronic commerce.

Finally, the *type of goods* is an important factor for determining the negotiation and matchmaking mechanism used in a trading scenario. For example, a standardized item (e.g., a stock) does not require a complex ontology. The items are easy to describe and negotiations focus mainly on the price. Complex goods like insurance products or cars, however, require a much more sophisticated framework. We need a more elaborate set of taxonomies and standards to describe all attributes of a product and there are often more attributes to negotiate on than simply the price. Besides, a time sensitive information or a perishable good may impose tight constraints on the duration of the negotiation.

1.2. Auction-based Negotiations

In this paper we will concentrate to a large part on auction-based negotiation protocols and extensions thereof and their use for electronic commerce infrastructures. Auctions are a particularly successful multi-lateral negotiation protocol and account for an enormous volume of transactions on the Internet. A reason a monopolist chooses to sell by auction rather than simply posting a price is that he does not know the bidders' valuations (see [8], p.704). Moreover, in Internet commerce multi-lateral negotiations are not rare, simply because participants have access to a global market and there will be multiple buyers and sellers even for very exotic kinds of products.

Auctions are also a critical enabler for negotiations in agent-based electronic commerce environments. Some agent environments focus on the intelligence of agents and concentrate on teaching the agents effective strategies for negotiation (e.g. genetic programming). The need for broad adaptability of agents, however, suggests that as little as possible should be encoded directly into automated agents, simply because an artificial agent must guard against dynamic strategies that could extract private information like reservation prices [9]. Other agent environments focus more on the environment rules, requiring relatively little processing from the software agents. A goal is to design the protocols (mechanisms) of the interaction so that desirable social outcomes follow even though each agent acts based on self-interest [10]. Incentive-compatible auction mechanisms can avoid strategic behavior of agents by making truth-telling a dominant strategy. If one can construct a direct auction mechanism for which truthfully revealing one's true willingness-to-pay is a dominant strategy, then there is no need for the agents to worry about keeping the willingness-to-pay private [11].

Low transaction costs on the Internet lead to an interest in the design of new auction mechanisms and people build exchanges for many goods and services which where previously the domain of fixed pricing rules. There is a myriad of possible auction rules and the design space for creating new auction formats is huge. So far, auction theory explains only a small proportion of the variety of possible auction schemes. Over the past few years much research has been done to extend the framework of auctions in order to enable more powerful exchanges. For example, combinatorial auctions are an approach to achieve efficient allocations in cases, where bidders place bids on combinations of goods. These bids allow to express dependencies and complementarities between goods [12]. Multi-attribute auctions allow to provide bids on goods with several negotiable attributes. This is important in tenders or procurement auctions, where bidders often provide very different kinds of goods and services in their bids. Multi-stage auctions describe an auction process that is divided into several stages [13].

In this paper we develop a classification scheme for negotiation situations in electronic commerce and classify different negotiation protocols based on this scheme. We start in section 2 with an overview of the microeconomic morphology of different market situations and extend it through additional criteria to a classification of negotiation situations in electronic commerce. In section 4 we describe the classic auction schemes used for negotiations on a single item. Based on this we describe several new approaches like multi-attribute auctions in section 5 and several multi-unit auction schemes in section 6. Finally, we summarize the findings in section 7.

2. A Classification Scheme for Negotiation Situations in Electronic Commerce

In this section we give an overview of the microeconomic theory and the morphology used to describe different market structures. An economic environment consists of individual economic agents together with an institution through which the agents interact [14]. The agents may be buyers and sellers and the institution may be a particular type of market. The agents are defined by their economically relevant characteristics: preferences, technology, resource endowments, and information. An economic institution specifies the actions available to agents and the outcomes that result from each possible combination of agents' actions. Any environment where agents have limited resources and a preference over outcomes can be

Sellers / Buyers	One	Several	Many
One	Bilateral monopoly	Restricted monopoly	Monopoly
Several	Restricted monopsony	Bilateral Oligopoly	Oligopoly
Many	Monopsony	Oligopsony	Polypoly

Table 1: Market structures

modeled as a resource allocation problem. Decentralized resource allocation is a central topic of economics.

A *mechanism* is a protocol by which agents can realize a solution to the resource allocation problem. The mechanism maps messages or signals from the agents into a solution. In a *market-based mechanism* we assign to each resource a price in form of money. Prices are non negative real numbers that determine the exchange value of resources in a market. They provide an aggregation of global information and enable agents to make rational decisions. Economists developed a large body of theory describing different market structures and the way prices are determined in these situations. A widespread microeconomic morphology of market structures is the classification along market participants on the buyer's and on the seller's side (see Table 1).

A monopoly in this classification is a situation where one seller sells a good to many buyers and a polypoly is one where each participant in the market, whether buyer or seller, is so small, in relation to the entire market that he or she cannot affect the product's price. A monopsony on the other hand is a situation in which there is a single buyer and multiple sellers. The situation is rather rare in business-to-consumer markets but it is often the case in business-to-business markets (e.g. in case of large food retailers or car manufacturers or labor markets with one big employer in a geographical region).

Another way to classify markets is the kind of goods traded. Economists distinguish between a market with homogeneous goods and heterogeneous goods. Goods traded on a market can be homogeneous as it is the case with stock exchanges, where identical commodities are traded (e.g. stocks of AT&T), or they can also be heterogeneous, like it is the case with journals or newspapers, where some are close substitutes. In the case of homogeneous goods there are no differences whatsoever between the goods traded on a market. Consequently buyers do not have any preferences over one product or the other. Heterogeneous goods can be found in many real-world markets and describe situations, where buyers have preferences for certain products.

A *monopolistic competition* describes a market structure in which product differentiation exists, i.e. there is a large number of firms producing and selling goods that are close substitutes, but that are not completely homogeneous from one seller to another. Retail trade is often cited as an industry with many of the characteristics of monopolistic competition. Similarly economists call a situation a *monopsonistic competition*, when there are many buyers but the inputs are not homogeneous and some buyers prefer some sellers' inputs to other sellers' inputs. Markets with heterogeneous goods are also called markets with *imperfect competition*. In contrast economists speak of *perfect competition* as a set of idealized assumptions about market conditions (homogeneous products or services; perfect market knowledge and certainty of each participant; atomism of market participants; free entry, exit and mobility of resources) (see [15] pp.304-308). Of course, the type of mechanism deployed depends heavily on the market structure discussed in the previous section.

- Nearly perfect competition is given in many markets for wheat, corn or shares of a company (stock exchanges). In these markets many buyers ask for homogeneous goods provided by many sellers. In theory prices achieved under perfect competition are *Pareto efficient*, as there is no way to make one participant better off without making some other worse off.
- In a bilateral monopoly bargaining, i.e. one-to-one negotiation is used to determine the prices and conditions of the deal. The result of bargaining is more or less indeterministic and depends on a number of parameters like the bargaining skills and power of the negotiators. Game theory explored these situations in form of non-cooperative games and provided deeper insight into the dynamics of bilateral negotiations (see [16], [17]).
- *Monopolies* consist of a single seller and multiple buyers on the other side. There is a large amount of economic literature describing pricing strategies in the case of a monopoly. If the seller has complete information (e.g. about the market demand curve), a profit-maximizing price can be set by the seller. Price discrimination [18] is a wide spread method to maximize prices in situations, where market segmentation is feasible. In cases with incomplete information the monopolist can use auctions as a market mechanism to determine prices.
- *Monopolistic competition* assumes that there is product differentiation and consequently, there are preferences of buyers for certain sellers. The market for automobiles for example is not purely competitive, since there are not multiple producers of identical products. In these cases double-sided auctions do not work. Due to the consumer preferences sellers are no price takers and can set prices considering the interdependencies with other sellers.

This is only a rough description of the microeconomic framework of taught, and by no means complete. Micro-

Number of Participants	Single-Unit		Multi-Unit	
	Homogeneous Goods	Heterogeneous Goods	Homogeneous Goods	Heterogeneous Goods
1:1	1	2	3	4
1:n	5	6	7	8
m:n	9	10	11	12

Table 2: Classification of Negotiation Situations in Electronic Commerce

economic theory is an excellent starting point, however, for the designer of an electronic marketplace, there are more characteristics that come into play. Table 2 serves as a roadmap for the rest of the paper.

Like in microeconomic theory, an important characteristic of negotiations in electronic commerce is the number of participants on each side, ranging from one-to-one bargaining situations (1:1) to many-to-many type of negotiations. We also distinguish between homogeneous and heterogeneous products traded on a market. Besides we also want to distinguish situations where only a single unit of a good is traded at a point in time and multi-unit negotiations. The simultaneous assignment of multiple goods may improve the quality of an allocation and reduce the time required for the negotiation. In the multi-unit case we can again distinguish between identical, homogeneous goods and heterogeneous goods. In the case of multi-unit negotiations on identical goods, bids contain price-quantity pairs. In the case of heterogeneous goods bidders can have preferences for certain combinations of goods.

In the next sections we describe negotiation protocols and systems. In our analysis we focus on auction mechanisms, as these are the most stable format of negotiation protocols currently used. We start with an overview of one-to-one negotiation support tools (category 1-4) in section 3 and introduce single-unit and multi-unit auction mechanisms thereafter.

3. Negotiation Protocols for One-to-one Bargaining

Over the past decade there have been several approaches to support or automate one-to-one bargaining processes, ranging from negotiation support systems (NSS) to intelligent agents which bargain the details and finally close the deal without further user interaction (for a review of the topic see Rosenschein and Zlotkin [19]). NSS are a special form of decision support systems which assist human negotiators to make a deal. The literature places a relatively heavy emphasis on human factors such as behavioral characteristics, cognitive differences, and negotiation theories, and most of these approaches focus on one-to-one negotiations on single as well as multiple attributes. While NSS can often make negotiations more productive than would be possible without them, they require constant human input, and both the initial problem setup and all final decisions are left to the human negotiators. NSS have seen commercial use in purchasing [20, 21] and in operations management [22]. Recently, they have also been used over the Internet, with notable success in international applications where cultural barriers play a crucial role [23].

Several approaches from the Distributed Artificial Intelligence (DAI) field try to achieve automated bargaining. It typically requires programming computer agents to negotiate with each other. In systems like ADEPT [4, 22], bargaining automated agents are programmed with rules-of-thumb distilled from intuitions about good behavioral practice in human negotiations. Another good example for agent-supported bilateral bargaining is Kasbah [24]. Kasbah is a marketplace for negotiating the purchase and sale of goods using intelligent software agents. Software agents in Kasbah receive their complete strategies through a World Wide Web form from the users who specify the way in which the acceptable price can change over time. The danger is that these agents are badly exploited by new agents that have been programmed to take advantage of the weaknesses of these agents. Binmore and Vulkan [25] emphasize the advantages of using game theory to predict the outcome of agent-based negotiations. Game theory has often been criticized for ist “hyper-rational” view of human behavior, however, in the context of agent negotiations, such hyper-rationality may be an appropriate model [11]. Currently, much promising research is going on in the field of agent-based one-to-one negotiations, however, the applicability of these models has not been demonstrated as yet in practice. In the next sections we concentrate on auction mechanisms, following the standard view among economists that an auction is an effective way of resolving the one-to-many negotiation problem.

4. Single-unit Auctions

Some of the most thoroughly analyzed negotiation protocols are single-unit auction mechanisms on a single item. In the following sections we try to give an overview of auction schemes which can be used in one-to-many and many-to-many situations. We start with an overview of single-sided and double-sided auctions (categories 5 and 9 in Table 2) and provide an overview of game-theoretic as well as experimental results.

4.1. Basic Auction Schemes

In an auction a bid taker offers an object to two or more potential bidders who send bids indicating willingness to pay for the object [26]. Auctions have been defined as "a market institution with an explicit set of rules determining resource allocation and prices on the basis of bids from the market participants" [8]. Oral or open-cry auctions reveal price quotes and require public and adjustable bids. After a certain elapse time the auction clears, meaning it matches buyers and sellers and determines the price. In case of an *English auction* the winner is the remaining participant bidding the highest price. In a *Dutch auction* the price at which an item is offered for sale starts from a high level and declines steadily until one of the buyers stops the clock and buys the good at that price. This auction is often used in Holland for sale of flowers. Sealed-bid auctions do not reveal price quotes and require private, committed bids. The highest bidder acquires the object and pays the seller his own bid price in a *first-price sealed-bid auction*, and pays the second highest bid price in a *second-price* or *Vickrey auction*. There have also been several authors who investigated these single-sided auctions in the context of procurement and sourcing.

Double-sided auctions (category 9 in Table 2) admit multiple buyers and multiple sellers at once. The continuous double auction (CDA) matches bids in the order received. When a new buy bid is processed, the auction checks whether the offered price would match the lowest (i.e. best) existing sell bid, and vice versa. On detection of a match, the auction clears at the price of the existing bid, and generates a new price quote. The CDA is a common mechanism for organized exchanges, such as stock and commodity markets. A periodic version of the double auction termed a call market or clearing-house instead collects bids over a specified interval of time, then *clears* the market at expiration of the bidding interval. Double Dutch auction, a laboratory generalization of Dutch auction in which two price clocks are used alternately until they converge to a single price. Wurman, et al. [6] introduce the (M+1)st-price auction, an incentive compatible form of a double-sided auction. In general, double auctions are not nearly as well understood theoretically as single-sided auctions. In the next section we summarize the most important game-theoretic models describing auction games.

4.2. Game theoretic Models

There is a solid theoretical foundation for single-sided auctions. The most thoroughly researched auction model is the *symmetric independent private values (SIPV)* model. In this model all bidders are *symmetric*/indistinguishable and all bidders have a *private valuation* for the good which is *independent and identically distributed*. The bidders are *risk neutral*, and so is the seller. Under these assumptions, the bidders' behavior can be modeled as a non-cooperative game under incomplete information.

It is interesting to find out, if the auctions achieve the same equilibrium price, or if we can rank the different auction formats in any order. SIPV assumes strategic equivalence between the Dutch auction and the first price sealed-bid auction as well as the English auction and the Vickrey auction. Strategic equivalent bidding behavior in the Dutch auction and the first price sealed-bid auction is intuitive to many people. In an English auction the bidders have a dominant strategy of bidding up to their private valuation. In the Vickrey auction the dominant strategy is to bid the true valuation v. Bidding below v reduces the chance of winning the item with no increase in profit since the second-highest price is paid and bidding above v and winning as a result of the higher bid results in losses. The dominant bidding strategy in both cases does not depend on the number of bidders, risk attitudes, or the distribution from which private values are drawn. Thus, English and Vickrey auction converge to a dominant equilibrium. Thus, one only has to compare the outcomes of two auctions.

Let n be the number of bidders participating in an auction. If the distribution of valuations is uniform and the lowest possible valuation v is zero, and bidders are symmetric, risk-neutral, and hold independent private values, McAfee and McMillan [8] show that the bidder's optimal bid is $(n-1)v/n$; in other words, the bidder bids a fraction $n-1/n$ of his valuation v. As the number of bidders $n \to \infty$, the optimal strategy converges to bidding exactly the bidder's valuation. Thus, the surprising outcome of the SIPV model is that with risk neutral bidders all four auction formats are payoff equivalent. This is also known as the *revenue equivalence theorem* (see [27], p. 372 ff). Thus, according to the SIPV model, the four standard auctions share the same equilibrium payoffs. There are several examples of auctions that violate the prerequisites of revenue equivalence, and thus fail to be payoff equivalent.

Another approach to analyze auctions is the *common value model*. In these cases the object for sale has an unknown common value rather than known private values. In a famous experiment, Bazerman and Samuelson [28] filled jars with coins and auctioned them off to MBA students. Many auctions involve some common value element, where the value of the good is not known or unsure during the auction. As an illustration you may think of oil companies interested in the drilling rights to a particular site that is worth the same to all bidders. A frequently observed phenomenon in these auctions is the so called winner's curse, where the winner bids more than the good's true value and suffers a loss. The main lesson learned from the common value model is that bidders should shade their bids, as the auction always selects the bidder as winner who received the most optimistic estimate of the item's value.

4.3. Experimental Analysis of Basic Auction Schemes

Experimental economists conducted a considerable number of auction experiments testing the results of auction theory described in the last section. Another scientific purpose of experiments is to discover empirical regularities in areas for which existing theory has little to say. Kagel and Roth [29] give a comprehensive overview of experimental auction analysis. Tests of the revenue-equivalence theorem involve two basic issues. Some test the strategic equivalence of first-price and Dutch auctions and of second-price and English auctions. Others test revenue equivalence between first-price/Dutch auctions and second-price/English auctions.

In many auction experiments subjects do not behave in strategically equivalent ways in first-price and Dutch auctions or in English and second-price auctions. Some experiments report higher prices in first-price compared to Dutch auctions, with these higher prices holding across auctions with different numbers of bidders. Kagel et al. [30] also report failures of strategic equivalence in second-price and English auctions. Bidding above the dominant strategy in second-price auctions is relatively wide spread, whereas in English auctions market prices rapidly converged to the dominant strategy price.

5. Multi-attribute Auctions

Several authors investigated tenders and procurement auctions (see [31] or [32]). These auctions are mostly deployed in monopsony situations like governmental or corporate procurement, where a bid taker auctions off goods or services he wants to buy. Laffont and Tirole [33] describe many of the issues involved in procurement negotiations ranging from the costs of setting up a tender to evaluating the bids in such a process. They also mention the need that auction theory must be generalized to “multidimensional bidding” (see category 6 of Table 2).

In procurement auctions, bidders often provide very different goods and services in their bids. A good example is the procurement of large food retailers [34]. The suppliers in the market consist of large companies as well as a large number of small and medium sized enterprises such as bakeries and breweries. The buyers are a small number of large food retailers who aggregate the demand and distribute it to the end consumer. Purchasing managers have their own preferences for product quality, price, terms of payment and delivery and they are looking for the offer that best satisfies these preferences. The overall utility of a deal for the buyer contains not only the price of the item, but a combination of the different attributes. Conventional procurement auctions only automate negotiation on the price. It would be comfortable to have a mechanism that takes multiple attributes of a deal into account when allocating it to a bidder. In other words, the mechanism should automate multilateral negotiations on multiple attributes of a deal.

Only little theoretical work has been done in this field so far (Koppius [35] gives a good overview about existing approaches and research questions). Che [36] studied design competition in government procurement by a model of two-dimensional auctions, where firms bid on price and quality. The bids are evaluated by a scoring rule designed by the procurer. He showed that under certain conditions three proposed auction schemes yield the same expected outcome, and in some schemes quality is either overvalued or undervalued. Branco [37] derives an optimal auction mechanism for the case when the bidding firms’ costs are correlated. In this case the procurer uses a two-stage auction: in the first stage he selects one firm; in the second stage he bargains to readjust the level of quality to be provided.

In the following we describe a generic procedure for multi-attribute auctions which we introduced in [34]. The buyer first has to define his preferences for a certain product in form of a utility function. The buyer has to reveal his utility function to suppliers, whereas the suppliers do not have to disclose their private values. The mechanism then designates the purchase to the supplier who best fulfills the buyer's preferences this means who provides the highest overall utility for the buyer.

In other words, we have a vector Q of relevant attributes of a bid and index the n attributes by i and a set of bids B and index the m bids by j. A vector $\boldsymbol{x_j} = (x^1{}_j \ldots x^n{}_j)$ is specified, where $x^i{}_j$ is the level of attribute i in bid b_j. In the simple case of an additive utility function $U(\boldsymbol{x_j})$ the buyer evaluates each relevant attribute $x^i{}_j$ through a utility function $U_i(x^i{}_j)$. The individual utility function $U: Q \rightarrow R$, translates the value of an attribute into ”utility units”. The overall utility $U(\boldsymbol{x_j})$ for a bid b_j is then given by the sum of all utilities of the attributes. For a bid b_j that has values $x^1{}_j \ldots x^n{}_j$ on the n relevant attributes, the overall utility for a bid is given by

$$U(\boldsymbol{x_j}) = \sum_{i=1}^{n} U_i(x^i{}_j)$$

The utility units introduce a virtual currency on this market that expresses the overall utility of a bid to the buyer. A reasonable objective in allocating the deal to the suppliers is to allocate them in a way that maximizes the utility for the buyer, i.e. to the supplier providing the bid with the highest overall utility for the buyer:

$$max\ U(\mathbf{x}_j)\ and\ 1 < j < m$$

This function gives us the utility of the winning bid and can be determined by various auction schemes. Alternatives with the same overall utility are indifferent and can be substituted by one another. Depicted graphically, these alternatives lie on the same indifference curve. In a multi-attribute English auction or a multi-attribute first-price sealed bid auction the winner gets the price specified in $\mathbf{x}_j$. In a multi-attribute second-price auction, however, we take the overall utility achieved by the second highest bid U_{max-1} and transform the gap to the highest overall utility (U_{max} - U_{max-1}) into money which can be charged by the winning bidder in addition to his bid price. Bichler, et al. [34] describe a details of the mechanism and outline an Internet-based brokerage service implementing multi-attribute auctions. Experimental tests conducted so far show that multi-attribute auctions achieve a higher overall utility compared to single-attribute auctions and the efficiency of the outcomes is quite high.

6. Multi-unit Auction Schemes

Most classic auction theory deals with single indivisible goods. An interesting extension to classic auction theory is the multi-unit auction, where there is more than one item or good to be allocated simultaneously. For single-unit auctions, a bid simply indicates whether it is to buy or sell, and at what price. A *multi-unit* bid generalizes this by specifying a set of price-quantity pairs for multiple identical goods (category 7 of the classification scheme). The first-price auction has two multi-unit generalizations which are used in practice – *discriminatory auctions* in which the bidders who bid the highest prices pay their bid, and *uniform-price auctions* in which all successful bidders pay the lowest accepted bid.

Properties of single unit first-price and English auctions extend to multi-unit auctions in which each bidder demands at most one unit of the item. Uniform-price auctions in which the *k* successful bidders pay the lowest accepted price correspond to second-price auctions in the sense that each bidder has a dominant strategy of bidding the private valuation. Discriminatory auctions correspond to first-price auctions in the sense that with risk neutrality, expected revenue is the same as the uniform price auction and with risk aversion, bids will be higher, yielding greater expected revenue for the seller. Revenue equivalence generally fails in the case of multi-unit auctions, where bidders are allowed to buy several units, depending on the price. Hansen [38] showed that first-price auctions lead to a higher expected price and revenue equivalence is not valid any more. The theory of multi-unit auctions, however, is not well developed. Combinatorial auctions described in the next section are a promising new approach which can also be deployed in case of multiple identical goods. These mechanisms are especially useful in situations, where one has to assign multiple heterogeneous goods simultaneously and bidders have preferences over different combinations of goods (categories 7, 8, 11and 12).

6.1. Combinatorial Auctions

Goods are said to be combinatorial when the value of a bundle of goods is not equal to the sum of the values of the same goods unbundled, i.e. the bidders' valuations are not additive. Examples of goods which are thought to exhibit such a property include airport landing slots, electromagnetic spectrum licenses, land parcels, oil leases and shipping space. A slot at a certain airport, for example, is more or less valuable to an airline depending upon whether the airline obtained an appropriate time slot at an appropriate paired city [39]. In these cases sequential auctions are difficult and would lead to speculation of what the others will bid in future auctions. Conducting the auctions for all the goods in parallel is of little help to this basic problem. Bidders might even run into deadlock problems each waiting what the others will bid in a certain auction in order to optimize their own bidding.

Several solutions have been proposed to this problem. After the early recognition of the combinatorial features of the airport slot problem, the combinatorial allocation problem received significant attention during the design process for the Federal Communication Commission's (FCC) auction of spectrum rights for Personal Communication System services. In this case the bidders were allowed to retract their bids. Retracted items were opened for re-auction and if the new winning price was lower than the old one, the bidder that retracted the bid had to pay the difference [12]. Another approach would be to set decommitting penalties up front or to sell options for decommitting, where the price of the option would be paid in advance.

All these approaches try to fix inefficient allocations achieved in sequential or parallel auctions, adapting a basically non-combinatorial process in some manner to take account of combinatorial values. *Combinatorial auctions* are an approach to achieve efficient allocations in the first step. Here bidders can place bids on combinations of goods which allows to express dependencies and complementarities between goods. This type of auction mechanisms is also called multidimensional auction [40] or matrix auction [41] and can be used for the assignment of multiple heterogeneous goods or services to multiple bidders (category 8 and 12). The potential advantage of allowing combinatorial bids in a simultaneous auction is that it allows bidders to express their synergistic values.

Goods/ Bidder	(1)	(2)	(3)	(1,2)	(2,3)	(1,3)	(1,2,3)
A	5	32	40	65	10	-20	-60
B	5	-10	30	-30	40	80	90
C	-10	80	50	35	-20	45	15
D	5	40	35	40	60	-30	50

Table 3: Matrix for the allocation of goods

This should result in greater revenue for the bid-taker and in an economically more efficient allocation of assets to bidders [39].

In the following we give an example for the assignment of multiple heterogeneous goods to bidders in a procurement scenario (see [42] for a detailed example). Bidders in this scenario calculate a bid for each combination of goods (2^n-1 combinations). Of course, the valuation of a combination of goods may differ significantly from the sum of the valuations and may even be negative, depending on the bidder's preferences for certain combinations of goods. Bidders transmit their bids to the auctioneer who determines an efficient allocation by setting up a matrix (see Table 3) with all combinations in the columns and the bidding agents in the rows. The cells of the matrix contain bidders' bids for each combination. The algorithm for this assignment problem has to take into account that a bidder cannot get more than one bid assigned. Beyond this, columns/combinations of goods that have any good in common must not be selected jointly. The shaded cells of Table 3 show the optimum allocation for an example with three jobs and four bidders. The optimum overall allocation is 160. Bidder B gets the goods 1 and 3 assigned and bidder C gets good 2.

6.2. The Generalized Vickrey Auction

One mechanism for determining the prices in this resource allocation problem is the Generalized Vickrey Auction (GVA), described in Varian [11]. The GVA is an incentive compatible mechanism, in which true revelation is the dominant strategy for a bidder. Therefore, the bidder has to report its entire utility function. This is particularly useful in the field of agent-based electronic commerce infrastructures. Automated agent's can be rather simplistic, because their actions depend only on their local information. Moreover, transaction costs are reduced compared to open-cry auction schemes.

Suppose there are $i = 1,..,I$ bidders and n goods, i.e. $j = 1,..,2^n-1$ job-combinations. b_{kj} represents the bid of a bidder k for job combination j and v_{kj} is his true valuation for a combination of goods j. x^*_{ij} are the variables of the optimal assignment (with x^*_{ij} = 1 if bidder i receives the combination j and x^*_{ij} = 0 otherwise) and $x^{*\neg k}_{ij}$ are the variables of the optimum assignment with the row of bidder k skipped. The price for a bidder k in the efficient allocation is computed by deducting the sum of the bids of all other bidders in x^*_{ij} from the sum of the bids in $x^{*\neg k}_{ij}$, i. e. the price paid by the bidding bidders is

$$p_k = \sum_{\substack{i=1 \\ i\neq k}}^{I} \sum_{j=1}^{2^n-1} b_{ij} x^{*\neg k}_{ij} - \sum_{\substack{i=1 \\ i\neq k}}^{I} \sum_{j=1}^{2^n-1} b_{ij} x^{*}_{ij} .$$

In the example of Table 3 with an efficient allocation of 160 the price of bidder C results from deducting the sum of the bids of all other bidders in the efficient allocation (here 80) from the sum of the bids in the optimum assignment with bidder C skipped (this would sum up to 120 in the example). Therefore, C has to pay p_C = 120 - 80 = 40 for job (2). Gomber, et al. [42] show that the dominant strategy for a bidder k in this case is to make bid $b_{kj} = v_{kj}$, i.e. to reveal his true valuation.

6.3. Determination of Winners in Combinatorial Auctions

While bidding in combinatorial auctions is easier, as bidders do not have to speculate on other bidders' behavior in other auctions, it requires much more effort to determine the winner, i.e. the revenue maximizing bids in these auctions. The actual mechanics of a combinatorial auction and the costs associated with determining the winner are quite high. In a non-combinatorial multi-unit auction determining the winner can be done in $O(am)$ time where a is the number of bidders, and m is the number of items. In contrast, Sandholm [12] showed that the number of allocations in a combinatorial auction is $O(m^m)$ and that determining the winner so as to maximize revenue is *NP*-complete. This does not scale beyond auctions with a small number of items.

Several researchers address this problem. Rothkopf, et al. [39] investigate a set of restrictions that could be imposed upon allowed combinations, and which can make the computation of the best set of bundles tractable. They use dynamic programming to solve the problem. Sandolm [12] proposes a search algorithm for winner determination in polynomial time under a number of restrictions and describes an Internet-based implementation called eMediator. In the GVA also the determination of prices requires additional computational effort. Therefore, Gomber, et al. [42] propose a simplified method for price determination called Pricing Per Column (PPC), however, this mechanism is not incentive compatible in a game theoretic sense.

6.4. Multi-stage Extended Vickrey Auctions

In this section we consider an approach to achieve an efficient allocation in negotiation situations, where multiple services have to be assigned to a number of bidders, but it is not clear at the beginning how the services should be decomposed (a subclass of categories 8 and 12 of our classification scheme). This situations not unlikely in transportation and logistics. The Multistage Extended Vickrey Auction (MEVA) [43] is based on the concept of dividing the auction process into several stages instead of just one stage as conventional auction theory assumes. Game theory states that multi-stage auctions can be modeled as an extensive game and thus should be equivalent to a single-stage auction. Engelbrecht-Wiggans [13] was one of the first to investigate multi-stage single-unit auctions and showed that a multistage process can sometimes yield increased revenues.

In MEVA jobs are auctioned off in an iterative bidding process whose number of iterations i equals the number of participating bidders. In each iteration a Vickrey auction is carried out and coalitions with i participants make a bid. In the first iteration, each single agent makes a bid for the job. The auctioneer stores all bids and their respective bidders, but does not announce them. In the second iteration the auctioneer calls on coalitions with two participants to make their bids, and so on. Bilateral negotiations lead to coalition formation. Finally, the bidder or the coalition of bidders with the highest bid of all iterations is awarded the job. The price corresponds to the second highest bid of all iterations. The step of coalition formation in each stage should lead to an efficient allocation, i.e. the job should be awarded to the "best" coalition among all.

7. Summary

Different negotiation situations in electronic commerce require different negotiation protocols to achieve an efficient allocation. In electronic commerce it is often necessary to develop matchmaking mechanisms for goods which have not been traded on an exchange before. This requires extensions to the existing framework of theory.

The main objective of this paper is to disclose relations between different kinds of negotiation situations on the one hand and adequate market mechanisms on the other. Starting with the identification of relevant attributes for negotiations in electronic commerce, a classification scheme based on these characteristics is derived. We then describe approaches to support one-to-one negotiations and give an overview of classic auction theory to support multi-lateral negotiations. Finally, we introduced new approaches like multi-attribute and combinatorial auctions.

8. References

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