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# Auctions and Electronic Markets

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## 1. Introduction

Adam Smiths' *invisible hand* argument presented the concept that opening up a market will result in a globally efficient mechanism where consumers have the ability to choose freely what to buy, sellers or service providers are allowed to choose freely what and how to produce and sell, which in turn leads the market to settle on product and price distributions that are beneficial to all members of the community. Over the past decade, the Internet has facilitated the proliferation of new markets, called electronic Marketplaces (eMarkets) and corresponding opportunities for service providers and consumers alike. According to Feldman adopting an eMarket approach to service provisioning helps to improve economic efficiency, reduce margins between price and cost, and speed up complicated business deals, where the services they provide will expand many companies purchasing and selling abilities and will make processes more dynamic and responsive to economic conditions, thereby helping to realise the goal of Adam Smiths' *invisible hand*.

To enable transactions within eMarkets, electronic Commerce (eCommerce) is employed, allowing entities to conduct their business over the Internet [He, 2003]. According to the nature of such transactions, the following types of eCommerce are distinguished: Business-to-Business (B2B), Consumer-to-Consumer (C2C), Consumer-to-Business (C2B) and Business-to-Consumer (B2C). B2C refers to online retail transactions where the buyers are individual consumers and the sellers represent themselves as business cooperation's, whereas B2B refers to the transactions where both buyers and sellers are business cooperation's. With the rapid growth of the number of transactions conducted via electronic channels such as the Internet, there exists an ever increasing demand to develop advanced computational tools to streamline B2C and B2B eCommerce. Most of the initial Internet based eCommerce was focused on B2C markets. However B2B constitutes a much larger portion of the overall eCommerce landscape and it is widely believed that B2B will continue to grow and will be the predominant means of doing business in the near future [Shaw].

Agents are seen as a key enabler for eCommerce where according to He (2003) "Electronic Commerce is the most important allocation for Agent technologies, because it is reality-based and constitutes a massive market". To support the integration of eMarkets and agents, Collins et al, designed a generalised multi-agent market architecture that can provide explicit and integrated support for complex agent interactions, such as that required in eMarkets. They defined three fundamental elements of the generalised multi-agent market architecture, including an *exchange*, the *market* and the *market session*.

Within eCommerce and eMarkets, negotiations are ubiquitous and are considered an essential business activity for establishing trade relationships and fine-tuning terms and conditions in both B2C and B2B markets [Kim]. Given the ubiquity and importance of negotiations in various contexts, research into negotiation theories and techniques have attracted attention from multiple disciplines such as distributed AI [Kraus], social psychology [Pruitt], game theory [Nash, Rubinstein], operations research [Nash, Neumann], and more recently agent mediated electronic commerce.

It is the purpose of this chapter to examine the main concepts that relate to: Market design, auctions, automated negotiation, agents and eMarkets. The chapter will show how these related technologies work to enable the vision of Adam Smiths *Invisible hand* argument and how the Internet is paving the way towards a globally efficient mechanism for establishing trade agreements.

## 2. Market design

Ever since the conception of auctions in Roman times, their history has been traditionally fraught with misery. Auctions have been used in the sale of wives in Babylonia in 500 BC [Rawlinson], prisoners of war in ancient Rome, and African slaves in the 16th Century [Jenman]. Rules surviving from the auctions of these eras show that in some cases, at least, bids were called out sequentially with the bidder remaining at the end obtaining the object at the price she/he bid. A variant of this mechanism, in which a time limit is imposed on the bids, is reported by the English diarist and naval administrator Samuel Pepys (1633-1703). The auctioneer lit a short candle, and bids were valid only if made before the flame went out. Pepys reported that a flurry of bidding occurred at the last moment. At an auction on September 3, 1662, a bidder "cunninger than the rest" told him that just as the flame goes out, "the smoke descends", signaling the moment at which one should bid [Pepys]. In fact the word *auction* is derived from the Latin *augere*, which means *to increase*.

Early auctions mostly involved misery, trickery and low prices, used as a business of exploitation and sudden opportunity, and were rarely a serious part of traditional business. More recently however, auctions are used to sell artwork, United States Treasury bills, houses and corporations to name a few. The auction houses of Sotheby's and Christie's were founded in the mid 18th century, and one of the more recent Sotheby's chairmen, A. Alfred Taubman, was once quoted stating "*God help us if we ever take the theatre out of the auction business or anything else. It would be an awfully boring world.*" A. Alfred Taubman, lived up to his own personal *drama* however, with the media frenzy surrounding his conviction in conspiring and colluding with his counterpart at Christie's auction house to fix the commissions paid by sellers of art, antiques and celebrity bric-a-brac [New York Times, 2001].

At the beginning of the twenty first century, auction houses, such as Sotheby's and Christie's are being eclipsed, at least in the value of the goods they sell, by online auction companies. For example eBay, founded in September 1995, sold US$3.27 billion in 2004. Sotheby's and Christie's, on the other hand together sell around US$1 billion of art and antiques each quarter. The mechanism used by eBay shares a feature with the one that Pepys observed: all bids must be received before some fixed time. The way in which the price is determined differs. In an eBay auction, a bidder submits a "*proxy bid*" that is not revealed, the prevailing price is a small increment above the second highest proxy bid. As in the 17th century auctions, Pepys observed, many bidders on eBay act in the last moment – a

practice known as "*sniping*" in the argot of cyberspace. Other online auction houses use different termination rules, for example, Amazon waits ten minutes after a bid before closing an auction. The fact that last minute bidding is less common in Amazon auctions than it is in eBay auctions has attracted the attention of game theorists, who have begun to explore models that explain it in terms of the difference in the auction's termination rules.

Despite the long history of auctions and other exchanges, market design had not gained momentum as a scientific discipline until recently. The momentum has emerged due to the large body of theoretical and empirical market literature that has been published in the field, particularly in the area of auction based protocols. A driving factor for this research has been the growth of eCommerce transactions over the Internet which has presented a large number of challenges in the design of eMarkets that support such eCommerce transactions. eMarket designers now need to deal with  geographically distributed traders who have multiple complex factors that they need to consider in their negotiations. In general a market designer's task is to: create a meeting place for buyers and sellers; and a format for transactions that enforces a set of market rules that will lead to a "*desired*" outcome. This outcome of trade will be represented as the final allocation of traded objects and by the exchange of monetary payments between the participants. Market design is still in stages of infancy and comprises of tools and methodologies such as: equilibrium analysis; game theory; mechanism design theory; experimental economics; and computation. Within these methodologies, Game theory and mechanism design has provided some very valuable contributions to the field and as a result are further outlined below.

## 2.1 Game theory

Game theory is a set of analytical tools designed to help one understand the phenomena that we observe when decision makers interact. The basic assumptions that underlie the theory are that decision makers pursue well-defined exogenous objectives and take into account their knowledge and expectation or other decision makers' behaviour. In other words, decision makers can be said, to be rational and they reason strategically. Gibbons and Osborne & Rubenstein provide useful introductions into the subject.

Game theory assumes that there is a set of agents $n = \{i, i = 1, 2, …, n\}$. The action (strategy) space of agents is represented as $A_i$ , where $A_i$ is the set of all available actions to player $i$ , and an outcome $a = (a_1,…,a_n)$ is thus simply an action profile. The most common and easiest game to solve problems in Game theory is known as a Bayesian game. In a Bayesian game, let agent $i$'s possible payoff function be represented by $u_i(a_1,…,a_n;t_i)$ , where $t_i$ is called player $i$'s type and belongs to a set of possible types (or type space) $T_i$ . Each type $t_i$ corresponds to a different payoff functions that player $i$ may have. Given this definition of a player's type, saying that player $i$ knows his or her own payoff function is equivalent to saying that player $i$ knows her type. Likewise, saying that player $i$ , may be uncertain about the payoff functions of the other players is equivalent to saying that player $i$ may be uncertain about the types of the other players, denoted by $t_{-i} = (t_1,…,t_{i-1},t_{i+1},…,t_n)$ . We use $T_{-i}$ to denote the set of all possible values of $t_{-i}$, and we use the probability distribution $p_i(t_{-i}|t_i)$ to denote player $i$'s belief about the other players' types, $t_{-i}$, given player $i$'s knowledge of his own type, $t_i$ .

A key concept in game theory is a strategy which is a complete contingent plan, or decision rule, that defines the action an agent will select in every distinguishable state of the world.

For example, in an auction, the strategy of an agent would dictate what bid the agent should submit, given its type and the actions taken by the other agents. A pure strategy for player $i$ in a Bayesian game is a function which maps player $i$'s type into her strategy set, in that $a_i : T_i \to A_i$, so that $a_i(t_i)$ is the strategy choice of type $t_i$ of player $i$. A mixed strategy for player $i$ is $\alpha_i : T_i \to \Delta(A_i)$ so that $\alpha_i(a_i | t_i)$ is the probability assigned by $\alpha_i$ to action $a_i$ by type $t_i$ of player $i$. Each agent will have a preference over outcomes and will try to choose a strategy so that its preferred outcome occurs. These preferences are expressed in terms of utility functions, where $u_i(a_1,...,a_n;t_i)$ is some real number and if agent $i$ prefers outcome $u_i(a_1,..,a_n;t_i) > u_i(b_1,...,b_n;t_i)$, then we understand that player $i$ likes outcome $a = (a_1,...,a_n)$ strictly better than outcome $b = (b_1,...,b_n)$. The goal of each agent is to maximize it utility.

Game theory is interested in finding equilibria. An equilibrium is a strategy profile which satisfies certain properties. The best known equilibrium concept is the *Nash equilibrium*. A *Nash equilibrium* of a game $G$ in strategic form is defined as any outcome $(a_1^*,...,a_n^*)$ such that $(a_i^*,...,a_{-i}^*) \geq u_i(a_i, a_{-i}^*)$ for all $a_i \, \varepsilon \, A_i$ holds for each player $i$. The set of all Nash equilibria of $G$ is denoted $N(G)$. In Bayesian Nash equilibrium every agent involved is assumed to share a common prior knowledge about the distribution of agent types, type $F(t)$, such that for any particular game the agent profiles are distributed according to $F(t)$. In equilibrium each player or agent selects a strategy to maximize its expected utility in equilibrium with expected-utility maximizing strategies of other players, in other words each player's strategy must be a best response to the other player's strategies. That is, a Bayesian Nash Equilibrium is simply a Nash equilibrium in a Bayesian game. A stronger equilibrium concept in game theory is the dominant strategy equilibrium.

In the dominant strategy equilibrium, the problem of forming a conjecture about the action choice of other players does not arise, because there is an optimal way of taking an action *independently* of the intended play of others. Games with dominant strategy equilibria are easy for agents to play since it is obvious what their optimal strategy is and they do not need to worry about what the other agents are doing. While many games do not have dominant strategy equilibria, in many practical implementations it is possible to carefully design games in order to guarantee that dominant strategies of the agents are such that agents are best off truthfully telling their true preferences to the auctioneer.

### 2.2 Mechanism design

In a mechanism design problem one can imagine that each agent holds one of the "inputs" to a well formulated completely specified optimization problem, perhaps a constraint or an objective function coefficient, and that the system wide goal is to solve the specific instantiation of the optimization problem specified by the inputs [Hurwicz].

The system wide goal in mechanisms design is defined with a social choice function, which selects the optimal consequence, given an agent's type, where a social choice function $f : T_1 \times ... \times T_n \to C$, chooses a consequence $f(t) \, \varepsilon \, C$, given types $t_i = (t_1,...,t_n)$. A Mechanism $M = (S_1,...,S_n; g(.))$ defines the set of strategies $S_i$ available to each agent, and an outcome rule $g : S_1 \times .... \times S_n \to C$, such that $g(s)$ is the consequence implemented by the mechanism for strategy profile $s = (s_1,...,s_n)$. Game theory is used to analyze the consequences or outcome of a mechanism. Given mechanism $M$ with outcome function $g(.)$, we say that the mechanism implements a social choice function $f(t)$, if the consequence computed with equilibrium

agent strategies is a solution to the social choice function for all possible agent preferences. The equilibrium concept can be either Nash, Bayesian-Nash, dominant – or some other solution concept, so long as the strongest one is used [Varian, Jackson].

The most important properties, according to Bichler, for designing a mechanism include equilibrium, efficiency, stability, incentive compatibility and speed of convergence. A mechanism is efficient, meaning that the allocation resulting from the auction is *Pareto optimal*, where no agent can improve its allocation without making another agent worse off. This means that the auction is efficient if there are no further gains from trade, and that the goods are allocated to the agents who value them most highly. The solution is said to be *stable* if there are no subset of agents who could have done better by coming to an agreement outside the mechanism. If a mechanism is stable then it is Pareto efficient, although the reverse is not true. A direct auction *is incentive compatible* if honest reporting of valuations is a Nash equilibrium. A particularly strong and strategically simple case is a mechanism where truth telling is a dominant strategy. This is a desirable feature because as an agent's decision depends only on its local information, and it gains no advantage by expending effort to model other agents. Mechanisms that require agents to learn or estimate another's private information do not respect privacy. Speed of convergence is another important issue in markets where transactions need to occur at a rapid rate. A good example is the Dutch flower auction. Since these auctions deal with large volumes of perishable goods, each individual transaction needs to be completed quickly.

Mechanism design theory now forms an integral part of modern economics where it's most successful use has been its application to auction theory. These two areas intersect in the area of optimal auction design, where principles from mechanism design are combined with auction theory to design auctions that achieve the desired optimal outcomes [Bichler].

## 3. Automated negotiation

While market design helps decide the rules of the negotiation, and can also assist in the design of auctions to achieve optimal outcomes, a rationale for using auctions in eMarkets has yet to be discussed. It is the purpose of this section, where the reasons why automated negotiation techniques are important in eMarkets, how and why different auctions are appropriate for different situations, and the main auctions types and their optimal strategies as computed using Game theory are discussed.

According to Bichler, within negotiation, "current human-based procedures are relatively slow, do not always uncover the best solution", and are, furthermore, according to Beam and Segev (1997) constrained by issues of culture, ego and pride. In addition, human participants in the negotiation process often reach suboptimal agreements thereby "leaving money on the table". Human's inability to find better agreements is due to the fact that negotiation is a search process for the optimum agreement. The main difficulty in this optimisation search process is that each party involved in the negotiation has private knowledge and each side does not normally know this private knowledge and their corresponding utility functions. Furthermore both sides often have an incentive to misrepresent their preferences, thereby making the formation of an optimal agreement/solution an extremely challenging task. Essentially, both sides are in competition but must jointly search for possible agreements.

For the past few decades researchers in the field of economics, game theory and behavioural sciences have investigated this negotiation process. However despite the large amount of

research conducted a solid and comprehensive framework is still lacking. A basic principle of microeconomics and negotiation sciences is that there is not a single "*best*" protocol for all possible negotiation situations. Wurman et al, asserts that different negotiation protocols are appropriate in different situations, and, thus, any generic mediation service should support a range of options. To demonstrate this point  the abstract, in Table 1 below will analyse key countries (i.e. Britain, Switzerland and Denmark) and the chosen auction protocols used in the sale of the 3G spectrum licences, which cost European telecommunication operator's approx $700 billion US Dollars [Klemperer].

The sale of the European 3G spectrum licences began in Britain in March 2000. Because Britain was the first country to sell such licence agreements it had what is called "first moreover advantage". Britain originally planned to sell just four licenses but faced the problem that there was exactly four incumbent "2G" mobile phone operators who had advantages over the other bidders. In this situation if Britain decided to use an ascending auction protocol it would be susceptible to the problems of: collusion; and could deter the weaker bidder to enter the race since a weaker potential bidder knows that a stronger bidder can always re-bid to top any bid he makes. If Britain used a pure sealed bid auction this could allow a situation where a bidder with lower values could beat opponents with higher values leading to potentially an inefficient outcome compared to an ascending auction. As a result, Britain planned to use a hybrid of the ascending and sealed bid auctions, called "Anglo-Dutch" auction. In this configuration, the ascending auction continued until just five bidders remain, after which the five survivors made sealed bids. In this scenario the sealed bid stage would attract entry and so also raise revenue, while the ascending would mean less loss of efficiency that might result from a pure sealed-bid auction. In this auction nine new entrants' bids strongly against the incumbents, creating intense competition and record-breaking revenues of 39 billion Euros.

The Swiss auction experience presented the most embarrassing result, where it decided to use the ascending auction protocol. Although the auction received initially considerable interest from numerous bidders the type of auction protocol turned the weaker bidders off participating where the number of bidders reduced from nine to four. As a result the telecom operators just had to pay the reserve price for the spectrum licence agreements which were one thirtieth per capita of the UK and German prices, and one-fiftieth of what the government had once hoped for.

Denmark ran the last of the auctions in September 2001 and was in a particularly tricky position. Valuations were now low and to further complicate matters Denmark planned to sell the same number of licenses as it had incumbent operators. As a result it choose a sealed bid auction to give weaker bidders a chance of winning, in the hope of attracting new entrants and of scaring the incumbent operators into making higher bids. The auction was a resounding success, attracting a serious bid from a new entrant and shocking analysts with a revenue more than double most expectations.

What is visible from above is that one generic auction protocol does not fit all. The auction protocol selected must bear in mind a number of factors, such as the number of bidders, possibility of collusion, and market stability. The countries that borne these factors into their design produced an outcome that generated the most revenue for their corresponding governments while countries like the Netherlands that just copied other countries choice suffered the consequences.

Table 1. Abstract - discussing how one size does not fit all when it comes to auction protocol design [Klemperer]

Recent developments in electronic market research offer the promise that new negotiation protocols will not only leave less money on the table but will also enable new types of transactions to be negotiated more cost effectively. There have been many approaches for supporting or automating commercial negotiations, such as bargaining and auctions. Bargaining situations can concern as few as two individuals, who may try to reach an agreement on a range of transactions. Over the past decade, there have been several approaches to supporting or describing one-on-one negotiations, ranging from game theory to negotiation support systems to intelligent agents who bargain the details and finally close the deal without any further user interactions. According to Bichler, however, although much research has been accomplished, automated bargaining using agents is currently restricted to a small number of applications in commercial environments. The reason for this, is that game theory has failed, thus far, to describe human bargaining, where Linhart et at state that "*inadequate theories of bargaining exist only for the degenerate, polar cases of competition and monopoly*". In addition negotiation support systems require constant human input, both at the initial problem setup and all final decisions are left to the human negotiators, making automated bargaining not so automated.

McAfee [McAfee] defined an auction as "a market institution with an explicit set of rules determining resource allocation and prices based on bids from the market participants". Auctions constitute one type of dynamic pricing, in which the price of the product varies, depending on the demand characteristics of the consumer and the supply situation of the seller and are often used rather than posting a fixed price on an item, in cases where products have no standard value. In addition to price determination, according to Kagel (1997), auction theory is also important for practical, empirical and theoretical reasons. The roots of electronic auction and negotiation mechanisms are in auction and negotiation theory. See for instance, Raiffa, Milgrom, Kagel and Roth (1995), Klemperer, and Rothkopft et al.

Using auctions as a means of automating negotiation in eMarkets has been described by Binmore and Vulkan (1999) as "*an effective way of resolving the one to many bargaining problem*". According to experiments described in Kagel et al (1995) the outcome of market competition is more likely to conform to game-theoretical rationality than the outcome of a bilateral negotiation. In addition compared to the bargaining process, being a bid taker puts less of a burden on the seller's knowledge and abilities than being a negotiator in a bargaining process, simply because the human or agent does not need to know the range of possible buyer valuations. In general the price set by the eMarket i.e. the winning bid is on average below the item's true but unknown value, but with the introduction of more and more bidders, the price approaches its true value.

In addition, to further advocate the use of auctions in automated negotiation procedures, the technical infrastructure required to support auctions in an online environment is currently available and well accepted. Wurman (2001) outlined how auctions are a very efficient and effective method of allocating goods/service, in dynamic situations to the entities that value them most highly, whereas Bapna et al stated that "*Online auctions, bought about by the synergetic combination of Internet technology and traditional auction mechanisms present a significant new dimension for mercantile processes*". Intelligent software agents can also represented their owners in an auction, where the agent activities may involve monitoring, analyzing the market conditions and/or deciding when and how much to bid for the desired items.

There are many different forms of auctions, where [Wurman, 1998] defines a taxonomy of auction parameters that allows for approximately 25 million types of auctions. Beam and Segev (1997) also examined 100 online auctions and analyzed their characteristics. However despite this vast range of auction protocols there are only four common types of single sided auctions, which include: English, Dutch, First Price Sealed Bid (FPSB), and Second Price Sealed Bid (SPSB) which are outlined below. Included in the description of each of these auction types is the strategy that the human or agent needs to employ to receive the highest utility in the process. Within these auction types the Dutch auction and First-Price Sealed-Bid are strategically equivalent to each other, while the English auction protocol and the Second-Price Sealed-Bid auction are strategically equivalent to each other. To see how these strategies were computed in more detail, please see [Gibbons].

However, the strategies shown in Table 2 only hold true under the auction model more commonly known as the symmetric Independent Private Value (IPV) model and perceived valuations in the common-value-model. Under the IPV model, Bidder $i$ knows his own valuation, $v_i$, where this valuation is the true valuation in the independent-private-values models. Each bidder is assumed to know the number of bidders, their risk attitudes, and the probability distributions of valuations, and he knows everyone else knows that he knows this, and so on. At a Bayes-Nash equilibrium, each bidder bids an amount that is some function of his own valuation, such that, given that everyone else chooses his bid in this way, no individual bidder could be better by bidding differently [McAfee].

At the other model extreme, consider the sale of an antique that is being bid for all dealers who intend to resell it, or the sale of mineral rights to a particular tract of land. Now the item being bid for has a single objective value, namely the about the antique is worth on the market, or the amount of oil actually lying beneath the ground. However no-one of course knows its true value and so the bidders, perhaps having access to different information, have different guesses about how much the item is objectively worth. If $V$ is the unobserved true value, then the bidders' perceived values, $v_i$, $i=1,2,....,n$, are independent draws from some probability distribution $H(v_i|V)$. All agents know the distribution $H$. This is called the *common-value model.* A frequently observed phenomenon under this auction model is the so called *winner's* curse phenomena. In this situation the winner bids more that the goods 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 the winner who received the most optimistic estimate of the items value [McAfee].

Another important point to note that under these conditions the revenue equivalence theorem holds, which essentially states that in any auction that has [Klemperer] "*a given number of risk neutral potential buyers of an object has a privately known signal independently drawn from a common, strictly increasing, atomless distribution. Then any auction mechanism in which (i) the object always goes to the buyer with the highest signal, and (ii) any bidder with the lowest-feasible signals expects zero surplus, yields the same expected revenue (and results in each bidder making the same expected payment as a function of their signal)*". What the above states is that when the object goes to the buyer with the highest valuation, then the outcome of the auction is said to be *Pareto efficient*. The Revenue Equivalence Theorem also proves that for in [Vickrey] "*each of the English auction, the Dutch auction, the first-price sealed bid auction, and the second price-sealed bid auction yields the same price on average*". Therefore all four types of auctions yield the same expected revenue for the seller in the case of independent private values and risk neutrality.

| Auction Protocol | Description | Strategy |
|---|---|---|
| *Ascending Bid or English auction* | The price is successively raised until at least one bidder remains. This can be done by having an auctioneer announce prices, or by having bids submitted electronically with the current best bid posted. The essential feature of the English auction is that, at any point in time, each bidder knows the current best bid. Antiques, art work and houses are sometimes sold using this type of auction. | The agent's dominant strategy (the best thing to do, irrespective of what the others do []) is to bid a small amount more than the current highest bid and stop when the user's valuation is reached. For example, in Yahoo auctions, "*autonomic bidding*" allows users to input their maximum bid and an agent will bid incrementally when it is necessary to win the auction. |
| *Descending Bid or Dutch auction* | The agent's dominant strategy (the best thing to do, irrespective of what the others do [Gibbons]) is to bid a small amount more than the current highest bid and stop when the user's valuation is reached. For example, in Yahoo auctions, "*autonomic bidding*" allows users to input their maximum bid and an agent will bid incrementally when it is necessary to win the auction. | Strategically equivalent to First-Price Sealed –Bid |
| *First-Price, Sealed-Bid (FPSB) auction* | Each bidder independently submits a single bid, without knowledge of what bids is submitted by other participants. The object is sold to the bidder who makes the highest bid. This type of auction is used in auctioning mineral rights in government-owned land, and is sometimes used is the sales of artwork and real estate. Of greater quantitative significance is the use of sealed bid tendering for government procurement contracts - that is competing contractors submit prices and the lowest bidder wins and receives her price for fulfilling the contract. | The dominant strategy in First-Price Sealed -Bid of complete information is to bid the second highest bidders valuation, while in First-Price Sealed-Bid of incomplete information the dominant strategy, computed using game theory is that he bids a fraction $((n\text{-}1)/n)v$ of his valuation $v$, when a total of $n$ parties are bidding. Further analysis of this strategy is provided in [Gibbons]. |
| *The Vickrey or Second-Price, Sealed-Bid auction* | Operates in the same manner as FPSB and while the object is still sold to the bidder who makes the highest bid, the winning bidder pays the second-highest bidders bid, or "second price". While this auction has useful theoretical properties, it is seldom used in practice due to its vulnerability to a lying auctioneer, lower revenue when compared to the English auction and undesirable private information problems [Gibbons]. | The (weakly) dominant strategy used in Vickrey auctions is to bid the valuation $v_i$ for player $i$. Strategically equivalent to the English auction protocol. |

Table 2. Main auction types and corresponding strategies

## 3.1 Terms and extensions to the main auction protocols

In many real world situations, competition and negotiation involve many quality dimensions in addition to price. In Rothkopf and Harstad's critical essay, the authors

outlined how it would be useful to expand their limited focus, because isolated, single good auctions are not the most common or interesting auction type from a practical perspective. As a result there have been several extensions to the traditional auction paradigm in recent years, which are further discussed below.

One active field of study has been *multiple unit* and *multi-object* auctions. At multi-unit auctions, the objects for sale are assumed identical, so it matters not which unit a bidder wins but rather the aggregate number of units he wins. At multi-object auctions, the objects for sale are not identical, so it matters to a bidder which specific objects he wins. Thus an example of a multi-object auction would involve the sale of an apple, orange, and a pear, while an example of a multi-unit auction would involve the sale of three identical apples. In the auction's simplest case, the bidders are allowed to buy only one unit of merchandise. In the more realistic case, such restrictions cannot be imposed. The consequence of the additional quantity dimensions is that traditional bidding strategies and auction design mechanisms should be reconsidered and adjusted. As Bapna et al, and Rothkopf and Harstad, among others have pointed out, the strong theoretical results obtained for isolated single good auctions, are not necessarily transferable to the more complicated multiple unit situation.

Another extension is the development of *combinatorial auctions*, in which bidders desire to buy or sell bundles of goods rather than one single good. For example, a seller may want to sell several kinds of related goods where many bidders may have preferences over a combination of items. After the seller receives all the bids, it will decide a non-conflicting allocation among these goods that maximizes its revenue. These sorts of auctions are involved in many situations in the real world especially the computational issues associated with winner determination and final allocation [Kelly]. For example in the sale of the Germans spectrum licences, bidders placed bids on different combinations of spectrum licenses. However, combinatorial auctions are currently rare in practice. The main problems confronted in implementing these auctions are that they have computational uncertainty, in that there is no guarantee that the winning bids for such an auction can be found in a reasonable amount of time when the number of bidders become larger, and that the auction is cognitively complex and can lead participants to pursue perverse bidding strategies [Kelly].

*Double-sided auction* is a further auction type extension. The most common type of this auction type is the Continuous Double Auction (CDA), which allows buyers and sellers to continuously update their bids at any time in the trading period. This type of auction is easy to operate, efficient and can quickly respond to changing market conditions. A variety of CDA models have being constructed [Easley] and these vary in terms of whether bids/asks are for multiple or single units, whether unaccepted offers are queued or replaced by better offers and so on. Nevertheless all these protocols allow traders to make offers to buy or sell and to accept other trader's offers at any moment during a trading period. The messages exchanged generally consist of bids (offer to buy) and asks (offers to sell) for single units of the commodity, and acceptances of the current best bid or ask. Several bidding strategies have been proposed in the literature. The ZERO Intelligence strategy [Gode], generates a random bid within the allowed price range decided by the agent's budget constraint. The adaptive agent bidding strategy is based on stochastic modelling of the auction process using a Markov chain [Park]. A sequential bidding agent method using dynamic programming is proposed in [Tesauro]. In [He , 2003], heuristic fuzzy rules and fuzzy reasoning mechanisms are used to determine the best bid given the state of the marketplace.

Another extension to the traditional auction paradigm is *multidimensional auctions*, also referred to as multi-attribute auctions. Multi-attribute (reverse) auctions combine the advantages of auctions, such as high efficiency and speed of convergence, and permit negotiation on multiple attributes with multiple suppliers in a procurement situation. A multi-attribute auction is defined "*as an item characterized by several negotiable dimensions*" and first arose in the tenders and procurement area [Dasgupta]. The advances in information technology also allow the use of varied and more complex auction mechanism, where Fieldman [cf. Bichler] stated that ''*We've suddenly made the interaction cost so cheap, there's no pragmatic reason not to have competitive bidding on everything*''. If the multidimensional auction has the variable quantity, it is referred to as *multiple issue* auctions. Laffont and Tirole, describes many of the critical issues in procurement negotiations from an economics point of view and also mention the need for a generalization of auction theory to so called "*multidimensional bidding*". Perhaps since multidimensional/multiple issue auctions hold great promise for the improvement of B2B transactions, their development has largely been practice driven. Generalizations of standard auction theory to the multi-attribute case has been discussed by Thiel, Che, Branco and more recently David et al, and De Smet.

An important distinction to make with regards to auctions is that there exist forward or reverse auctions. In the forward auction the seller offers a product to numerous buyers, where the seller "controls" the market because a product is being offered that is in demand by a number of buyers. The price offered by the buyer continues to increase until a theoretical rational market price is met in the market. Supply and demand sets the price. In a reverse auction, the buyer "controls" the market because the item being offered is available from a number of sellers. The price offered by the sellers continues to decrease until a theoretical rational market price is achieved. The basic premise of a reverse auction is that a sufficient supply exists and seller's profit margins are sufficient to offer reduced prices. The reduced price will be offered because the suppliers can instantaneously observe the prices being offered by other sellers [Smeltzer, Carter].

## 4. Electronic marketplaces (eMarkets)

The previous sections described how optimal markets are designed using techniques such as Game theory and Mechanism design. They outlined how automated negotiation techniques aim to overcome the problem of "leaving money on the table" in the negotiation process and how auctions have been proposed (with the use of intelligent software agents) to overcome this problem. This section will describe the main elements that constitute real world eMarkets and a classification scheme to help distinguish and provide a comparison of eMarkets currently in existence.

A multi-agent eMarket is highly complex, possessing a large number of attributes connected to its architecture such as security, tools for communication between agents, and distribution of roles played by agents and the marketplace. According to He et al, it is important to classify eMarkets according to some attribute, where He et al, defines the most important classification attribute to be the negotiation attribute. In negotiations the topology can be classified according to:

*Nature of interactions between agents* – which is important for an eMarket to distinguish whether participants are allowed to negotiate on a multilateral basis i.e. with several other participants or not. On either side – on the buyer or sellers side – one or more participants

may be negotiating. Denoting the seller as M ("Merchant") and the buyer as C ("Consumer"), Figure 1 shows the three possible situations given by models A, B and C.

*Number of negotiating factors* – is an important characteristic in every negotiation as it represents the dimension of the space of negotiation issues. In more complicated "real" cases, a number of issues relating to price, quality, penalties, terms and conditions may be discussed i.e. multidimensional.

*Whether the negotiation constraints are fuzzy or crisp* – the preferences regarding the negotiation issues may also be represented as either crisp or fuzzy, which makes it possible to evaluate a proposal and generate a counter proposal based on a certain strategy. If the issues are crisp then the preferences for these issues cannot be changed to generate a proposal or counter proposal, where if the issues are fuzzy then the various entities can truly negotiate by proposing values outside of their preferences.
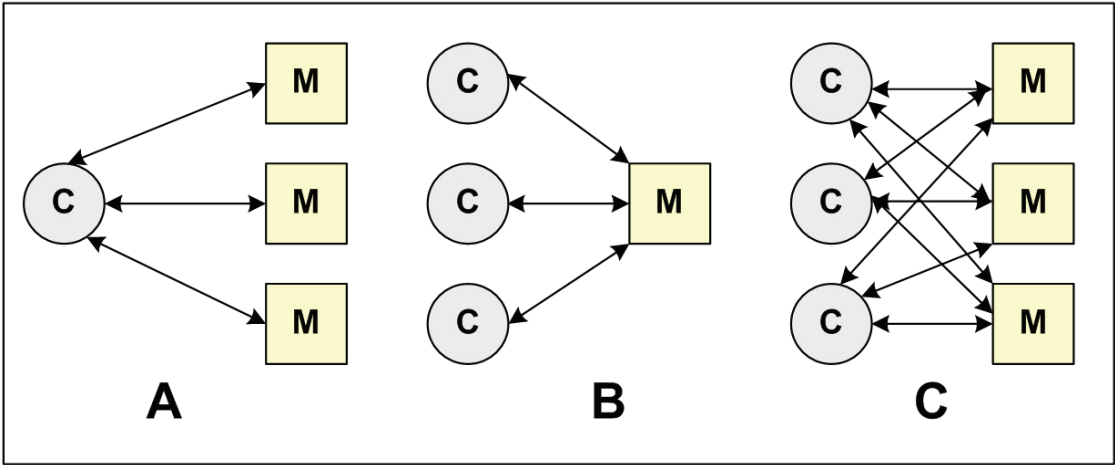


Fig. 1. Three models of competitive negotiation in eMarketplaces

Using the above attributes, Kurbel developed a classification scheme presented by using a technique of morphologic boxes, as shown in Table 3, where the field 'Type of Negotiation' corresponds to nature of interactions between entities i.e. A, B or C denoted in Figure 1. In addition to the classification technique presented by He et al, Guttmann et al, outlined how it is useful to explore the roles of agents as mediators in B2C and B2B eCommerce in the context of a common model, such as the Customer Buying Model (CBB) and the Business Buyer Model (BBT). However this classification scheme is not presented within the scope of this chapter, for further information please see the associated literature. Based on the used and presented classification scheme a survey of well known eMarkets is presented in the section below.

| Criterion | Possible Values | | |
|---|---|---|---|
| Type of e-marketplace | B2B | B2C | C2C |
| Type of negotiation model | 1:n (A) | m:1 (B) | N:m (C) |
| Negotiation Issues | One issue (price) | Many Issues | |
| Type of consumers constraints | Crisp | Fuzzy | |
| Type of merchants constraints | Crisp | Fuzzy | |

Table 3. Classification of controlled multi-agent e-marketplaces

## 4.1 Survey of electronic marketplaces (eMarkets)

Andersons Consulting's BargainFinder [Krulwich] was the first shopping agent for on-line price comparisons. Given a specific product, the BargainFinder agent requests its price from nine different merchant Web sites using the same request from a Web browser. The retailers play passive roles in this process, they just provide information to the buying agents. Although a limited proof of concept, BargainFinder offered valuable insights into the issues involved in price comparisons in the on-line world. However, value added services that merchants offer in their Web sites are bypassed by BargainFinder as it compares merchants based on price alone. Strictly speaking, eMarkets like BargainFinder are not multi-agent eMarkets because the merchants are statically represented through information about their products and not through software agents. Neither are the consumer's agents sufficiently intelligent as they possess some autonomy and very little features for cooperation. Nevertheless, some of these online shopping markets can be regarded as important steps on the way to multi-agent eMarkets.

Another similar example to BargainFinder is Priceline[1] which carries out the same set of tasks for airline tickets, hotel rooms and cars. However a more important contribution within this domain is Jango [Doorenbos], which can be viewed as an advanced BargainFinder providing a more intelligent solution by having the product requests originate from each of the consumers Web browsers instead of from a central site as in BargainFinder. Jango's modus operandi is simple: once a shopper has identified a specific product, Jango can simultaneously query merchant sites for its price. The results allow a consumer to compare merchant offerings based on price. However in many cases price is not the only important factor to the user. Other relevant issues, for example, might include delivery time, warranty and gift services. Also many merchants prefer their offering not be judged on price alone. Naturally the importance of different attributes will vary between consumers and so there needs to be a way for this information to be easily conveyed to the agent.

This limitation was overcome in the Frictionless[2] scoring platform, "*vendor scorecards*" a form of multi-attribute auction that was used to measure the performance of suppliers. For example, when evaluating the performance of different laptop computer suppliers, the key factors considered include reliability, responsiveness, environmental friendliness and business efficiency. A total score is then calculated for each supplier based on the weighted score of these individual constituent components. Although quick and easy to use, the Frictionless engine neglects one essential aspect of decision making in a vague environment with fuzzy constraints and preferences. A consumer has no means to enter into the system how important the different negotiation issues or product features compared to each other. All are assumed to be equally important. This problem was tackled by the Active Buyer's Guide System developed by Active Research, Inc. [Kurbel] The users are not only asked how desirable are certain product features for them but also how important is each product feature is when compared to others, and even how important are certain combinations of features compared to other combinations.

Two further eMarkets are MAGMA [Tsvetovatyy] (Minnesota AGent Marketplace Architecture) and MAGNET [Collins] (Multi-Agent NEgotiation Testbed) developed by

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[1] http://www.priceline.com/

[2] http://www.frictionless.com

University of Minnesota. MAGMA was an attempt to develop a prototype of an agent-based eMarket together with additional infrastructure including a banking system, communication, transport and storage system, plus administrative and policing systems. MAGMA includes trader agents, which are responsible for the buying and selling of goods and negotiating prices, and an advertising server for searching and retrieving adverts by categories. Negotiation is based on the Vickrey auction, where bids are submitted in written form with no knowledge of bids from others where the winner pays the second highest amount. In contrast to the MAGMA system, the MAGNET eMarket was intended to provide support for complex agent interactions such as automated contracting in supply-chain management. Evaluation of the bids received is based not on cost but also on time constraints and risk, providing a very simple multi-issue negotiation technique.

MIAMI Marketplace (MIAMAP) [Esmahi] is an open virtual eMarket where agents process their marketing transactions, providing a generalised mediation model that supports a variety of transactions types, from simple buying and selling to complex multiagent contract negotiations. The negotiation strategy presented from this work takes advantage of the services located within the market to construct beneficial contracts. In its findings Esmahi, states that the introduction of an explicit mediator can help resolve conflicts and add value to multiagent contracting. These eMarkets and the differences between them are compared according to method outlined in [Kurbel] the results of which are shown in Table 4.

Two further notable eMarkets specifically within the domain of telecommunications are the Digital MarketPlace (DMP) [Irvine] and the Telecommunication Service Exchange (TSE) [Griffin]. These eMarkets have been proposed to assist mobile users in being able to exert their bargaining power. This problem has emerged due to the fact that at present, mobile users are typically tied to their service provider via a long term contract lasting usually 12 months or more. Within this time mobile users cannot switch from one service provider to another to avail of special offers and services that the alternative service provider may be capable of offering. This causes an inefficiency of competition in telecommunications from the mobile user's perspective. However, allowing consumers to purchase services on a per request basis, while at the same time maintaining their contract with their chosen service providers however would provide more competition within the sector, and will force service providers to better serve the interests of users.

|  | Neg. Model | Type of Neg. | Issues | Type of consumers constraints | Type of merchants constraints |
|---|---|---|---|---|---|
| **BargainFinder** | A | Search and comparison | Price | Crisp | Crisp |
| **Frictionless** | A | Search and comparison | Price, product features, merchants services | Fuzzy | Crisp |
| **Active Buyers Guide System** | A | Search and comparison | Price, product features | Fuzzy | Crisp |
| **MAGMA** | A | Auction | Price | Fuzzy | Fuzzy |
| **MAGNET** | A | Auction | Price, time, constraints, risk | Fuzzy | Fuzzy |
| **MIAMAP** | A | Mediator | Cost, price, risk | Fuzzy | Fuzzy |

Table 4. Comparison of eMarkets

The DMP presents one such solution to this problem, where mobile users can purchase calls on a per call basis. Internally, the DMP adopts an eMarket where Buyers, service providers and network operators are represented by their respective agents such as: User Agents (UA); Service Provider Agents (SPA); and Network Operator Agents (NOA). The UA are responsible for acquiring the mobile user's preferences over attributes such price and QoS. Upon receipt of this request the UAs initiate an auction with the SPAs using a variant of First-Price Sealed-Bid (FPSB), where the buyer selects the bidder which maximises its objective function, while meeting its valuation. Although the system allows the User Agent (UA) to specify their requirements from a multi-attribute perspective, when the Service Provider Agent (SPA) receives the request it does not formulate a bid based on these attributes. Instead it responds with a single attribute, price when is then used by the UA along with the SPA performance rating (or commitment) to determine the winner of the auction round. This limitation inherently lies in the auction protocol chosen, First Price Sealed Bid, where it prevents the user from correctly evaluating, what it wanted in the original request to what it actually received in the call in terms of these attributes. It also prevents the UA in performing a proper comparison between the various service providers. The DMP is classified according to [Guttman] scheme below in Table 5.

| Criterion | Possible Values | | |
|---|---|---|---|
| Type of e-marketplace | B2B | B2C | C2C |
| Type of negotiation model | 1:n (A) | M:1 (B) | n:m (C) |
| Negotiation Issues | One issue (price) | | Many Issues (partially) |
| Type of consumers constraints | Crisp | | Fuzzy |
| Type of merchants constraints | Crisp | | Fuzzy |

Table 5. The Digital Marketplace (DMP) morphologic box classification

The TSE on the other hand supports both B2C and B2B transaction allowing mobile users to purchase services on a per request basis and also allows the dynamic formation of Virtual Organisations in the B2B to create composite services using a Service Oriented Architectural (SOA) approach to service provisioning. While the internal architecture is similar to the DMP with the existence of Buyer User Agents (BUA), SPA and NOA, the TSE also has two notable additional agents, those being the Trusted Intermediary Agent (TIA) and the Better Business Bureau Agent (BBBA). The TIA essentially acts as the auctioneer in the eMarketplace and is responsible for acting on behalf of the buyer in the market. The BBBA is a similar to the Better Bureau Agent employed in Kasbah [Chavez], where post purchase feedback and consumer satisfaction is monitored to provide a rating of the service provider in the eMarketplace. The negotiation model employed in the TSE is similar to that of MAGNET [Collins] using call for proposals, propose and accept/reject message sequence. However, the TSE allows the BUAs to specify their requests in terms of multiple attributes as well as the relative importance of each attribute in terms of each other using the multi-attribute auction protocol. The various SPA bids are then returned to the BUA and the winner is determined using a scoring function. A unique and novel feature of the TSE is that it is an exchange market infrastructure, as advocated by Collins et al, facilitating two separate but co-related markets, the B2B and the B2C. Table 6, further describes the TSE under the classification scheme discussed in [Guttman].

Online auctions are doubtless the largest class of Internet-based eMarketplaces. There are literally thousands of auctions both in the B2B, B2C and C2C areas. Bean and Segev (1998)

examined 100 online auctions and analyzed their characteristics. Examples of these marketplaces include eBay and Amazon, which both use a variant of the English auction to sell its goods over the Internet. To sell something on eBay, one has to provide a description of the item together with some constraints including payment method, where to ship, who will pay for the shipment, minimum bid and reserve price. In fact by providing this information the seller initializes an agent to negotiate about one issue – price. On the bidder side, one can employ a "phantom" bidding service that utilizes the common bidding strategy of 'sniping'. Such examples include eSnipe and Phantom Bidder. The Fishmarket [Napoli] electronic auction house is another example of an eMarketplace that uses the age-old institution of a fish market using the Dutch bidding protocol.

| Criterion | Possible Values | | |
|---|---|---|---|
| Type of e-marketplace | B2B | B2C | C2C |
| Type of negotiation model | 1:n (A) | M:1 (B) | n:m (C) |
| Negotiation Issues | One issue (price) | Many Issues | |
| Type of consumers constraints | Crisp | Fuzzy | |
| Type of merchants constraints | Crisp | Fuzzy | |

Table 6. The TSE characteristics for Negotiation Model A

## 5. Agents and eMarkets

Woolridge et al defined an agent as a "computer system, situated in some environment that is capable of flexible autonomous actions in order to meet its design objectives". Agents over the past number of decades have been applied to a wide range of applications, not least in the area of automated negotiation and auctions. In recent years initiatives such as the Trading Agent Competition (TAC) have attempted to drive research forward to enable scientists to evaluate programmed trading techniques in a market scenario by competing with agents from other design groups [Petric]. The following section will outline where agent technology has made the most impact with a particular emphasis on the topic of this chapter, eMarkets and auctions.

Within the area of Grid computing – the agent and grid communities are both trying to address the problem of "*coordinated problem solving in dynamic, multi-institutional (Virtual) Organizations*". Within this objective the Grid community has historically focused on what Foster et al, refers to as the "*brawn*" i.e. an interoperable infrastructure for secure and reliable resource sharing within dynamic and geographically distributed Virtual Organization (VO), while the agent community has focused on the "*brains*" i.e. on the development of concepts, methodologies, and algorithms for autonomous problem solvers. According to Foster et al, integrating the '*brawns*' of the grid, with the '*brains*' of the agent could result in "*a framework for constructing large scale, agile distributed systems that are qualitatively and quantitatively superior to the best practice today*".

Because of the horizontal nature of agent technology, it is also envisioned according to Luck et al, that the successful adoption of agent technology with Web services will have a profound, long term impact both on the competitiveness and viability of IT industries and also on the way in which future systems will be conceptualized and implemented. With Web services, the World Wide Web Consortium (W3C) has described agents as the "*running programs that drive Web services – both to implement them and to access them as computational*

*resources that act on behalf of a person or organisation*". In the previously discussed Telecommunication Service Exchange (TSE), the implementation of the B2B market within the exchange focused on dynamic Web service composition, using automated negotiation techniques and multi-attribute auctions to decide which atomic service element best suits a service provider's non-functional Quality of Service (QoS) requirements [Griffin].

A key aspect within eMarkets is the eCommerce and negotiation activities of such markets. Within these, agents are used to fully realise the economic benefits of its existence, where according to He et al "*Electronic Commerce is the most important allocation for Agent technologies, because it is reality-based and constitutes a massive market*". As a result the adoption of agent technology is a central element to the operations within any eMarket, where these agents negotiate of behalf of their owners. Automating these activities through the use of agents can save time, and in complex settings it has been shown by research by Das et al, that when agents and humans participate simultaneously in a realistic auction, the software agents consistently produce greater gains compared to their human counterparts. The application of agents in B2B eCommerce transactions has been viewed as particularly promising, since manual bidding would obviously not be practical, and negotiations in such eMarkets would have to be preformed by the selling and buying agents with sophisticated agent strategies. In B2C and C2C eMarkets agent technology is not foreseen to make as big an impact. The reason for this is that human customers like the bidding frenzy and they enjoy placing the bids and the entertainment value of an online auction is an important component of the experience [Beam, 1997]. The disadvantage of such frenzied actions is that the participants sometimes can fall victim to a phenomenon known as the "winners curse".

As previously stated these eCommerce transactions take place within an eMarket, where Section 5 provided an in-depth overview of existing implementations. In order for software agents to represent their human owners within the eMarket they need to communicate with each other. Such communication is normally represented through some kind of Agent Communication Language (ACL) and is used to share information and knowledge among agents in distributed computing environments, but also request the performance of a task. The main objective of ACL is to model a suitable framework that allows heterogeneous agents to interact and to communicate with meaningful statements that convey information about their environment or knowledge.

The most recent evolution of ACLs is the draft standard proposed by the Foundation for Intelligent Physical Agents (FIPA). This foundation is a non-profit association whose objective consists of promoting the success of emerging agent-based technology and was officially accepted by the IEEE at its eleventh standards committee meeting in June 2005. It operates through an open international collaboration of companies and universities who are active members in the field. FIPA assigns tasks (ontologies, semantics, architectures, gateways and compliance) to technical committees, each of which has primary responsibility for producing, maintaining and updating the specifications applicable to its tasks. FIPAs Agent Communication Language (FIPA-ACL) is based on speech act theory and messages are considered to be communicative acts, whose objective is to perform some action by virtue of being sent. FIPA-ACL also defines a set of interaction protocols, as detailed in Table 7 which deal with pre-agreed message exchange protocols for ACL messages. What is clear from the Table 7 is the incorporation of existing standard auction protocols into FIPA interaction protocols, demonstrating a clear importance of the use of agent technology with auction protocols.

| FIPA Identifier | Title of Interaction Protocol | Function |
|---|---|---|
| SC00026 | Request | Allows one agent to request another to perform some action |
| SC00027 | Query | Allows one agent to request to perform some kind of action on another agent |
| SC00028 | Request When | Allows an agent to request that the receiver perform some action at the time a given precondition becomes true |
| SC00029 | Contract Net | One agent takes the role of manager and wishes to have some task preformed by one or more other agents and further wishes to optimize a function that characterizes the task. For a given task, any number of the participants may respond with a Proposal message |
| SC00031 | English Auction | Auctioneer calls are expressed in Call for Proposals (cfp) acts, and are multicast to participants in the English auction. Participants propose bids in a propose act, and the auctioneer notifies winner in an accept-proposal act |
| SC00032 | Dutch Auction | Models the Dutch auction by using a series of acts such as inform-start-of-auction, cfp, propose, accept and reject proposal |
| SC00033 | Brokering | Is designed to support brokerage interactions in mediated systems and in multi-agent systems. A broker is an agent that offers a set of communication facilitation services to other agents using some knowledge about the requirements and capabilities of those agents |
| SC00034 | Recruiting | Is designed to support recruiting interactions in mediated and multi-agent systems, where a recruiter is another type of broker agent |
| SC00035 | Subscribe | Allows an agent to request a receiving agent to perform an action on subscription and subsequently when the referenced object changes |
| SC00036 | Propose | Allows an agent to propose to receiving agents that the initiator will do the actions described in the propose communicative act when the receiving agent accepts the proposal |

Table 7. FIPA ACL Interaction Protocol

## 6. Conclusion

In summary, it is important to note that the Internet does not really change much of the fundamental characteristics of the general negotiation process. However the expansion and integration of the Internet into our everyday lives has resulted in work being conducted to support the ever increasing demand of mostly B2B eCommerce transactions, where according to [cf. Bichler] "*Internet based electronic marketplaces leverage information technology to match buyers and sellers with increased effectiveness and lower transactions costs, leading to more*

*efficient "friction-free" markets*". The complexity to support such eMarkets lies in the fact that the parties involved in these transactions are located across geographically distributed locations with complex requirements that will form part of their trade agreements. As a result in the future, market design will play an ever more important role in the automated negotiation process, as sellers and service providers will want to ensure that the outcome is efficient giving them the highest utility possible. Of course, auctions play a crucial element in automated negotiation and while a huge variety of auctions exist, it is important to note that some of the more interesting auction types such as multi-attribute auctions consider multiple considerations in the negotiation. As a result, multi-attribute auctions will play a vital element in B2B eCommerce in the future. To automate such negotiations in B2B eMarkers, it is envisioned that agents will negotiate on behalf of their human owners, with implemented strategies calculated using Game theory to ensure the highest utility from the process.

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**Multiagent Systems**

Edited by Salman Ahmed and Mohd Noh Karsiti

Multi agent systems involve a team of agents working together socially to accomplish a task. An agent can be social in many ways. One is when an agent helps others in solving complex problems. The field of multi agent systems investigates the process underlying distributed problem solving and designs some protocols and mechanisms involved in this process. This book presents an overview of some of the research issues in the field of multi agents. It is a presentation of a combination of different research issues which are pursued by researchers in the domain of multi agent systems as they are one of the best ways to understand and model human societies and behaviours. In fact, such systems are the systems of the future.

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