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# Knowledge-based Coordination and Support for Software Agents in Supply Chains\*

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## Abstract

Auctions and negotiations are key exchange mechanisms used in supply-chain transactions involving complex goods (including services) that have high profit impact. Negotiation was a prolonged and difficult process making interactions with several partners simultaneously impossible while auctions' disadvantage is their focus on price and inability to make distinctions between individual buyers and/or sellers. Providing a single negotiator with software agents that are able to support her activities, advise her on the best course of action, and act on her behalf allows her to engage in multiple interactions with human and software-based counterparts. In the paper we discuss the ANIMA system, designed to support negotiators engaged in multiple bilateral negotiations, and its loose integration with the Invite multilateral e-negotiation system. We also present the results of the first two phases of the multilateral experiments in which human and software agents participate.

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## 1. Introduction

Auctions and negotiations are key exchange mechanisms used in supply-chain transactions involving complex goods (including services) that have profit impact (Handfield and Straight, 2003; Bajari, McMillan et al., 2009). Traditionally, a negotiation was a prolonged process during which the parties exchanged information on goods characterized by multiple attributes (Ferrin and Plank, 2002). Online auctions increased efficiency and effectiveness of the procurement processes (Smart and Harrison, 2002); their disadvantage is their focus on price and an inability to make distinctions between individual buyers and/or sellers (Emiliani, 2000). We designed procedures and systems for multi-attribute auctions and multilateral negotiations, and experimentally proved their effectiveness in supply chain procurement (Kersten, Pontrandolfo et al., 2012).

An analysis of the experiments' data led us to realize that it is not only possible but also advisable to augment these systems (Imbins for negotiations and Imaras for auctions) with knowledge-based components and design software agents capable of supporting human participants and engaging in e-market activities on their behalf. The potential advantages include:

1. Helping buyers to differentiate between individual service providers and/or sellers when they use both auction and negotiation mechanisms;
2. Automating adjustments to the auction parameters that correspond to the buyer strategy and type of procured goods;
3. Employing software agents to bid and negotiate on behalf of providers and sellers;
4. Employing software agents to analyse offers from multiple negotiating counterparts (sellers) and select a few for the buyer's assessment; and
5. Providing software agents with the capability of formulating context-dependent arguments and counter-arguments which reflect the agent's principal strategy, objectives and preferences.

This paper discusses the first phase of a project on software enhanced multi-issue multilateral negotiations. The data collected from the initial experiments shows that agents are able to negotiate with humans and, using a knowledge base, adapt their strategies to those that humans employ. These results will be used in the second phase for the design of a knowledge base that will be accessible by human and artificial users of Imbins (Kersten, Pontrandolfo et al., 2012).

Following a literature review given in Section 2, we discuss, in Section 3, design principles, and architecture of the proposed software environment. This environment includes components and agents that interact with Imbins, the multilateral e-negotiation. The environment is loosely integrated following the principles formulated in the Shaman architecture (Kersten, Kowalczyk et al., 2008). Results of experiments with our first generation of software agents are given in Section 4; they are followed by discussion on the results from the first phase of this project.

## 2. Related work

### 2.1 Negotiation software agents

Research on automated negotiations involving software agents has been extensive. One well-known early work in this direction was the construction of the Kasbah electronic marketplace (Chavez, Dreilinger et al., 1997; Maes, Guttman et al., 1999). Targeting primarily the c2c domain,

the marketplace allowed human users to configure agents, which would then be sent to the marketplace to negotiate with each other. Several types of agents ranging from competitive to conceding were provided. Negotiations included a single issue, i.e. price.

In B2B applications software agents have been proposed for automating various aspects of supply chain management. For example, Wang et al. (2009) present an agent-based architecture for dynamic supply chain formation. The agents act as brokers representing various entities within a supply chain; they negotiate agreements with each other in order to expand the chain. Huang et al. (2010) propose an architecture for automated negotiations between agents representing businesses and consumers. The buyer agents incorporate such components as searcher and negotiator, while seller agents feature a negotiator module whose strategy was set by the sales department.

There have been some experimental studies of human-to-agent negotiations. Huang and Lin (Huang and Lin, 2007) describe an agent representing a salesperson that employed persuasion and negotiation techniques while interacting with a customer. Their findings suggest that persuasion increased buyers' product valuation and willingness to pay. Negotiation increased the seller's surplus. Another related experimental work investigates the effects of framing on the subjective variables when employed by agents using persuasion/ argumentation tactics (Yang, See et al., 2010). The authors did not find significant differences in buyer satisfaction with the settlement or with the counter-part when compared across different frames.

It has been argued by many that complete automation of real-life negotiations, particularly in business contexts, does not seem to be a viable solution (e.g., Lin and Kraus, 2010). Automation in general is applicable only when tasks are well-structured, which is rarely the case in many business situations. However, since efficient policies can be set for multiple daily interactions with customers regarding products and services sales, it seems that a relatively high level of automation may be feasible.

## 2.2 Proactive decision and negotiation support

Sharing responsibilities between human negotiators and negotiation agents has been given some attention. Chen, Vahidov et al. (2005) propose a system in which agents actively support human decision-making in the negotiation process. The role of the agent is to: (1) advise the human user on the acceptability of the received offer, (2) help with the preparation of the counter-offer, and (3) critique offers composed by the user when they did not put forward this user's interests.

Vahidov and Kersten (2004) formulated a framework for situated decision support. Situated decision support systems maintain close links with the target problem domain by means of sensors and effectors as it monitors implementation of decisions and reacts to detected deviations. It includes a "manager" agent that enables reactivity and pro-activeness of the system. Based on the situated DSS concept, Vahidov (2008) proposed an agent-based approach to manage multiple simultaneous negotiations.

Kersten, Kowalczyk et al. (2008) proposed the overall framework for systems hosting various market mechanisms enabling human and agent participants to transact called "Shaman". In Shaman, various systems implement negotiation and auction mechanisms. Additionally, they may also incorporate decision support tools, as well as agents for the support and conduct of negotiations. These systems can inter-operate so that the user of one system may negotiate, for example, with the agent hosted by another system. Such an arrangement allows for the use of existing system solutions featuring exchange mechanisms. Hence, there is no need to develop

them from scratch.

## 2.3 Knowledge

In a recent article, Lin and Kraus (2010, p. 78-80), describe the negotiation environment in which software agents operate. The environment comprises models of the negotiation problem, participants and the process. We use the same typology as the one used in negotiations among humans. This allows us to distinguish between interacting entities (human and software) from stakeholders and other external influences (i.e., the environment). Furthermore, there is no single environment because human and software participants are likely to operate in their own environments.

If we focus on the negotiation per se, then we can identify three types of models: negotiator, problem and process (Kersten and Lai, 2008). Different instances of these three models have been implemented in negotiation support and e-negotiation systems (op. cit.)(see Kersten and Lai, 2008, for review). The degree to which the negotiator is formally represented in a model corresponds to the degree of automation of its activities (from communication facilitation to full automation). When a significant part of the negotiator's activities requiring knowledge is modeled and embedded in software, then we call it a negotiating software agent (NSA).

Many models embedded in NSAs are derived from decision analysis (Kraus, 2001); the assumption is that both the agents and their human or software counterparts exhibit full economic rationality. The decision-theoretic models could be quantitative and/or qualitative but the purpose remains the same; namely maximization of the agent's own or the human principal's utility which is a function of the negotiated issues (Sycara, 1996; Maes, Guttman et al., 1999; Benyoucef, Alj et al., 2001; Chen, Vahidov et al., 2005).

Efforts to make the NSA more similar to human negotiators and/or capable of communication other than the one directly transformable to utility values led to the enrichment of the negotiator's model and consequently to richer NSA's capabilities, including their consideration of the process and its outcomes (Traum, Marsella et al., 2008; de Melo, Carnevale et al., 2011). For these agents the negotiation outcomes go beyond utility maximization, they can assign importance also to trust building, future opportunities, and other non-issue specific outcomes.

Human negotiators have different attitudes, approaches, and perspectives. They may be cooperative, individualistic and competitive as well as analytic and calculating or emotional and relationship-oriented. The NSAs that possess these capabilities may negotiate better deals for their principals. They can also employ different strategies and adapt their tactics in order to achieve their objectives. In order to engage in negotiations that are meaningful to their human counterparts, they need to integrate several types of knowledge, including: (1) quantitative analytical systems which can be used to assess and compare offers and counteroffers, and determine concession levels, (2) qualitative analytical systems which represent acknowledged rules of behaviour such as rules underlying cooperative, individualistic and competitive behavior, and (3) heuristics which can be used to represent the negotiator's tastes, sensitivities, and emotions (Smith and DeCoster, 1999; Stanovich, 2010).

## 3. The ANIMA system and its environment

This section presents architecture and working principles for Agent-enhanced Negotiation Instances MAnagement (ANIMA) system. The architecture is based on the conceptual frameworks for Shaman and situated decision support briefly discussed above. The central idea is in

combining the computing capabilities of software agents and human judgment to effectively and efficiently manage multiple negotiation threads.

### 3.1 Architecture

Consider the following scenario: A procurement manager needs to purchase a complex and not well defined product. There are several sellers who may be contacted; some are located nearby others far away. Because, the manager needs to clarify the product design, she decides to conduct negotiations with the sellers. One difficulty is that setting sequential negotiations would take a long time and be costly due to travel and other expenses. Engaging in simultaneous face-to-face negotiations with several sellers is impossible due to the sellers' distribution and the need for secrecy. Even if there were a few sellers with whom the manager could meet, the cognitive load could be prohibitive to engage in effective and efficient negotiations. Our proposed solution is that the manager negotiates via the ANIMA system and the sellers (some of them may be human others—software agents) use an e-negotiation system (e.g., Imbins) which directly interacts with ANIMA. The agents that negotiate on behalf of the purchasing manager may make decisions independently, ask the manager for concrete advice or pass an offer they receive to the manager. All communication from the manager is received by the agents who act as both buyers and intermediaries.

The above scenario shows the use of the ANIMA system and its software agents (software intermediaries). Each agent is engaged in one bilateral negotiation, i.e., one negotiation instance. All active agents ( $AB_i, i = 1, \dots, N$ ) are thus jointly engaged in multilateral negotiations; the same as the procurement manager agent ( $AM_{ng}$ ). Agent  $AB_i, (i = 1, \dots, k)$  negotiates with agents  $AS_i (i = 1, \dots, N)$  representing sellers Agents  $AB_i, (i = k+1, \dots, N)$  negotiate with  $(N-k)$  human sellers.

The above scenario shows the use of the ANIMA system and its intermediating software agents (ISA). The major components of the system and the other systems it interacts with are illustrated in Figure 1.

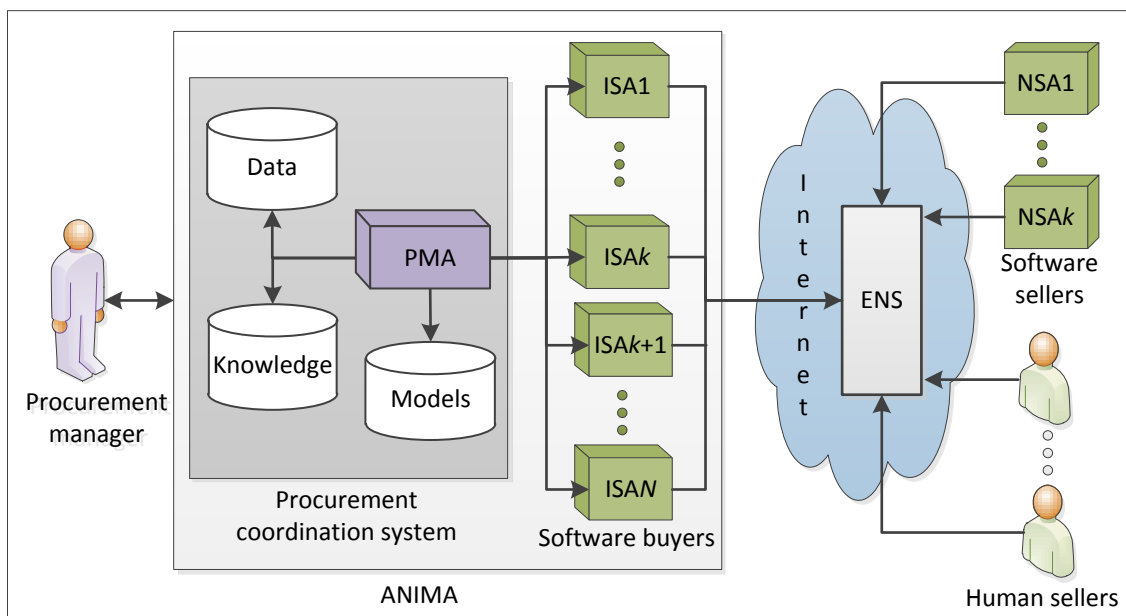


Figure 1. ANIMA's Architecture and its environment

When, in a given procurement situation the number of sellers is identified, ANIMA generates a number of ISA agents so that each one acts as an intermediary in a single negotiation instance. From the sellers' perspective ISA agents are negotiators, however, the ISAs' capabilities are limited and their activities are controlled by a single software agent called the procurement manager agent (PMA). Hence, while every active agent ( $ISAi, i = 1, \dots, N$ ) is engaged in bilateral negotiations they are managed by PMA engaged in  $N$  simultaneous bilateral negotiations (i.e., multilateral negotiations). The PMA agent is also the single point of contact for the procurement manager, who may intervene at any point in the process and who may also be asked by the PMA for advice or a decision.

The ISA agents communicate with their counterparts (human or software) via an e-negotiation system. ANIMA uses the facilities of the Imbins multilateral e-negotiation system <http://invite.concordia.ca/imbins>) to interact with the counterparts in negotiations (Kersten, Pontrandolfo et al., 2012). Imbins keeps track of negotiation instance state variables, and provides data visualization and negotiation support aids to its users. Imbins also manages two-way communication between human and software participants. There are  $k$  negotiation software agents (NSA) that act as sellers and  $N-k$  human sellers, hence there are  $N$  agents generated by ANIMA;  $k$   $ISAi$  agents negotiate with  $k$   $NSAi$  selling agents and the remaining  $N-k$  agents  $ISAi$  negotiate with  $N-k$  human sellers.

The ISA agents receive and assess offers and messages from their counterparts via the Imbins system (see Figure 1). The result of their assessment is used to request clarification, propose a counteroffer which may be accompanied by a message, and/or undertake some other negotiation activity. Because one ISA agent is engaged in a bilateral negotiation the information that this agent conveys to the seller (human or software) needs to take into account the situation of the parallel negotiations. Therefore every ISA passes to the PMA agent the information received from the seller together with its own partial assessment. The PMA agent formulates an overall assessment and decides on key parameters which values shape the ISA's response. The PMA agent may also ask the procurement manager (on whose behalf he operates) to decide on the course of action.

There may be many different divisions of labor and responsibility between the procurement manager, PMA and NSAs. Clearly, the procurement manager has to have ultimate responsibility and the ability to intervene at any point in time. Because of the multilateral type of negotiation and the need to give the procurement manager a single point of contact rather than interact with  $N$  different software agents, we opt for a PMA that is a sophisticated and well supported with knowledge and model bases (see Figure 1). NSA's capabilities are limited to local decisions and wording of messages both defined by the parameters given by PMA.

### 3.2 Negotiating software agents

Negotiation software agents need to have a set of preferences and be able to aggregate them in order to compare different alternatives. They also need an overall negotiation strategy which will allow them to decide on concessions and the content of verbal communication with their counterparts.

Both the concession and the message form and content need to conform to the strategy and also take into account the state of the negotiation and knowledge of the counterpart. In e-procurement, it is also necessary to know the state of the entire process, i.e., the state of every agent. This is because other agents may make commitments that affect the buying capability of the given agent.



In order to associate the NSA's strategy with the content of a message, the agent needs to be able to assess the status of the negotiation. This assessment may, however, lead to strategy modification and, consequently, to the selection of a different offer and/or message.

### 3.2.1 Negotiation problem model

The negotiation problem model describes the object that will be negotiated (product, service or their mix) and the *hard constraints* on the type and characteristics of the object. We define a constraint as hard when no agent can modify it without an agreement given by the procurement manager. The PMA agent may ask about loosening a constraint (e.g., increase the budget) or the manager may initiate a modification.

The types of negotiations considered here include multiple issues (e.g. price, warranty, penalties for delays, etc.). Issues can be represented as a vector  $\mathbf{x}$  of issue values (options), i.e.,  $\mathbf{x} = [x_1, \dots, x_n]$ , where  $x_i$  is a value of issue  $i$  (e.g., price of \$3.25, 1 year of warranty). Issues have the same quality as hard constraints, that is, an issue cannot be removed or a new issue added without the manager's agreement.

Without loss of generality, we assume that issues take discrete values. In case of continuous scale discretization with a required precision can be made. Let  $X_i = \{x_{1i}, \dots, x_{n_i i}\}$  be the set of possible values for issue  $i$ , ( $i = 1, \dots, n$ ). Then the set of all possible offers (i.e., alternatives) is given by:

$$X \subseteq \prod_{i=1}^n X_i. \quad (1)$$

The possible set of alternatives  $X$  may be a subset of the product of the issue sets when not all configuration of issue options are allowable (e.g., warranty of 2 years cannot be given when price is \$2 or less). That is, we have two types of hard constraints: (1) number of permissible single issue options; and (2) number of permissible configurations of issue options, i.e., alternatives.

### 3.2.2 Procurement manager model

The ISA agents may appear and vanish as new counterparts join and depart the negotiation. The task of the PMA agent is to manage the overall process of negotiations by gathering information from the fleet of negotiating agents and advising them on the key parameter values that govern different negotiation threads. In doing so the manager agent relies on the embedded knowledge, as well as the local data and models.

The manager, including her organization, needs to specify the problem model and information which reflects the interests, needs and expectations. The following categories of information describing the manager and her organization relevant for the offer assessment are distinguished:

1. Reservation levels  $RL_i$  established on all or selected issues  $i$ ;  $x_i \geq RL_i$  ( $i = 1, \dots, N$ );
2. Budget ( $B_0$ );
3. Aspiration levels  $AL_i$  established on all or selected issues  $i$ ;  $x_i \geq AL_i$  ( $i = 1, \dots, N$ ); and
4. Breakeven value BV, which is the aggregate of all or some of the issues below wherein no agreement can be reached (BV may be expressed in monetary terms).

Two additional important types of information that the agents require are preferences and concessions; they are discussed in Section 3.2.3

### 3.2.3 Preferences

The PMA agent elicits preferences from the procurement manager using one of the preference elicitation methods (e.g., the Swing method or conjoint analysis). Without loss of generality, we assume that the preferences are aggregated into a utility function which calculates attractiveness of a particular offer:

$$f: X \rightarrow U, \quad U = [0, 100]. \quad (2)$$

The ISA agents access ANIMA's preference and concession-making models as well as a knowledge-base which guides them in: (1) the implementation and adjustment of a concession-making strategy; and (2) composition of messages associated with the selected strategy implementation.

Thus, an ISA has a capability to assess the utility of each offer. Agents representing the procurement manager ( $ISA_i, i = 1, \dots, N$  indicated in Figure 1) obtain preferences and the utility function from the managing agent PMA, this agent gets this information from the procurement officer using one of the known preference elicitation and utility construction procedures.<sup>1</sup>

### 3.2.4 Strategies and concession-making

In addition to being capable to assess any given offer in an offer space the agents also need guidance regarding to what utility level is acceptable at a given stage in current negotiations. This guidance (or strategy) is provided by the concession schedules that describe how the acceptable utility levels change in the course of negotiations depending on time. The utility curves showing the dependency of the acceptable utility level  $u^a(t)$  at time  $t$ , are given for the interval covering the beginning and end of the negotiation session.

An early use of such curves in single-issue agent negotiations is shown in the Kasbah marketplace (Guttman, Moukas et al., 1998). For the agents described in this work we have included the capability of modelling utility curves of up to the 3<sup>rd</sup> power. Thus, using quadratic formula agents we can model a range of individualistic, neutral, or collaborative strategies. In particular, if the second derivative is positive, i.e.,  $d^2u^a(t)/dt^2 > 0$ , then the agent is unwilling to give concessions unless it is pressed by time. Thus, this models individualistic behaviour. Furthermore, the larger its value, the more individualistic the agent will behave. However, if the derivative is less than 0, an agent will concede early, but then slow down as it approaches its reservation level. A near-zero derivative means that the agent gives up equal amounts of utility throughout the negotiation; thus the agent is neither individualistic, nor cooperative. A cubic form of equation allows an agent to model more complex behaviour, such as "first collaborative then individualistic".

Observe that the representation of an individualistic strategy can be fully modelled with a concession function describing solely the agent's utility. Both collaborative and competitive strategies also require consideration of the counterpart's (seller's) utility. This utility may not be known a priori, but it may be progressively approximated during the negotiation. The adjustments may be made by the manager or they may be introduced by the knowledge base of the procurement coordination system. This system may also control the shift from one strategy to another or a strategy modification (e.g., the degree of concessions).

An agent's algorithm works as follows. The first offer made by an agent (acting as a buyer or a seller) is the best possible offer for the agent. Subsequently, when an agent receives an offer, the utility is calculated according to given preference structure and compares to the acceptable

<sup>1</sup> In some experiments the preferences and utility function are given by the experimenter.



utility level at that point in time, is given by the agent's concession curve.

If the utility of an incoming offer is greater than the acceptable level, the agent accepts it. Otherwise the agent generates a counter-offer. While producing a counteroffer the agent starts with the offer sent by the counter-part and applies iterative improvement algorithm to modify it, in order to bring it to the desired utility level. In this respect, the algorithm targets the same objective as the "smart" strategy proposed in (Faratin, Sierra et al., 1998; Faratin, Sierra et al., 2002). The process ends when either the agent or the opponent accepts the offer, or one of the parties terminates the negotiation thread, or when the allotted time expires.

### 3.2.5 Strategies and messages

Apart from sending offers an agent also can send messages to try to induce a desired response from the counter-part. The type of message sent by an agent depends on the values of both situational and internal parameters. Assume  $Z$  constitutes such a set:

$$Z = \{Z_1, Z_2, \dots, Z_l\}$$

An example of such variables includes: the utility of the last received offer, the difference between the utilities of the last offer by the counter-part and the current target utility level; relative time remaining to negotiation completion; absence of offers from the counter-part within the past specified time period, and others. An agent identifies the occurrence of a given specified situation defined on the set:

$$\Theta \subseteq Z_1 \times Z_2 \times \dots \times Z_n.$$

For the identified situation  $\Theta$ , the agent chooses the type of a message based on the mapping

$$g: \Theta \rightarrow T, \quad T = T_1, T_2, \dots, T_N,$$

where  $T_j$  represents a particular type of a message.

A concrete message is chosen randomly from the set of canned-text messages. The mapping is implemented in form of the "If-then" rules. For example, if the distance between the agent's desired utility level and that of the received offer is smaller than some predefined value, the chosen message could be "I think we are getting close to an agreement".

## 3.3 The PMA agent

The negotiating agents are given reservation levels, the utility concession curve, and the preference structure as given in conducting negotiations. These agents may appear and vanish as new counter-parts join and depart the negotiations. The task of the manager agent is to manage the overall process of negotiations by gathering information from the fleet of negotiating agents and advising them on the key parameter values that govern different negotiation threads. In doing so the manager agent relies on the embedded knowledge, as well as the local data and models. The manager agent has its objectives given by the human principal. If the principal is a seller then the objectives may include sales targets, available resources and capacities, as well as other relevant constraints specified for a given planning period. The manager is also given the limits within which it can manipulate the importance factors (weights) assigned to different issues involved in the negotiations.

The manager agent periodically analyses the overall situation in terms of the deviation from the set targets and may intervene by sending the negotiating agents an updated set of control parameters. Let  $D$  denote the set of deviations of key variables describing the overall actual situation from the target values:

$$D = \{D_1, D_2, \dots, D_M\}$$

An example of such deviations includes the difference between the target and the actual unit sales. Then the set of overall situations in which the manager agent could intervene is defined as:

$$\Delta \subseteq D_1 \times D_2 \times \dots \times D_M$$

The manager agent instructs the agents by means of the following mapping:

$$h: \Delta \rightarrow A$$

Here,  $A$  denotes the set of applicable actions. These actions may include adjustments made to the competitiveness level of negotiation agents (adjustment to the concession curve), as well as the adjustments made to their preference structures. Technically, this mapping is performed by the knowledge stored in form of the “If-Then” rules. An example of such rules is as follows:

IF the difference between actual and target unit sales is very large,  
THEN increase competitiveness significantly.

The human user provides the managing agent with the target objective values and constraints. Thus, the manager agent has a limited authority in managing a fleet of negotiation agents involved in multiple negotiation instances. The manager agent advises the human user on the on-going overall situation and generates alerts when the limits of authority are reached.

The human user is responsible for producing the target objectives for the manager agent in terms of sales and resource consumption. This decision-making process is outside the scope of the current work and may be done with the use of a decision support system that helps with the assessment of the impact of decisions on the key business performance variables

## 4. Experiments

### 4.1 Supply chain context

As mentioned earlier, there has been previous work on the application of agents to supply chain management. However, the past work tends to emphasize the large degree of automation of the supply chain management negotiation tasks. In our view, complete automation of business negotiations does not represent a viable solution, as there are many ill-defined and circumstantial and yet critical factors in real-life business contexts that require human judgment. The proposed architecture looks to effectively combine human judgment with the computing power of software agents in managing multiple negotiations.

The work that is closest in the spirit to the current one has been reported by Vahidov and Amini (2009). In that work the authors have proposed the application of situated decision support framework to managing interaction with customers and suppliers in a supply chain. The authors adapted the scenario from the “Trading agent competition” tournament. In that scenario an agent interacts with the suppliers to buy computer parts on one hand and with the customers to sell assembled computers on the other hand. However, their scenario targeted single-issue auctions, rather than multi-issue negotiations.

A business within a supply chain may be in a position to employ various exchange mechanisms. Table 1 describes various configurations of the business’ relationships with its suppliers and buyers where negotiations are involved.

Configurations 1 and 3 as shown in Table 1 are the simplest ones, since negotiation agents may

be used on one side only (e.g. either with suppliers or with customers). The other configurations present interesting challenges to the design of agent-enhanced negotiations. In configurations 2 and 4, bidding is employed on one side or other, and the mix of negotiations vs. auctions requires a design of bidding agents and their coordination with the negotiation agents. In number 5 there are negotiations on both sides and the employment on both sides of managing agents with proper coordination mechanisms may be advantageous.

Table 1. Interactions with suppliers and customers

Configuration	Interaction with suppliers	Interaction with customers
1	Fixed-price	Negotiation
2	Auction	Negotiation
3	Negotiation	Fixed-price
4	Negotiation	Auction
5	Negotiation	Negotiation

While these dynamic configurations are worth investigating, the scope of the present work is limited to employing the negotiations on one side, thus fitting Configurations 1 or 2. Specifically, our initial experiments target software agent – human negotiations where the latter act as customers. Adapting some aspects of the case used in the trading agent competition, we have conducted experiments where the selling agents negotiated the sales of computers to customers.

## 4.2 Design

In order to empirically assess the perspectives of employing negotiation agents in interactions with humans we conducted experiments. These initial experiments did not include the “manager” agents as the purpose was to explore the feasibility and impacts of pairing up humans with agents. However, we did include cases of collaborative and competitive behaviour, as well as the case where behaviour changed in the process of negotiations to emulate the instructions from the manager agent (i.e. its reaction to the overall situation.)

The negotiation case developed for the experimental study involved sales of desktop computers. While normally, within supply chain this would imply selling a batch of machines to customers, to simplify the experimental task, we only considered sales of single computers. There were five issues that included the price, type of monitor, hard drive, service plan, and software loaded. Each option for each issue had a corresponding level of utility (attractiveness), these levels being different for the buyers vs. sellers. In order to calculate the total utility of the offer the issues were assigned different weights. These were then used in an additive utility function to estimate the level of attractiveness of an offer. Agents used this information in order to decide on the acceptability of the received offers and generate offers.

All agents acted on the seller side, and they were not aware of the buyers’ preference structures. The weights were slightly different for sellers than buyers to facilitate tradeoffs, which have been considered one of the key integrative negotiation characteristics (Raiffa, Richardson et al., 2003). Thus, agents would decide on the utility of the next offer first, according to their concession schedules, and then generate the corresponding offer.

The concession schedules included: competitive, collaborative, and competitive-then-collaborative (Figure 2). The competitive agents (CM) tend to make smaller concessions in terms of utility of generated offers in the beginning of the negotiation period. However, as they approach the end of the period, they would start making larger concessions in search of an agreement. Collaborative schedule (CL) implies making large concessions in the very beginning of the negotiation period in search of a quick agreement.

Competitive-then-collaborative schedule (CC) models a more complex behaviour of the agents. In the beginning of the process an agent behaves competitively, however, in the middle of the negotiation period it changes its profile to a collaborative one. Thus, the schedule emulates the situation whereby agent behaviour changes. In this particular case the agent is considered competitive in the beginning. However, if the overall sales volume is lower than expected, the manager agent may decide to move to a more collaborative mode.

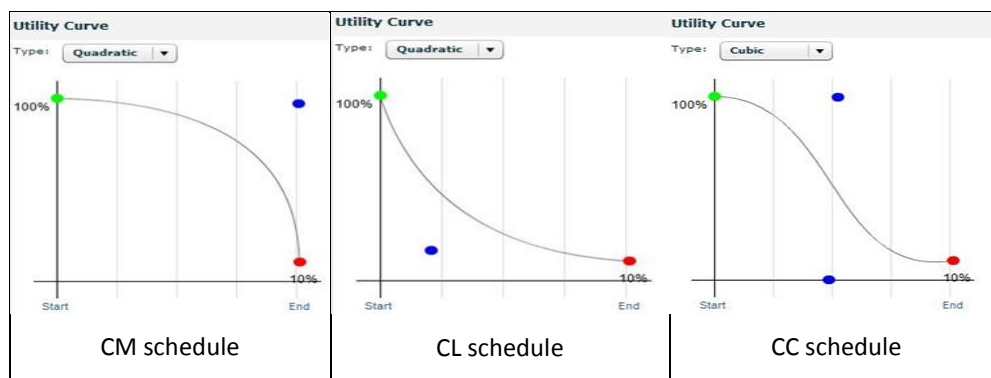


Figure 2. Three concession schedules

In the current work we were interested in the objective outcomes of agent – human negotiations, as well as the perception of humans as to whether they were negotiating with a machine or a human counter-part. The subjects in the study were university students enrolled in the introductory course on information technology. Thus, the negotiation case was well in line with the learning objectives of the course. The treatments included pairing up the subjects with various types of agents described in an earlier section. We also paired up humans with humans in a control group.

The experiment was conducted via the web, whereby subjects could perform their tasks from any location in an asynchronous mode during a two-day period. The subjects were invited to join the negotiations via email containing the link to the system. Negotiations began by sellers making the first offer. The agent sellers then checked for the status of negotiations at fixed intervals of time (every 3 hours). At those points in time, if they had not received new offers, they would wait until the next period of time elapsed. If an offer was received they would evaluate it and would either accept it, or would make a counter-offer. All interactions took place in form of structured offer exchange without freestyle messaging.

Human subjects were free to terminate the negotiation at any time without reaching an agreement with their counter-parts. After either reaching an agreement, or terminating the negotiations the human subjects were asked a question that read: “I was negotiating with: 1) a human; 2) a computer; 3) not sure.”

### 4.3 Results

The distribution of answers depended on the type of the agent strategy employed. For example, in competitive-then-collaborative category a much larger proportion of subjects thought they were negotiating with a human counter-part as compared to those who had an impression they were dealing with a machine (25 vs. 8). This can be explained by the fact that CC concession schedule results in more complex behavior, less obvious behaviour that could be more readily ascribed to humans, rather than machines. Similar, though less prominent results were obtained in competitive agent category (33 vs. 15). On the other hand, the collaborative category was the only one where the number of “human” vs. “machine” responses was equal (21 each). Perhaps, the subjects expected their human counter-parts to be more competitive, rather than conceding.

Table 2 shows the proportions of agreements for different compositions of dyads. The largest proportion of agreements was reached in the collaborative agent category. This is an intuitive result, since collaborative agents make large concessions early in the negotiations process, and thus they have a higher chance of making a deal with the human counter-parts. It is interesting to see that human-to-human dyads have the lowest record in terms of proportion of agreements made. Thus, the agent-involved dyads have reached more agreements than purely human dyads.

Competitive agents were able to reach an agreement in 53% of cases. Competitive-then-collaborative agents made agreements in 75% of cases, falling between the CL and CM categories, but higher than neutral category.

Table 2. Proportions of agreements

Category	Agreements (%)
Competitive	53
Neutral	70
Collaborative	82
Competitive-collaborative	75
Human-human	50

Table 3 compares the utilities of reached agreements for sellers and buyers across different categories. In human-human dyads the sellers achieved much lower utility levels than buyers. This could be explained by the adopted reference frames. Since both sellers and buyers in this category were undergraduate student subjects, they tended to shift the price levels downwards to what they considered to be acceptable regions. Nonetheless, as it can be seen from the table, the human sellers had reached the lowest levels of utility.

Table 3. Utilities of agreements

Category	Seller utility	Buyer utility
All agent categories	46.8	65.6
Competitive	63.2	44.9
Neutral	43.8	69.7
Collaborative	36.5	79.0
Competitive-collaborative	40.4	71.9
Human-human	35.9	73.0

Competitive agents considerably outperformed their human “colleagues” (63.2 vs. 35.9). Collaborative agents did only slightly better than humans, reaching 36.5 utility. However, they had a much higher proportion of agreements than humans. Competitive-then-collaborative agents reached the average utility level of 40.4, and the neutral ones had a slightly higher value of 43.8. Thus, agents did better than human negotiators.

## 5. Discussion

The approach which we propose is novel in the following three aspects:

1. It proposes formal methods for multi-attribute auction and multilateral negotiations which can be experimentally studied and used to build knowledge bases for the human and artificial e-market participants;
2. It proposes an integrated environment in which humans and software agents can collaborate, compete and inform themselves and others; and
3. It proposes a platform for coordination mechanisms in agent-based supply chains, agent-mediated auctions and negotiations, and multi-agent market modelling.

In the first phase of the project we designed negotiating software agents (NSA's) capable of participating in bilateral negotiations. We also conducted mixed negotiation experiments; NSA's were negotiating with humans. The results of these experiments are discussed in Section 4.

In the second phase of this research we designed the e-negotiation system Imbins and software agents that are capable of negotiating via Imbins with a procurement manager. Then, in April 2012, we conducted mixed multilateral multi-issue negotiation experiments. The part of the overall supply-chain environment which was recently developed and experimentally tested is shown in Figure 3; it corresponds to the e-procurement situation depicted in Figure 1 from which the ANIMA system is removed.

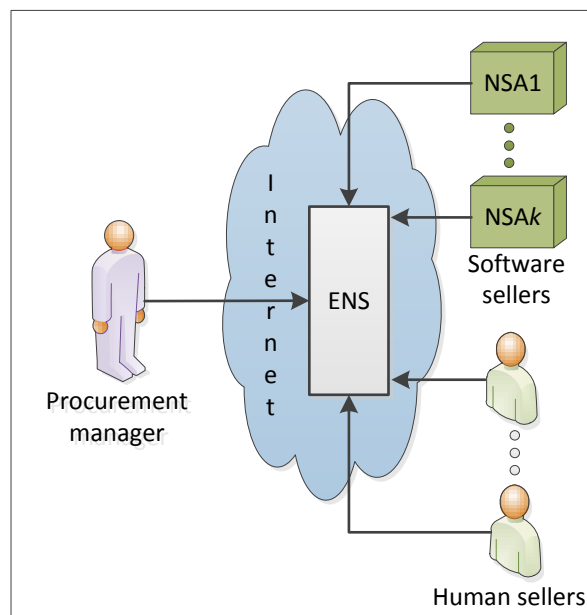




Table 1. Mixed multilateral e-negotiations via Imbins

We conducted a series of experiments in which one buyer negotiated with two or four human sellers and, in some treatments also with one or two NSAs. We ask some buyers to negotiate employing an individualistic strategy and others to employ an integrative strategy; both types received instructions regarding their strategies. Neither the buyers nor the sellers were told about NSAs participation.

Negotiation results, in which the buyer followed a cooperative strategy, are shown in Table 5. In total there were 61 multilateral negotiations with between two and four human sellers and between 0 and 2 NSAs. The agents followed either cooperative or competitive concession tactics. They were able to make offers which were accompanied by messages or send messages to the buyers in which they were requesting information, offers, or explanations. These messages were formulated based on the model presented in Section 3.2.4.

The negotiations took between 62.5 and 100.6 hrs., on average. The most effective and shortest negotiations involved four human sellers. In the longest negotiation there were three human sellers and one NSA; the agent followed a cooperative concession tactic. The agent's tactic appears to make a significant difference because the configuration three human sellers and one competitive NSA took on average 24 hrs. longer to negotiate a contract.

Only cooperative agents reached an agreement, both in the 3+1 and 2+2 negotiation; in the latter there was one competitive and one cooperative NSA. The agents exchanged more offers than the humans who won the contract and they reached a higher profit; human sellers reached 14 in 3+1 negotiations and 17.7 in 2+2 negotiations, while NSA reached respectively 20.7 and 26.2. While in both negotiations there were four sellers; having a competitive NSA seller appears to improve the results negotiated by the cooperative NSA.

Table 4. Human and agents' negotiation with cooperative buyers

No. of human sellers	3	4	3	3	2
No. of NSA sellers	0	0	1 Coop.	1 Indiv.	2 mixed
No. of instances	13	13	13	11	11
Time (hrs.)	89.5	62.5	100.6	76.0	82.5
Agreements (%)	100%	100%	92%	91%	91%
NSA agreements (%)	-	-	58%	0%	70%
Agreements (humans)					
Sellers profit	13.8	15.8	14.0	18.4	17.7
Buyers profit	58.2	57.6	60.8	53.6	61.7
No. of winner's offers	3.9	3.1	5.8	3.6	4.3
Agreements (agents)					
Sellers profit	-	-	20.7	-	26.1
Buyers profit	-	-	55.1	-	50.4
No. of winner's offers	-	-	7.7	-	6.6

From the perspective of the analysis of the NSA participation, the results in which the buyer was individualistic were very similar. Also in this treatment no competitive NSA reached an agreement and the profit reached by the cooperative NSAs was higher than the profit reached by the human winners.

One general result of the experiments in which one buyer negotiates with several sellers (people and/or NSAs) is that the cognitive load for the buyer is large and the buyer's ability to engage effectively in several negotiations is very limited. Therefore, we are now working on the design of an ANIMA system in which the NSA agents will be able to combine different types of knowledge (model-based and rule based) and use it for the purpose of situation assessment, communication and concession-making.

The outcomes of this research will be a new generation of e-market systems and software agents capable of: combining auction and negotiation mechanisms and using them separately; aiding individual buyers and sellers in managing complex transactions; supporting both buyers and sellers in their achievement of joint and individual substantive outcomes (e.g., revenue, costs, deadlines, and quality); as well realizing relational outcomes (e.g., trust, satisfaction with dealing, reliability, and rapport).

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