CIRRELT

Centre interuniversitaire de recherche sur les réseaux d'entreprise, la logistique et le transport

Interuniversity Research Centre on Enterprise Networks, Logistics and Transportation

Collaborative Agent-Based Negotiation in Supply Chain Planning using Multi-Behaviour Agents

Pascal Forget
Thibaud Monteiro
Sophie D'Amours
Jean-Marc Frayret

December 2008

CIRRELT-2008-54

Bureaux de Montréal :
Université de Montréal
C.P. 6128, succ. Centre-ville
Montréal (Québec)
Canada H3C 3J7
Téléphone : 514 343-7575
Télécopie : 514 343-7121

Bureaux de Québec :
Université Laval
Pavillon Palasis-Prince, local 2642
Québec (Québec)
Canada G1K 7P4
Téléphone : 418 656-2073
Télécopie : 418 656-2624

www.cirrelt.ca

Université Laval · UQÀM · HEC Montréal · École Polytechnique Montréal · Université de Montréal

Collaborative Agent-Based Negotiation in Supply Chain Planning Using Multi-Behaviour Agents

Pascal Forget[1,2,*], Thibaud Monteiro[3], Sophie D'Amours[1,2], Jean-Marc Frayret[1,4]

[1] Interuniversity Research Centre on Enterprise Networks, Logistics and Transportation (CIRRELT)

[2] Département de génie mécanique, Pavillon Adrien-Pouliot, Université Laval, Québec, Canada G1K 7P4

[3] Laboratoire de Génie Industriel et Production Mécanique (LGIPM), Université Paul Verlaine de Metz, Ile du Saulcy, F-57045 Metz Cedex 01, France

[4] Mathematics and Industrial Engineering Department, École Polytechnique de Montréal, C.P. 6079, succursale Centre-ville, Montréal, Canada H3C 3A7

Abstract. In order to work efficiently, supply chain partners must coordinate their actions. When planning is distributed instead of being centralized (as in most cases), it is necessary to use specific coordination protocols between partners in order to act in a coherent manner. On many occasions, partners negotiate in order to act mutually to satisfy their needs. Negotiation is used as a coordination mechanism to find an acceptable agreement between partners or to collectively search for a coordination solution. Agent-based supply chain planning systems can integrate automated negotiation in order to implement negotiation capabilities. While various negotiation mechanisms (or behaviours) can be used in many situations, planning agents using case-based reasoning abilities can learn which to select under specific conditions. This paper proposes to study the performance of the use of a variety of negotiation behaviours and to compare this strategy to the use of a single one. A review of automated negotiation in general and specifically adapted to supply chain planning is first presented, followed by an empirical analysis from simulations of one-to-one collaborative negotiation behaviours. Partners have equivalent negotiation powers and are fully cooperative. These heuristic-based negotiation behaviours are implemented in an agent-based supply chain planning platform, using Multi-behaviour planning agents. Simulations are based on a study case from the lumber supply chain.

Keywords. Automated negotiation, agent-based planning systems, supply chain planning, simulation, lumber industry.

Acknowledgements. The authors gratefully acknowledge the FORAC Research Consortium and the Natural Sciences and Engineering Research Council of Canada (NSERC).

---

* Corresponding author: Pascal.Forget@cirrelt.ca

Dépôt légal – Bibliothèque et Archives nationales du Québec,
Bibliothèque et Archives Canada, 2008

1 Introduction

Collaborative supply chain members must interact in order to satisfy customer needs. These interactions can take various forms, such as information exchanges or requests for actions to be performed, or more advanced forms like cooperation and coordination (managing their interdependencies). In a context such as supply chain production planning level, a certain degree of cooperation is needed in order to serve a common goal: delivering products to customers. Supply chain members that neglect cooperation do not take into account the constraints and preferences of others and risk reducing the level of service of the supply chain. Coordination is used to structure information exchanges between members in order to manage their interdependencies. It can be third-party directed (or centralized), downstream directed (from customers to initial suppliers), upstream directed (from initial suppliers to customers) or use mutual adjustment (see Frayret et al. 2004 for a complete classification). These coordination mechanisms specify the way information is transmitted between members to foster the emergence of a coherent behaviour.

In terms of mutual adjustment, various forms of mechanisms can be deployed, such as a feedback-loop (a downstream coordination followed by an upstream coordination) or joint production plan establishment. Another way is to permit direct negotiation between members to find an acceptable solution. This paper presents different negotiation protocols to coordinate collaborative production activities between two supply chain members. They can negotiate together the quantities and delivery dates of products, based on their production constraints, in order to coordinate their plans and deliver on time products to the customers.

The definition of negotiation is variable depending on the author. It can be broadly defined as a discussion between two or more parties with the intent of reaching an agreement (Kersten, 2003) or viewed as a distributed search through a space of potential agreements (Jennings et al. 2001). Others have proposed more specific definitions. For example, Nawa (2006) defined it as an attempt to coordinate the interaction of two or more parties with heterogeneous, possibly conflicting preferences, which search for a compromise that is satisfactory and mutually beneficial to all participants. Bichler et al. (2003) concluded that negotiation is an iterative communication and decision-making process between two or more parties who cannot achieve their objectives through unilateral actions; exchange information comprising offers, counter-offers and arguments; deal with interdependent tasks; and search for a consensus which is a compromise decision. Whatever the definition, it seems that the basic competencies of a negotiator should permit him to propose an offer and respond to proposals.

The development of agent-based planning systems for supply chains has presented opportunities to develop automated negotiation mechanisms to support human negotiations and maybe, in very specific context, replace human negotiations. The distributed nature of agent-based systems makes it easier to represent negotiators as autonomous agents using their own decision-making model. Even if current automated negotiation models are still primitive when compared to complex human decision making, basics aspects of negotiation are similar, like the importance of time, private or local information and the importance of adapting strategies (Nawa, 2006).

Negotiations occur in many supply chain decision processes, for example, channel negotiations in marketing, management–labour negotiations, transfer price negotiations, coalition formation negotiations, profit sharing negotiations and production planning negotiation. The literature furnishes a variety of approaches to optimize the negotiation mechanisms, from a local perspective or a collective perspective, suggesting a number of automated negotiation possibilities for supply chain. A negotiator will act differently with a competitor or with a member of its own organization. Typically, its behaviour is expected to be more selfish in the first case and more altruistic in the second. Moreover, different negotiation mechanisms can be used in a specific situation, each driving the decision process toward different outcomes. As well, with the same negotiation partner, many negotiation behaviours can be used and can show very different outcomes depending on the environmental conditions. Given this variety of possibilities, there is no universally best approach for automated negotiation that will outperform others in every situation (Jennings et al. 2001). This raises the need for autonomous agents to be capable of adapting their negotiation behaviours following the changes in the environment.

The objective of the paper is to present results from the simulation of different negotiation behaviours under specific situations, using multi-behaviour agents who have the ability to choose the best negotiation behaviour for each situation. This paper is organised as follows: in Section 2, a general literature review is provided on automated negotiation, which characterizes the negotiation environment and reviews different negotiation methods. Section 3 presents a specific review on supply chain automated negotiations, distinguishing contributions addressing contract negotiations and production planning negotiations. Section 4 describes the application context of this study, including a description of the agent-based planning platform used for simulations, the multi-behaviour agent model and the forest industry study case. Parameters and negotiation behaviours used for simulation purposes are presented in Section 5, with an analysis of the preliminary results. A conclusion is presented in Section 6.

2 Automated Negotiation

The automation of negotiation promises multiple advantages, such as increased efficiency and fast agreement emergence, especially for common and repetitive situations. This section is meant to give an overview of the main characteristics of automated negotiations, decision mechanisms that can be followed by negotiation agents and negotiation methodology developments.

2.1 Negotiation characteristics

There are various forms of automated negotiations, depending on the situation the negotiation partners are involved in. *Collaboration level, number of participants, number of issues*, *decision sequence* and use of the *learning ability* are all characteristics that require different automated negotiation designs.

The *collaboration level* is the degree of interest in partners' performance. A low collaboration level indicates a self-interested agent that makes decisions following mostly local goals. At the opposite end of the scale, a high collaborative level is an altruistic agent that puts the partner's goal (or societal goals) before its own. Between these two extremes, there are agents that show a balance between egotistic and altruistic behaviours. Instead of dividing the collaboration level into three class (self-interested, altruistic and balanced), it can be seen as a continuum of balance between both extremes. For long-term relationships, such as in supply chains, it can be profitable to take a part of partners' needs into account in order to build a strong collaboration, even if partners do not belong to the same company (i.e. Xue et al., 2007; Homburg and Schneeweiss, 2000; Fink, 2004; Jiao et al., 2006; Dudek and Statdler, 2005; Ito and Salleh, 2000; Nagarajan and Sosic, 2008; Kraus, 1997). At the other end of the continuum, pure self-interested negotiating agents are very common in the literature (i.e. Nawa, 2006, Binmore and Vulkan, 1999, Oliviera, 2001; Arunachalam and Sadeh, 2005), especially in game-theory approaches. Opponents use the best strategy for themselves, which cannot be explicitly imposed from outside and try to get the maximum from the negotiation. Some authors have analyzed the performance of changing opportunistic strategies when facing changes in the environment (Klein et al., 2003; Matos et al., 1998).

A major impact on the way negotiations are performed is the *number of participants* involved. The most common negotiation found in the literature (and in the real-world context) is one-to-one negotiation, where an agent negotiates with only one other agent. It is basically characterized by a sequence of propositions and counter-propositions, where each negotiator is free to use its own strategy to build his next offer. The other situation is the one-to-many negotiation, where an agent negotiates with many agents at the same time. It is the standard form of auctions and more details will be presented in the following section. The Contract Net Protocol is a well-known example, where an agent sends a demand to multiple agents, and then receives offers and makes a choice. Sandholm and Lesser (1995) extended the Contract Net Protocol for decentralized task allocation in a distributed network for vehicle routing. The negotiation follows an announce-bid-award cycle and is done in real-time; in that immediately upon award of a contract, the exchange of goods is made. Beam and Segev (1997) present a state-of-the-art review on electronic marketplace, a common form of one-to-many negotiation. Many-to-many negotiation is another form but is rarely discussed in the literature. This occurs when more than two agents negotiate together to find a compromise acceptable for all of them (Lomuscio et al. 2003; Kraus and Wilkenfeld, 1991; Oliveira and Rocha, 2001, Dworman and Kimbrough, 1995).

Negotiation can be characterized by the *number of issues* (also called objects) negotiated. The simpler form is single-issue negotiation, where only one issue is discussed, which is generally the price. More complex forms include multiple issues that need to be added and compared in order to accept or refuse the offer. Participants usually use a utility function to evaluate an offer with single or multiple issues. In multiple issues, the value that each agent puts on a specific issue can be objective (such as the price) or subjective (level of service, quality, etc.) and vary from one agent to the other. While price seems to be the most common issue, others exist, depending on the domain. It can be quantity, delivery time, quality, warranty, etc. Monteiro et al. (2004) presented a multi-criteria negotiation based on cost, quantity and delay for a distributed control of a client/provider relationship. In fact, it can be anything that presents a value for one participant.

The *decision sequence* across the supply chain influences how the negotiation will be managed. If an agent possesses enough information to respond to a negotiation proposal, it can make a decision locally and respond quickly to its client. But if it needs to check with its own supplier before making any counter-proposal (or initiating a new negotiation round with its supplier), there is a decision sequence that must be followed and directly influences the negotiation time. That is the case particularly in make-to-order supply chain where each change in products orders (in term of quantity or dates) must be verified with suppliers before committing to clients. Subsequently, these suppliers may need to contact their own suppliers to change plans. The negotiation initially started cannot be completed until all partners have mutually agreed to meet each supply needs.

Some authors classify automated negotiation on the basis of the *learning ability* of the agents. Non-learning agents are initially created with their complete set of protocols and strategies, relying on a detailed set of instructions for each possible situation. Learning agents have the ability to acquire experience from previous negotiations. Learning becomes interesting when information is incomplete about partners and when the environment cannot be fully expressed. In such scenarios, the ability to learn allows agents to improve their strategies as they interact with their opponents in order to adapt to different scenarios (Nawa, 2006). In particular, it is important for the negotiating agents to be able to adapt their strategies to deal with changing opponents, topics, concerns and user preferences (Gerding, 2000). The machine learning domain presents multiple techniques to implement learning abilities in automated negotiation and the reader is referred to Mitchell (1997) for a detailed review.

2.2 Decision mechanisms

While contextual characteristics of negotiation are important for designing automated negotiation, the way in which negotiation agents process information and make their decisions is also of primary importance. Four decision mechanisms for automated negotiations are presented here: game-theoretic negotiation, heuristics-based negotiation, argumentation-based negotiation and auctions.

2.2.1. Game theoretic negotiation

Game theory has its root in economics. It studies interactions between self-interested agents. The objective of game theory is to determine the best (most rational) decision an agent can make, using mathematical modelling. In order to do so, the agent must take into account the decisions that other agents can make and must assume that they will act rationally as well. A solution in game theory is generally found when agents' strategies are in equilibrium: an agent's strategy is the best response to the other's strategies. Tools from game theory can help managers understand and predict the outcome of a negotiation and then help them make strategic decisions in complex supply chain systems (Nagarajan and Sosic, 2008).

Game theory can be divided into two main approaches. Non-cooperative game theory is strategy oriented, meaning it studies what players will do in a specific context in order to win over their opponent. Cachon and Netessine (2004) presented a state-of-the-art survey on non-cooperative game theory techniques applied to supply chain management. In contrast, cooperative game theory studies how players can cooperate to reach a win-win situation when the global gains are higher with cooperation than without. Forming sustainable coalition and sharing profit among partners are two important topics of cooperative game theory and are presented in detail in Nagarajan and Sosic (2008).

A frequently mentioned drawback of game theoretic approaches is the perfect rationality assumption. In order to select the best strategy, the agent must know the entire environment as well as the opponent's knowledge. Otherwise, it is not possible for the agent to estimate the most rational choice. In principle, once each agent has the necessary data from its opponent, there is no need for any simulation of the negotiation process, because game theory provides a prediction of the outcome that would follow the use of the optimal strategies that can be employed immediately (Binmore and Vulkan, 1999). In other words, decisions are made a priori, presuming other agent's behaviours. Unfortunately, in real-world business situations, opponents have private information hidden from their supply chain partners. In distributed supply chain planning, this translates into private planning decision models and information on capacity utilization, manufacturing capabilities, customer demand, etc. In order to overcome this problem, negotiation models based on game theory use approximations in practice, assuming bounded rationality instead of perfect rationality. Despite this limitation, game theory remains an ideal tool for automated negotiation when it is possible to characterize possible strategies and preferences of participants. Kraus and Wilkenfeld (1991) and Binmore and Vulkan (1999) presented game theory applications in automated agent negotiation. Axelrod (1981) studies the conditions under which cooperation can emerge from egotistic agents. His work is formulated using an iterated Prisoner's Dilemma, where agents have a long-term incentive to collaborate, but a short-term advantage to defect.

2.2.2. Argumentation-based negotiation

In the negotiation approaches presented previously, agents cannot justify to their partner why they refuse an offer or what part of the offer was problematic. Counter-proposals do not include the explanations of the changes and considerably limit the potential of negotiation. The idea behind argumentation-based negotiations is precisely to give this additional information to agents, helping the negotiation process by identifying part of the negotiation space that does not need to be explored. The basic form of argumentation is the critique, in the form of new information about the rejection of a proposal. Two types of critiques can be identified, which are the suggestion of a constraint on the negotiation space and the indication of the refusal of a particular part of a proposal (instead of the whole proposal). Jennings et al. (2001) pushed forward the concept by proposing the persuasion in automated negotiation. This can take the form of a justification about why the partner should accept a proposal. This can increase the negotiation space by adding an area that was not used before. By revealing new information, the partner can be persuaded that a certain proposal is better than it thought. Threats and rewards, such as used in human argumentation, can also be used by agents to accept a proposal. An example of a threat would be to withdraw all orders if the last proposal is not accepted. A reward could be a bonus offered if an order can be delivered at a specific time. The agent must be able to calculate the value of the argument itself and the credibility of the agent giving the argument. Different authors have presented applications of argumentation-based negotiation models (Buttner, 2006; Atkinson et al., 2005; Capobianco et al., 2005).

2.2.3. Auctions

Negotiation and auctions have traditionally been considered as different classes, with specific characteristics and applications. Traditional auction can be seen as a bidding process over a single issue with rules of action, that can be *single sided*, like the ascending-bid auction (English auction), the descending-bid auction (Dutch auction), the first-price and the second-price sealed-bid auction (Vickrey auction), or *double sided*, such as stock exchange mechanisms (see Bichler et al. 2002 for details). Today, new kinds of auction protocols using new technologies can be applied to various sorts of negotiation situations. The definition of auction includes advanced bidding procedures that blur the distinction between auction and negotiation. On-line auctions can be seen as a hybrid of traditional auction and negotiation, where bidding is over multiple and various objects, using utility as a measure of preference instead of price. Neumann et al. (2003) presented a review of six auction-negotiation commercial and academic systems, including eBay, LiveExchange, AuctionBot, GNP, AMTRAS and eAuctionHouse. These systems are compared according to various characteristics, including the negotiation set-up, the offer specification, the submission, the offer analysis, the matching, the allocation, the acceptance and the information transparency.

2.2.4. Heuristic-based negotiation

A way to overcome the game theory limitations described previously is to use heuristic methods. Heuristic-based negotiation is based on search strategies where the objective, instead of finding the optimal solution, is to find a good solution in a reasonable time. Multiple approaches can be used, depending on the search strategy deployed. Agents do not need to be perfectly rational and information can be kept private. Basically, the space of possible agreements is represented by contracts having different values for each issue. Using its own utility function, an agent must compute the value of each contract. Proposals and counter-proposals are exchanged over the different contracts and search terminates either when the time limit has been reached or when a mutually acceptable solution has been found. Kraus (1997) presented a review of applications of heuristics to negotiations and pointed out where it represents an advantage over other approaches. Klein et al. (2003) worked on a simulated annealing based approach for negotiation of multi-interdependent issues in contracts. Rahwan et al. (2007) have worked on defining a method for designing heuristics-based negotiation strategies for negotiation agents, by analyzing the environment and the agent capabilities. They illustrate their methodology by using strategies from the Trading Agent Competition (TAC). The negotiation protocol presented in this paper is heuristics-based. A global objective (in this case, customer satisfaction) is followed and in a limited period of time, supply chain members search locally for a better arrangement, without looking for the “best” production plan possible.

3 Automated Negotiation in Supply Chain Planning

The last decade has been rich in the development of applications of automated negotiation capabilities to supply chains, based on the characteristics and the decision mechanisms presented previously. In all the available research, many authors have covered what can be considered *contract negotiations*. They regard various issues such as contract selection (Jiao et al., 2006), profit sharing (Nagarajan and Sosic, 2008; Cachon and Lariviere, 2005), price agreement (Homburg and Schneeweiss, 2000), coalition formation (Oliveira and Rocha, 2001; Nagarajan and Bassok, 2002; Sandholm, 2000) and service procurement (Sierra et al., 1997). This paper is particularly interested in *production operation planning negotiations* between supply chain partners. This is mainly about negotiating quantities and delivery dates to build coherent production plans between partners. Although this review is far from being exhaustive, it gives an idea of the richness of the work that has been published.

While contract negotiations focus on defining terms of contracts, production planning issues can require supply chain partners to negotiate to modify plans. Various authors have presented approaches to handle negotiation over production schedules. Fink (2004) developed a negotiation approach for the coordination of production schedules between two planning agents. Taking asymmetric information and opportunistic behaviour into account, a mediator generates candidate schedules, which are accepted or rejected by the agents according to local goals. This approach enables the definition of negotiation rules to be verified by the mediator, forcing both agents to behave in a cooperative manner. Similarly, Dudek and Stadtler (2005) proposed a non-hierarchical, collaborative negotiation-based scheme to synchronize operation plans between two independent supply chain partners linked by material flows. Their approach allows the partners to adjust iteratively supply need quantities and dates in order to find mutually acceptable solutions. Although this approach is explicitly collaborative, it can also be applied by self-interested, opportunistic agents. Simulations suggested that the scheme closely approaches optimal results as obtained by central coordination. Also, Ertogral and Wu (2000) proposed an auction-based approach to coordinate production plans between negotiating agents from a supply chain. The approach is applied to the multi-level multi-item capacitated lot sizing problem (MLCLSP). Applied to the construction supply chain, Xue et al. (2007) proposed an agent-based collaborative negotiation platform to improve effectiveness and efficiency in planning activities between decision-makers.

Another important aspect in production planning is procurement from suppliers. When multiple suppliers are available in the supply chain, the planning agent must select the best ones according to the situation and its local constraints. This can be carried-out through negotiation-based auction approaches such as MAGNET (Collins et al., 2002). They proposed an agent-based negotiation system, where self-interested agents negotiate with suppliers to coordinate tasks constrained by temporal and capacity considerations. Khouider et al. (2008) developed negotiation models to select suppliers based on mathematical modelling, using local production constraints and transportation constraints. The models are incorporated in an agent-based system where each decision centre is represented by a self-interested agent programmed to adopt win-win behaviour. In addition to proposing the negotiation system, they simulated how simultaneous negotiations can be managed to minimize the opportunity loss. Chen et al. (1999) presented negotiation-based framework for supply chain management where functional agents (a production planning agent) can use one-to-one negotiation and auction protocols to select suppliers and then, schedule production. In a similar context, for replenishment of parts and materials, Ito and Salleh (2000) proposed a blackboard-based negotiation using open tender. Using this approach, candidate suppliers compete with one another in an open environment and the most appropriate candidate is selected as a result of open competition.

Figure 1 presents a positioning of different applications regarding the characteristics of automated negotiation discussed in this section, comparing the cooperation level continuum (from pure adversarial to pure collaborative) and the number of participants (one-to-one, one-to-many and many-to-many). Table 1 resumes agent-based supply chain negotiation contributions presented in this section.

Figure 1 Supply chain negotiation applications positioning

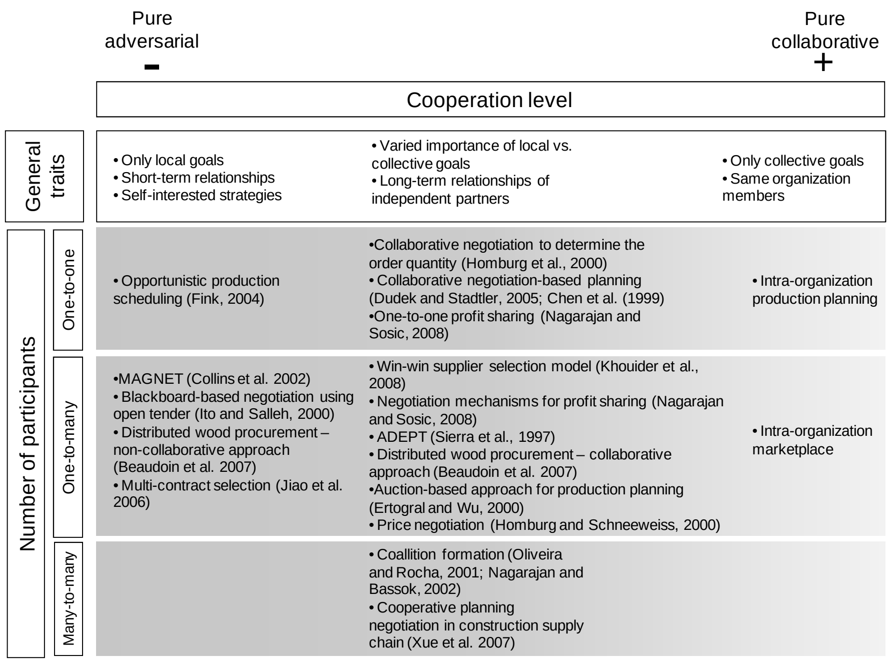


Table 1 Agent-based supply chain negotiation contributions

Application	*References*	*Contributions*
Contract	Jiao et al. (2006)	Multi-contract negotiation system for contract selection on a global supply chain view
	Nagarajan and Sosic (2008)	Negotiation mechanisms for profit sharing between a client and multiple suppliers
	Cachon and Lariviere (2005)	Revenue sharing contract negotiations in supply chains
	Homburg et Schneeweiss (2000)	Automated negotiation structure to find maximum order quantity for a fixed price
	Oliveira and Rocha (2001)	Negotiation protocol to include individual companies in a virtual organization
	Nagarajan and Bassok (2002)	Study of the impacts of negotiation power on preferences for joint coalition or to stay independent
	Beaudoin et al. (2007)	Comparison of multi-firm negotiation approaches for distributed wood procurement planning
	Sierra et al. (1997)	ADEPT project uses agents to negotiate price, deadline and quality for network services
Production planning and scheduling	Fink (2004)	Negotiation approach for the coordination of production schedules between two planning agents
	Dudek and Stadtler (2005)	Non-hierarchical, collaborative negotiation-based scheme to synchronize production plans between two independent supply chain partners
	Ertogral and Wu (2000)	Auction-based approach for planning production between supply chain partners
	Chen et al. (1999)	Negotiation-based framework for supply chain using one-to-one negotiation protocols to schedule production between two partners
	Xue et al. (2007)	Agent-based negotiation platform for cooperative planning in construction supply chain
Supplier selection	Collins et al. (2002)	MAGNET is an agent-based negotiation system for coordination with suppliers, using temporal and capacity constraints
	Khouider et al. (2008)	Negotiation models to select appropriate suppliers, based on local and transportation constraints
	Chen et al. (1999)	Negotiation-based framework using an auction protocol to select appropriate suppliers
	Ito and Salleh (2000)	Blackboard-based negotiation using open tender to find appropriate candidate supplier

The number of emerging approaches for negotiation has raised the need to compare them in order to study which is prevalent in different situations. Beaudoin et al. (2007) compared different planning and coordination approaches for procurement planning, using negotiation in a supply chain environment. They studied the wood procurement problem in the Canadian forest industry, where different mills share procurement areas and must negotiate different issues, such as volume division, procurement activity timing and transaction prices. Through simulation, they compared the profitability levels of four negotiation-based procurement planning approaches. A web-based multi-agent simulation platform was developed in 2003 for the first Supply Chain Management Trading Agent Competition (TAC-SCM). For a specific supply chain problem (the assembly of PCs), self-interested agents must effectively coordinate their sourcing, procurement, production, and customer bidding decisions. Arunachalam and Sadeh (2005) presented a review of different agent strategies used during the competition and discuss how this kind of competition-based research can be useful.

Confronted with the vast possibility of negotiation approaches, different authors have proposed agents that can adapt their behaviour according to the situation. Krovi et al. (1999) examined the impact of several negotiation variables on agent behaviours as well as the outcome of the negotiation through simulation of the agents and the environment. Their simulation model helped them identify the best strategy to use depending on time constraints and information availability. Similarly, Matos et al. (1998) presented an empirical study on the adaption of different negotiation strategies in different environments between a buyer and a seller, depending on the time and resources available. On a service management application, Faratin (2000) compared different negotiation mechanisms. He developed a meta-level deliberation mechanism that helped negotiation agents make a choice about which one to use for different environments.

This paper follows the same logic of comparing various negotiation approaches, but applied to the lumber supply chain context. Based on external demand and supply characteristics (instead of opponent characteristics), negotiation agents use simulation capabilities to learn when to use different negotiation behaviours. The deliberation mechanism uses a case-based reasoning approach, where agents apply what gave good results during simulations. By adapting negotiation behaviours to their environment, these agents look at improving negotiation results and ultimately, increasing the supply chain performance.

4 Application context

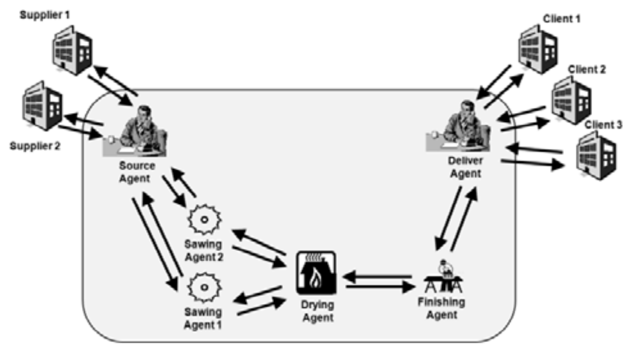
4.1 An agent-based planning platform for the lumber industry

The experimental results presented in this paper are based on agent-based simulations of the lumber supply chain. To this end, an Internet-based planning platform built on an agent-based architecture for advanced planning and scheduling (Frayret et al., 2007) has been used. The objective of this platform is to propose a new approach for planning the lumber supply chain. It allows the different production centres to independently react to changes and plan production, while maintaining feasibility and coordination with partners. By distributing planning decisions among specialized planning agents, the platform aims to increase supply chain reactivity and performance. The platform can also be used for simulation purposes in order to allow supply chain designers or production managers to simulate different scenarios, such as adding a new partner, building a new plant, moving production resources to another plant or changing the decoupling point position, adding new machinery, etc. In this paper, simulation is used in order to study the impact of using different negotiation behaviours between planning agents.

This agent-based architecture is based on the functional division of planning domains. Figure 2 presents an example of a simple supply chain, where planning responsibilities are divided among specialized production planning agents (sawing agent, drying agent and finishing agent), a source agent, a deliver agent and a warehouse agent. Each of these agents is responsible for supporting the planning of its production operations. The suppliers and customers are represented as agents or human planners, depending on the degree of simulation required. The implementation of the experimental platform was carried out with the collaboration of a consortium of Canadian lumber companies.

In the supply chain configuration illustrated in Figure 2, agents' planning problems are radically different, both in terms of production philosophy and constraints. Different planning algorithms have been developed to resolve the three sub-problems of operation planning and scheduling, taking advantage of some of the specificities of the overall planning context. The overall objective in the three models is to minimize lateness of delivery to the final customer. The sawing agent uses a mixed integer linear programming model (MIP) solved with ILOG CPLEX. It is designed to identify the right mix of log types and cutting patterns to use during each shift in order to control the output of the overall divergent production process. For the drying problem, a constraint programming approach was designed as an anytime algorithm, solved using ILOG SOLVER. Finally, a MIP model was designed to address this finishing planning problem and is resolved using ILOG CPLEX. Details on the different models can be found in Gaudreault et al. (2008).

Figure 2 A supply chain configuration example from the FORAC planning platform



Because each agent is responsible for monitoring locally specific environmental parameters, if a change occurs in supply chain operations, any agent can initiate a replanning process and even involve other agents by sending a revised demand or supply plan. For example, such a form of collaboration can be triggered by an agent who needs products to fulfill inventory, has lost production or has received a new order. Because agents are collectively responsible for planning supply chain operations, agent's environments also include all messages received from other agents specifying a new or modified requirement plan, a new or modified replenishment plan, a contingency situation, or a high priority requirement process.

4.2 Multi-behaviour agent model

The multi-behaviour agent (Forget et al., 2008a) has been designed to give agents alternative behaviours to face different situations more efficiently. While mono-behaviour agents construct plans using the same planning behaviour continuously, multi-behaviour agents can learn which planning behaviours to adopt in many different situations, depending on the environment. The multi-behaviour agents used within the context of this paper is reactive. In other words, it presents three basic behaviour categories, inspired by the coordination mechanisms found in the literature (Shen et al., 2001; Frayret et al., 2004; Moyaux et al., 2006, Schneeweiss, 2003). They are identified as *Direct Reaction*, *Reaction with Anticipation* and *Negotiation*. When facing a change in its environment, the agent must decide which planning behaviour it should adopt using different selection criteria, such as available time to make a decision, chance of success of a particular task flow and source of the perturbation. The multi-behaviour agent uses a reactive rule-based reasoning approach where it learns through simulations which planning behaviour offers the best performance for various situations.

Direct reaction behaviours are simple sequences of planning tasks (or planning task flows) which use only local information with no feedback loop. Simulations have been made previously (Forget et al., 2008b) in order to test the impact of using multiple direct reaction behaviours in an application to the lumber supply chain. Various team behaviours have been tested in different environmental conditions and this showed that different performance levels are reached according to the behaviour selected. They also presented possible profit gains by using the best team behaviour in every situation instead of using the same one over the entire time horizon. *Reaction with anticipation* behaviours consist of more advanced forms of planning task flows that include the use of a more or less accurate decision model of its partner. This partner decision model allows the agent to influence its own decision planning according to a closed-loop anticipation feedback of its partner's potential decisions. In brief, the agent adapts its own decision according to an anticipated response of its partner. Anticipation in supply chain planning can be interesting in situations where communication is limited or time is constrained. For example, we have developed such behaviour in the drying agent. This agent uses an anticipation model of the finishing agent in order to have a more accurate response in terms of finished products production volumes. In other words, because of this anticipation, the drying agent can anticipate the production operations of the finishing agent and thus has the possibility of directly anticipating its own contribution to the final customer need satisfaction. Finally, *negotiation* behaviours involve some forms of exchange with partners during planning. In other words, it is an open loop feedback of its partner's decision model that is directly used by the agent to influence its decision. This may take the form of a proposal and counter proposal. For instance, when the agent is not able to respond to its partner's needs, it can offer changes in delivery dates or alternative products. Following this, an iterative exchange of proposals is started, where both agents try to find a compromise. These proposals can take the shape of new constraints, which can be used by partners to re-plan production and send a new demand plan. For a detailed description and examples of planning behaviours, the reader is referred to Forget et al. (2008a). A design framework for multi-behaviour agents is presented in Forget et al. (2008c).

For simulation purposes, this paper presents the results of an implementation of multi-behaviour agents in the agent-based planning platform presented before. It then becomes possible to simulate different negotiation behaviours in various supply chain environments and use the advantage of adaptability to increase the global performance.

4.3 Lumber supply chain study case

In order to simulate negotiation behaviours in the agent-based planning platform, an industrial study case has been used. Inspired by a real lumber supply chain, this case includes the design of a network structure of partners and production centres. We also specified the capacity, initial inventory, number of products and demand orders. The production planning agents (sawing, drying and finishing) have been parameterized following realistic industrial examples in terms of production lines, production hours and production processes specific to the lumber industry (e.g. cutting patterns). An initial inventory was determined for each production centre, corresponding to approximately one week of production at full capacity. The sawing production centre uses one general sawing line with a maximum capacity of 120 000 FBM (Foot Board Measure) per day when the most efficient process is used. The drying production centre is composed of unlimited air dry spaces and three kiln dryers. Air dry spaces are outside zones where green lumber can dry slowly. Air dried products lead to higher quality final products, but take longer to be dried. Kiln dryers have a loading capacity of 120 000 FBM and are open all year around (7 days per week, 24 hours per day). When a drying process is started, the kiln dryer must remain closed for a period from two and a half to four days, depending on the wood species and the process selected. Finally, the finishing production centre uses one line, with a capacity of 600 000 FBM per day.

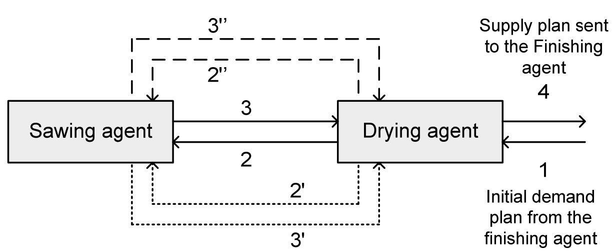
5 Negotiation Framework

The lumber supply chain studied in this paper presents different negotiation possibilities according to which agents are involved in the negotiation process and how many of these agents participate at the same time. Four types of negotiation are possible: collaborative one-to-one, collaborative one-to-many, adversarial one-to-one and adversarial one-to-many. Collaborative one-to-one negotiations are usually between agents from the same organization, or more generally between agents who share a common goal. Negotiation between a drying agent and a finishing agent from the same company is one example. If two or more drying agents are part of the negotiation with a finishing agent but still from the same company, it is a collaborative one-to-many negotiation. When the negotiation occurs between agents whose local goal is dominant over the common benefit, such as a source agent and a supplier agent from two different companies, it is an adversarial one-to-one negotiation. When many supplier agents are involved, it is an adversarial one-to-many negotiation.

5.1 Negotiation process description

In this paper, we study the collaborative negotiation process between two different planning agents, sawing agents and drying agents, from the same company. The reader interested in adversarial negotiations between forest companies in a similar context is referred to Beaudoin (2007) as introduced earlier. The specific negotiation issues studied here deal with delivery dates, substitute products and quantities of products. In the context of one-to-one negotiation, one sawing agent and one-drying agent are used in the experiments. The negotiation framework is depicted in figure 3.

Figure 3 Negotiation framework



In this limited context, the external demand (1) to be satisfied takes the form of demand plans sent by the client (finishing agent) to the drying agent. These plans are made of products of two species (spruce and fir), three different sizes (2x3, 2x4 and 2x6) and various volumes, over a 30-day horizon. A typical demand plan specifies, for each day, the volume of each product requested. The sawing and drying agents must plan their production using their local capacity constraints in order to maximize their delivery performance. In order to do so, they iteratively exchange demand and supply plans which they must agreed upon to coordinate their operations. In other word, once the drying agent has planned its operations, it derives an initial demand plan (2) that it sends to the sawing agent. When the sawing agent receives a demand plan, its task is to make a proposal (i.e. a supply plan), which, in turn, is derived from its own local operations plan (3). Then, the drying agent re-plans and sends a new supply plan (4) to the finishing agent.

The negotiation proposed in this paper is one-sided, meaning that only the drying agent has an active role in the search for a compromise plan, which is made through a local heuristic search in the neighbourhood of the initial demand plan (2) sent by the drying agent. More specifically, when the drying agent is not fully satisfied by the supply plan received from the sawing agent, it selects a specific negotiation behaviour (i.e. negotiation strategy) in order to make a slight modification to this initial demand plan and send it back to the sawing agent (2’). In turn, the sawing agent computes again a new supply plan and sends it to the drying agent (3’). When this new supply plan is received, the drying agent can either stop the negotiation and send supply plan to the finishing agent (4), or make a new adjustment to its initial demand plan (2’’), as shown in Figure 3.

In this negotiation process, each time the drying agent receives a new supply plan from the sawing agent, it introduces it as a constraint in its own operations planning process and computes its own delivery performance. This is how each proposal (i.e., supply plans) sent by the sawing agent are evaluated by the drying agent in order to pursue the negotiation process.

5.2. Drying agent negotiation behaviours

In this negotiation process, the drying agent does not know a *priori* how the sawing agent will be able to maximize its delivery performance. Consequently, we have developed three different negotiation strategies in order to perform different types of local heuristic search. These strategies include the *Priority*, *Substitution* and *Lot sizing* behaviours. As mentioned previously, these behaviours aim at slightly modifying the initial demand plan derived by the drying agent. Because these behaviours propose different types of modification to the plan, the neighbourhood that is explored using each of them is different, thus providing different types of local search.

5.2.1. Priority negotiation

Priority negotiation involves the modification of the delivery dates of certain volumes demanded. A new tentative demand plan is thus generated by first identifying the volume which is tentatively planned to be the latest to be fulfilled. This volume is then permuted in the demand plan with the first volume of the same species that is planned to be delivered on time. Equivalent volume of wood must be permuted. For example, if the drying agent is unsatisfied with the initially received supply plan, it can identify the latest volume, a volume of two million FBM 2x4 spruces planned to be late for 15 days, and permutes it with a two millions FBM of 2x6 spruces planned on time. With this new demand plan, both agents explore an alternative plan that may or may not result in a better global delivery performance. For different rounds of negotiation, the second latest volume can be permuted or more than one volume can be permuted at a time.

5.2.2. Substitution negotiation

In the substitution negotiation, substitutable products are used when it is possible to replace late volumes. The solution is possible in the lumber industry, where different species of wood can be used to produce similar products for the final client, while necessitating more process time (and being more costly). Similar to the priority negotiation, a new tentative demand plan is generated by identifying the latest volume and substituting its species with an equivalent one. The volume and the delivery date are unmodified. For example, fir products are proposed as a substitute for spruce products. On the production level, fir products need two additional days in the kiln dryer. This negotiation behaviour can be interesting in case of a supply shortage of a particular product. For multiple negotiation rounds, other late volumes can be tried or more than one substitution can be performed in the same demand plan.

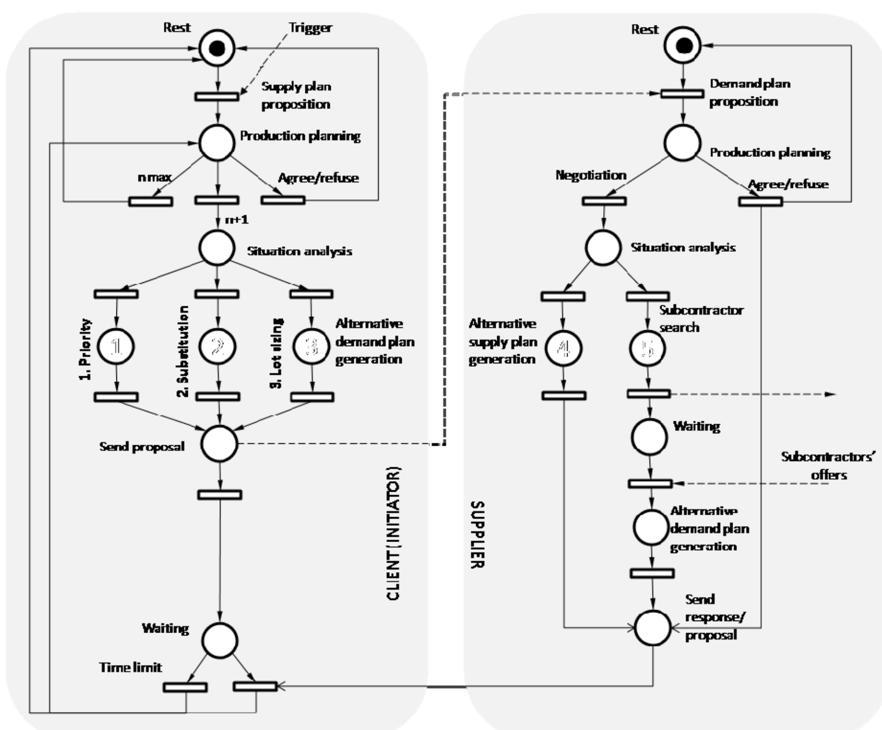
5.2.3. Lot sizing negotiation

Lot sizing negotiation is about modifying the size of volumes. New plans are generated by the drying agent by first identifying the latest wood volume and then, breaking down this volume into smaller volumes. These new volumes are required to be delivered earlier than the initial volume. The idea is to match the supplier's maximum capacity per day. For example, if a volume of one million FBM of 2x3 spruces is due on a Friday, the new tentative plan can ask for 300 000 FBM on Wednesday, 300 000 FBM on Thursday and 400 000 FBM on Friday. Again, for multiple rounds, other late volumes can be broken down or more than one volume can be divided.

5.3. Generalized negotiation protocol

The negotiation protocol used in these experiments is the one-to-one negotiation protocol presented in Figure 3 between the drying agent and the sawing agent. As explained, the tested protocol was one-sided, in other words, led by the drying agent. However, it is possible to generalize this simple protocol in order to capture a negotiation process where both agents can contribute/lead the heuristic local search. Indeed, the sawing agent could also take the initiative of adjusting its supply plan according to local information it possesses. Furthermore, it could also take the initiative of exploring the possibility of subcontracting part of the production. These extended functions are captured in the generalized negotiation protocol presented in Figure 4.

Figure 4 One-to-one generalized negotiation protocol



This protocol is first triggered when the drying agent receives a supply plan that is different from the initial demand plan it sent. The drying agent re-plans its production and decides whether the plan is accepted, refused or suitable for a compromise. If so, the drying agent triggers a negotiation process. By doing so, it analyzes the situation and, based on previous simulation results, selects the preferable negotiation behaviour to adopt (i.e., Priority, Substitution or Lot sizing). Following this behaviour, a new demand plan is generated and sent to the sawing agent. Upon reception, the sawing agent builds a new production plan and decides whether it is accepted, refused or still suitable for some compromises. If the supplier decides to negotiate, it sends a new supply plan, using similar or different negotiation behaviours, or looks for a sub-contractor who can fulfill the volume.

When the client receives the proposal, the negotiation protocol starts again. A maximum number of propositions is set (n max) to limit the number of proposition exchanges and a time limit is used for each negotiation. If the time limit or the maximum number of propositions is reached, the initial supply plan is automatically accepted.

6 Experiments

Experiments of one-to-one negotiation behaviours between two multi-behaviour agents were performed using the planning platform configuration presented in Figure 2. More specifically, the negotiation on production plans between a drying agent and a sawing agent was simulated. As stated before, the main objective of these experiments was to verify the advantage if using multiple negotiation behaviours in this context. But also, these experiments can be pursued to build the decision knowledge needed for multi-behaviour agents to analyze the situation and choose the right negotiation behaviour.

In order to simulate changes in the environment, experiments have been reproduced in different environmental conditions. Two aspects of the environment have been modified, which are demand intensity and supply intensity. The demand intensity corresponds to the finishing agent demand and is set successively at 90%, 100% and 110% of the total capacity of the supply chain. The supply intensity is set at 50% and 100% for the spruce supply, where 50% simulates a shortage of logs. The performance indicator used to compare the different approaches in the different conditions is the sum of volume of lumber (in FBM) planned to be delivered late per day. Each negotiation includes three rounds (R1, R2 and R3), where a different change is proposed following the same negotiation behaviour. The changes applied to each round are based on the examples provided for each negotiation behaviour in section 5.2. Table 2 presents the performances from the three rounds of negotiation, for different environmental changes and different negotiation behaviours. The initial round's performance is presented on top and the best performance is in grey.

Table 2 Preliminary lateness performances for three negotiation rounds (in 100 000 FBM)

	Demand 90%		Demand 100%		Demand 110%	
	Supply 50%	Supply 100%	Supply 50%	Supply 100%	Supply 50%	Supply 100%
Initial round	11.0	0.1	21.5	1.3	32.4	5.9
Priority R1	11.3	0.4	21.7	1.3	32.6	5.6
Priority R2	11.0	0.0	21.5	1.2	32.4	6.1
Priority R3	11.6	0.4	22.0	1.5	32.9	6.1
Substitution R1	3.6	0.1	9.7	3.2	18.2	11.4
Substitution R2	1.1	1.5	6.0	5.1	14.8	13.2
Substitution R3	1.6	2.5	8.1	9.8	17.0	17.0
Lot R1	11.0	0.0	21.5	1.5	32.4	6.9
Lot R2	11.0	0.0	21.5	0.4	32.4	6.7
Lot R3	11.0	0.0	21.5	1.3	32.4	6.6

In this experiment, the substitution negotiation was preferable when supply dropped to 50%. This is explained by the unawareness of the supplier of substitution products. When a specific product is unavailable, it becomes late. When supply was sufficient, lot negotiation obtained the best results at demand intensity level of 100%, while the priority negotiation was preferable at demand intensity of 110%. While data are scarce and are only preliminary, results show an advantage to modifying the negotiation behaviour in order to obtain better performance, when compared to the initial production plan performance. Table 3 presents the lateness performance gain (in percentage) for the supply chain to use the preferable negotiation behaviour for a specific environment, when compared to the initial round, when no negotiation is started.

Table 3 Gain in percentage to use the preferable negotiation behaviour

Demand 90%		Demand 100%		Demand 110%	
Supply 50%	Supply 100%	Supply 50%	Supply 100%	Supply 50%	Supply 100%
89.8%	100%	72.0%	67.7%	54.1%	5.1%

7 Conclusion

Using multi-behaviour agents in an agent-based supply chain planning platform, the objective of this paper was to report the results of the simulation of various collaborative negotiation behaviours and verify the advantage of adapting them to the environment. The preliminary results presented in this paper show that some negotiation behaviours perform well in certain conditions but poorly in others, reinforcing the need for adaptive planning agents such as multi-behaviour agents.

The next step is to test the negotiation behaviours over the entire supply chain and study how to coordinate these negotiations between all planning agents. It would also be interesting to compare negotiation behaviours to reaction and anticipation behaviours in terms of performance and identify when each prevails. A natural extension of the paper will be to develop a generic protocol for one-to-many negotiations, for situations when more than one supplier is available. New experiments with new environmental conditions must be performed and analyzed.

Acknowledgements

The authors gratefully acknowledge the FORAC Research Consortium and the Natural Sciences and Engineering Research Council of Canada (NSERC).

References

Arunachalam, R. and Sadeh, N.M. (2005) 'The supply chain trading agent competition', *Electronic Commerce Research and Applications*, Vol. 4, pp. 66–84.

Atkinson, K., Bench-Capon, T. and McBurney, P. (2005) 'A Dialogue Game Protocol for Multi-Agent Argument over Proposals for Action', *Autonomous Agents and Multi-Agent Systems*, Vol. 11, No. 2, pp. 153–171.

Axelrod, R. (1981) 'The Emergence of Cooperation among Egoists', *The American Political Science Review*, Vol. 75, No. 2, pp. 306–318.

Beam, C. and Segev, A. (1997) 'Automated Negotiations: a Survey of the State of the Art', *Wirtschaftsinformatik*, Vol. 39, No. 3, pp. 263–268.

Beaudoin, D., Frayret, J.M. and LeBel, L. (2007) 'Negotiation-based distributed wood procurement planning within a multi-firm environment', Working paper CIRRELT-2007-10, Universite Laval, Canada.

Bichler, M., Kalagnanam, J., Lee, H.S. and Lee, J. (2002) 'Winner Determination Algorithms for Electronic auctions: A Framework Design', *Proceedings of the E-Commerce and Web Technologies: Third International Conference (EC-Web 2002)*, Aix-en-Provence, France.

Bichler, M., Kersten, G. and Strecker, S. (2003) 'Toward a Structured Design of Electronic Negotiations', *Group Decision and Negotiation*, Vol. 12, pp. 311–335.

Binmore, K. and Vulkan, N. (1999) 'Applying game theory to automated negotiation', *Netnomics*, Vol.1, pp. 1–9.

Buttner, R. (2006) 'The state of the art in automated negotiation models of the Behavior and Information perspective', *International Transactions on Systems Science and Applications*, Vol. 1, No. 4, pp. 351–356.

Cachon, G., M. Lariviere. (2005) 'Supply chain coordination with revenue sharing contracts', *Management Science*, Vol. 51, No. 1, pp.30–44.

Cachon, G. and Netessine, S. (2004) 'Game theory in supply chain analysis', *In*: Simchi-Levi, D., Wu, S.D., Shen, M. (ed.), *Handbook of Quantitative Supply Chain Analysis: Modeling in the eBusiness Era*, Kluwer.

Capobianco, M., Chesnevar, C.I. and Simari, G.R. (2005) 'Argumentation and the Dynamics of Warranted Beliefs in Changing Environments', *Autonomous Agents and Multi-Agent Systems*, Vol. 11, No. 2, pp. 127–151.

Chen, Y., Peng, Y., Finin, T., Labrou, Y., Cost, S., Chu, B., Sun, R., Wilhelm, B. (1999) 'A negotiation-based Multi-agent System for supply chain management', *Proceedings of the Third Conference on Autonomous Agents, Workshop on Agent based Decision-Support for Managing the Internet-Enabled Supply-Chain*, Seattle, USA.

Collins, J., Ketter, W., Gini, M. (2002) 'A multi-agent negotiating test bed for contracting tasks with temporal and precedence constraints', *International Journal of Electronic Commerce*, Vol. 7, No. 1, pp. 35–57.

Dudek, G. and Stadtler, H. (2005) 'Negotiation-based collaborative planning between supply chains partners', *European Journal of Operation Research*, Vol. 163, pp. 668–687.

Dworman, G. and Kimbrough, S. (1995) 'On Automated Discovery of Models Using Genetic Programming: Bargaining in a Three-Agent Coalitions Game', *Journal of Management Information Systems*, Vol.12, pp.428–438.

Ertogral, K. and Wu, S.D. (2000) 'Auction-theoretic coordination of production planning in the supply chain', *IIE Transactions*, Vol. 32, pp.931–940.

Faratin, P. (2000) *Automated Service Negotiation between Autonomous Computational Agents*. PhD. Thesis. University of London, England.

Fink, A. (2004) 'Supply chain Coordination by Means of Automated Negotiations', *Proceedings of the 37th Hawaii International Conference on System Sciences, IEEE* , Hawaii, USA.

Forget, P., D'Amours, S. and Frayret, J.M. (2008a) 'Multi-Behaviour Agent Model for Planning in Supply Chains: An Application to the Lumber Industry', *Robotics and Computer-Integrated Manufacturing*, Vol. 24, pp. 664–679.

Forget, P., D'Amours, S., Frayret, J.M. and Gaudreault, J. (2008b) 'Motivations for multi-behaviors agents in supply chain planning', *Proceedings of the 7th International Conference on Modeling and Simulation (MOSIM 08)*, Paris, France.

Forget, P., D'Amours, S., Frayret J.M. and Gaudreault, J. (2008c) 'Design of Multi-behavior Agents for Supply Chain Planning: An Application to the Lumber Industry', *In*: Kordic, V. (ed.), *Supply Chains: Theory and Application*, (pp. 551–568), Vienna: I-TECH Education and Publishing.

Frayret, J.M., D'Amours, S. and Montreuil, B. (2004) 'Coordination and Control in Distributed and Agent-Based Manufacturing Systems', *Production Planning & Control*, Vol. 15, No. 1, pp. 42–54.

Frayret, J.M., D'Amours, S., Rousseau, A., Harvey, S. and Gaudreault, J. (2007) 'Agent-based Supply Chain Planning in the Forest Products Industry', *International Journal of Flexible Manufacturing Systems*, Vol. 19, No. 4, pp. 358–391.

Gaudreault, J., Forget, P., Frayret, J.M., Rousseau A. and D'Amours S. (2008) 'A Multi-Agent and OR-Based Approach to Operations Planning in the Lumber Industry', *Proceedings of the 13th Annual International Conference on Industrial Engineering: Theory, Applications and Practice (IJIE)*, Las Vegas, USA, September 2008.

Gerding, E. H.,van Bragt, D.D. and Poutre, J.L. (2000) '*Scientific approaches and techniques for negotiation: a game theoretic and artificial intelligence perspective*', Technical report SEN-R0005, CWI.

Homburg, C. and Schneeweiss, C. (2000) 'Negotiation within Supply Chains', *Computational and Mathematical Organization Theory*, Vol. 6, pp. 47–59.

Ito, T. and Salleh, M.R. (2000) 'A blackboard-based negotiation for collaborative supply chain system', *Journal of Materials Processing Technology*, Vol. 107, pp. 398–403.

Jennings, N.R., Faratin, P., Lomuscio, A.R., Parsons, S., Wooldridge, M. and Sierra, C. (2001) 'Automated negotiations: prospects, methods and challenges', *Group Decision and Negotiation*, Vol. 10, pp. 199–215.

Jiao J., You X. and Kumar A. (2006) 'An agent-based framework for collaborative negotiation in the global manufacturing supply chain network', *Robotics and Computer-Integrated Manufacturing*, Vol. 22, pp. 239–255.

Kersten, G.E. (2003) 'E-Negotiations: Towards Engineering of Technology-based Social Processes', Research Paper INR 02/04, InterNeg.

Khouider, S., Monteiro, T. and Portmann, M.C. (2008). 'Cadre de modelisation pour evaluation par simulation des mecanismes de negociation dans les entreprises en reseau', *Proceedings of the 7th International Conference on Modeling and Simulation (MOSIM 08)*, Paris, France

Klein, M., Faratin, P., Sayama, H. and Bar-Yam, Y. (2003) 'Negotiating Complex Contracts', *Group Decision and Negotiation*, Vol. 12, pp. 111–125.

Kraus, S. (1997) 'Negotiation and cooperation in multi-agent environments', *Artificial Intelligence*, Vol. 94, pp. 79–97.

Kraus, S. and Wilkenfeld, J. (1991) 'Negotiations over Time in a Multi Agent Environment: Preliminary Report, *Proceedings of the Twelfth International Joint Conference on Artificial Intelligence (IJCAI)*, pp. 56 – 61.

Krovi, R., Graesser, A.C. and Pracht, W.E. (1999) 'Agent Behaviors in Virtual Negotiation Environments', *IEEE Transactions on systems, man and Cybernetics – Part C: Application and reviews*, Vol. 29, No.1, pp. 15–25.

Lomuscio, A.R., Wooldridge, M. and Jennings N.R. (2003) 'A Classification Scheme for Negotiation in Electronic Commerce', *Group Decision and Negotiation*, Vol. 12, No. 1, pp. 31–56.

Matos, N., Sierra, C. and Jennings, N.R. (1998) 'Determining successful negotiation strategies: an evolutionary approach', *Proceedings of the Third International Conference on Multi-Agent Systems (ICMAS-98)*, Grenoble, France, pp. 182–189.

Mitchell, T.M. (1997) *Machine Learning*, WCB/McGraw-Hill.

Monteiro, T., Ladet, P., and Bouchriha, H. (2004) 'Multi-criteria negotiation for a distributed control of a client/provider relationship', *Journal of Decision Systems*, Vol. 13, No. 1, pp. 63–89.

Moyaux, T., Chaib-draa, B. and D'Amours, S. (2006) 'Supply Chain Management and Multiagent Systems: An Overview', *In*: Chaib-draa, B. and Muller, J.P. (ed.), *Studies in Computational Intelligence*, (Vol. 28, pp.1–27), Berlin: Springer-Verlag.

Nagarajan, M. and Bassok, Y. (2002) 'A Bargaining Framework in Supply Chains (The Assembly Problem)', Working paper USC. Obtained through the Internet: http://ssrn.com/abstract=1021602 [accessed 19/9/2008].

Nagarajan, M. and Sosic, G. (2008) 'Game-theoric analysis of cooperation among supply chain agents: Review and extensions', *European Journal of Operational Research*, Vol. 187, pp. 719–745.

Nawa, N. E. (2006) 'Agents that Acquire Negotiation Strategies Using a Game Theoric Learning Theory', *International Journal of Intelligent Systems*, Vol. 21, pp. 5–39.

Neumann, D., Benyoucef, M., Bassiland, S. and Vachon, J. (2003) 'Applying the Montreal Taxonomy to State of the Art E-Negotiation Systems', *Group Decision and Negotiation*, Vol. 12, pp. 287–310.

Oliveira, E. and Rocha, A.P. (2001) 'Agents advanced features for negotiation in electronic commerce and virtual organisations formation process', *Lecture Notes in Computer Science*, Vol. 1991, pp. 77–96.

Rahwan, I., Sonenberg, L., Jennings, N.R. and McBurney, P. (2007) 'STRATUM: A Methodology for Designing Heuristic Agent Negotiation Strategies', *Applied Artificial Intelligence*, Vol.21, pp. 489–527.

Sandholm, T. (2000) 'Agents in Electronic Commerce: Component Technologies for Automated Negotiation and Coalition Formation', *Autonomous Agents and Multi-Agent Systems*, Vol.3, pp. 73–96.

Sandholm, T. and Lesser, V.R. (1995) 'Issues in automated negotiation and electronic commerce: Extending the contract net framework'. *Paper presented at the First International Conference on Multi-Agent Systems (ICMAS-95)*, San Francisco, USA.

Shen, W., Norrie, D.H. and Barthes, J.P. (2001) *Multiagent Systems for Concurrent Intelligent Design and Manufacturing*, London: Taylor and Francis.

Sierra, C., Faratin, P. and Jennings, N.R. (1997) 'A service-oriented negotiation model between autonomous agents'. *Paper presented at the conference Modeling Autonomous Agents in a Multi-Agent World, (MAAMAW 97)*, Ronneby, Sweden.

Xue, X., Lu, J., Wang, Y. and Shen, Q. (2007) 'Towards an Agent-Based Negotiation Platform for Cooperative Decision-Making in Construction Supply Chain', *In*: Nguyen, N.T. et al. (ed.), *Lecture Notes in Computer Science, KES-AMSTA 2007, LNAI 4496*, (pp. 416–425), Berlin: Springer-Verlag.