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COLLABORATIVE AND ADAPTIVE SUPPLY CHAIN PLANNING

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À Édith,
ma muse

*"It is not the strongest of the species that survives, nor the most intelligent that survives.
It is the one that is the most adaptable to change."*

Charles Darwin

"In preparing for battle I have always found that plans are useless, but planning is indispensable."

Dwight D. Eisenhower

Résumé

Dans le contexte industriel d'aujourd'hui, la compétitivité est fortement liée à la performance de la chaîne d'approvisionnement. En d'autres termes, il est essentiel que les unités d'affaires de la chaîne collaborent pour coordonner efficacement leurs activités de production, de façon à produire et livrer les produits à temps, à un coût raisonnable. Pour atteindre cet objectif, nous croyons qu'il est nécessaire que les entreprises adaptent leurs stratégies de planification, que nous appelons comportements, aux différentes situations auxquelles elles font face. En ayant une connaissance de l'impact de leurs comportements de planification sur la performance de la chaîne d'approvisionnement, les entreprises peuvent alors adapter leur comportement plutôt que d'utiliser toujours le même. Cette thèse de doctorat porte sur l'adaptation des comportements de planification des membres d'une même chaîne d'approvisionnement. Chaque membre pouvant choisir un comportement différent et toutes les combinaisons de ces comportements ayant potentiellement un impact sur la performance globale, il est difficile de connaître à l'avance l'ensemble des comportements à adopter pour améliorer cette performance. Il devient alors intéressant de simuler les différentes combinaisons de comportements dans différentes situations et d'évaluer les performances de chacun.

Pour permettre l'utilisation de plusieurs comportements dans différentes situations, en utilisant la technologie à base d'agents, nous avons conçu un modèle d'agent à comportements multiples qui a la capacité d'adapter son comportement de planification selon la situation. Les agents planificateurs ont alors la possibilité de se coordonner de façon collaborative pour améliorer leur performance collective. En modélisant les unités d'affaires par des agents, nous avons simulé avec la plateforme de planification à base d'agents de FORAC des agents utilisant différents comportements de planification dits de réaction et de négociation. Cette plateforme, développée par le consortium de recherche FORAC de l'Université Laval, permet de simuler des décisions de planification et de planifier les opérations de la chaîne d'approvisionnement. Ces comportements de planification sont des métaheuristiques organisationnelles qui

permettent aux agents de générer des plans de production différents. La simulation est basée sur un cas illustrant la chaîne d'approvisionnement de l'industrie du bois d'œuvre. Les résultats obtenus par l'utilisation de multiples comportements de réaction et de négociation montrent que les systèmes de planification avancée peuvent tirer avantage de disposer de plusieurs comportements de planification, en raison du contexte dynamique des chaînes d'approvisionnement. La pertinence des résultats de cette thèse dépend de la prémisse que les entreprises qui adapteront leurs comportements de planification aux autres et à leur environnement auront un avantage concurrentiel important sur leurs adversaires.

Abstract

In today's industrial context, competitiveness is closely associated with supply chain performance. In other words, collaboration between business units to ensure coordination is essential to produce and deliver products to final clients on time and at a reasonable price. To reach this objective, we believe it is important that companies adapt their production by adapting their planning strategies to the situations, instead of using a single one, and by knowing the impact of their methodologies on supply chain performance. In this thesis, we examine the possibility of integrating multiple planning methodologies, here called behaviours, to each supply chain member. Because these members can choose between different behaviours and the different combinations of behaviours will have an impact on the overall performance, it is difficult to know which set of behaviours is preferable to increase this performance. It then becomes interesting to simulate these sets of behaviours in different situations and evaluate their performance.

To make the use of the different possible planning behaviours, using agent-based technology, we developed a multi-behaviour agent model with the ability to adapt its behaviour to the situation. These planning agents have the ability to coordinate their actions in a collaborative way to increase the global performance. By modelling business units as agents, we simulated agents using different reaction and negotiation behaviours with the FORAC agent-based planning platform. This platform, developed by the research consortium FORAC is designed to simulate supply chain decisions and plan supply chain operations. The careful design and assembling of these planning behaviours together form organizational meta-heuristics that allow the agents the collective capability to generate different production planning response. Simulations are based on a case illustrating the lumber industry supply chain. Results on reaction and negotiation behaviours show that advanced planning systems can take advantage of using multiple planning behaviours, because of the dynamic context of supply chains. The relevance of this thesis relies on the premise that companies which adapt their planning behaviours to their partners and to the environment will gain a clear advantage over competitors.

Preface

This Ph.D. thesis entitled "Collaborative and Adaptive Supply Chain Planning" includes three papers that have been published or submitted for publication. I am the main author of the three papers and I was responsible for both writing and editing. I have also contributed largely to the ideas and concepts proposed. The first paper entitled "Multi-Behaviour Agent Model for Planning in Supply Chains: An Application to the Lumber Industry" has been published in the *Robotics and Computer-Integrated Manufacturing Journal* (vol. 24, p. 664–679). The co-authors Sophie D'Amours, professor at Université Laval (Canada), and Jean-Marc Frayret, professor at Polytechnique de Montréal (Canada), who are both my advisors, contributed by proposing ideas, discussing concepts and reviewing the paper. The second paper entitled "Performance Analysis of Multi-behaviour Agents for Supply Chain Planning" has been accepted for publication by the journal *Computers in Industry*. The co-authors Sophie D'Amours, Jean-Marc Frayret and Jonathan Gaudreault, research professional at Université Laval (Canada), contributed as reviewers. The third paper entitled "Collaborative Agent-based Negotiation in Supply Chain Planning using Multi-behaviour Agents" is in correction to be submitted to the *European Journal of Industrial Engineering*. The co-authors are Thibaud Monteiro, professor at Université de Metz (France), Sophie D'Amours and Jean-Marc Frayret. They contributed to this article as reviewers and they proposed several ideas. None of the papers presented in this thesis have been modified from the published or submitted version.

In addition to these three articles, I am the first author or co-author of other contributions, including a book chapter, two submitted papers and two published conference proceedings. These extra contributions are the following:

- P. Forget, S. D'Amours, J.M. Frayret & J. Gaudreault. (2008). Design of Multi-behaviour Agents for Supply Chain Planning: An Application to the Lumber Industry, *Supply Chains: Theory and Application*, Ed. V. Kordic, I-TECH Education and Publishing, ISBN 978-3-902613-22-6, 2008, pp. 551-568

- P. Forget, S. D'Amours, J.M. Frayret & J. Gaudreault. (2007). Supply Chain Relationship Design Using a Multi-Behaviour Agent Model, *International Journal of Electronic Business: a* *special issue on Innovative Organizing of Customer and Supplier Networks in the Digital Economy* [Submitted]

- J. Gaudreault, P. Forget, J.M. Frayret, A. Rousseau & S. D'Amours. (2008). Distributed Operations Planning for the Lumber Supply Chain: Optimization and Coordination, *International Journal of Industrial Engineering* [Submitted]

- P. Forget, S. D'Amours, J.M. Frayret. (2006). Collaborative Event Management in Supply Chains: an Agent-based Approach. In *IFIP International Federation on Information Processing*, Volume 220, Information Technology for Balanced Manufacturing Systems, ed. Shen, W. (Boston: Springer), pp.89-98

- S. D'Amours, J.M. Frayret, A. Rousseau, S. Harvey, P. Plamondon & P. Forget. (2006). Agent-based Supply Chain Planning in the Forest Products Industry. In *IFIP International Federation on Information Processing*, Volume 220, Information Technology for Balanced Manufacturing Systems, ed. Shen, W. (Boston: Springer), pp.17-26

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This thesis could not have been completed without the support of many people. I would like to express my deep gratitude to Sophie D'Amours, my advisor, who gave me her time, ideas, encouragements and opinions. During this work, she has been a guide and an inspiration for me. I would like to thank Jean-Marc Frayret, my co-advisor, who with his wisdom and spirit, was always able to transform my few words into excellence. I am also grateful to the FORAC research consortium and the Natural Sciences and Engineering Research Council (NSERC) for having funded my work during all these years.

I would also like to thank the research professionals who participated to my work, especially Jonathan Gaudreault, Christian Rouleau, Sébastien Lemieux, Alain Rousseau and Thibaud Monteiro. They gave me valuable feedback and helped to concretize my ideas. They all made sure I was not flying too far off the ground. Special thanks to Connie Van Horne who by her numerous corrections of my work, helped me improve my English writing skills.

I am grateful to my parents, Suzanne and Serge, who never stopped supporting me in my studies, from the first year to the last.

I dedicate this thesis to Edith, my love and the mother of my daughter, who always helps me push my limits a little further, making sure I surpass myself every day.

Québec, December 2008.
Pascal Forget

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List of abbreviations

MRP: Material Requirement Planning

MRP II: Manufacturing Resource Planning

ERP: Enterprise Resource Planning

AI: Artificial Intelligence

OR: Operational Research

MPC: Manufacturing Planning & Control

DSS: Decision Support System

SCEM: Supply Chain Event Management

APS: Advanced Planning and Scheduling

DAI: Distributed Artificial Intelligence

MAS: Multiagent System

ABS: Agent Building Shell

RFID: Radio Frequency Identification

SCM: Supply Chain Management

ABS: Agent Building Shell

CPFR: Collaborative Planning, Forecasting and Replenishment

BDI: Belief-Desire-Intention

CEM: Collaborative Event Management

d-APS: distributed Advanced Planning and Scheduling

FIPA: Foundation for Intelligent Physical Agents

TF: Taskflow

CP: Constraint Programming

CSR: Commitment-based Sense-and-Respond

MIP: Mixed Integer Programming

SCOR: Supply Chain Operations Reference

FBM: Foot Board Measure

JIT: Just-In-Time

BO: Backorders

MLCLSP: Multi-Level multi-item Capacitated Lot Sizing Problem

Chapter 1

Introduction

1.1 Overview of the research context

During the last decade, organizations from all industries faced the dynamic context of globalization. A multiplication of competitors, sales price decrease, mass customization, new environmental norms and new information technologies are all changes that have forced them to find new ways to survive. The Canadian lumber industry is a good example of this disruptive context, while companies had once a competitive advantage, many of them are now striving to offer their product or service at a more competitive price.

Different approaches have been pursued by lagging organizations to regain the advantages they had and increase their productivity. Some tried to re-engineer their production processes or buy new equipment using the latest technology. Others invested in innovation to offer customers products before they actually ask for them. Cost reduction is another approach used, which includes: developing systems to optimize transportation or production scheduling, redesigning plant layouts and plant locations, or outsourcing part of the production to emerging countries with low labour costs.

Another approach put forward is to work closer with supply chain organizations to become more efficient. This leads to supply chain management (SCM), that is the process of effectively managing the flow of materials and finished goods from raw material to production facilities and finally, to customers. A lack of coordination leads to inefficiencies such as reduced profit, high inventory levels and long delivery times. By increasing coordination, organizations from the same supply chain can become more efficient and therefore more competitive. The objective is to plan production for each member in a way that increases their financial performance by reducing inventories and delays.

Managing efficiently the supply chain is a difficult task since it involves many members with individual goals and constraints. Traditional planning approaches, most of them centralized, have difficulty handling challenges raised by the inherent characteristics of supply chains. First, some organizations are reluctant to share private information, which limits the possibility of exchanging information, or makes centralized planning impossible. Also, the number of changes along the supply chain necessitates to quickly react and communicate changes to all partners. Another difficulty is the complexity of modelling local constraints and physical information for every organization, and keeping this information continuously up-to-date in a centralized system. Planning systems such as Material Requirement Planning (MRP), Manufacturing Resource Planning (MRPII) or Enterprise Resource Planning (ERP) are used to assist production managers in planning production for a single plant or even supply chains. But when multiple organizations are involved, managers are faced with the problems enumerated above.

Information technologies, such as the Internet, have enabled the development of new ways to increase coordination between partners, but mechanisms must be used to coordinate partners in an efficient way. Different distributed planning paradigms have been proposed to manage the supply chain without requiring a central planning system. The basic idea shared by distributed paradigms is to give local entities the ability to plan their activities and to use coordination mechanisms, such as communication channels and retroaction loops, to ensure the global coherence of the system. Among them, agent-based planning systems use agent technology to represent entities (i.e. companies, departments and machines) and their interactions. In other words, agents take autonomous decisions based on local and global information, and communicate with each other to coordinate their actions. An agent is a computer system capable of autonomous actions in its environment to meet its internal objectives. It has owns different characteristics such as autonomy, reactivity, proactivity and social abilities. Agents follow their internal objectives, or goals, to plan their own actions. These goals can be shared with other agents where a certain level of collaboration can emerge, or can be in opposition to others, in adversarial contexts. Many have applied this technology to various domains (Jennings et al., 1998; Weiss, 2003), including supply chain contexts (Shen & Norrie, 1999; Shen et al., 2001; Parunak, 1998, Caridi & Cavalieri, 2004; Frayret, 2002).

In complex and dynamic contexts such as supply chains, members need to adapt their behaviours to specific situations. When a decision must be taken in a few minutes or a compromise must be found with a supplier, the local planning behaviour must be adapted. In the same way, when demand for final customers is very high or supplies are running out, different planning behaviours can be used to generate alternative production plans and result in very different solutions. While most production planning systems use a single planning behaviour for all situations, they do not tackle the advantage of adaptive planning.

While agents can represent different subjects like materials or machines, here agents represent planning centres. These centres are independent decision entities within the supply chain, such as plants, warehouses, buyers or vendors. Confronted to certain environmental changes such as increased or decreased demand, an agent must locally build a new production plan using its own planning behaviour, communicate a new demand plan to its suppliers (if needed) and a new supply plan to its clients (also if needed). Coordination emerges when all agents agree on what they receive from their respective suppliers.

When an agent builds a local production plan, it uses a planning behaviour. It can use an optimization model to find an acceptable solution or to find the best possibility. These behaviours offer good local results but agents generally do not have an idea of their impacts on their partners or on the global performance of the supply chain. An agent's decision to delay some products or to build up inventory can be or cannot be advantageous for global performance. Planning behaviours can usually be changed by modifying the model's parameters, either specific to the planning context (e.g. delays, capacity) or to the solution approach itself (e.g. number of iterations, starting solution, maximum searching time), leading to different production plans. Also, the coordination mechanism between agents can be changed, which modifies the communication of supply and demand plans. The sequence of information exchanges between agents and the number of feedback (or negotiation) loops can have an important impact on the supply chain coordination and inevitably, on the overall performance.

While many adaptations can be applied to planning behaviours, agent designers can hardly know which parameters or coordination mechanisms are preferable for the agent and for the supply chain. In fact, because of the dynamic nature of supply chains, where the environment changes rapidly, it is not certain that a specific choice will remain preferable over time. This is where adaptive agents have the advantage of changing planning parameters depending on the environment. In a simulation context, or in real world situation, an adaptive agent can select a planning behaviour and observe the impact on the supply chain performance. Then, through multiple attempts, it could learn which one offers the best results in which situations.

In this thesis, collaboration is defined as the act of working together toward common goals by different organizations, in order to achieve higher performance. In such a context, these organizations can be asked to take action decreasing their local performance in order to increase global performance. This can be straightforward in internal supply chains, when all business units are part of the same company. In the case of external supply chains, where partners are from various companies, they can be reluctant to share the profits for the benefit of the supply chain. Profit redistributing mechanisms can be employed to convince partners to act contrary to their local needs in order to create value for the supply chain that would not be available without it. We believe that collaboration is essential today to increase the competitiveness of the supply chain and all partners must contribute.

1.2 Objective of the thesis

In this thesis, we tackle the agent-based supply chain planning problem, more precisely the use of collaborative and adaptive agents in an agent-based supply chain planning system. The main objective of this thesis is to validate the hypothesis that collaborative and adaptive planning increases the supply chain performance. By designing an agent with the ability to use multiple planning behaviours and coordination mechanisms, referred to as a *multi-behaviour agent*, it becomes possible to simulate various environments in an agent-based planning platform and observe how agents using different planning behaviours perform. It is also possible to verify whether using multiple sets of agent behaviours is more advantageous than using a single one in a changing environment.

As is it presented in this thesis, a multi-behaviour agent uses learning abilities to learn and remember which planning behaviour performs well in each situation. Automated learning is a complex subject and has not been covered in the context of this thesis. The focus is put on the interest of adapting behaviours, based on knowledge matrix.

The hypothesis of this thesis assumes that the level of environmental change occurring on a normal basis in the supply chain is sufficiently important to take advantage of adaptive behaviours. Indeed, in a supply chain with very few changes, it will be less interesting to adapt planning behaviours. Simulations of each potential change could indeed be made to identify the best planning behaviour, and therefore adaptation would rarely be needed. The application context of this thesis is however different because the lumber supply chain presents such an important variation in various ways. This is mainly due to the variable nature of the basic material (wood), the dynamic nature of the market and the price volatility. For the simulations presented in this thesis, two environmental parameters have been changed alternatively, these being the demand intensity and the proportion of *contract* and *spot* orders. Contract orders represent guaranteed volumes between two partners, with premium for on-time deliveries and penalties for backorders. At the opposite, spot orders are not guaranteed volumes, where a late order is a lost order. There is no premium and no penalty for backorders. In the forest industry, the demand intensity can vary depending on external factors such as the state of the economy, laws, export taxes, exchange rates and regulations. From week to week, the demand intensity can show important variation, which an adaptive agent can take advantage of. In terms of proportion of contract and spot orders, it represents a middle term change. Such strategic repositioning can be made on a yearly basis, in order to accept more or fewer contracts. From another point of view, depending on the precise work to be done, the proportion of contract and spot orders can be very different from month to month, as for example having no contract to be produced for a certain period and only contract in another period. Planning behaviours can be adapted following precisely what is required to be delivered in a specific period of time.

1.3 Thesis organization

This thesis follows the organization illustrated in Figure 1.1. Since this is a paper-based thesis, the problem is presented in three different papers. Each major step of the thesis is presented in a different paper.

Following the identification of the research objective and a literature review on supply chain planning and agent-based technology, we present the first paper entitled "MULTI-BEHAVIOUR AGENT MODEL FOR PLANNING IN SUPPLY CHAINS: AN

APPLICATION TO THE LUMBER INDUSTRY". To understand the concepts of collaboration for production planning agents, we propose a collaborative event management (CEM) approach between two supply chain members. We also propose an agent conceptual model including the basic competencies for adaptive planning agents. These concepts helped us to develop a multi-behaviour agent model capable of adapting its planning behaviour to its environment. Using three behaviour categories, *reaction*, *anticipation* and *negotiation*, the multi-behaviour agent can analyze its environment and decide which behaviour to adopt. Then, we discuss the possible implementation of such agents in an agent-based planning platform adapted for the lumber supply chain. Different planning behaviours for each category are proposed.

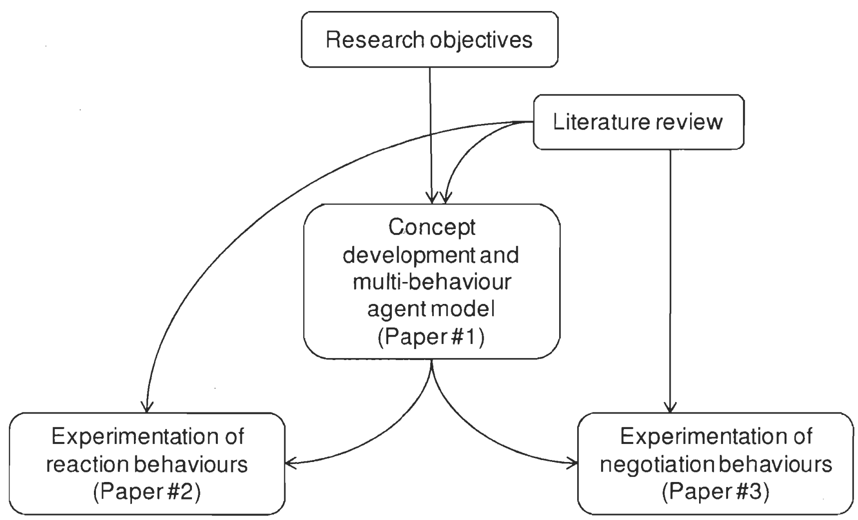

Figure 1.1. Thesis organization

The second paper, entitled "PERFORMANCE ANALYSIS OF MULTI-BEHAVIOUR AGENTS FOR SUPPLY CHAIN PLANNING", presents simulation results of multi-behaviour agents. We develop an experimental plan to test multi-behaviour agents in various situations met in the lumber industry. Composed of different reaction planning behaviours, nine coherent sets of planning behaviours, or team behaviours, are simulated on the FORAC agent-based planning platform. Variations are applied to customers' demand and we analyze the variability of supply chain performance depending on the team behaviour selected. Performance is observed in terms of total lateness for contract demand, total inventory, adjusted revenues and delivery performance for spot demand. An estimation of average gains shows the advantage of adapting agents' behaviour in various situations.

The third paper is entitled "COLLABORATIVE AGENT-BASED NEGOTIATION IN SUPPLY CHAIN PLANNING" and discusses the possibility of implementing negotiation behaviours in collaborative supply chain planning. We review the different types of automated negotiations and how they have been applied to supply chain planning. We present a generalized protocol for adaptive and collaborative one-to-one negotiations. We identify three different negotiation behaviours which can be used to coordinate production plans: *priority*, *substitution* and *lot sizing* negotiations. Simulations between two planning agents, sawing and drying, are performed for different situations on the FORAC agent-based planning platform, using the lumber supply chain study case. Results shows that various performances in term of lateness can be achieved following the negotiation behaviour used by the drying agent, suggesting an advantage for agents to change negotiation behaviour depending on the environment.

The remainder of this thesis follows this order. Chapter 2 presents a literature review of the emergence of using adaptive planning in supply chains. From the current planning systems used in industry, we present the development of advanced systems and how it can increase supply chain performance. Special attention is given to agent-based systems applied to manufacturing systems and supply chain planning. In Chapter 3, we describe the research methodology followed in the thesis. We present the agent-based planning and simulation platform used in this research and explain how it was used to support the research. Chapter 4, 5 and 6 present in sequence the three articles described previously. Each of these chapters presents a different contribution and proposes a literature review adapted to the specific needs of the contribution. These parts of the literature review complete the review presented in Chapter 2. Chapter 7 concludes this thesis with a summary and a discussion of research opportunities that deserve further development.

1.4 Overview of the forest products industry

The concepts presented in this thesis have been applied to study cases related to the forest products industry. In Canada, this industry is one of the largest employers in the country and provides more than 750 000 direct and indirect jobs (FPAC, 2008). The importance of this industry for the country's economy is major and there is a constant need to improve practices. In recent years, the forest products industry has faced difficulties never met before. The conjunction of growing international competition, the rise in value of the Canadian dollar and the reduction of cutting rights has forced the closing of many plants all over the country (CIFQ, 2009). It is now more important than ever to rethink how competitive advantage can be regained. This makes adaptation of planning behaviours a particularly interesting approach for supply chain planning.

In the next decade, the Canadian forest products industry will have to reconsider different aspects of their practices if they want to remain competitive and their production planning approaches can be one of them. Technologies like the one presented in this thesis can help increase supply chain performance and lead the Canadian forest products industry to a stronger position. In fact, this industry represents a perfect context for this technology. The industry is already highly distributed, with many organizations interacting at all production levels. Another interesting aspect is the large amount of stochastic disturbances in many aspects of the supply chain, mainly due to the highly heterogeneous aspects of the resource: uncertain process output, production of co-products and by-products, price variation in the spot market and demand variation in commodity markets.

1.5 Contribution of the thesis

This thesis presents a new approach enabling supply chain collaborative planning using adaptive planning agents. The concepts development and the experimentation performed for this thesis represent different scientific contributions.

The first contribution is to propose a multi-behaviour agent model capable of using different planning methodologies and being able to learn when to use the preferred one. We describe how the model works and how it can be applied to an agent-based planning system. We underline how a collection of multi-behaviour agents can lead to higher global performance in a supply chain context and we present examples of planning behaviours.

The second contribution is the experimentation of different simple planning behaviours (reaction behaviours) in the study case of the lumber supply chain to analyze the potential of using agents that could adapt their planning behaviour. Using the FORAC agent-based planning platform (detailed in Chapter 3), we simulate demand variations and analyze different performance indicators for the supply chain. While most planning systems use single planning behaviours, we show the possible advantage that can be gained by giving agents the possibility of adapting themselves to different demand variations.

The third contribution is the proposition of different collaborative negotiation behaviours for automated negotiation between planning agents. Experiments are proposed to test the different behaviours and to estimate their value. Because some situations require more than a simple behaviour to find a collective solution and it is sometimes needed to exchange more information, we propose a generalized one-to-one collaborative negotiation protocol. We simulate the negotiation behaviours using multi-behaviour agents in the FORAC agent-based planning platform. We compare the possible gains in using different negotiation behaviours in various situations and the initial solution found without using any negotiation. Again, results show an advantage in adapting the negotiation behaviours to the environment.

1.6 Limitation

Some limitations of this thesis must be pointed out in order to give a clear picture of the contributions. First, during simulations, agents were confronted to different environments that are not exceptional and that can occur every day, such as demand variation, contract level variation and new demand orders. These variations are normal and do not represent perturbation of the planning process. Indeed, the technology presented in the thesis could be adopted to handle perturbations, such as machine breakdowns or supply shortages, but this has not been simulated.

Also, the developments of the multi-behaviour agents were not pursued with the objective of proposing a finished and usable planning tool, but more to verify the interest of collaborative and adaptive planning. Concepts of learning ability have been proposed to build a complete agent model, but have not been tested or implemented into the simulations. Also, the various configurations of planning behaviours and the analysis of the performances were hand-made. Similarly, the selection of specific team behaviour was forced on agents, instead of letting them decide when to adapt. Indeed, such a mechanism must be implemented but was not done during this thesis.

Finally, the financial interest of using multi-behaviour agents and adapting planning behaviours has not been verified. Possible gains are presented in articles 2 and 3, in terms of different performance indicators and show that an agent that could adapt its planning behaviour with the other agents holds the potential to approve supply chain performance. In order to measure the interest of using the technology into real supply chains, these gains must be compared to the implementation costs inherent in the use of such a technology. This study has not been done because of the difficulty of estimating these implementation costs.

Chapter 2

Towards Adaptation in Supply Chain Production Planning

This chapter presents the major developments leading to adaptive production planning in supply chains. Because adaptive planning is a central theme in this thesis, it is interesting to first understand how production planning is handled and understood by the industry and academics and what advantages could be obtained from introducing adaptive planning methodologies.

In most of the manufacturing industries, production planning is handled locally and there is no global approach to the management of the supply chain. In these cases, supply chain production planning is hierarchical (or sequential), which means that orders are transmitted from one supply chain organization to another, each of them being responsible for producing what is required. There is no explicit effort to manage the interdependencies or increase the supply chain performance. Following the trend towards managing supply chains and offering an integrated planning, centralized planning systems have been developed. They acquire information from all departments or organizations to help a central planner to build integrated production plans. In the last decade, different distributed planning approaches (instead of centralized planning) have been proposed by researchers to plan supply chains, such as holonic and agent-based planning systems. In this last approach, the different planning centres are represented as specialized agents who build production plans and can communicate with the other agents to ensure a certain degree of coherence. This planning approach is still new for the industry and very few implementations have been carried out at this date, if any.

This chapter first reviews the centralized planning systems used for supply chains and underlines the need for adaptive planning. Then, a review of agent-based technology as a distributed planning approach is proposed for production planning. Next, more specific to our problem, the use of agent-based technology applied to supply chain planning is presented.

Also, different adaptive agents are presented and explained. Finally, we discuss the research opportunities emerging from this literature review.

2.1 Centralized supply chain production planning systems

Supply chains represent a major challenge in terms of information exchange, collaboration and adaptation to plan production efficiently, compared to a single company. In fact, production planning has always represented an important preoccupation in many research areas, such as Artificial Intelligence (AI), Operational Research (OR), industrial engineering and management (Moyaux, 2001). Today, centralized systems can be found to support planning production, such as *information systems* and *decision support systems*. These systems are run on a computer that manages all production planning activities. In the case of information systems, the most well known example is ERP systems. Essentially, these systems gather all available production information for every department and give employees the tools to communicate, exchange information, plan production and control variations. In the case of decision support systems, it includes systems like the Manufacturing Planning & Control (MPC) systems, Decision Support Systems (DSS) and Supply Chain Event Management (SCEM) systems, which help managers make the best decisions for planning the supply chain and proposing solutions. These decision support systems help people manage the supply chain efficiently and lead to improved performance. The main advantage with centralized systems is that they make it possible to see the entire supply chain and optimize some parts.

On the other hand, centralized production planning systems present multiple disadvantages. In a distributed context such as supply chain, where different members work together to deliver goods to final customers, planning problems rapidly become too complex and difficult, if not impossible, to be solved centrally. This is due to the quantity of information needed to plan correctly every organization, such as production line information, constraints, etc. Also, centralized systems are slow to react because they need to update the information from all organizations in real time, process it, build new plans and communicate them (Alvarez, 2007). Another problem is the reluctance of certain members to share private information that can be crucial to their competitiveness (Azevedo et al., 2004). In a centralized system, critical information about all organizations must be known, such as production capacity and output, and some organizations do not want this information to be transmitted to a central system.

To overcome some of these problems, new solutions have been proposed, mostly based on state-of-the-art data-collection technologies and information diffusion across the supply chain. They differ on the degree of use of new technologies and on the way they respond to signals. The Viewlocity Adaptive Supply Chain Management system (Viewlocity, 2008) is a supply chain planning and event management application helping managers to react to changes. The infrastructure enables the users to be warned when exceptions happen using various alert functionalities (phone, e-mail, PDAs, etc.) and provides the communication support needed to collaborate with supply chain partners to solve these exceptions. Workflows can be predefined so the system proposes the course of action to follow. Once approved, the actions are executed and the production plan is updated and sent to all partners. The SAR Blue Enterprise system developed by IBM (Lin et al., 2002) is another event management system used to manage supply chain changes, but goes further than dealing with exceptions. It is based on the Sense-and-Respond concept of organizations (Haeckel, 1999), which focuses on identifying customer needs, new opportunities and supply trends at the moment they are changing. Such systems enable the automatic sensing of complex internal and external business environmental changes, and responds quickly with the best available policies in order to achieve the business objectives. The system is versatile since it is based on an agent-based framework (concept presented in the next section) that can be adapted to different business models. The supply chain management solution mySAP SCM from SAP (SAP, 2008) is a complete ERP system that uses information visibility across the entire supply chain as a way to offer adaptation possibilities to all partners. It includes an event management application (SAP EM) to monitor specific information, using RFID (radio frequency identification) and sensors, and generates reports to coordinate planning activities with partners. These systems present state-of-the-art event management technologies, which are effective systems to handle perturbation. In most case, they warn planners that a situation change and actions must be performed. They can also propose sequence of actions. But in no case they plan production and adapt their production strategies to the perturbations encountered.

More evolved systems such as Advanced Planning and Scheduling (APS) systems, considered as state-of-the-art technology for production planning (Frayret et al., 2007), use the advantage of OR techniques, heuristics or constraint programming to optimize parts of the production, by identifying optimal or close to optimal solutions to complex planning problems. These systems are usually implemented as specialized decision-support systems that planners can use to optimize production plans. APS is defined as a *hierarchical planning system* in the sense that decision problems are broken down into different decision levels. In fact, APS systems represent an alternative to centralized systems which cannot solve the global problem due to its complexity. The reader is referred to Stadtler (2005) for a complete description of APS.

2.2 Need for new approaches

A great amount of effort in research and development has been deployed to develop planning systems for supply chains more adapted to supply chain context. The main difficulties that must be dealt with are changing environment, autonomous decision making of companies, collaboration and information exchanges sometimes limited or difficult, and difficult or impossible central coordination. Different researchers have highlighted requirements of next generation planning systems to overcome these difficulties:

- Re-configurable production systems, founded on autonomous and intelligent modules, interacting dynamically to reach local and global goals (Caridi et al., 2004);
- Intelligent, flexible, extensible, fault tolerant and reusable intelligent systems (Shen et al., 1999);
- Systems that adapt to short-term changes in products, production plans and machine states while keeping good production performance, respecting delivery dates and keeping inventory levels low (Cantamessa, 1997);
- Fast information exchange throughout the supply chain on inventory levels, quality, production output and demand (Frayret et al., 2007);
- Fast coordinated reaction to correct any deviance from the plan (Frayret et al., 2007);
- New planning methodologies based on negotiation, cooperation, autonomy and proactivity (Azevedo et al., 2004).

These needs show the way for the development of new approaches for supply chain planning, with a clear emphasis on distribution and adaptation to face the challenges of our present era. New paradigms must be found to tackle the inherent complexity of supply chain planning. Collaboration between different supply chain partners becomes a critical factor to respond to rapid changes in customer needs and to increase the overall supply chain performance (Jung et al., 2005).

2.3 Agent-based planning systems

Different organizational paradigms have been studied to operate distributed systems, such as fractal factory, bionic manufacturing, holonic manufacturing and the NetMan paradigm (see Frayret et al., 2004 for a review). These paradigms are generic frameworks that can be used to design distributed manufacturing systems. They differ from each other in the way they handle specific problems, manage information and coordinate actions.

Among the intensive developments of recent decades, researchers have been looking at solving complex problems, which are problems leading to an explosion of possibilities. Supply chain production planning falls into this category. OR techniques can provide very good results for complex problems, but still, it is difficult to select the best technique for dynamic contexts and when multiple problems must be resolved at the same time, processing time explodes. In the eighties, the concept of intelligent agent was born to help resolve this kind of problem. Since these initial contributions, agent-based technology has largely been recognized as a promising paradigm for the next generation of supply chain production planning systems (Shen et al., 2001).

While the scientific community is not in full agreement as to the definition of agent, a majority agree with its central quality: autonomy. It must be able to make autonomous decisions, using available information, with a certain level of control over its actions (Frayret et al., 2007). In fact, an agent is a software component situated in a certain environment and is capable of autonomous actions in this environment to meet its internal objectives (Jennings et al., 1998). Four basic characteristics of agent can be pointed out (Wooldridge et al., 1999):

i. Autonomy: the agent is able to act with a certain degree of control over its actions and its internal state;

ii. Reactive: the agent perceives its environment and reacts promptly to changes in order to satisfy its internal objectives;

iii. Proactive : the agent is able to behave according to its objectives by taking initiatives;

iv. Social abilities: the agent is able to interact with other humans or agents in order to satisfy its objectives.

However, the definition of agent is not limited to this. Other authors name many other characteristics such as network-centric, communicator, semi-autonomous, deliberative, predictive, adaptive, flexible, persistent and mobile (Weiss et al. 1999). The learning ability is another interesting ability for an intelligent agent, but it does not create unanimity in the scientific community. The reader can find a more detailed description of agents in Russel and Norvig (2003).

Depending on the type of environment and the nature of the problem, agents can be designed in various ways. The literature presents many ways to classify agent architectures. Shen et al. (2001) proposed two classifications, by behaviours and by internal organisation, as presented in Table 2.1:

Table 2.1. Agent architecture classifications (adapted from Shen et al., 2001)

By behaviour	***By internal organization***
Reactive architecture	Modular architecture
Deliberative architecture	Subsumption architecture
Hybrid architecture	Blackboard architecture
Collaborative architecture	Layered architecture

From the behaviour perspective, four architectures can be distinguished: reactive, deliberative, hybrid and collaborative. The reactive architecture links specific inputs to specific outputs. A reactive agent has no internal representation of its world, but uses sensors to monitor specific changes in its environment. In simple environments, reactive agents can perform very well, while in more complex environments, they can show a lack of intelligence and adaptability (Shen et al., 2001). In contrast, agents with deliberative architecture use their internal knowledge of their environment and their objectives (or goals) to select the best action. Specific information from the environment is recorded and translated into knowledge.

The Belief-Desire-Intention (BDI) architecture (Rao & Georgeff, 1992) is an example of a deliberative architecture, where the agent uses its knowledge about its environment (belief) and its internal objectives (desire) to build a plan of action (intention). This architecture makes it possible to plan a sequence of actions in order to meet long term goals. The main disadvantage is the slow reaction time in dynamic environments, where situations can change while the agent is processing to find a suitable action. Hybrid agents use the advantages of both reactive and deliberative architectures. Such agents can present several behaviours to handle different environments, such as reactive behaviour for dynamic environments and deliberative behaviour for complex environments. The InteRRaP agent model (Muller, 1997) uses a hybrid architecture. When the agent encounters a new situation, it first tries to find a set of predetermined actions in its *behaviour layer*. If no set is found, the agent uses its *plan layer*, used for deliberation about what actions could be used to create a new set of actions and solve the problem. If the problem is still not solved, the agent uses its third layer, the *cooperation layer*, where the agent collaborates with other agents or humans to find a solution adapted to the environment but with unknown action. The main disadvantage of such architecture is the difficulty to coordinate the balance between reactive and deliberative behaviours. Collaborative architectures are used by agents who work together to solve problems. It is the synergy from their cooperation that permits solving complex problems that are beyond the capability of a single agent (Shen et al., 2001). Agents using the Contract Net protocol (Smith, 1980) have a simple collaborative architecture, compared to agents who use complex negotiation protocols, which must have more advanced collaborative architectures.

From the internal organization perspective, an agent's architecture can be modular, subsumption, blackboard and layered. A modular architecture is basically an organized assembly of modules (e.g. perception, interpretation, decision making, planning, execution, etc.) with fixed connections. The information flow between these modules is defined by the designer and does not change during the existence of the agent. Most deliberative agents, such as DIDE (Shen & Barthès, 1996) and DESIRE (Brazier et al., 1998) are modular. Subsumption is a particular case of modular architecture, where modules are vertically linked. All modules have a master-slave relationship of inhibitions, where the decision of a module can be cancelled by another module. Each module is programmed to answer to a very specific trigger of the environment. Brooks (1986) first proposed this architecture to permit the design of simple agents able to act in complex environment. For the blackboard architecture, the basic idea is the use of a global database shared by multiple agents (known as the blackboard), acting as the memory of the system. This database is used to communicate, store information and compute data. Finally, the layered architecture represents an organization of modules such that the bottom layers are used for perception and action, and the top layers for reasoning. Most layered architectures are hybrid, such as InteRRaP. When ascending the layers, the level of abstraction of the knowledge raises, in order to facilitate reasoning.

When many agents work together on a same problem (or a group of problems), it is called distributed artificial intelligence (DAI) or multiagent systems (MAS). Inspired by human organizations, a MAS is a group of agents, possibly heterogonous, each of whom possess their own capacity to solve problems and are able to interact to reach a collective goal (Frayret, 2002). Wooldridge (2002) identified three important characteristics of MAS:

i. Autonomy: the agents composing the MAS are partially or completely autonomous;

ii. Local views: agents have only a limited view of the system;

iii. Decentralization: there is no central agent controlling the others.

Agents in MAS can cooperate, share expertise, work in parallel, tolerate errors from an agent, give multiple points of view, accelerate information collection, etc. Also, they can reduce the complexity of a problem by dividing it in smaller sub-problems, associate an agent to each sub-problem and coordinate agent activities (Ferber, 1995). Agent-based systems focus on implementing individual and social behaviours in a distributed context, using notions such as autonomy, reactivity and goal-directed reasoning (Bussmann et al., 2004). Instead of being hierarchical, some MAS are *heterarchical*, which means there is no authority relation between agents (Duffie et al., 1996).

The coming of MAS represents a real breakthrough in the academic world, involving researchers from heterogeneous and various domains, often at quite a distance from each other, such as biology, network and mobile technology, information management, transportation, computer games, defense systems, and manufacturing. Among them, researchers working in production planning have seen in MAS the possibility of distributing decisions in complex supply chain planning problems. Indeed, the natural similarities between MAS and supply chains make it an interesting approach to represent each planning centre by an agent, using its own decision model with the local information available. The distribution of decisions is needed to introduce adaptation of local behaviours to environment changes. Then collaboration is used to coordinate these autonomous entities to increase the overall supply chain performance. The next section presents how agents have been used by researchers in the manufacturing context and more specifically to plan supply chains.

2.4 Agents in manufacturing systems

At the beginning, agent-based systems were applied by academic researchers mostly at the enterprise level, within a single company. Agents are used to support human decision-making in time-consuming activities such as inventory management and scheduling production, without the need for centralized protocols. Agent-based technology has been applied to multiple manufacturing applications, such as enterprise integration, product design, planning and scheduling, maintenance, inventory management and distribution. Shen et al. (2006) presented a state-of-the-art review of agent-based systems for intelligent manufacturing. They described more than 70 completed or ongoing projects on various related domains, such as manufacturing integration, production planning and scheduling, production control, transportation and inventory management. Among them, about 30 research projects specifically address scheduling, planning and control. Caridi & Cavalieri (2004) presented a survey and classification of the different application domains of more than 100 published multi-agent projects, denoting their degree of maturity. Shen et al. (2001) published a book entirely dedicated to collaborative design and production management using agent-based systems. More recently, Frayret et al. (2007) have presented more than 60 agent-based systems to resolve various production problems.

Agent-based manufacturing systems can manifest a variety of characteristics by which they can be distinguished and classified. Table 2.2 presents a series of contributions and classifies them as enterprise integration, product design, planning and scheduling, maintenance, inventory management and distribution. Other authors have classified these contributions to the field in terms of the type of production system (i.e. job shop, flow shop, flexible manufacturing, process manufacturing), the organizational architecture (i.e. hierarchical, heterarchical, holonic) or the communication protocols used (i.e. message passing, blackboard) (see Shen et al., 2006; Caridi & Cavalieri, 2004; Frayret et al., 2007).

Table 2.2 Agent-based manufacturing systems at enterprise level

Application	***References***	***Project description***
Enterprise integration	Pan and Tenenbaum (1991)	IA FRAMEWORK : large number of computerized assistants known as Intelligent Agents (IAs) for enterprise integration
	Roboam and Fox (1992)	EMN: support the integration of activities of the manufacturing enterprise throughout the production life cycle with six levels
	Peng et al. (1998)	CIIMPLEX: multi-agent system made up of a group of agents that gather information and collaborate for enterprise integration
	Cost et al. (1999)	JACKAL: Java-based multi-agent development platform to support intelligent integration of enterprise planning and execution through a simple business scenario
	Shehory and Kraus (1998); Shen et al. (2000b)	METAMORPH II: heterarchical architecture with mediators for the integration of a company's operations (e.g. design, planning, scheduling, execution, distribution). Agents are used to represent manufacturing resources (such machines and tools).
Product design	Mori and Cutkosky (1998)	Development of a multi-agent system for the design of electronic board subassemblies
	Ozawa et al. (2000)	Concurrent engineering of electromechanical products, with special focus on coordination between mechanical and electronic departments in order to anticipate design infeasibilities
	Park et al. (1994)	Hierarchical architecture for the concurrent design of industrial cables, where four peripheral agents are interfaced with a central node
Planning and scheduling	Liu and Sycara (1996)	Scheduling tasks of production jobs using agents
	Daouas et al. (1995)	Heterarchical architecture for flow shop scheduling of assembly lines, combining multi-agent with simulated annealing
	Choi and Park (1997)	Scheduling of ships assembly using multiple intelligent agents in an heterarchical architecture
	Parunak (1998)	Multi-agent paradigm for air supplying to a painting shop developed for a General Motors assembly plant, where each humidifier, burner, steam generator is controlled by an autonomous agent reacting to different environment configurations
	Sikora and Shaw (1997)	Agents coordinating automated and manual lines in printed circuits manufacturing

	Gupta et al. (1998)	Distributed planning of automated process for sheet metal bending where each component of the sheet metal bending press-brake is controlled by a specialized agent
	Kouiss and Pierreval (1997)	Hierarchical architecture for dynamic scheduling in a flexible manufacturing system for real-time job allocation to resources
	Parunak et al. (1998)	AARIA: Manufacturing scheduling and control using autonomous agents to represent physical entities, processes and operations
	Riha et al. (2001)	EXPLANTECH: Agent-based production planning using the ProPlanT technology. Production agents use a tri-base acquaintance model
	Fletcher et al. (2001)	Agent-based system for task allocation in a sawmill
	Lin and Solberg (1994)	Heterarchical architecture for adaptive scheduling and monitoring in a dynamic manufacturing environment
Maintenance	Zhang et al. (2003)	Multi-agent framework using a price-based coordinating approach in a maintenance network
	Yu et al. (2003)	POMAESS: E-maintenance integrating remote maintenance processes and experts for maintenance decision-making, using case-based reasoning
Inventory management	Kim et al. (2003)	Warehouse planning using hybrid agent-based scheduling and control for higher level optimization
	Ito and Mousavi Jahan Abadi (2002)	Hierarchical agent-based architecture for material handling and inventory planning in warehouse
Distribution	Fisher et al. (1993)	Hierarchical agent architecture for a shipping company, where agent allocates transportation orders to trucks agents and cooperate or compete with other ship company agents for transportation orders.
	Fisher and Muller (1995)	Inventory storage agents for warehouse management

In response to the heightened interest of managers in increasing integration efforts with supply chain partners, along with the growing popularity of supply chain management approaches, many research projects have been presented using agent-based technology to support supply chain activities. Different authors have proposed literature reviews on the topic (Frayret et al., 2007; Shen et al., 2006), using classifications such as simulation systems, planning systems and negotiation systems. Table 2.3 presents some contributions on agent-based supply chain systems, according to their purpose.

Table 2.3 Agent-based supply chain systems

Purpose	***References***	***Project description***
Coordination	Fox et al. (1993)	ISCM: set of cooperating agents, where each agent performs one or more supply chain management functions, and coordinates its decisions with other relevant agents.
	Jeong and Leon (2002)	Distributed decision-making agent-based system using agents to coordinate problem solving agent
	Monteiro et al. (2007)	Coordination of planning decisions in a multi-site network system, using planning and negotiation agents. The negotiator agent is responsible for limiting the negotiation process and facilitating cooperation between production centres.
	Montreuil et al. (2000); Frayret (2002)	NETMAN: Agent-based framework for production network modelling and operations coordination through negotiation protocols and optimizations tools
	Sadeh et al. (1999)	MASCOT (Multi-Agent Supply Chain Coordination Tool): multi-agent architecture for supply chain coordination based on a blackboard communication paradigm to support supply chain key functionalities
Supply chain integration	Sauter and Parunak (1999)	ANTS (Agent Network for Task Scheduling): architecture that decomposes each firm into a supply chain, made up of producers and consumers, to facilitate the natural integration of other firms
	(Shehory and Kraus 1998); Shen et al. (2000b)	METAMORPH II: hybrid agent-based mediator-centric architecture to integrate partners, suppliers and customers through mediator agents within a supply chain network
	Labarthe et al. (2007)	Methodological framework for agent-based modeling and simulation of supply chains
Decision support	Hinkkanen et al. (1997)	Supply chain dynamics modelling approach based on software components
	Strader et al. (1998)	Multi-agent simulation platform for decision support of supply chain managers
	Swaminathan et al. (1998)	Multi-agent framework for modelling supply chain dynamics
Contract negotiation	Babanov et al. (2003)	MAGNET: Supply chain contract negotiation with temporal and precedence constraints
Task allocation	Jiao et al. (2006)	Supply chain task allocation using modified contract-net negotiation process to manage interdependent suppliers simultaneously
Planning and simulation	Frayret et al. (2007)	Agent-based platform for supply chain planning and simulation, using specialized planning agents, applied to the lumber supply chain

Among these projects, some are particularly relevant to this thesis and need to be presented. Montreuil et al. (2000) introduced the NetMan architecture, an operation system for networked manufacturing organizations that aims to provide a collaborative approach to operations planning. In NetMan, agents possess models of their suppliers and customers permitting an anticipation of the impacts of an agent's decision on its neighbouring agents. Although the authors created an architecture able to manage unplanned events, they do not present planning behaviours to solve problems in specific conditions. The authors presented an application to a bus manufacturing supply chain. The ExPlanTech multi-agent platform (Pechoucek et al., 2005) gives decision-making support and simulation possibilities to distributed production planning. Relying on communication agents, project planning agents, project management agents and production agents, the platform uses negotiation, job delegation and task decomposition instead of classic planning and scheduling mechanisms to solve coordination problems. In order to reduce communication traffic, social knowledge is precompiled and maintained, which represents information about other agents. The FORAC experimental agent-based planning platform (Frayret et al., 2007) presents an architecture combining agent-based technology and OR-based tools. The platform is designed to simulate supply chain decisions and plan supply chain operations. Each agent can be designed with specific planning algorithms and is able to start a planning process at any time, following a change in its environment. The agent's environment is made of the other supply chain agents, demand from customers, supply from suppliers and internal production output of the agent. More details about this platform are presented in Chapter 3.

Many of the previously enumerated systems present approaches for managing a community of agents and ensuring coherence in their actions. While their planning agents are adaptive in the sense that they act when a certain event is noticed, they generally do not propose agents that can modify their actions according to their environment, nor can they learn which action is preferable for their community. In other words, these agents usually know a single planning behaviour when an action is required. In the next section, we present different agent architectures which possess multiple levels of responses for various situations. These are adaptive planning agents.

2.5 Adaptive planning agents

Several architectures and agent models have been adapted to a supply chain context, specifically to improve supply chain performance by planning activities and adapting to changes. The variety of possible changes, their stochastic distribution and their interactions, make the supply chain management highly complex. In evolutionary biology, adaptation is defined as the characteristic of an organism to change in order to live successfully in its environment. Organisms not adapted nor adapting to their environment will move or disappear. In the context of this thesis, adaptation is defined as the ability to change behaviour depending on changes in a dynamic environment. In psychology, the term used for this context is adaptive behaviour. In agent-based technology, adaptation can be over the local planning behaviours of the agent, where each agent adapts itself individually, or it can be done in a team of agents, where these agents collaborate and adapt to the situation together. Here, we present some well-known adaptive agent systems that can be used in a supply chain planning context.

The InteRRaP architecture (as introduced previously) provides an interesting approach where agents react and deliberate in response to different situations, using different capability levels. InteRRaP is a layered-based model, composed of three different layers: a behaviour layer, a plan layer and a co-operation layer. The agent can build action plans, depending on whether an event requires a reactive response, local planning or collaboration for planning. For a specific situation, the agent first tries to find a corresponding rule in the behaviour layer, which represents the reactive part of the agent. If no rule is known, the agent uses its second layer, the plan layer, where deliberations are executed to build a plan to solve the problem. If no solution is found, the agent uses its last layer, the co-operation layer, where it collaborates with other agents to find a feasible solution. The Agent Building Shell (ABS) (Fox et al., 2000) is a collection of reusable software components and interfaces needed for any agent involved in a supply chain management system. The ABS is designed to handle different situations and stochastic events in a supply chain. In this architecture, most work has been focused on defining communication and collaborative aspects. This is done through timely dissemination of information and coordinated revision of plans across the supply chain. The tri-base acquaintance model (3bA) (Marik et al., 2001) is a collaboration capable wrapper added to an agent. It provides the possibility of dealing with different situations in a global perspective instead of resolving problems only in a local view. This is accomplished by using information about other agents without the need of a central facilitator. These authors present an example of application in supply chains and they define the social knowledge needed to increase the efficiency of agents.

2.6 Research opportunities

A lot of research has been pursued on distributed paradigms in order to tackle the difficulties of planning complex and dynamic contexts such as supply chains. Agent-based planning systems have been proposed to distribute the problem among specialized planning agents to reduce complexity and add reactivity to the supply chain. While some researchers have focused on developing architectures of interacting agents, others have worked on proposing intelligent agent models that can make autonomous decisions in various situations.

Different researchers have worked on developments of the FORAC agent-based planning platform, from agent-based clients to advanced planning models. Among these, Santa Eulalia et al. (2009) performed simulations to test different tactical planning and control approaches for planning agents and showed how an agent-based planning platform can help managers to make tactical decisions. Lemieux et al. (2008) developed a client simulator, generating various demand plans for simulation purpose. Using this virtual agent-based client, they proposed a methodology to run planning simulations and evaluate the performance of the supply chain. Generations of demand plans used in this thesis are made from these developments. Also, Gaudreault et al. (2009) presented a distributed planning approach for the supply chain, using the FORAC agent-based planning platform. They reformulated the coordination problem as a tree, which call for an optimization using a distributed tree search algorithm. The idea was to generated a high number of plans and explore among them the best solution found.

Complementary to these studies, this thesis identifies adaptive planning as an important factor to increase supply chain performance. Planning systems must be able to follow environment changes. Adaptive planning agents can change their planning behaviours to adapt to their environment in order to maximize the performance for the supply chain. Some agents show adaptive behaviours by trying different behaviours until the problem is resolved.

Supply chain planning systems could take advantage of planning agents with the ability to learn which planning behaviour is preferable for the current situation (based on information from the environment) and adapt itself accordingly. To the best of our knowledge, no agent-based supply chain planning system possesses such ability. There is a need to understand how planning agents can adapt their behaviour while knowing the impact of their decisions on their partners and on the supply chain. Simulations must be performed to verify the possible gains in implementing adaptive and collaborative agents in a supply chain planning system. As a result, this thesis presents a multi-behaviour agent geared with different types of planning behaviours, from simple ones (reaction) to more complicated ones (negotiation), which can use simulation to learn, in coordination with the other agents, the preferable behaviours in different situations for its supply chain.

Chapter 3

Research methodology

This chapter presents the research methodology followed during this thesis. First, a description of the methodology is given. Next, the agent-based platform used for simulation purposes is presented, including details of the platform architecture, the agent architecture, the planning models and the demand generator. Finally, we discuss how this platform was used to simulate adaptive behaviours and how results were obtained.

3.1 Methodology description

With the main objective of increasing the supply chain performance using agent-based technology, different achievements were realized that act as the building blocks of the thesis. Following our intuition that collaboration is a major cornerstone, the first step was to develop the conceptual bases of collaboration between production units and how this collaboration translates to agents. We developed a collaborative model for production units, named *Collaborative Event Management* approach. It identifies how and when collaboration can be used in production planning. Then, we developed an agent conceptual model, describing the different competencies needed for agents to plan supply chain. Depending on its competency level, an agent can be more or less evolved in order to show only technical competencies (*function-driven*), technical and deliberative competencies (*goal-driven*), or technical, deliberative and collaborative competencies (*collaborative goal-driven*).

Following these developments, we formulated the hypothesis that collaborative planning agents that could adapt their planning behaviours would work better, enhancing the supply chain performance. At this point, the objective became the validation of this hypothesis. To do so, based on the agent conceptual model described previously, we developed an adaptive agent-model. This *multi-behaviour agent*, using a decision meta-model, can decide which planning behaviour to apply depending on what it understands from its environment. The internal goal of the agent is to maximize the global performance of the supply chain. Three classes of behaviours are defined, which are *reaction*, *anticipation* and *negotiation*, presenting different levels of complexity.

The second step was to verify our hypothesis by implementing and simulating different planning behaviours in an agent-based planning platform. We decided to simulated reaction behaviours, the simplest case of planning behaviour. This was performed by: (1) developing alternative planning behaviours as well as coordination mechanisms; (2) developing different environmental scenarios representing different planning conditions; (3) configuring the FORAC agent-based planning platform with these alternative behaviours; (4) running one planning cycle of each configuration for each environmental scenario. Here, the idea was to test different sets of planning behaviours for the planning agents in various conditions. From these simulations, different supply chain performance indicators were collected, including total lateness, total inventory, adjusted revenues and spot delivery performance. The analysis of this information mainly concerned verifying whether or not there was a dominant set of planning behaviours for the planning agents. In other words, we wanted to verify if the best results obtained for each type of environment were reached by different planning behaviours or by only one. The presence of different planning behaviours providing the best obtained results would show that there is a possible advantage for agents to adapt their behaviour when the demand environment changes.

In the third step, we decided to simulate another type of planning behaviour included in the multi-behaviour agent, which is the negotiation behaviour. The main difference between reaction and negotiation behaviours is the possibility for negotiating agents to exchange counter-offers and to obtain direct feedback of partner's appreciation. Three different one-to-one negotiation protocols were developed, presenting three negotiation behaviours for collaborative planning between two agents. These are *priority*, *substitution* and *lot sizing* negotiation behaviours. These behaviours define the rules on how the negotiating agents can modify their initial demand plan to build a counter-offer. Different rounds of negotiation can be performed, following the same behaviour or not. For successive rounds of the same behaviour, changes on items in the counter-offer are random. This time, the total lateness indicator was collected for all negotiation behaviours, for different initial demand orders.

Again, the analysis of the results was about finding if there is dominant negotiation behaviour or not, depending on the different demand environment.

3.2 Agent-based planning platform

Simulation of the various planning behaviours have been performed on an experimental agent-based planning and simulation platform (referred to in the thesis as the FORAC agent-based platform) developed by the FORAC Research Consortium at Université Laval (Québec, Canada). Built as a research instrument but also as a planning system for the lumber industry, the platform couples the advantages of agent-based technology to solve distributed problems and the power of OR techniques for complex problems. This section presents details of its conception, more specifically on the platform architecture, agent's architecture, production planning models and demand generator.

3.2.1 Platform architecture

By representing production centres as planning agents, the FORAC agent-based planning platform enables the planning of these centres independently and uses coordination mechanisms to maintain feasibility. Two particular issues are handled by the platform, which are supply chain planning and simulation. On the one hand, it allows companies to manage supply chain planning, using planning agents to help human planners in their tasks. On the other hand, it can be used to simulate different supply chain scenarios and analyze performances. Both can be used in conjunction in order to simulate planning activities. Supply chain scenarios can be used for virtual supply chain planning. Supply chain simulation tools (such as the demand generator) are then used to simulate the planning coordination between the different production centres. Finally, a simulation analysis is run to analyze the performance of the supply chain. Figure 3.1 presents a general overview of these abilities of the platform.

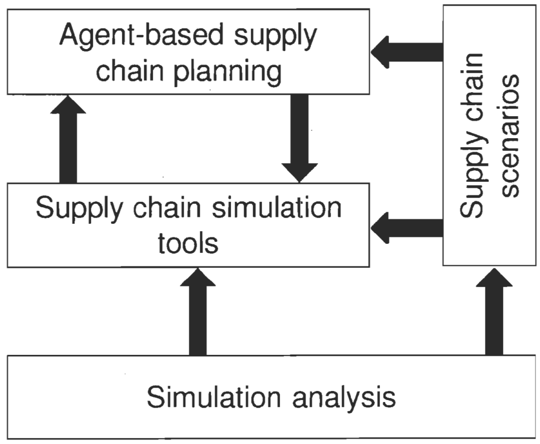

Figure 3.1. Platform general overview (adapted from Frayret et al., 2007)

The platform architecture follows the natural division of the supply chain planning activities. These are divided among specialized planning agents, each responsible for a particular production centre. This functional division is based on the SCOR model (Stephens, 2000). The production planning agents used for this lumber supply chain application are the sawing agent, the drying agent and the finishing agent. Other agents are used to support the supply chain planning process, such as the source agent, the deliver agent and the warehouse agent. Figure 3.2 presents an example of the functional division applied to the planning platform. External suppliers and external clients can be represented by planning agents, being humans or replaced by simulation agents, when the platform is used for simulation purposes. Agents can be added or removed, depending on the needs of the supply chain.

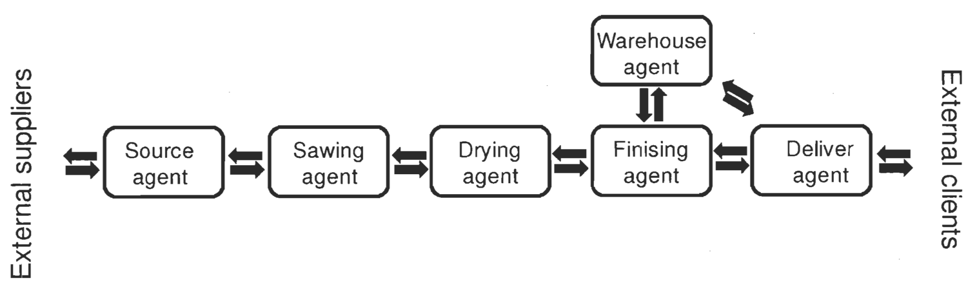

Figure 3.2. Example of the platform functional division

3.2.2 Agent architecture

Agent's action over internal objects or other agents are made possible by task flows (TFs), which are sequences of tasks, usually triggered by specific events. Such events can be the reception of a new demand order (or demand plan) by a client or the reception of a supply plan by its supplier. The same event can trigger multiple TFs for different agents. In order to interact, planning agents use conversation protocols inspired from the Foundation for Intelligent Physical Agents (FIPA) standards (www.fipa.org). Like TFs, conversation protocols are made up of a sequence of tasks triggered by a specific event. This event is a request for conversation by a source agent to a target agent. Figure 3.3 shows an example of such a protocol between two planning agents. As displayed, the protocol (on the left-hand side) has different states (here four), each of these states specifying a task for one agent or both. In this example, after the source agent has initiated a conversation request (the event in this case), the protocol is started by both agents. State 1 asks the target agent to execute task 1R, which is request for information. When the information is transmitted, both agents go to state 2, requiring the source agent to execute task 2S, which is a decision to make. The agent can agree, refuse or request new information. If it agrees, both agents go to state 3 and must execute their tasks (3S and 3R). If it refuses, state 4 is reached instead of state 3. Finally, if it requests a new information, both agents go back to state 1, requesting a new information.

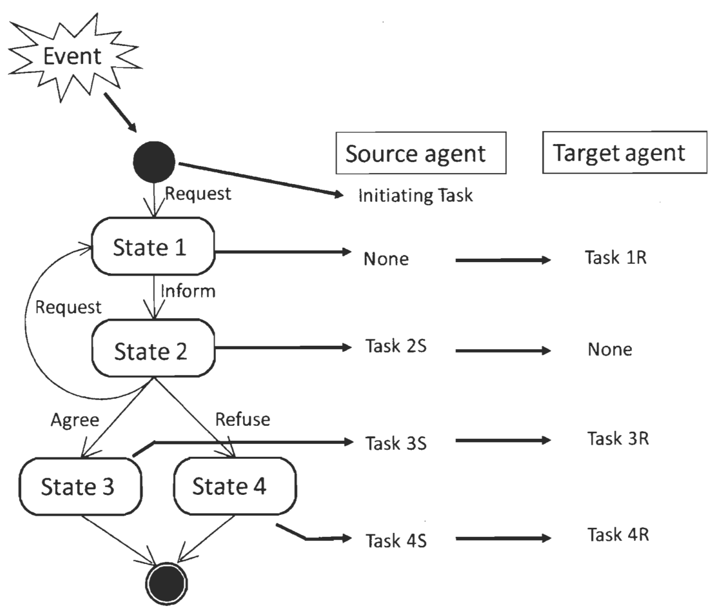

Figure 3.3. Example of a communication protocol between two agents

Each agent is built using the same internal architecture (Figure 3.4). Human users can modify the agent parameters using web controls. Adjustments can be made on several aspects, such as the mathematical models used for planning, the TFs and the conversation protocols. The object models repository includes all objects the agent can use and modify, for example production plans, demand plans, etc. In order to manage actions, each agent possesses four internal managers: flow manager, event management, task manager and conversation manager. These give the agent the ability to understand which tasks are involved in which TF, in order to answer a specific event with the right TF. It also gives the possibility to handle conversations.

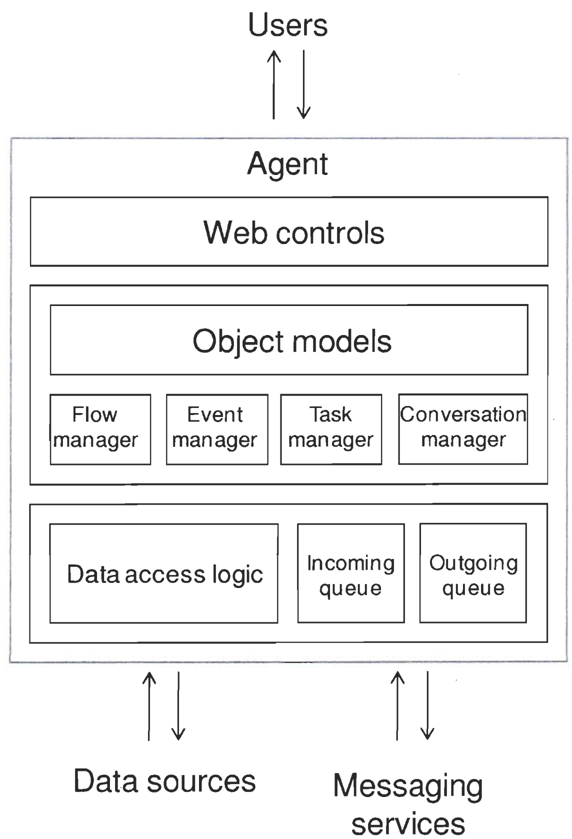

Figure 3.4. Internal agent architecture

3.2.3 Production planning models

Each production agent (e.g. sawing, drying and finishing) uses specialized production planning models to build production plans. The agent planning problems are very different, mainly because of the nature of the production context they are used in. Planning of a sawing centre involves balancing several production lines, while planning a drying centre is about filling kiln dryers. These planning/scheduling models have been developed in order to take advantage of the specificities of each production centre, all with the local objective of minimizing the backorder costs to its immediate client. These models are solved separately, using the local information available to each agent. This distributed solving approach is not optimal, but it makes it possible to find very good planning solutions without requiring centralized planning. When a need for a demand plan or supply plan is received, the agent runs its planning model and generates a new production plan, which is used to generate the following demand and supply plans for its immediate supplier(s) and client(s). Details of these models fall outside the scope of this thesis. A general overview is given here to give the reader an idea of how planning is achieved. For more information, the reader must refer to (Gaudreault et al., 2008).

For the sawing agent, a mixed integer linear programming model (MIP) has been developed and is solved using ILOG CPLEX© (version 9.000). In the sawing production centre, logs are cut down into various sizes of lumber. When logs are cut, many lumbers of different dimensions are obtained at the same time from a single log, which is called *co-production*. Production matrixes are used to determine which products can be obtained from a specific class of logs, using different cutting patterns. The goal of this model is to find the right mix of log types and cutting patterns to schedule on the production lines. Production constraints, production costs and inventory costs are taken into account. More than one product type can be processed during the same work shift, but some limitations are given due to setup times and capacity constraints. Solutions close to the optimal can be found in little time. Planning decisions are about which cutting patterns to use and which quantities of each log class to consume at each production shift.

In the case of the drying agent, a constraint programming (CP) approach was designed as an anytime algorithm, solved by ILOG SOLVER© (version 6.000). Lumber drying is used to reduce the lumber moisture content in order to meet customer requirements. The production operation takes days and is done in batches within large kiln dryers or by using air dry sites. Bundles of lumbers of different lengths (e.g. 8-foot and 16-foot) can be dried in the same time, but they must be of the same dimension (e.g. 2x3, 2x4, and 2x6) and species. The planning decisions are about what drying processes to perform (air dry and/or kiln dryer), what loading pattern to use and when to perform them. In air dry, the duration must be determined, while in kiln dryer, air temperature, humidity parameters and duration must also be defined.

The finishing planning model is a heuristic, described in Gaudreault et al. (2008). The finishing process is about planing, sorting and trimming dried lumber and these three operations are performed on the same single production line. To simplify the problem, this line is considered as a single machine. Lumbers with the same dimensions but of different lengths can be processed during the same production campaign (a batch of product of the same dimension). Again, the objective is to reduce backorders and the decisions, in order to plan the finishing operations, are which lumber dimension to process during each campaign, when to process it and for how long, and in what quantity.

3.2.4 Demand generator

When the planning platform is used for simulation purpose, demand orders from external clients must be virtually generated. This allows the inclusion of variability into demand patterns. In order to permit such generation of external demand, a demand generator has been developed (Lemieux et al., 2008). Based on predetermined parameters such as demand quantity, distribution function, minimum and maximum limits, random errors and seasonality, it is possible to create demand orders close to reality. Every product composing an order from every client can be parameterized differently.

3.3 Simulation using the platform

By performing simulation on supply chain planning, this thesis used the two abilities of the FORAC agent-based platform: supply chain production planning and supply simulation. Planning agents are used to plan individually their production and collaborate with their partners to coordinate activities. Simulations are performed by generating demand from external clients and simulating demand environmental changes from these client demands, for various intensities and contract/spot orders proportions. Planning behaviours of agents are alternatively modified to test different team behaviours.

In Chapter 5, reaction behaviours are simulated by modifying between each simulation run the planning behaviour of agents. A planning behaviour represents a specific planning process used by an agent to plan production. To create new planning behaviours, modifications are made on each agent's planning models (sawing, drying and finishing agents) and on the coordination mechanism used between agents. For different demand orders from initial clients that present environmental variations, each set of planning behaviour (called *team behaviour*) is simulated. At each simulation round, every agent plans its local production and communicates the results to its immediate partners. The coordination mechanism specifies the order of local planning actions and the number of plans generated by each agent.

Using the demand generator, four 30-day demand plans were generated, presenting amounts of volume approximately equivalent to the maximum capacity of the supply chain (100% intensity). Each external client's demand plans are made up of 45 different product types, corresponding to different lengths, dimensions and quality of lumber pieces. The proportion of contract vs. spot was set to 50%. These four demand plans specify the volume of each product, in Foot Board Measure (FBM), for each day. A normal distribution of quantity was used, with no seasonality. A random error of ± 5% was added to each quantity. Then, from these initial four plans, new plans were created manually by multiplying the quantities by 0.5 to obtain an intensity of 50% and by 1.5 for an intensity of 150%. We understand there is a certain degree of correlation between these new plans and the parent's plans. The decision to present four replications was to overcome this correlation. Finally, these 12 plans were modified manually to change the proportion of contracts volume, by assigning differently certain volumes. This gave the 0%, 25%, 75% and 100% contract proportion of the demand plans, added to the initial 50% contract proportion of the initial plans. From these plan generations and manual modifications, a total of 60 different demand plans were used as demand orders from external clients.

For each simulation using a different external client's demand plan, different configurations of planning models are used. These configurations are applied specifically to the drying agent model's scheduling strategy, the deliver agent model's priority rule and the finishing agent model's penalty rule. The coordination mechanism configuration is applied to the entire supply chain. In total, nine team behaviours presenting different arrangements of configurations are simulated. At each run, a demand plan is transmitted to the deliver agent, which starts the supply chain planning process, where each agent locally plans its production and communicates with its partners to coordinate plans. When the planning process of the platform is ended (i.e. when each planning agent has a feasible production plan), different performance indicators are analyzed for the entire supply chain. The indicators are contract lateness, supply chain inventory, adjusted revenues and spot delivery performance. These indicators have been selected because they give different perspectives of the same production plan. A planner using one or many of them can make a clever choice, depending on the status and the values of his company. While many would use only the revenue indicator, other many want to use lateness or inventory levels, or combine them. If a company has a lot of inventory, a plan minimizing the inventory would be appreciated. In the case of a company proposing a delivery on time, lateness must be prioritized and minimized.

In Chapter 6, simulations are run for different negotiation behaviours between two planning agents, the sawing and the drying agents. Generation of demand plans from external clients follows the same logic as presented before, except that configurations were hand-made to create plans of 90%, 100% and 110% intensities, and contract proportion of 50% and 100%. Following this, six different demand plans are used. These plans are made of products of two species (spruce and fir) and three different dimensions (2x3, 2x4 and 2x6), over a 30-day horizon. The three negotiation behaviours proposed are in fact three counter-proposition rules to direct the modifications that must be applied by the initiator agent (the agent who starts the negotiation process) to its initial demand plan, mainly because the supply plan received is not acceptable. The first rule is the *priority* negotiation, which involves the modification of the delivery dates of certain volumes demanded. The second rule is the *substitution* negotiation, where substitutable products are used when it is possible to replace late volumes. The third rule is the *lot sizing* negotiation, where the size of certain volumes is modified.

For these simulations, for each new external client's demand plan, the platform planning process is fully completed and the lateness performance indicator is recorded, which represent the initial performance with no negotiation involved. Then, the drying agent's demand plan is manually modified following one of the negotiation rules previously defined. This new demand plan acts as a counter-offer from the drying agent to the sawing agent. Upon the transmission of this plan to the sawing agent, the platform starts a new planning process from this point and the performance indicator for the supply chain lateness is also recorded. For each negotiation behaviour used by the drying agent, three consecutive negotiation rounds are simulated. In the second and third round, a different modification is made to the demand plan. In the end, a total of 60 planning simulations are performed, including the six initial planning results. This time, only the lateness indicator has been studied, because we considered this indicator strongly indicates differentiation capacities.

Chapter 4

Multi-behaviour agent model for planning in supply chains: An application to the lumber industry

In this first paper, we consider the problem of adaptive and collaborative agent-based supply chain planning. We develop the concepts of agent-based collaborative planning and how it can be applied to supply chains. A collaborative event management approach between two supply chain partners is proposed. Also, the basic competencies for adaptive planning agents are combined in an agent conceptual model. Based on these developments, we present our multi-behaviour agent model that can adapt its planning behaviour to its environment. Composed of three behaviour categories, reaction, anticipation and negotiation, the multi-behaviour agent can analyze its environment and decide which behaviour to adopt. Different planning behaviours for each category are proposed, with a scenario and a simulation plan. This paper has been published in the *Robotics and Computer-Integrated Manufacturing Journal* (vol. 24 (2008), p. 664–679), with Pascal Forget as first author and Sophie D'Amours and Jean-Marc Frayret as co-authors.

Résumé

Les menaces internationales récentes envers les industries occidentales ont encouragé les compagnies à améliorer leurs performances de toutes les façons envisageables. Plusieurs travaillent à gérer plus rapidement les perturbations, à réduire les inventaires et à échanger de l'information rapidement à travers leur chaîne d'approvisionnement. En d'autres mots, ils essaient d'être plus agiles. Pour atteindre cet objectif, il est critique d'utiliser des systèmes de planification qui présentent des stratégies de planification adaptées aux différentes situations rencontrées. En raison du regroupement des organisations, le développement des chaînes d'approvisionnement intégrées et l'utilisation des systèmes d'information inter-organisationnels ont augmenté l'interdépendance des organisations et, du même coup, leur besoin pour une collaboration accrue afin de gérer les perturbations de façon synchronisée. Ainsi, l'agilité et la synchronisation sont tous deux critiques pour assurer une performance globale satisfaisante.

Pour aider le développement d'outils d'amélioration de l'agilité et pour promouvoir la gestion collaborative des perturbations, la technologie à base d'agents tire avantage de l'habileté des agents à prendre des décisions autonomes en utilisant des mécanismes de collaboration distribués. De plus, en raison de l'instabilité et du contexte dynamique des chaînes d'approvisionnement d'aujourd'hui, les agents de planification doivent être en mesure de supporter plusieurs approches de planification. Cet article propose un modèle d'agent à comportements multiples qui utilise différentes approches de planification dans un système de planification distribuée. Une implantation a été réalisée dans la plateforme de planification à base d'agents de FORAC, dédiée à la planification de la chaîne d'approvisionnement de l'industrie du bois d'œuvre.

Abstract

Recent economic and international threats to western industries have encouraged companies to increase their performance in any way possible. Many seek to deal quickly with disturbances, reduce inventory and exchange information promptly throughout the supply chain. In other words they want to become more agile. To reach this objective it is critical for planning systems to present planning strategies adapted to the different contexts, to attain better

performances. Due to consolidation, the development of integrated supply chains and the use of inter-organizational information systems have increased business interdependencies and in turn the need for increased collaboration to deal with disturbances in a synchronized way. Thus, agility and synchronization in supply chains are critical to maintain overall performance.

In order to develop tools to increase the agility of the supply chain and promote the collaborative management of such disturbances, agent-based technology takes advantage of the ability of agents to make autonomous decisions in a distributed network through the use of advanced collaboration mechanisms. Moreover, because of the highly unstable and dynamic environment of today's supply chains, planning agents must handle multiple problem solving approaches. This paper proposes a multi-behaviour planning agent model using different planning strategies when decisions are supported by a distributed planning system. The implementation of this solution is realized through the FORAC experimental agent-based platform, dedicated to supply chain planning for the lumber industry.

4.1 Introduction

Recent economic and international threats to western industries have encouraged companies to increase their performance in any possible way. Many seek to rethink their planning systems in a way to quickly react to and correct deviance from established plans, respond to demand, reduce inventory and exchange information promptly throughout the supply chain (Frayret et al., 2004). In other words companies want to become more agile. Agility can be described as the association of flexibility, which is the ability to react to changes by presenting different solutions, and high responsiveness, which is the ability to react in a timely manner. To reach this objective it is critical for planning systems to present planning strategies adapted to different contexts in order to reach better overall performances. Due to consolidation, the development of integrated supply chains and the use of inter-organizational information systems have increased business interdependencies and in turn the need for increased collaboration to deal with disturbance in a synchronized way. Global organization forces have recognized that performance is not a feature of a single firm, but the complex output of a network of interconnected firms (Montreuil et al., 2000). Thus, agility and synchronization in supply chains are critical to maintain overall performance. Efforts have been deployed to increase supply chain performance as a way to remain competitive with international consortiums. Developed mainly to improve efficiency between partners by increasing coordination and communication, supply chain management (SCM) has been studied in multiple ways, e.g. (Stadtler, 2005; Strader et al., 1998).

For years supply chains have been (and mostly are still) managed in a hierarchical way, where demand plans (customer orders in a context of dynamic demand) are calculated locally and transmitted to suppliers. This sequential planning gives full autonomy to each company and organizational unit involved, but no effort is invested in synchronizing plans and using partner capacity. In fact, the only synchronization tool is the actual demand plan sent to suppliers in order to improve demand forecast and reduce the bullwhip effect (Lee et al., 1997).

The distributed decision-making paradigm provides an interesting approach to increase agility by permitting local correction of the plan, while promoting a global coherence in the supply chain. This is done by keeping planning decisions distributed, yet using close collaboration mechanisms between organizational units to ensure synchronization of production plans. Agent-based technology provides a natural platform that takes advantage of the autonomy of agents and their ability to make decisions in a distributed context, using collaboration and goal-driven decisions. A distributed agent-based Advanced Planning and Scheduling system (d-APS) could maintain a real-time plan by re-planning locally and allow for collaboration between agents to deal with disturbances.

At the same time, the highly instable and dynamic environments of supply chains require an increased ability for planning systems to correct deviance from disturbance in an adapted way. This can become possible by increasing the intelligence of planning agents, in order to give them sufficient competencies to use the right strategy for the right situation. There is a need to clarify what competencies are needed and how they can be used in an agent-based system to show efficient behaviours to react promptly to disturbances and to correct unwanted situations.

In this paper, Section 4.2 provides a literature review on supply chain planning and how disturbances are handled in such complex environments. Different uses of agent-based technologies in supply chains and different agent architectures proposed in the literature are presented. Then, Section 4.3 describes the Collaborative Event Management approach, which proposed how collaboration between production units could be used to deal efficiently with disturbances. In Section 4.4, we explain the experimental agent-based planning platform developed by the FORAC Research Consortium, which is dedicated to supply chain planning for the lumber industry. Our contributions to the literature are presented in Sections 4.5, 4.6 and 4.7. In Section 4.5, an agent conceptual model is presented, geared with tools designed to improve agility and synchronization in supply chains. Section 4.6 details the multi-behaviour agent model, which is an extension of our conceptual model. Section 4.7 describes a possible implementation of the agent, using different planning protocols, in order to give an idea of the full potential of the agent. We describe briefly how we plan to simulate and test the agent model. Finally, in Section 4.8, we present our conclusion.

The North American lumber industry represents a perfect context for this technology. In fact, this industry is highly distributed, with many production units interacting in all activity levels. The main advantage of this industry is the large amount of stochastic disturbances in many aspects of the supply chain, mainly due to the highly heterogeneous aspect of the resource, uncertain process output, production of co-products and by-products, price variation in the spot market and demand variation in commodity markets.

4.2 Literature review

4.2.1 Planning in supply chains

Global supply chains involving different companies represent an important planning challenge. Partners do not exchange private information easily and are reluctant to share a common database (Stadtler, 2005). When organizational units are part of the same company, which can be called an internal supply chain or intra-organizational supply chain, centralized information and planning systems are sometimes used. Gathering information in a centralized management system and redistributing plans can ensure synchronization and optimization of plans. Decision support systems, such as Advanced Planning and Scheduling (APS) systems are sophisticated sets of decision support applications using operational research (OR) techniques to find optimal solutions to complex planning problems (Frayret, 2002). However, even in an internal supply chain, when the number of organizational units grows, planning problems become more complex and hard to handle. Also, because of the quantity of information only available locally and the time it takes to plan the entire supply chain, plans are sometimes not feasible and the supply chain demonstrates low reactivity. In fact, currently available software solutions generally do not provide the necessary support to network organizations and are clearly insufficient in planning and coordinating activities in heterogeneous environments (Azevedo et al., 2004; Stadtler, 2005). Moreover, planning, scheduling and traditional control mechanisms are insufficiently flexible to react to rapid changes in production modes and client needs (Maturana et al., 1999). In other words, traditional systems have not been developed to work in decentralized, dynamic and heterogeneous environments.

In recent years there has been a trend of new management systems emerging. Because coordination cannot be implicitly transmitted from a top level, collaboration and coordination mechanisms are needed to insure synchronization and consistency throughout the supply chain. This opened the way to an entire new research domain, which is SCM, where researchers are interested in coordination and decision making between supply chain partners to optimize the supply chain performance (Strader et al., 1998).

4.2.2 Dealing with disturbances in supply chains

A major difficulty in supply chain planning is dealing with disturbances in an efficient way. In fact, disruptions and uncertainties have been a problem since the beginning of systemized manufacturing and remain an important subject (Aytug et al., 2005). Disturbances can take different forms, such as change in demand, machine breakdown, late delivery, employee sickness, etc. In a dynamic environment, as in a production plant, as soon as a plan is released, it is immediately subject to random disruptions that quickly render the initial plan obsolete (Abumaizar et al., 1997). The traditional way to avoid disturbance related problems is to keep large inventories. In fact, inventory exists as an insurance against uncertainty (Davis, 1993). While costly, this approach considerably reduces flexibility, because stocked products must be sold even if demand has changed. In contrast, less stock means reducing the overall inventory investment, freeing up available cash flow and improving end-customer service (Davis, 1993). Keeping low inventory requires close collaboration with partners to ensure precise information on needs.

Companies develop business interdependencies since the behaviour of one can influence another. In a highly dependent network of entities, when activities are tightly planned, disturbances can have important repercussions throughout the supply chain. For example, a major mechanical breakdown in a strategic third-tier supplier can reduce supply availability for several days, which can have tremendous impacts on the whole supply chain, translating to a delay for the final client. Another example is a quick change in demand pattern. When such change happens, every demand plan exchanged between each partner must be updated. If it is not done in a very short period of time, inventories will pile up and money will be wasted. To counter these problems and their repercussions on the supply chain, Collaborative Planning, Forecasting & Replenishment (CPFR) methodologies are used and forecasts are prepared jointly.

Much work has been done on dealing with disturbances and uncertainty in a production context. Aytug et al. (2005) present a literature review on production scheduling facing uncertainties in the context of a shop floor. Some researchers have presented works on

Reactive Scheduling, e.g. Kerr and Szelke (1995), which is dedicated to the continuous adaptation of the schedule in a real-time context, with the objective of minimizing perturbations to the initial schedule. Confronted with disturbances, other researchers have worked on finding approaches to modify plans while minimizing impacts on performance using OR techniques, e.g. (Abumaizar et al., 1997; Akturk and Gorgulu, 1999; Barua et al., 2005) and artificial intelligence (AI) techniques, e.g. (Szelke and Markus, 1995). Replanning is about repairing or starting a new plan in order to adapt to a new context. Robust scheduling is another approach to deal with disturbances, where the objective is to build a schedule with the best worst-case performance, e.g. (Daniels and Kouvelis, 1995). Authors have also presented classifications, management frameworks and planning system requirements to deal efficiently with disturbances (Cloutier et al., 2001; Davis, 1993; Fox et al., 2000; Pryor and Collins, 1996).

4.2.3 Agent-based system in supply chains

A new trend of distributing decisions has resulted in the development of planning systems with agent-based architectures. These approaches are rooted in multi-agent technologies, coming from the AI domain (Weiss, 2003). Agent-based systems focus on implementing individual and social behaviours in a distributed context, using notions like autonomy, reactivity and goal-directed reasoning (Bussmann et al., 2004). The emergence of agent-based systems has represented a real breakthrough in the research world, including researchers from various domains, such as biology, sociology, transportation, management, production, logistics and the military. Agent-based systems are computer systems made from a collection of agents, defined as intelligent software with specific roles and goals, interacting with each other to make the most appropriate decision according to the situation, in order to carry out their part of the planning task (Marik et al., 2001). Distributed planning demonstrates many advantages over central planning. For complex problems, sub-problems are easier to solve than centralized problems. Because decisions are distributed to different entities, reactivity to changes is increased. Also, due to the fact that local problems are smaller, it is possible to add more detail in resolution, which is likely to improve feasibility of plans. The challenge here is that global supply chain performance is linked to agent collaboration capabilities to find acceptable compromises, insuring synchronization of plans.

Agent-based technology has already been applied to different areas in SCM. Parunak (1998) presents industrial applications and case studies of agent-based systems, and Shen and Norrie (1999) describe more than 30 research projects addressing scheduling, planning and control. More recently, Caridi & Cavalieri (2004) present a survey and a classification of the different application domains of published multi-agent projects, denoting their degree of maturity. More specifically, agent-based planning systems have been proposed to manage supply chains and deal with disturbances. Montreuil et al. (2000) present the NetMan architecture, an operation system for networked manufacturing organizations that aims to provide a collaborative approach to operations planning. Although the authors created an architecture able to manage unplanned events, they do not present specific behaviours to solve problems following disturbances. Based on intelligent *holons*, Fletcher et al. (2001) present a conceptual architecture of a lumber processing system to improve flexibility and fault tolerance. The ExPlanTech multi-agent platform (Pechoucek et al., 2005) gives decision-making support and simulation possibilities to the manufacturing process. With meta-agents and production agents, they use negotiation, job delegation and task decomposition instead of classic planning and scheduling mechanisms. Building on these research works, we propose to extend the representation of coordination mechanisms in order to increase supply chain agility and synchronization.

4.2.4 Agent architectures

Agents can be designed in various ways, following the internal description of their functions and the connections between them. The architecture of an agent has a direct impact on its behaviour and how it reacts when confronted with different situations. Several classifications of architectures are proposed in the literature, e.g. (Bussmann et al., 2004; Shen et al., 2001). Basically, three main architectures are prominent: reactive, deliberative and hybrid agents. Reactive and deliberative agents represent extreme cases of behaviours, whereas hybrid agents are positioned somewhere between the two.

A reactive architecture basically links specific inputs to specific outputs. For a specific observation in the environment, the agent has a pre-determined action. These agents have no internal representation of their world and no symbolic representation of knowledge. Although this architecture can perform very well in simple environments, an agent can show a lack of intelligence and adaptability in a more complex world. An evolved reactive architecture is presented by Brooks (1986), which is the *subsumption* architecture, also called behaviour-based architecture. Instead of a single specific reaction to an input, the reactive agent is decomposed into behaviours which are small independent processes that can be triggered, and where some cancel others. Instead of implementing a simple reactivity mechanism, the agent shows an emergent intelligent behaviour, resulting from adaptation to its environment. The main advantage of this architecture is the fast adapted response, because no complex processing is needed. The disadvantage is the difficulty in creating oriented behaviours that follow long term goals and strategies.

In contrast, deliberative agents use their knowledge about their environment and their internal goals to plan and execute actions. They translate information from the world into symbolic knowledge, which they use to update their internal data base. The Belief-Desire-Intention (BDI) architecture (Rao and Georgeff, 1992) is a well-known example of a deliberative architecture, where the agent uses its knowledge about the world (belief) and its goals (desire) to build a plan of action (intention). The advantage of this architecture is the possibility to plan a sequence of actions, in order to meet long term goals. The agent can understand a complex environment and make an appropriate decision following a set of specific inputs. The disadvantage is the slow reaction time in dynamic environments, where situations can change while the agent is processing to find a suitable action. Also, the problem of knowledge representation is complex and comprises an entire research domain where researchers have been studying new approaches for decades, e.g. (Newell, 1982).

Hybrid agents fit in between these extremes to find an optimal balance of these behaviours. Many authors have presented such architectures. The InteRRaP architecture (Muller, 1997) is a layered-based model, composed of three different layers: a behaviour layer, a plan layer and a co-operation layer. For a new situation, the agent first tries to find a rule in the behaviour layer, which consists of the reactive part of the agent. If no rule is known, the agent uses its second layer, the plan layer, where deliberations are executed to build a plan to solve the problem. If no solution is found, the agent uses its last layer, the co-operation layer, where it collaborates with other agents to find a feasible solution. Hybrid agents try to compile advantages of both reactive and deliberative architectures, using the best behaviour in each situation. The main disadvantage is the difficulty for the designer to co-ordinate the different layers in order to see an emergent coherent and intelligent agent behaviour (Bussmann et al., 2004).

4.2.5 Hybrid agent architecture in supply chain planning

Several architectures and agent models have been adapted in supply chain context, specifically to improve supply chain performance by planning activities and reacting to disturbances. The variety of possible disturbances, their stochastic distribution and their interactions make the supply chain highly complex. This is why it is necessary to use deliberative behaviour to react to a situation with the best action possible. On the other hand, because the context of supply chains necessitates immediate reaction to changes, fast replanning and instant reply to customer, there is a need for agility only available through reactive behaviours. This is why hybrid agents exhibit the most potential in a supply chain context.

As presented earlier, the InteRRaP architecture provides an interesting approach able to react and deliberate when confronted with disturbances, using different capability levels. The agent can build action plans, depending on whether an event requires a reactive response, local planning or collaboration for planning. The Agent Building Shell (ABS) (Fox et al., 2000) is a collection of reusable software components and interfaces needed for any agent involved in a SCM system. The ABS is geared to handle perturbations caused by stochastic events in a supply chain. In this architecture, most of the efforts have been focused on defining communication and collaborative aspects. This is done through timely dissemination of information and coordinated revision of plans across the supply chain. The tri-base acquaintance model (3bA) (Marik et al., 2001) is a collaboration capable wrapper added to an agent. It provides the possibility of dealing with disturbances from a global perspective instead of resolving problems only with a local view. This is accomplished by using information about other agents without the need of a central facilitator. These authors present an example of applications in supply chains and they define the social knowledge needed to increase the efficiency of agents.

This review gives important inputs on how to handle disturbances in manufacturing supply chains more efficiently. Many agent-based solutions are proposed to help SCM by using social behaviours like communication and collaboration. Although collaboration is necessary to insure synchronization of plans, it may not be acceptable for all situations, especially when high responsiveness is needed. Inevitably, there is a need to specify how and when collaboration should be used, especially in a disturbed environment.

4.3 Collaborative event management

To emphasize the importance of collaboration when dealing with disturbances in manufacturing supply chains, we first introduce the Collaborative Event Management (CEM) approach. This approach represents our general vision on how collaboration should be exploited to deal with disturbances (or events) within any manufacturing system in a supply chain. Due to interdependencies between business partners, there is a need to coordinate the production planning processes to solve problems resulting from disturbances in a timely and efficient way. In a CEM perspective, we represent manufacturing activities in three different phases (see Figure 4.1), which are the *planning phase*, the *control phase* and the *shop floor / simulation phase*, by presenting the interactions between two different production units.

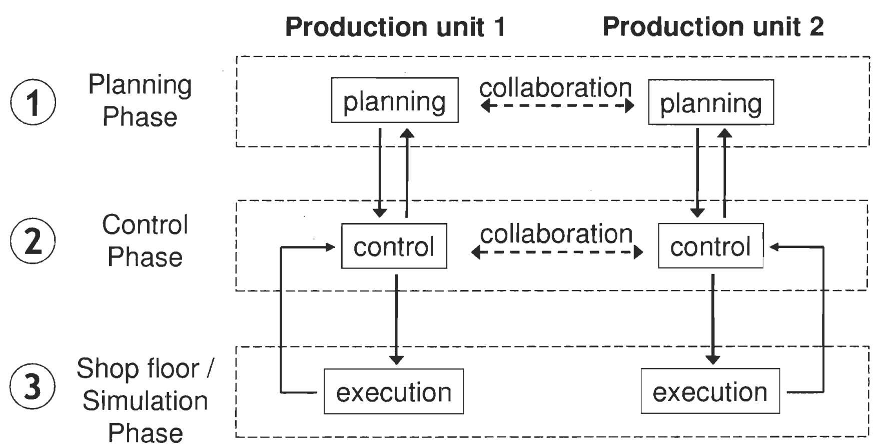

Figure 4.1. Manufacturing phases in CEM

The planning phase (1) includes the creation of the initial plan by both production units individually. After initial planning, they collaborate and coordinate efforts to adjust plans, in order to reach the best profit. This collaboration between units is essential to insure production plan synchronization, in order to avoid delays and unfeasibly solutions. Capacity anticipation and scheduling anticipation can be used to help build feasible plans and facilitate collaboration. Also, if a direct communication channel is not available or time is limited, it is possible to substitute collaboration by anticipation of partner's objectives. When completed, production plans are transmitted to the control phase (2), where validation and scheduling are performed. At this time, the control phase is used to dedicate resources to specific production tasks and make sure plans can be followed. The shop floor / simulation phase (3) uses scheduling plans transmitted to execute (or simulate) production. When a production unit is no longer able to follow the plan (because of a perturbation of any kind), a local solution is sought and deployed. When it is not possible to find such a solution, a feedback message is sent to the control phase, where collaboration can be used between production units to find a compromise in order to deal with the perturbation. Examples of compromises include changes in delivery dates, changes in products and new production plans.

CEM puts collaboration at the heart of the planning activities, but leaves place for local correction when it is possible. With extended collaboration protocols and anticipation of the impacts of their decisions, it is possible to propose problem solving techniques to face unforeseen disturbances. Such an approach can smooth transitions in the supply chain, reducing safety stocks and lead times usually kept to cope with undesired impacts. CEM provides input to create agents with appropriate characteristics, especially when applied to an agent-based planning system, like the FORAC experimental platform.

4.4 FORAC Agent-based planning platform

For many years, the planning processes in the North American lumber industry have not been questioned. Due to the highly heterogeneous nature of the resource (i.e. trees) and the inherent complexity of forecasting production throughput, the dominant thinking was to produce the maximum volume with the resource available (*push production*). Because of the commodity nature of the final product and the standards of sizes and grades, production is oriented towards large batches to take advantage of economies of scale (Frayret et al., 2007). This industry can be characterized by large inventories, low flexibility and low agility. The recent economic and international threats to the lumber industry have encouraged companies to rethink their planning processes to increase their performance. In order to compensate for the lack of control over the stochastic elements related to lumber production, an increase in the exchange of information between the different production centres is necessary, as is their ability to react quickly in a coordinated manner to changes. Also, in order to better fulfill client needs and reduce missed sale opportunities, a mix approach of *pull* and *push production* must be put forward. In other words, instead of producing a maximum of products and offering them to the clients, specific client orders can be produced, with the objective to produce what is needed.

With the purpose of developing a new planning approach for the lumber supply chain, the FORAC Research Consortium of Université Laval (Quebec, Canada) has developed an experimental Internet-based planning platform built on an agent-based architecture for advanced planning and scheduling (APS), with interaction mechanisms inspired from Foundation for Intelligent Physical Agents (FIPA) standards. This architecture combines agent-based technology with OR techniques to take advantage of the ability of agents to integrate distributed decision problems, and the ability of OR to solve complex decision problems (Frayret et al., 2007). Because of the distributed context of the supply chain and the use of agents, this experimental platform can be described more precisely as a distributed APS (or d-APS), where the first issue is to plan and coordinate all supply chain operations. This platform allows the different production centres to plan and correct deviance independently in line with their own needs, while maintaining feasibility and synchronization by collaborating with partners. By using a mix of pull and push production, each agent tries first to answer client's needs, and then complete the production plan with other products. By distributing planning decisions among specialized planning agents, using adapted optimization tools, the experimental platform increases agility in the supply chain. Also, the use of advanced conversation protocols between the agents insures the synchronization of production plans and a global feasibility for the supply chain.

4.4.1 Description of a planning unit

The agent-based architecture presented by FORAC is based on the natural division of the planning domains. Planning units divide activities between specialized production planning agents: a sawing agent, a drying agent and a finishing agent. This functional distribution is inspired by the SCOR model proposed by the Supply Chain Council (Stephens, 2000). Each of these agents is responsible for supporting the planning of its production centre in terms of production output each day. Other agents are also part of the architecture, such as the deliver agent, source agent and warehouse agent. This paper focuses particularly on production planning agents. Figure 4.2 presents an example of a planning unit, including external exchanges with suppliers and customers.

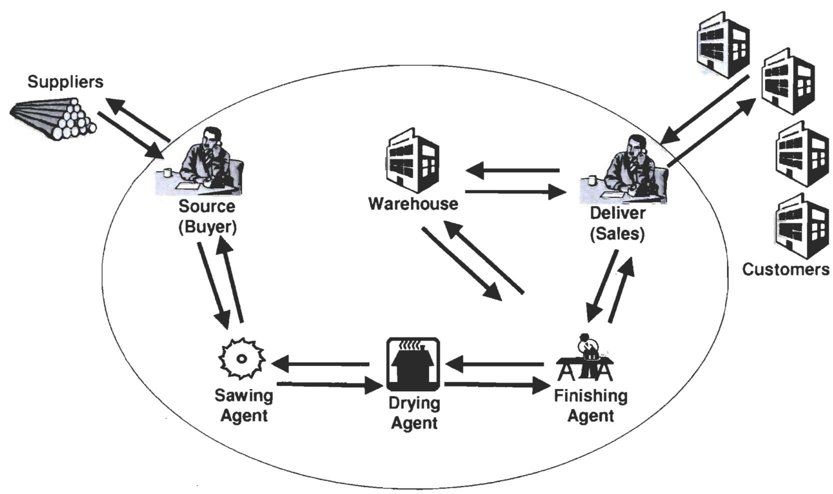

Figure 4.2. Example of a planning unit from FORAC experimental platform

The planning sequence used in a planning unit to plan the internal supply chain upon receipt of a new demand plan (from outside the planning unit) is divided in two distinct planning phases: the infinite supply plan and the finite supply plan. During the first phase, the deliver agent receives a demand plan from one or many customers. These customers can be part of the same company or different companies. Upon reception, the deliver agent sends a demand plan to the warehouse agent to verify if products are in stock. For non-available products, it sends a demand plan to finishing agent. Using this demand plan, along with resource constraints and lead times, the finishing agent builds its plan considering infinite supply and transmits it to the drying agent. Again, using the demand plan, local constraints and considering infinite supply, the drying agent transmits its preferred plan to the sawing agent. This process continues until suppliers outside the planning unit receive the infinite demand plan. When suppliers answer the demand plans, the source agent receives a supply plan and starts a return loop. This represents the second phase of the planning process, the finite supply plan. The process is largely the same, however plans are built with finite supply, which is the information transmitted by the immediate supplier. For further information the reader is invited to read (Frayret et al., 2007).

If an event occurs in the internal supply chain operations, any agent can initiate collaboration with its internal clients and suppliers by sending a revised demand or supply plan. This can be triggered by an agent who needs some products to fulfill inventory, lost production or new demand. This explains why agents are also responsible for continuously monitoring their environment and reacting to disturbances. Because of the interaction context, an agent's environment is also made up of 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 to process.

4.4.2 Actions and task flows

Each planning agent has available objects which can be modified by local actions or actions from other agents. Actions are made possible by task flows (TFs), which are sequences of tasks, usually triggered by specific events. A planning agent's standard TF is the planning protocol (see Figure 4.3), which is triggered upon reception of a new demand plan from a client. Here, objects are represented by boxes and actions are presented in bold characters. This protocol is divided into two segments, where the first concerns the infinite production plan and the second the finite production plan.

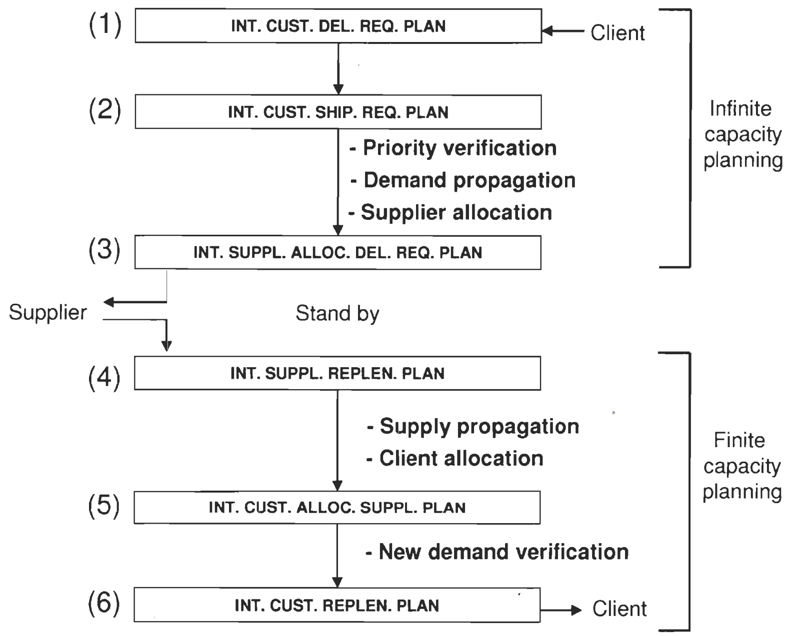

Figure 4.3. Current planning protocol

Basically, when an agent receives a new demand plan, the object *Internal Customer Delivery Requirement Plan* (1) is modified. An offset corresponding to transportation delay is calculated and it modifies the *Internal Customer Shipping Requirement Plan* (2). From this last object, the agent starts different actions in a consecutive manner. First, a *Priority Verification* is pursued, which checks if the new requirement is urgent or if it is possible to wait until the next urgent requirement. Next, a new production plan is generated, using previous demand and new demand. This action is called *Demand Propagation*, because it is about translating demand from the client into demand to the supplier. In this first segment, because it is an infinite (or uncapacited) supply plan, the agent plans as if the supply was available and deliverable in time. In other words, it represents a wish that would optimize its production output. Then, a *Supplier Allocation* is conducted, which is the distribution of demand to the different suppliers. Optimization algorithms are executed in *Demand propagation* and *Supplier Allocation* actions, using linear programming, constraint programming (CP) and heuristics. This allocation modifies the *Internal Supplier Allocation Delivery Requirement Plan* (3), which is transmitted to concerned suppliers. At this time, the agent enters a standby period, waiting to get answers from suppliers.

The second segment starts upon the reception of supply plans from suppliers. This event modifies the *Internal Supplier Replenishment Plan* (4) object. From this supply plan, the agent starts a *Supply Propagation*, which is a new production plan built using real supply, called here finite supply. The production planned from this feasible plan is then allocated to the different clients (*Client Allocation*). This event triggers the modification of the *Internal Customer Allocation Supplier Plan* (5) object. Then, verification of new orders is done to make sure no new demand arrived while processing, to avoid transmitting an already out-of-date supply plan to client. Finally, an *Internal Customer Replenishment Plan* (6) is modified and transmitted to clients. From there, if the client is another agent, the same planning protocol is started again.

4.4.3 Validation

The validation of these developments was carried out with the collaboration of a Canadian lumber company. Real data was used to test the performance of the agent-based APS. A supply chain configuration has been developed in order to address the planning of drying and finishing activities inside one plant. This configuration included different types of data, such as production processes, products, orders, on-hand inventory, selling prices, resource costs, forecasted supply, capacity and on-going work. This test covered 100 products, distributed over two kilns and one finishing line, in a planning horizon of 6 weeks.

The first step of this validation was to model the drying and finishing processes with the partner's production manager. Loading patterns for kilns were known and available, but finishing processes were unknown. Work was done to define in detail these processes, which resulted in 89 drying processes and 20 finishing processes. Customer order files and on-hand inventory data were extracted from the ERP system. The sales team provided the data on final product prices and resource costs. Each week, the partner's production manager sent the execution plan, including supply from the sawing line, daily capacity of the finishing line and on-going work. The needed information was then translated into XML format and introduced into the experimental platform.

Approximately 80 exchange protocols, 100 tasks and 50 workflows were involved in the experimental planning platform. We then generated production and logistics plans, and presented these to the production manager for comments. This interactive validation phase allowed to review and adjust the planning parameters and algorithms. By studying the real plan prepared by the manager, it was possible to evaluate the performance of the platform in terms of number of late customer orders, production value, resource utilization, etc. These indicators, easily obtained by the platform, were precious to evaluate the performance of both plans and identify possible improvements. The validation process took approximately one year and many corrections have been made on the platform. Currently, plans generated by the platform offer considerable improvements when compared to plans prepared by the partner's production manager. Also, the actual planning times for drying and finishing operations have been reduced dramatically.

The validation phase was crucial not only to verify the concept of the experimental platform and evaluate its performance, but also to collect information on how the concept could be improved. The process to increase agility and synchronization of the supply chain has been started, especially when compared to general practice in the lumber industry. Nevertheless, much more can be achieved by using the full potential offered by agent-based technology and advanced planning protocols. This leads us to the proposition of a new planning agent model.

4.5 Conceptual planning agent model

4.5.1 Enhancement of current planning agents

Agent-based planning systems, such as the experimental platform developed by the FORAC consortium, represent a promising way to develop new planning systems in the supply chain, to improve global performance. Although much energy has been deployed to define and deploy the experimental platform, there still exist possibilities for improvement, especially in the definition and design of the planning agent. By developing a new conceptual agent model, the objective is to describe the characteristics needed to enhance agility and synchronization of current planning agents. Facing disturbances, these agents use reactive TFs, triggered by specific messages (from partners or disturbances). The hypothesis is that agility and synchronization can be improved by using adapted behaviours (or strategies) depending on the situation and on the environmental context. To deploy agents with different behaviours, agents must possess the ability to make choices and the capability to evaluate these choices following specific criteria or goals.

4.5.2 Model description

The agent conceptual model must present the competencies needed in order to show behaviours adapted to a dynamic supply chain context. Inspired by Hoffmann (1999) and Salvador and Forza (2005), competency is defined here as the underlying attributes of an individual determining his capacity to successfully complete a task within a given environment. All competencies can be classified into three categories, which are attitudes, abilities and knowledge. Attitudes are the tendencies to act in a consistent way, following how an individual thinks and feels. Abilities are capabilities to perform specific tasks with the appropriate tools or techniques. Knowledge is defined here as the explicit understanding of information. In other words, the agent knows what the impact of the information is and how this information can be used. This has a direct impact on the agent's behaviour (Newell, 1982).

Integrating agent technology and OR tools, the conceptual model (Figure 4.4) is composed of three distinct layers, describing the different competencies required for supply chain planning. Other agent architectures present a three-layer approach, such as InteRRaP (Muller, 1997), but the model presented here is a conceptual one. Here, the objective is to describe the basic capabilities in order to serve as a guideline for further developments, instead of a precise arrangement of functionalities.

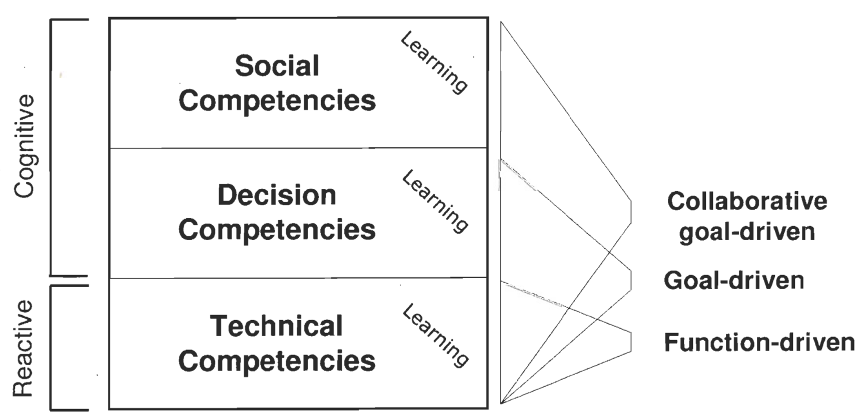

Figure 4.4. Agent conceptual model

4.5.2.1 Competency layer descriptions

The bottom layer of the agent model is the *Technical Competency* layer. This decision layer includes all tools, tasks and existing TFs, such as OR tools and algorithms, conversation protocols, negotiation protocols and queries. Goals in this layer are related to minimizing effort while maximizing results. The agent has knowledge of its tools and tasks, how to use them and when to use them. An agent that primarily uses this layer would show a *Function-Driven* behaviour. Current agents deployed in the experimental platform exhibit such behaviour. When they face a disturbance, they build a new production plan, send a new demand plan to suppliers and later, send a new supply plan to clients. At this point, a superior reasoning behaviour could be achieved by giving new possibilities to agents, other than starting a global re-planning protocol. Sometimes, different tools could be used to deal with the same situation. It would be to the agent's great advantage to have capabilities of analyzing the situation more deeply allowing it to make a clever decision.

This is where the *Decision Competency* layer permits the evolution from reactive behaviour to cognitive behaviour. It includes the explicit knowledge of local goals and the progress toward these goals at any time. Geared toward the optimization of the goals it has been assigned to, the agent is primarily concerned with a set of performance metrics that represents what the systems designer has developed. In brief, the agent knows only the impacts of its decisions in terms of this set of metrics. Here, when a disturbance occurs, the agent has the capability to choose which task, TF, optimization algorithms or complete plan would fit better, according to its own goals. The agent must have a representation of its goals and mechanisms to update and measure the achievement toward these internal goals. An agent oriented in the decision layer and technical layer would present a *Goal-driven* behaviour. This additional competency clearly gives some advantage to the agent, but it is still unaware of the impact of its decisions on its partners, or on the supply chain. It needs a broader conception to be able to make decisions in the interest of the majority.

The *Social Competency* layer fills this gap by integrating the welfare of partners through collective goals. The agent is now aware of the impacts of its decisions on other agents and on the whole supply chain. While choosing actions to correct deviations from plan, the agent possesses the ability to capture the entire potential of the network and be able to minimize impact on others. This layer includes mechanisms to obtain and update collective goals.

Collective goals include other agent goals and network tactical goals (i.e. specific product, client selection, supplier selection). If the agent cannot have direct access to other agent goals or collective goals, it must be able to anticipate them. It needs the ability to use collaboration protocols with anticipation of other agent reactions. With this competency layer, the agent can choose which task, TF or plan responds best to collective goals. Agents covering the three previous layers exhibit a *Collaborative goal-driven* behaviour.

4.5.2.2 Learning competency

Embedded in each layer, the *Learning competency* gives the agent the potential to increase its knowledge in each competency layer. A specific action or sequence of actions that demonstrated positive results in a situation could be learned and remembered for the next occurrence. The idea is to advance the articulation of the human decision-making process in our agent model. Various works have presented learning in agent-based systems as a way to improve the performance of manufacturing systems and supply chains. Shen et al. (2000a) present an interesting literature review on the subject and propose learning techniques adopted in the MetaMorph project. They distinguish learning from history (case-based reasoning) and learning from the future (by simulation). Alonso et al. (2001) argue that learning is the most crucial characteristic of intelligent agent systems and present different learning perspectives and techniques. Although this subject is not detailed in this article, it will be studied in the near future, with the objective of being fully implemented in the experimental platform.

From this conceptual agent model presenting basic abilities, there is a need to clarify how these competencies can be used to increase agility and synchronization in a planning system. An extended agent model must be designed to implement an agent able to choose the correct planning action when confronted with a specific disturbance.

4.6 Multi-behaviour agent model

The agent conceptual model presented in the above section gives the basic competencies necessary in a planning agent involved in dynamic supply chain planning. These competencies are quite general and there is a need to clarify how they interact in order to describe a coherent global behaviour able to achieve planning activities. In this section, an agent meta-model is presented, explaining the basic planning steps confronted in any disturbance. Then, the multi-behaviour agent model is described in detail, designed to offer different planning behaviours from which the agent can choose depending on the situation.

4.6.1 Agent meta-model

The agent meta-model is a high level view of interactions between a planning agent and its active environment (Figure 4.5). Before actually building an operational plan, the agent must decide which TF, or sequence of tasks, will be used, with the ultimate objective to build the best operational plan possible. Because the agent is not controlled by a central planning system, it is free to decide what it will perform, using its own preferences. In this meta-model activities are presented as boxes and results are ovals.

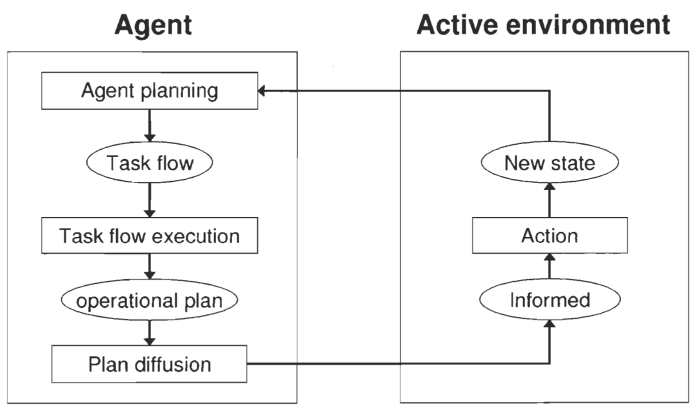

Figure 4.5. Agent meta-model

4.6.1.1 Meta-model description

From a new state in the environment, the agent first starts the *Agent Planning* phase. This phase is about planning the tasks of the agent. In other words, the agent deliberates to decide what it is going to perform, using different selection criteria, such as time available, chance of success of a particular TF, source of the disturbance and private goals. This is where cognitive abilities are used since the agent has to choose every task, TF and protocol it is going to perform to answer the disturbance. Its execution leads to the selection (or creation) of a TF. The next phase is the *TF Execution*, which is chiefly the allocation of resources (machine, labour, etc.) to specific production tasks (for example, processing product A on machine 1 on day 4). Using a pre-determined algorithm, a production plan is built, creating demand plans for suppliers and supply plans for clients. Different techniques can be used here, from simple heuristics to complex CP algorithms. The description of these production planning techniques is beyond the scope of this article, but the reader will find detailed information in Gaudreault et al. (2008). The execution of a TF leads to the creation of an operational plan. The *Plan Diffusion* phase distributes operation plans to every interested agent in the environment, including production staff related to the agent.

On the active environment side, which includes all other agents, upon diffusion of operational plans, the environment becomes informed. *Actions* are performed in the environment, in order to respond to the change induced by the new operational plan. These actions lead to a new environment state. The planning agent always watches the environment for a new state it can recognize. When it happens, the planning loop starts again. Even when no new state is noticed, the planning agent can perform a TF. In these cases, the agent tries to increase its own performance instead of remaining idle.

4.6.1.2 Agent reasoning

Agent planning is when reasoning is performed to choose between different planning alternatives. Researchers have proposed approaches to select the best TF in a shop floor context, using case-based reasoning and heuristic search techniques (Aytug et al., 2005). Here, a utility evaluation method is used to compare different TFs, using specific parameters. Four parameters are used:

1. *TF*: sequence of tasks used to solve planning problem created by a disturbance;

2. *Types of disturbances (Dist)*: new demand, new supply, execution problem, inventory error, etc.;

3. *Available respond time (Time)*: transmitted by the client as a time limit inside which an answer must be transmitted (acceptance or refusal);

4. *Intensity of disturbance (Int)*: percentage of changes since the last demand plan in term of quantity of products.

Utility can be defined as the degree of usefulness of a state to an agent (Fishburn, 1970; Russel and Norvig, 2003). When alternative actions are possible to an agent, it chooses the action leading to the state with the highest utility. Utility theory is used to represent and reason about preferences, which are defined by the goals of the agent, as pre-defined by its designer. Examples of goals are maximizing demand satisfaction, minimizing number of late deliveries and maximizing profit. The agent calculates the utility of a TF, reflecting the expected performance in terms of progress towards goal completion. A way to implement the utility function is to use a learning database to store information about past performance of TFs confronted in disturbances and specific parameters.

From a list of TFs, the rational agent performs a reasoning function. This function checks the utility of each available TF and selects the one with the highest utility. This statement can be represented as in equation 4.1.

$$\text{Reasoning}(ListTF, Dist, Time, Int) := \underset{\forall\, TF \in ListTF}{\text{argmax}} \ \text{utility}\,(TF, Dist, Time, Int) \qquad (4.1)$$

The *Agent Planning* phase also includes a reactive path to select a TF. Disturbances in a specific context can identify special situations such as no deliberation or utility calculation is needed. The responsiveness in these situations is improved since the agent does not have to evaluate every possible TF. This is particularly interesting for situations where standard responses offer excellent results when confronted to specific disturbances. For example, if a planning agent receives a new demand plan requiring more than a 50% change when compared to the last demand plan received, it is strongly advised to run a complete infinite replanning TF. These special situations must be chosen very carefully and can be adjusted when required.

Since the agent must present agility, it must be able to answer a disturbance with adapted actions, with high responsiveness. This way, different agent planning strategies can be employed and different production planning algorithms can be used. To integrate all these possibilities, a more detailed model is needed.

4.6.2 A new planning agent model

Using the agent meta-model as a basis, the multi-behaviour agent model (Figure 4.6) is an evolution of the concept. The model presents three basic behaviours to react to a new state in a planning context. Inspired by coordination mechanisms presented in Frayret et al. (2004), these planning behaviours are *Reaction*, *Anticipation* and *Negotiation*. Any TF planned by the agent can be characterized by one of these behaviours. The agent does not choose a specific behaviour, but chooses an adapted TF, which can be associated to a planning behaviour.

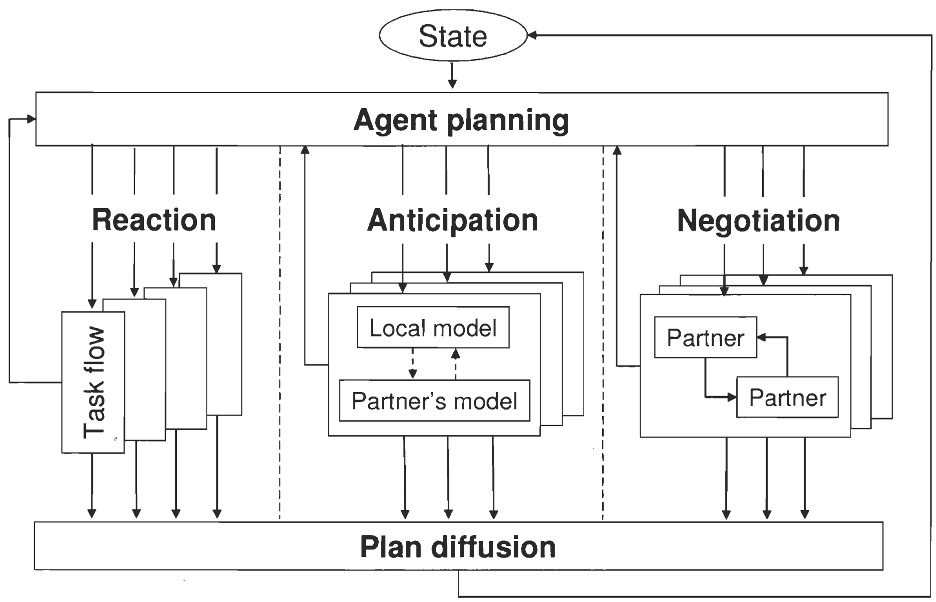

Figure 4.6. Multi-behaviour agent model

The *Reaction behaviour* is about using TFs where no new information is collected during processing. The agent knows a certain number of TFs and can use one of them to respond to a disturbance. Different optimization algorithms and objective functions can be used, depending on the situation and on the available time. This behaviour can be qualified as greedy, because the agent uses only what is the best for him. No knowledge about partners is used and there is no way to check if the proposed plan will satisfy the partner. These TFs are mainly used in well-known situations where no mutual adjustments are required. A large variety of TFs can be available, some of them taking much time but leading to optimal solutions, others finding acceptable (but not optimal) solutions in a very short period of time.

The *Anticipation behaviour* is a planning strategy using a partner model in addition to its local model. Basically, it is about integrating information about partners into its optimization model. Depending on the situation, emphasis can be placed on local or collective goals. Collaboration between planning partners through anticipation has been studied in hierarchical relation types (Schneeweiss and Zimmer, 2004) (also called upstream planning) and in a distributed context (Schneeweiss, 2003). The partner model is used to plan production in a way to maximize partner satisfaction, especially for production that has not been specifically asked for (push production). When no full disclosure is possible between partners (because of confidentiality needs), a partner's models are still used but represent a more approximated anticipation.

The *Negotiation behaviour* describes TFs sending proposals to partners, in the form of alternative plans. When the agent is not able to respond to 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. While both anticipation and reaction behaviours are non-convergent planning strategies, where the agent does not search for a compromise, the agent using a negotiation TF is fully informed and tries to reach an agreement. 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. Before undertaking a negotiation protocol, the planning agent must determine a negotiation space, which specifies what parts of the plan can be changed. This way, the negotiation is narrowed and leads to a compromise faster. Negotiation between planning partners in supply chains has been studied in distributed relations (Dudek and Stadtker, 2005; Stadtler, 2005). Dudek and Stadtler (2005) propose a negotiation-based scheme between two supply chain partners, using a convergence mechanism based on exchange of local associated costs.

Before diffusing the instructions to partners (*Plan Diffusion*), if there is still available time, the agent can perform other TFs. In Figure 4.6, this is represented with feedback arrows. In this way another reaction TF can be executed, after undertaking a reaction TF that failed (because no feasible solution was found using this strategy). Strategies can be implemented so that the agent would first try a quickly resolved TF and then try a more sophisticated one depending on the time remaining.

4.6.3 Advantages of the multi-behaviour agent

Compared to a purely reactive or deliberative agent, the multi-behaviour agent presents advantages similar to hybrid agents. For well-known situations, reaction TFs are used, but in situations where more information can be advantageous, the agent is able to demonstrate mutual adjustment capabilities, using anticipation or negotiation. The multi-behaviour agent is a hybrid agent designed specifically to answer production planning problems, using different behaviours.

The main advantage is the possibility of adjusting the behaviour according to external factors. For example, when a client sends a demand plan and requests an acceptance or a refusal in a short time frame, the agent is able to use its fastest response, which is one of the reaction TFs. In this case, instead of entirely re-planning the production plan (that would take a certain amount of time), it would use on-hand inventory and try to satisfy the client's needs. In contrast, if a large amount of time is available, the agent would take time to send new demand plans to suppliers. This example is detailed in the next section.

Another advantage is the possibility that the agent can use collective goals in addition to local goals. Anticipation TFs use inputs from a partner's model in order to integrate both local and collective goals. Depending on the relative importance of these goals, a balanced solution can be reached. The possibility of anticipating collective goals when communication is not possible (or too long to achieve) represents an appreciable advantage, as better decisions can be taken with limited knowledge. Also, negotiations TFs use direct input from a partner. Instead of using an approximate model of collective goals, real local goals of partners are integrated in the final solution. These mutual adjustment approaches help planning agents find better solutions that would increase collective performance instead of only individual performance.

Although this description of advantages seems promising, it is still based on an untested agent model. A proof of concept is needed and performance measurements must be developed to claim any real advantages. This requires the implementation of the multi-behaviour agent architecture in a real-world supply chain context, where manufacturing activities are planned and confronted with stochastic disturbances.

4.7 Implementation in the lumber supply chain

In order to implement the multi-behaviour agent, it is necessary to develop different TFs in order to react efficiently to disturbances. Among the different disturbances present in the lumber industry (i.e. a major kiln breakdown, out of stock report, unmet harvest, etc.), this section focuses on a specific disturbance scenario, which is the reception of a new demand plan. A description of these TFs corresponding to the different planning behaviours is then necessary.

4.7.1 Reception of a new demand plan

The scenario retained here is the reception of a new demand plan by the planning agent from a client. A demand plan is formed of different product orders, requested for different dates. Following this new state, the planning agent must decide if the fulfillment of the new demand is possible or not. This decision is not as simple as it appears, mainly because of the time constraint. In many industries, such as the lumber industry, the available response time to give an answer is not unlimited and is sometimes in fact quite short. The main problem is giving an answer to the client in a way to maximize its satisfaction and to maximize local profit, inside the available time limit.

When the available respond time is large, the best option is to run a full production planning similar to the one previously presented in Figure 4.3. Because available time is rarely that large, alternative planning processes must be available. Also, when the agent decides that it is not possible to accept the client demand, if available time remains, it can still try to find another solution. Alternative plans can be proposed to clients, considering the modifications needed in its production plan, the resource availability and the delivery dates requested. This is where the Reaction, Anticipation and Negotiation TFs are involved.

4.7.1.1 Agent planning reasoning flow

In the agent planning phase, the agent must select the best TF, using either a reactive or a deliberative path. Applied to the new demand plan scenario, the reasoning flow can be represented as in Figure 4.7. Upon reception of a new demand plan, the agent must first check if it corresponds to a special situation. If this is the case, it triggers a specific TF (for example, TF #1). Otherwise, a reasoning task is performed, in order to evaluate the utility of the available TF and select the one with the highest utility. The selected TF is then executed.

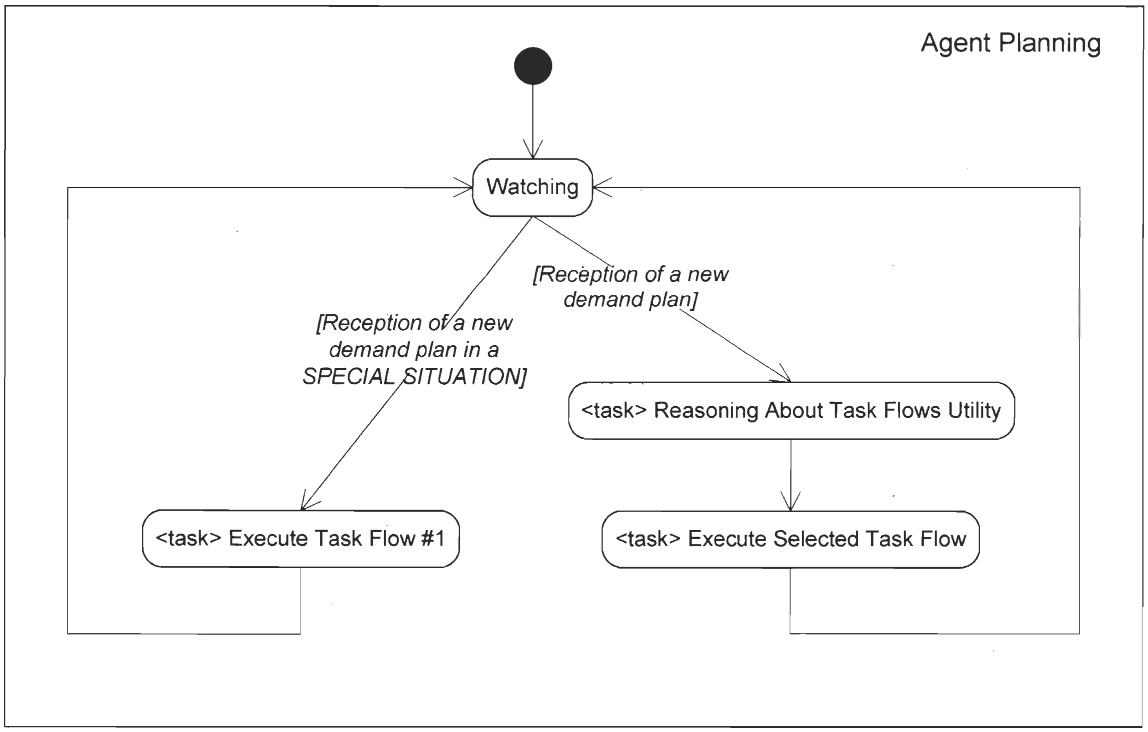

Figure 4.7. Example of an agent planning reasoning flow

4.7.1.2 Reaction task flow

All Reaction TFs require performing a production planning task. This can require building a new production plan or adapting the current one. The infinite production planning previously presented (first segment of Figure 4.3) is an example of a Reaction TF triggered by reception of a new demand plan. Other Reaction TFs can be used in order to answer different needs. For example, instead of running a full infinite production planning, which takes quite a long time because suppliers have to send demand plans to their own suppliers, the agent can try to fill the new needs by re-allocating available stocks. It can also re-allocate supplies previously reserved for other clients, without involving any new delay. Another option is to re-run a finite production planning task without asking for new supplies. Figure 4.8 presents an example of Reaction TFs.

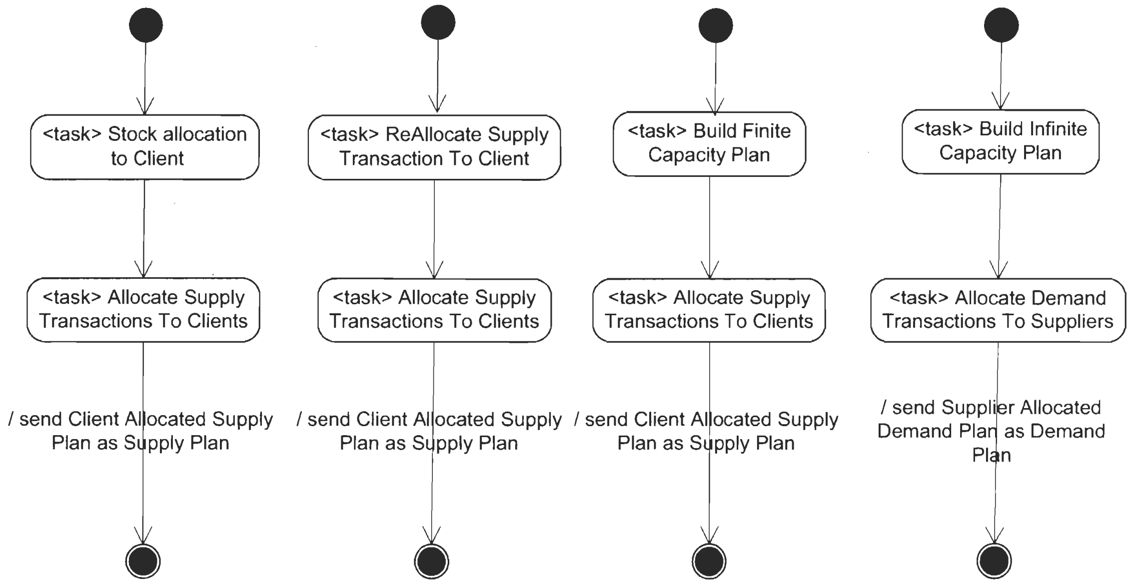

Figure 4.8. Examples of reaction task flows

4.7.1.3 Anticipation task flow

As introduced previously, Anticipation TFs are about using a partner's model in order to guide production planning. When the planning agent receives a new demand plan, it can anticipate information from its client and supplier, in order to plan its production in the best possible way. For example, because the experimental planning platform proposes a mix of pull and push production (pull production is required by the client, while push production is offered by the supplier but not required by the client), the planning agent plans push production with the remaining production capacity. In this case, it is possible to anticipate client's needs for push production, following a model of its inventory. Also, the agent can anticipate its supplier's production capacity to create a demand plan (in pull production) in line with the capacity limit. Another example is the offer of alternative products. When the agent is not able to fulfill the demand plan from its client, it can offer substitute products that the client would possibly accept (for example sending fir instead of pine). Figure 4.9 presents examples of such TFs.

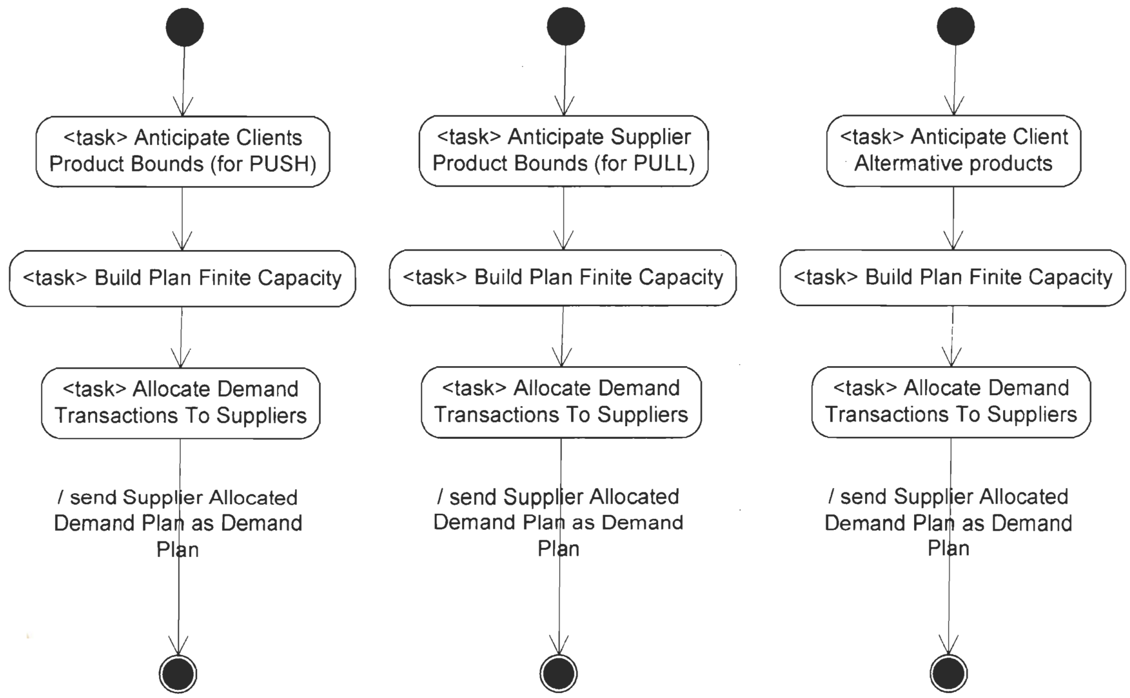

Figure 4.9. Examples of anticipation task flows

4.7.1.4 Negotiation task flow

The last behaviour concerns direct communication with partners, in the form of a negotiation protocol. This behaviour is preferred when a partner's model is incomplete or when the partner's input is needed. It is particularly useful in situations where the planning agent is not able to offer a positive answer to the client, but time is available to transmit production limits to the client. For example, if the agent is not able to produce what is asked in the demand plan, it can transmit a new set of boundaries, in order to give to the client new data to rerun a new demand plan. These boundaries can take the form of limits on specific products (for example, maximum of 2000 million FBM of pine on November 16). Upon reception of these new boundaries, the partner builds a new production plan in finite capacity using these new boundaries. After checking if these changes are acceptable to him or not, the partner will send an acceptance message or a new set of ultimatum boundaries on the same product. These ultimatum boundaries represent a final offer to the initiator. If these last boundaries are not accepted, the deal is over and the demand plan is erased. Figure 4.10 presents an example of a Negotiation TF.

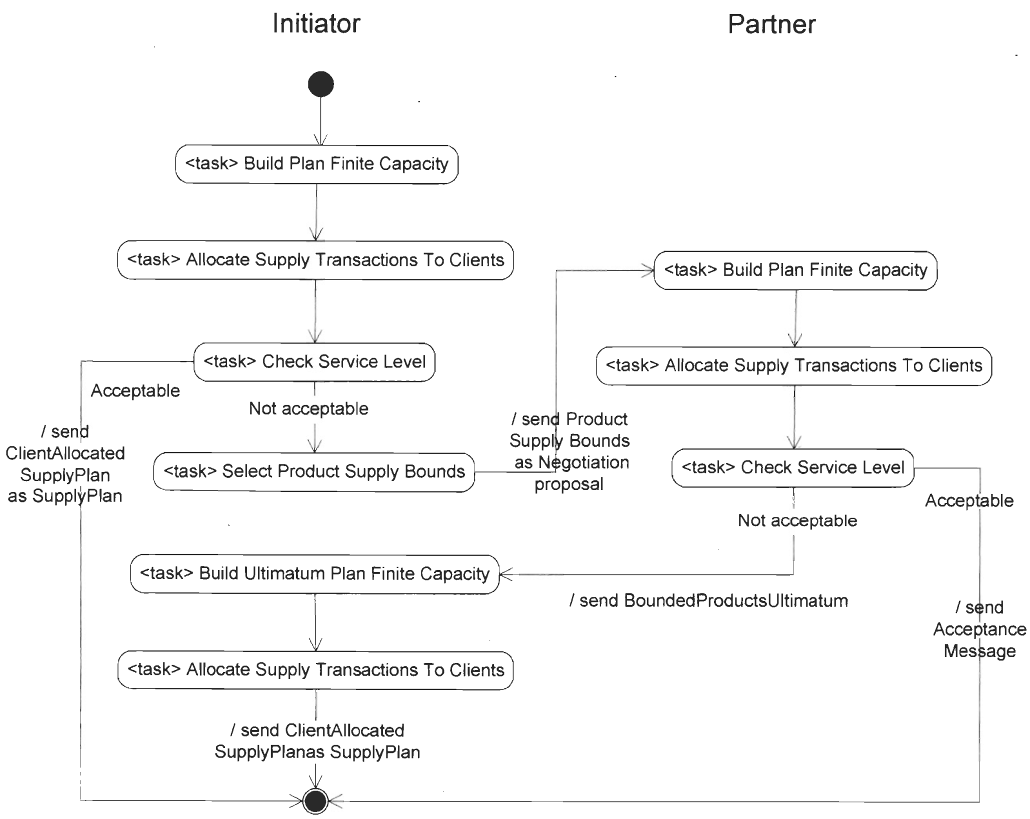

Figure 4.10. Example of a negotiation task flow

4.7.1.5 Scenario progress

Based on this demand plan scenario and on the TFs presented (Figures 4.8- 4.10), an example of the scenario progress can be described. In this case, the client gives a delay of one hour to accept or refuse its demand plan, and this new plan involves a total increase of 20% of the demand for this period on time. According to the multi-behaviour agent model (Figure 4.6), the first action taken by the planning agent is to plan what to do by evaluating which TF is the most appropriate. With this short delay, the agent clearly does not have time for negotiation or infinite production planning (both requiring waiting time). The remaining options need to be evaluated using its utility function. The planning agent can try to fit the new demand plan into the current production plan by building a new finite production plan. Another possibility is to reassign stocks or on-line productions promised to another client to accommodate the new client. From the utility evaluation of these options, a decision is taken, such as building a finite production plan. The selected TF is executed, resulting in the creation of a new supply plan for its client. If the client is completely satisfied, the demand plan is transmitted. If the client is not satisfied (meaning the planning agent is not able to deliver every product in time) and if there is still available time, another TF can be performed. The agent reruns a new utility evaluation and tries to find a new solution. In this example, by reassigning supplies, the agent can find a way to fit the client's demand plan in. The agent updates its production plan and sends an acceptance message to its client.

This example demonstrates the planning possibilities of the multi-behaviour agent model and the advantages of using such an agent model in a supply chain planning system. By adapting its behaviour to the situation, using reaction, anticipation or negotiation protocols, the agent can react promptly and use the best strategy for each different situation.

4.7.2 Simulation plan

In order to prove the concept of the multi-behaviour agent and test its performance, implementation and simulation must be undertaken on the FORAC experimental platform. Implementation will be gradual and behaviours will be developed successively. The first implementation will be the Reaction work flows. This step includes the development of the agent planning capability, including the utility evaluation function. All reaction TFs must be created and tested independently. Also, performance statistics must be compiled for each of these TFs in order to give information about the chance of success of executing a TF in a specific situation. At this stage, it will be possible to simulate all Reaction TFs on the experimental platform, by designing a supply chain made of Reaction planning agents (agents using only Reaction TFs). Performance tests will be possible by comparing key performance factors (i.e. resource use, rapidity of response, etc.) of this supply chain with the current implementation.

The second implementation will involve the Anticipation behaviour. This includes the introduction of partners' models, in order to give the planning agent information about clients and suppliers. Here, testing will be possible by comparing a supply chain made with agents using exclusively Anticipation TFs with a Reaction supply chain and the current implementation. Comparison can also be made concerning priority given to a partner's model or on the local model. This will be used to decide whether to follow local or collective goals first.

The final implementation will be the Negotiation behaviour. All Negotiation protocols will be developed, including convergence mechanisms to ensure reaching compromises. Again, comparison of performances will be possible with previously the mentioned supply chain configurations.

4.8 Conclusion

Supply chain planning agent models which use the advantage of reactivity, utility evaluation, anticipation and negotiation, such as the multi-behaviour agent, can be a powerful tool to reach appreciated gains when implemented in a distributed planning system such as the FORAC experimental platform. Following the conceptualization of the required intelligent behaviours and their implementation, future work is needed. For example, different agent configurations will be tested in real-world planning situations to determine the different situations where specific behaviours react well and those where they react badly. In a different perspective, it will be of great interest to increase research efforts on the learning competency, with both its implications and impacts. A multi-behaviour agent geared with learning abilities would be able to update its utility functions to modify its preference for an action which gave good results in the past. This is highly promising and should lead to an even more agile and performing supply chain.

Chapter 5

Study of the Performance of Multi-behaviour Agents for Supply Chain Planning

The second paper presents experimental results of testing the use of different planning behaviours in various environmental conditions. We develop an experimental plan to simulate various situations met in the lumber industry using multi-behaviour agents for planning production. Composed of different reaction planning behaviours, nine team behaviours are simulated on the FORAC agent-based planning platform. Variations are applied to customers demand and we analyze the variability of the supply chain performance depending on the team behaviour selected. Performance is measured in terms of total lateness for contract demand, total inventory, adjusted revenues and delivery performance for spot demand. An estimation of average gains demonstrates the advantage of adapting the team behaviour in various situations. Multi-behaviour agents can select the most appropriate planning behaviour and coordinate efforts to increase the supply chain performance. This paper is currently in press by the journal *Computers in Industry*, with Pascal Forget as the main author, with Sophie D'Amours, Jean-Marc Frayret and Jonathan Gaudreault as co-authors.

Résumé

Dans le contexte industriel actuel, la compétitivité est étroitement associée à la performance de la chaîne d'approvisionnement. La coordination entre les organisations est essentielle pour améliorer cette performance, de façon à fabriquer et livrer les produits aux clients à temps et à un prix compétitif. Tandis que les systèmes de planification actuels suivent des procédures standards de planification de la production, nous proposons dans cet article que les différents partenaires de la chaîne d'approvisionnement adaptent ensemble leurs processus de planification locaux (que nous appelons les comportements de planification) aux différentes situations pouvant survenir dans l'environnement de la chaîne d'approvisionnement. Par contre, la possibilité pour les partenaires de choisir entre différents comportements de planification amène une nouvelle difficulté. Puisque tous les comportements individuels ont un impact sur la performance globale, il devient difficile de connaître quel comportement est préférable pour chaque partenaire pour améliorer cette performance. En utilisant la technologie à base d'agents, des expérimentations de simulation ont été entreprises pour vérifier la possibilité d'améliorer la performance de la chaîne d'approvisionnement en utilisant des agents à comportements multiples pouvant s'adapter à l'environnement. Ces agents ont été implantés dans une plateforme de planification à base d'agents, en utilisant un cas virtuel de l'industrie du bois d'œuvre. L'analyse de la performance montre que des systèmes de planification avancés peuvent prendre avantage à utiliser une variété de processus de planification plutôt qu'un seul, principalement en raison du contexte dynamique des chaînes d'approvisionnement.

Abstract

In today's industrial context, competitiveness is closely associated to supply chain performance. Coordination between business units is essential to increase this performance, in order to produce and deliver products on time to customers, at a competitive price. While planning systems usually follow a single straightforward production planning process, this paper proposes that partners adapt together their local planning process (i.e. planning behaviours) to the different situations met in the supply chain environment. Because each partner can choose a different behaviour and all behaviours will have an impact on the overall

performance, it is difficult to know which is preferable for each partner to increase this performance. Using agent-based technology, simulation experiments have been undertaken to verify if multi-behaviour planning agents who can change planning behaviours to adapt to their environments can increase supply chain performance. These agents have been implemented in an agent-based planning platform, using a case study illustrating a lumber supply chain. The performance analysis shows that advanced planning systems can take advantage of using multiple planning processes, because of the dynamic context of supply chains.

5.1 Introduction

New economic challenges and recent trends regarding globalization have forced companies of many industries, including the Canadian lumber industry, to question aspects of their organizations. Many of them have reengineered their organizational processes and business practices and adopted supply chain management best practices. One aspect studied by many researchers recently is supply chain planning, which deals with the management of customer orders through the supply chain. Each partner involved must decide quantities to produce, production and delivery dates, distribution modes, and allocate resources to each product needed, with respect to production capacities and transportation delays. Coordination between production partners is essential in a supply chain context in order to deliver products on time to customers and at a competitive price. As changes occur all the time in such a complex system, production centres have to react to deviances and create new plans, while coordinating changes with partners.

In this paper, we address the adaptation of supply chain production planning systems to handle changes. Decentralized approaches are typically used to increase adaptation, giving different partners the responsibility to plan their production locally. The challenge of these approaches is to provide coordination schemes insuring coherent supply chain behaviour and global competitiveness. Agent-based technology provides a natural approach to model supply chain networks and describe specific planning agents. In such distributed planning systems, global performance is directly linked to how well the agents perform together. However, when different planning processes can be used by each agent to plan local production, it becomes difficult (or impossible) for each agent to identify the preferable one, especially in the dynamic context of supply chains. In fact, the local planning process (we call it here *planning behaviour*) leading to the highest performance for the supply chain can change with the environmental conditions. It then becomes necessary to use agents with the ability to adopt different planning behaviours and to be able to learn the preferable one in various situations.

In order to handle this problem, multi-behaviour agents have been proposed (Forget et al., 2008). These planning agents can adapt by selecting a planning behaviour according to the status of the supply chain. Here, a planning behaviour is defined as a planning process used by an agent to solve a planning problem. Using simulations, these agents can test the impacts on the supply chain performance of using a specific behaviour, depending on various factors such as customer demand and partners' behaviours as well. Depending on the observed results, agents can coordinate their actions by choosing a coherent *team behaviour* specifying a specific planning behaviour for each agent, leading to the best supply chain performance. We term team behaviour the combination of all agents' individual planning behaviours of agents in the supply chain.

This paper presents the simulation methodology and the performance analysis of an implementation of multi-behaviour agents in a lumber supply chain case study. Section 5.2 provides a literature review on supply chain planning and agent related subjects. In Section 5.3, the simulation methodology is detailed, including descriptions of the agent-based experimental platform, the multi-behaviour agent model, the lumber supply chain study case and the design of experiments. In Section 5.4, a performance analysis is presented. Finally, Section 5.5 concludes and provides an overview of intended future work.

5.2 Literature Review

5.2.1 Distributed Supply Chain Planning

Traditionally, centralized planning systems have been used for production planning in a single company, with a single or several facilities. Offering a complete and aggregated view of production activities, they usually use optimization algorithms to find near-optimal production plans. In a distributed context like supply chains, where multiple partners work together to deliver goods to final customers, planning rapidly becomes difficult, if not impossible, to solve centrally. Centralized planning systems tend to be rigid under dynamic system environments and are less likely to succeed than distributed approaches (Alvarez, 2007). Also, supply chain partners are usually reluctant to share private information that can be crucial to their competitiveness.

Different organizational paradigms have been studied to operate distributed systems, such as fractal factory, bionic manufacturing, holonic manufacturing and the NetMan paradigm. The reader is referred to Frayret et al. (2004) for a review. These paradigms are generic frameworks that can be used to design distributed manufacturing systems. They differ from each other in the way they handle specific problems, manage information and coordinate actions. In fact, in the context of supply chains, these distributed approaches have contributed to the development of agent-based supply chain planning systems. Agent-based planning systems are computer systems made from a collection of software agents, with specific roles and goals, interacting with each other to make the best decisions according to the situation and their goals in order to carry out their part of the planning task (Marik et al., 2001). Agent-based systems focus on implementing individual and social behaviours in a distributed context, using notions such as autonomy, reactivity and goal-directed reasoning (Bussmann et al., 2004).

Several articles present reviews of research projects related to planning, scheduling and control, using agents (Shen et al., 2006; Caridi & Cavalieri, 2004; Frayret et al., 2007; Moyaux et al., 2006). Among these projects, Montreuil et al. (2000) presented NetMan, which is an operation system for networked manufacturing organizations that aims to provide a collaborative approach to operations planning in the context of a motor coach company. In the NetMan platform, the agents possess models of their supplier and customer permitting an anticipation of the impacts of the agent's decision on their neighbouring agents. The ExPlanTech multi-agent platform (Pechoucek et al., 2005) provides decision-making support and simulation capabilities to distributed production planning. Relying on communication agents, project planning agents, project management agents and production agents, the platform uses negotiation, job delegation and task decomposition to solve production coordination problems. In order to reduce communication traffic, social knowledge is precompiled and maintained, which represents information about other agents. The FORAC agent-based planning platform (Frayret et al., 2007) presents an architecture combining agent-based technology and operation research-based tools. The platform is designed to plan supply chain operations and simulate supply chain activities. Each agent can be designed with specific planning algorithms and is able to start a planning process at any time, following a change in its environment. The agent's environment is made up of the other supply chain agents, demand information from customers and supply availabilities from suppliers. More details of this platform are given in Section 5.3.1.

5.2.2 Coordination in supply chains

Without coordination, a group of agents can quickly degenerate into a chaotic collection of individuals (Shen et al., 2006). The coordination between planning centres is essential because decisions concerning production planning are interdependent and have an impact on partners (Moyaux et al., 2006). These interdependencies need to be managed, which requires the building of coordination mechanisms to maintain a certain level of coherence between the different decision centres. These coordination mechanisms can in fact be understood as rules that partners use to carry out their own planning activities. Different categories of coordination mechanisms have been identified by Frayret et al. (2004) in the context of distributed systems. These categories propose to overcome certain limits of previous classification schemes in order to include new forms of coordination mechanisms encountered in agent-based manufacturing systems, including a distinction between coordination before and during activities.

Negotiation is a common supply chain coordination approach, where partners look at finding mutual agreement on planning issues. Jiao et al. (2006) argue that negotiation is crucial to successfully coordinate different supply chain entities. Various negotiation strategies can be deployed, including contract-based negotiation, market-based negotiation, game theory-based negotiation, plan-based negotiation and AI-based negotiation (Shen et al., 2001). Dudek and Stadtler (2005) proposed a negotiation-based scheme between two supply chain partners, using a convergence mechanism based on exchange of local associated costs. Different agent-based manufacturing systems using negotiation have been proposed (see Shen et al., 2006 and Shen et al., 2001). Among them, Jiao et al. (2006) present an agent-based framework that enables multi-contract negotiation and coordination of multiple negotiation processes in a supply chain. Monteiro et al. (2007) proposed a new approach to coordinate planning decisions in a multi-site network system, using a planning agent and negotiation agents. The negotiator agent is responsible for limiting the negotiation process and facilitating cooperation between production centres. Chen et al. (1999) proposed a negotiation-based multi-agent system for supply chain management, describing a number of negotiation protocols for functional agent cooperation.

While most of these agent-based supply chain planning approaches use specific coordination and optimization mechanisms to produce coherent production plans, they can be insufficient to face changing conditions. In many situations, it can be advantageous to use a different approach, more adapted to the state of the environment. This raises the need for adaptive multi-behaviour agents, who can adapt their planning behaviour to their environment and change their local coordination and optimization mechanisms.

5.2.3 Adaptive Agent-based Planning

When the environment is characterized by high levels of variability, which is often the case of supply chains (e.g. supply quality variability, demand volatility, poor delivery reliability and new production introduction), planning agents are expected to create or review production plans continuously. In some situations, it can be advantageous for agents to adapt to the context. Adaptation can be over their local planning behaviours, where each agent adapts itself individually, or it can be done as a team, where agents collaborate to adapt to the situation together. Different adaptive agent models have thus been proposed in the literature, some of which were specifically designed to improve the performance of the supply chain.

One of the most well known is the InteRRaP architecture (Muller, 1997). This layer-based agent model provides an approach to react and deliberate when confronted with changing situations, using different cognitive capability levels. Depending on the situation, the agent can use a reactive response, local planning or collaboration planning with other agents. The Agent Building Shell (ABS) (Fox et al., 2000) is a collection of reusable software components and interfaces needed for any agent involved in a supply chain management system. The ABS is geared to handle changes caused by stochastic events in a supply chain. An interesting simulation is presented using ABS agents to analyze the impact of coordination in supply chains when facing changes. Another adaptive agent model is the tri-base acquaintance model (3bA) (Marik et al., 2001). It provides the possibility of dealing with changes in a global perspective instead of resolving problems from a local perspective. This is accomplished by using information about other agents without the need for a central facilitator. These authors present some applications to supply chains and they define the social knowledge needed to increase the efficiency of agents. In the MetaMorph adaptive agent-based architecture (Maturana et al., 1999), mediator agents are used to facilitate the coordination of heterogeneous agents. These mediators assume the role of system coordinators and encapsulate various mediation behaviours (or strategies) to break decision deadlocks. Jeng et al. (2006) proposed an agent-based framework (Commitment-based Sense-and-Respond framework – CSR) which is an adaptive environment for continuous monitoring of business performance and reacting to changes, using multiple decision agents. An application to the microelectronic supply chain is presented.

The multi-behaviour agent is an adaptive agent model presented by Forget et al. (2008) and has been designed to give the agents alternative behaviours to face different situations more efficiently, individually or as a team. 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, and change its behaviours when needed. The multi-behaviour agent presents three basic behaviour categories, inspired by the coordination mechanisms found in the literature (Frayret et al., 2004; Moyaux et al., 2006; Shen et al., 2001; Schneeweiss, 2003). These categories are identified as *Reaction*, *Anticipation* and *Negotiation*. The reaction behaviours are simple sequences of planning tasks or planning TF using local information and no feedback. Anticipation behaviours are based on the use of anticipation functions that approximate other agents' decision models in order to offer superior or improved plans to them. Negotiation behaviours are more complex TFs involving feedback loops to find an acceptable compromise for both negotiating agents. Figure 5.1 presents the multi-behaviour agent model.

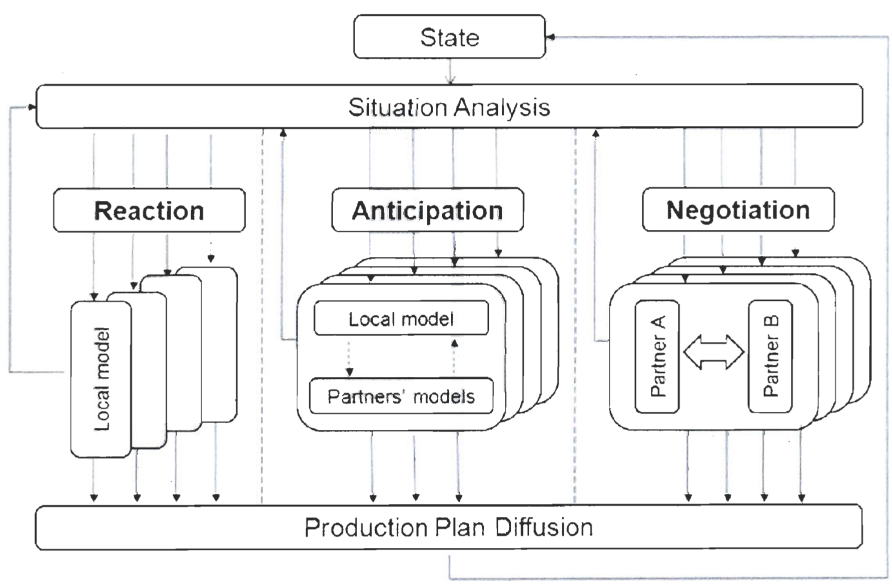

Figure 5.1. Multi-behaviour agent model

Basically, when facing a state change in its environment, the agent must select the planning behaviour to adopt, using different selection criteria, such as available time to make a decision, chance of success of a particular TF and source of the perturbation. Researchers have presented several approaches to select the best TF in a shop floor context, using case-based reasoning and heuristic search techniques (Aytug et al., 2005). The multi-behaviour agent uses a rule-based reasoning approach where it learns through simulations and run-time experience which planning behaviour offers the best performance for various situations. For these experiments, we focused on simulating various reaction behaviours. Also, the implementation of the learning ability has not been performed yet, focusing our efforts on verifying the performance gain of using multiple behaviours. For a detailed description and examples of planning behaviours, the reader is referred to (Forget et al., 2008). A design framework for multi-behaviour agents is presented in (Forget et al., 2008b).

These agent architectures all offer the possibility of adapting their planning behaviour when certain situations occur, some individually and others as a team. Some of them know beforehand which behaviour must be used for each situation, while other agents successively try different alternatives. More advanced agents compile the performance of past experiences and learn from it: these are learning agents.

5.3 Simulation methodology

Simulation experiments have been undertaken to verify whether multi-behaviour planning agents that can change planning behaviours to adapt to its environment can increase supply chain performance. These agents have been implemented in an agent-based planning platform, using a case study illustrating a lumber supply chain. In this section, we describe the agent-based experimental planning platform used for simulation and then, a description of the lumber supply chain case study is provided. In the following, the design of the experiment is detailed.

5.3.1 Agent-based planning platform

With the purpose of developing a new approach for planning the lumber supply chain, the FORAC Research Consortium has developed an experimental Internet-based planning platform built on an agent-based architecture for advanced planning and scheduling (Frayret et al., 2007). This platform allows different production centres to independently react to changes and plan production, while maintaining feasibility and coordination with one another. By distributing planning decisions among specialized planning agents geared up with adapted optimization tools and by providing coordination mechanisms, the platform increases supply chain reactivity and performance. Another major capability of the platform concerns simulation functions. It becomes possible for supply chain designers or production managers to simulate changes in certain aspects of the supply chain. These simulations can be strategic (e.g. adding a new partner, building a new plant, moving production resources to another plant), tactical (e.g. changing decoupling point, adding new machinery) and operational, such as the number of work shifts and the number of employees. In this paper, the simulation functions of the platform are used at the operational level, in order to simulate multiple production planning behaviours.

The agent-based architecture presented is based on a functional division of planning domains, inspired by the SCOR model proposed by the Supply Chain Council (Stephens, 2000). Figure 5.2 presents an example of a simple supply chain, dividing activities 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 centre in terms of production output each day. The suppliers and customers are represented as software 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. A supply chain configuration has been developed in order to address the planning of sawing, drying and finishing activities inside a lumber mill and real data was used to test performance.

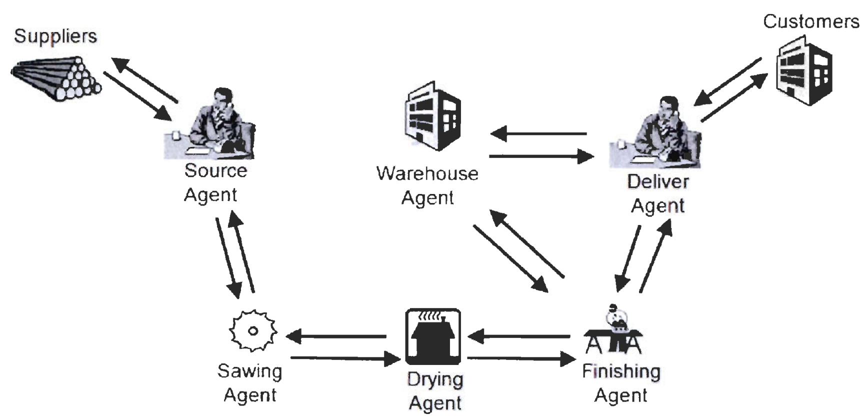

Figure 5.2. Supply chain example from the FORAC planning platform

The agents' planning problems are radically different with regard to their nature, both in terms of production philosophy and constraints. In order to individually plan for the different production agents, planning algorithms have been developed to resolve the three operations planning/scheduling problems. In practice, the planning models have been designed in order to take advantage of some of the specificities of the overall planning context. The objective is to minimize lateness for 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 (Gaudreault et al., 2008). Finally, a MIP model was designed to address the finishing planning problem and is resolved using ILOG CPLEX.

If a change occurs in the supply chain operations, any agent can initiate collaboration with other agents by sending a revised demand or supply plan. For example, collaboration can be triggered by an agent who has received a new demand. To this end, agents are continuously monitoring their environment and reacting to changes. Because of the interaction context, an agent's environment is also made up of 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 to process. For a more detailed description, the reader is referred to Frayret et al. (2007).

5.3.2 Lumber supply chain study case

In order to simulate multi-behaviour agents, an industrial study case has been created. Inspired by a real lumber supply chain, decisions were made concerning the number of partners, production centres, 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). A total of 45 different products are available to customers, corresponding to different lengths and quality of lumber pieces. An initial inventory has been determined for each production centre, corresponding to approximately one week of production at full capacity.

More precisely, the sawing production centre uses one general sawing line for 8 feet to 16 feet lengths, working 7 days per week, 16 hours per day. The maximum capacity for this production centre is 233 million FBM (Foot Board Measure) per year when the most efficient processes are used. The drying production centre is composed of unlimited air dry spaces, 5 small kiln dryers and two large kiln dryers. Air dry spaces are outside zones where green lumber can dry slowly. Air dried products usually lead to a higher quality final product, but take longer to be dried. Small kiln dryers have a loading capacity of 137,000 FBM and are open all year around (7 days per week, 24 hours per day). Large kiln dryers have a loading capacity of 237,000 FBM and are also open all year. Finally, the finishing production centre uses one line, working 7 days per week, at 16 hours per day. Its maximum capacity is 219 million FBM per year. Table 5.1 presents the production centre details.

Table 5.1. Production centres details

	Production lines	**Availability**	**Maximum capacity**
Sawing center	• one general line for 8' to 16' lengths	• 7 days/week, 16 hours/day	• 233,000,000 FBM per year
Drying center	• unlimited air dry spaces	• 7 days/week, 24 hours/day	• Unlimited
	• 5 small kiln dryers	• 7 days/week, 24 hours/day	• 137,000 FBM per load
	• 2 big kiln dryers	• 7 days/week, 24 hours/day	• 237,000 FBM per load
Finishing center	• One line	• 7 days/week, 16 hours/day	• 219,000,000 FBM per year

5.3.3 Design of experiments

The details of the experiment design are presented as follows. We describe the inputs, which are the environmental conditions, the controllable variables, which are the team behaviours, and the outputs of the experiments, which are the results for different performance indicators. The main objective of these experiments is to verify if, for various environmental conditions, the best results are obtained with mono-behaviour agents (using the same team behaviour in every situation) or with multi-behaviour agents where team behaviours are adapted.

5.3.3.1 Inputs

The system was submitted to different demand order variations. Two design factors describing demand orders have been used: (1) *contract proportion* (contract demand versus spot demand in terms of volume) and (2) *demand intensity*. For the contract proportion factor, we distinguish a contract demand (regular demand from a contract customer, providing a premium bonus) with a spot demand (one-time order, irregular frequency). When a supplier is late for a spot demand, it is considered lost because the customer usually changes supplier. However, in the case of a late contract demand, it is not lost, but a penalty for each day is charged. Five different contract proportions have been used in the simulation, which are 0%, 25%, 50%, 75% and 100% of contract orders. In the lumber industry, some companies have a majority of contracts (close to 100% of contracts), while others prefer to rely only on spot market (0% of contracts). The demand intensity factor represents the percentage of production capacity required to answer the demand. Three levels of demand intensity have been used, which are 50%, 100% and 150%. The demand intensity of 100% has been estimated by pushing an infinity of supply into the supply chain and observing the maximum production output that can be produced. For the two extremes, a demand intensity of 50% is common when the economic context is running slowly, while an intensity of 150% is possible in periods of economic growth. When the demand intensity varies, both contract and spot demand are affected.

Basically, in each experiment, planning agents have to prepare a production plan for the following 30 days, knowing a set of incoming demand orders spread over the horizon. These demand orders follow a specific combination of demand intensity and contract demand proportion. A total of four demand sets from customers were generated by a random demand generator, in order to perform four replications of every experiment. This generator creates random demand, according to predetermined settings such as distribution functions of demand quantity, minimum/maximum limits, random errors and seasonality. It offers the possibility of adding variability to the system by confronting the multi-behaviour agents with different patterns and situations. Every product can be set in a different manner to follow a different demand pattern. Also, for different customers, a product can have different demand patterns. Values have been determined following examples available from the lumber industry. More details on the demand generator can be found in (Lemieux et al., 2008).

5.3.3.2 Controllable variables

In order to respond to the different inputs, controllable variables can be modified, creating different reaction planning behaviours for each planning agent. We identified four controllable variables that can be modified in the planning system, which are *scheduling strategy*, *priority*, *penalty* and *coordination mechanisms*. The first three variables can be classified as optimization variables while the last one modifies the coordination mechanism. The planning algorithm used by an agent can be parameterized to present two different scheduling strategies: *just-in-time* (JIT) or *forward*. JIT scheduling aims to plan orders at the latest possible date without being late, while the forward scheduling plans orders as soon as possible. Priority drives the weight of spot versus contract orders. Here, three cases are studied: priority over the contract orders, priority over the spot orders, and finally, spot and contract orders with equal priority. Penalty is a penalty factor that can be applied only on backorders or set equal to inventory holding costs and backorders. These three optimization variables presented here can be modified for all agents in the same time or only some of them, generating different production plans.

Another way to change the planning behaviour is to modify the coordination mechanism between agents. Two mechanisms are studied: *downstream* and *two-phase*. Downstream planning is characterized by plans which are constrained by the downstream supply. In this case, the products harvested in the forest dictate what will be processed in the supply chain, without using information on customer demand. Two-phase planning is a coordination mechanism using the downstream planning combined with an upstream planning approach. This approach involves a hierarchy of subproblems that implicates each agent twice. The agent first makes a temporary plan to compute its supply needs and sends this information to its supplier. In turn, the supplier tries to satisfy this demand and responds with a supply plan that does not necessarily meet all demand (e.g., some deliveries may be planned to be late or some products can be replaced by substitutes). The agent can generate a second production plan constrained by the supply plan. Figure 5.3 presents the coordination mechanisms between the three production planning agents.

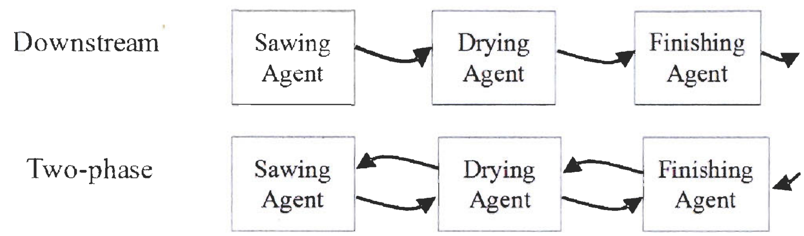

Figure 5.3. Coordination mechanisms

5.3.3.3 Fractional Factorial Experiment

Combining these controllable variables, we identified nine different planning behaviours mixes, presenting a variety of team behaviours for the supply chain (see Table 5.2). The three optimization variables presented in the last section have been applied to a different agent: the scheduling strategy variable has been applied to the drying agent, the priority variable to the deliver agent and the penalty variable to the finishing agent. The coordination mechanism variable has been applied to the entire team. This selection of team behaviours makes the experiment a fractional factorial experiment and is based on the experience of managers and researchers.

Table 5.2. Team behaviours used in experiments

Team behaviour	Drying Agent Scheduling Stragegy	Deliver Agent Priority	Finishing Agent Penalty	Coordination Mechanism
1	JIT	Contract	Back orders	Two-phase
2	Forward	Contract	Back orders	Two-phase
3	JIT	Contract	Back orders	Downstream
4	JIT	No priority	Back orders	Two-phase
5	JIT	Spot	Back orders	Two-phase
6	JIT	Contract	Equal	Two-phase
7	Forward	Contract	Equal	Two-phase
8	Forward	No priority	Back orders	Two-phase
9	Forward	Spot	Back orders	Two-phase

5.3.3.4 Outputs

In order to analyze the different team behaviours, different outputs have been identified, showing different levels of supply chain performance. Depending on the choice of a specific performance indicator, the preferable team behaviour may differ. In certain environments, a specific team behaviour can dominate others for all indicators, but in another, the same behaviour can show poor results. Here, the results are analyzed regarding four performance indicators: (1) *total lateness on contract-based orders*, (2) *supply chain inventory*, (3) *adjusted revenues* and (4) *delivery performance on spot-based orders*. Total lateness is the quantity of backorders (BO) for contract-based orders. It is expressed as the quantity of FBM multiplied by the number of days late. Supply chain inventory is the sum of the average of FBM in inventory, per month. The adjusted revenues are based on revenues generated by the sales of products to customers, where inventory holding costs and lateness penalties are subtracted. A penalty cost is associated with lateness in contract-based orders (1.5% per day for backorder) and a premium bonus is given for the fulfilled contract-based order (5%). A daily inventory holding cost of 0.5% of market value is charged. This indicator is partial since it does not include production costs but is sufficient to compare planning behaviours. Finally, the spot delivery performance is the percentage of spot orders delivered on time.

5.4 Performance analysis

5.4.1 Team behaviour performance

Using the different demand sets generated, four replications were produced. We used the average of all replications to draw graphs and observed the evolution of the performances.

Figures 5.4 - 5.7 present team behaviour performances in various conditions (demand intensity and contract proportion), for different performance indicators (total lateness, supply chain inventory, adjusted revenues and delivery performance on spot). In each graph, depending on the set of environmental conditions, each team behaviour follows a different performance evolution. This implies that the preferable team behaviour is not always the same and that there is an advantage to considering all of them instead of choosing the same for all situations.

In Figure 5.4, the three graphs present the performance evolution in term of lateness. Because the team objective is to minimize this indicator, behaviours 5 and 9 offer the best performances in most conditions. But when the proportion of contracts approaches 100% contracts, behaviour 6 offers the best results for 100% and 150% demands. In Figure 5.5, for the average inventory performance indicator, the supply chain team still aims to minimize this indicator. Behaviour 8 gives the best results at 50% and 150% demand for all contract proportions, but at 100% demand, behaviours 2 and 7 seem to perform better most of the time. Figure 5.6 presents results for the adjusted revenues performance indicator. This analysis is particularly interesting since it combines information from lateness and inventory data. As we can see, at 50% demand, behaviour 9 is dominant. But when the demand intensity grows to 100% and 150%, behaviour 3 gradually offers the highest performance. Finally, the three graphs in Figure 5.7 present the delivery performance for spot demand. This time, behaviour 7 is dominant for a 50% demand (but followed very closely by behaviour 1) and behaviour 3 is dominant for 100% and 150% demand.

While it can be hazardous to explain the reasons behind the evolutions of each behaviour and why one behaviour performs better for a specific situation, a hypothesis can be proposed. For example, in the adjusted revenues curves (Figure 5.6), as the demand intensity increases, behaviour 3 becomes more and more interesting to select. In fact, behaviour 3 is characterized by downstream team coordination, instead of a two-phase coordination like the other behaviours. This specificity gives bad results when it is important to fit the production to the demand (in low demand intensity context) but can be advantageous when demand is so important that nearly every product can be sold (in high demand intensity).

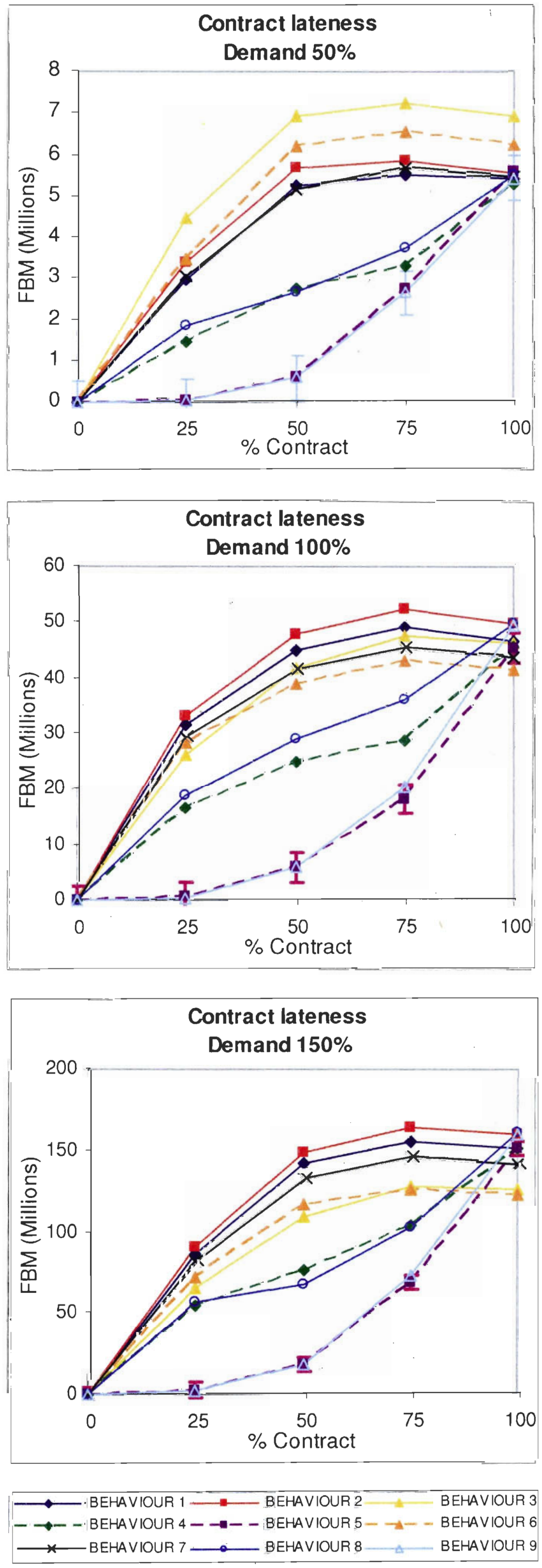

Figure 5.4. Performance for contract lateness

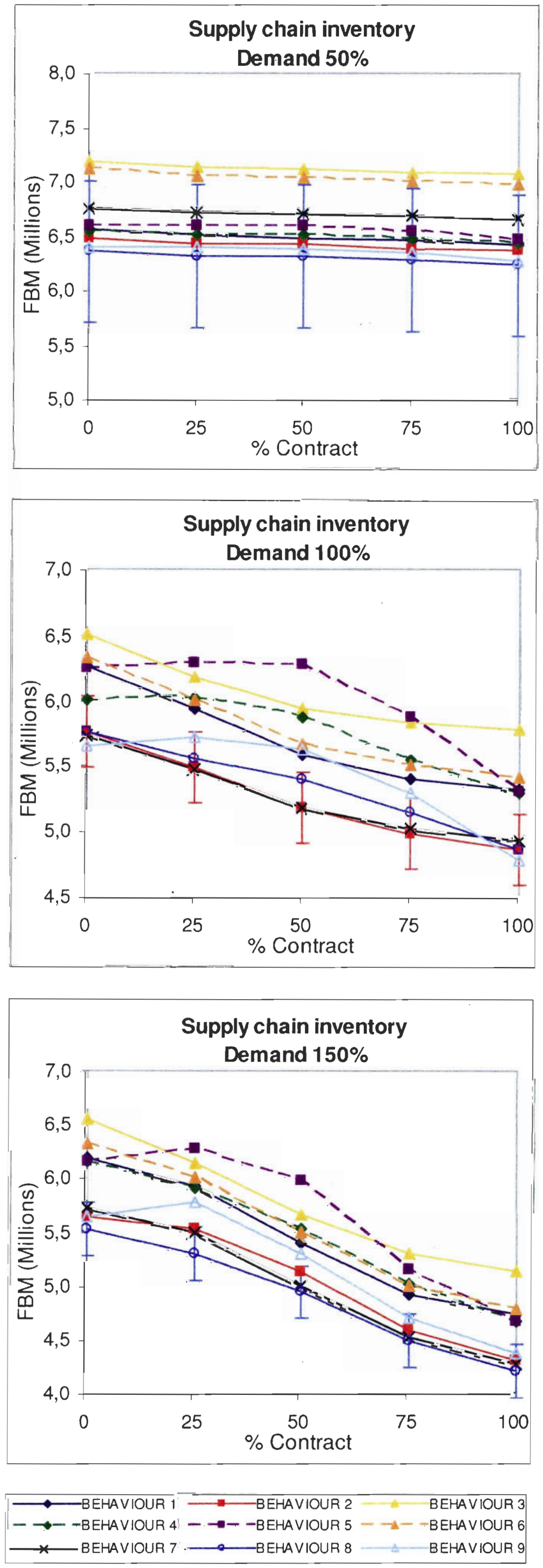

Figure 5.5. Performance for average inventory

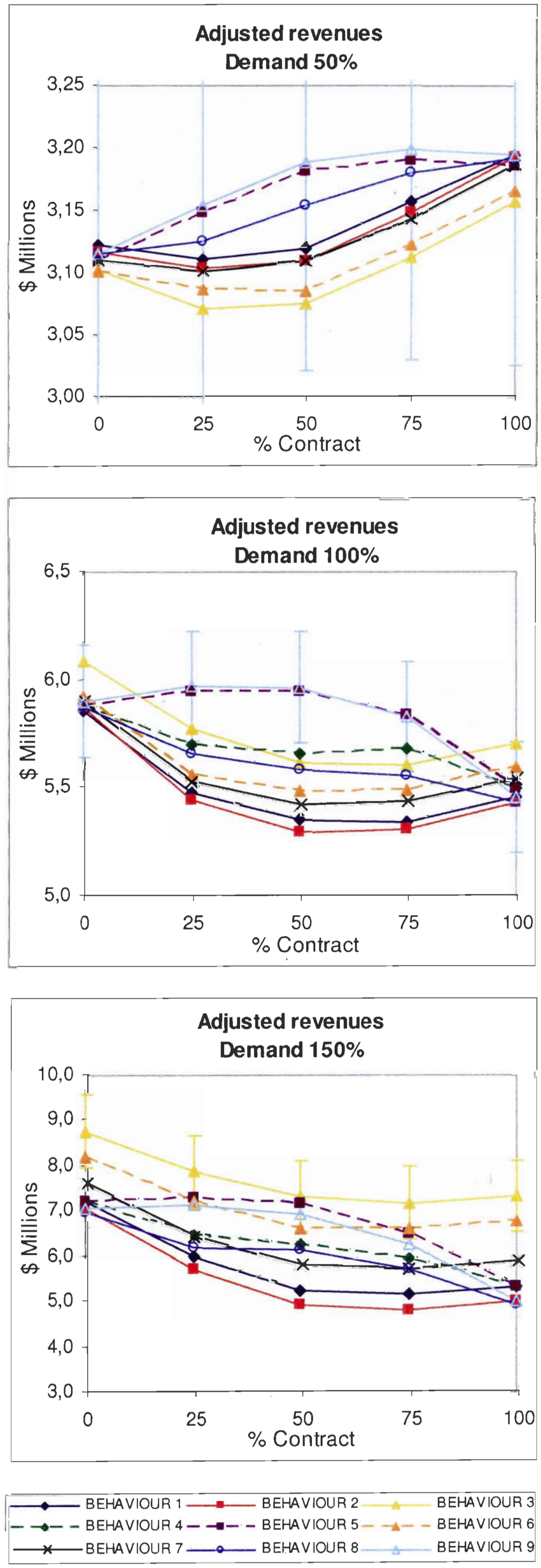

Figure 5.6. Performance for adjusted revenues

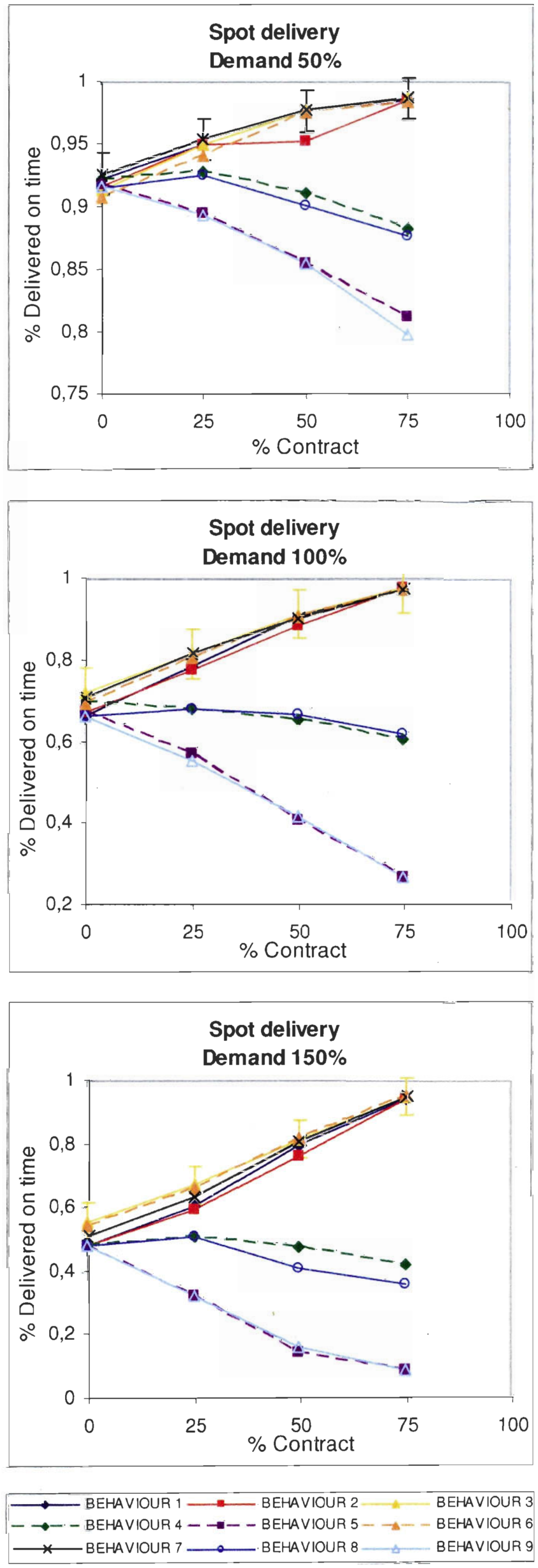

Figure 5.7. Performance for spot delivery

5.4.2 Similar behaviours

In some situations, behaviour performances are very similar and it can be difficult to determine without any doubt which behaviour is preferable. The study of the standard deviations of the preferable identified behaviours for the four replications tested (vertical lines in Figures 5.4-5.7) shows that some behaviours are too close to be significantly different. This happens when the preferable behaviour standard deviation includes other behaviours. In these situations, there would be not only one preferable behaviour but a sub-group of preferable behaviours, from which the planning agent can choose. The similarities of behaviours are particularly clear in Figures 5.5 and 5.6 at a 50% demand (top graphs). In these cases, almost all behaviours are equivalent for all contract proportions. This means that for a low degree of capacity usage, no planning behaviour is preferable.

Conclusions from a standard deviation study can vary depending on the number of replications. It is possible that the strong standard deviations presented in Figures 5.5 and 5.6 may decrease (or increase) from the results obtained here from four replications by going through more replications.

5.4.3 Knowledge matrix

Performances are gathered in a knowledge matrix, including the preferable team behaviours for the different environmental conditions. This matrix is imbedded in the agent and can be updated by run-time learning. Table 5.3 presents an example of such a matrix derived from this simulation. When a sub-group of preferable behaviours is identified (instead of a single behaviour), the others are also added. In this knowledge matrix, the team behaviour with the best performance observed is written first, followed by similar behaviours between brackets. While this matrix presents, for clarity purposes, only four intervals of contract proportion, a multi-agent can directly use the performance curves to calculate the preferable behaviour for a specific environmental condition.

Table 5.3. Knowledge matrix

Environment \ Indicator		Contract Lateness	Supply Chain Inventory	Adjusted Revenues	Spot Delivery
Demand 50%	Contrat <=25%	5 (9)	8 (1,2,4,5,7,9)	9 (1,2,3,4,5,6,7,8)	7 (1,2,3,6)
	25%< Contrat >=50%	5 (9)	8 (1,2,4,5,7,9)	9 (1,2,3,4,5,6,7,8)	7 (1,2,3,6)
	50%< Contrat >=75%	9 (5)	8 (1,2,4,5,7,9)	9 (1,2,3,4,5,6,7,8)	7 (1,2,3,6)
	Contrat >75%	9 (4,5)	8 (1,2,4,5,7,9)	9 (1,2,3,4,5,6,7,8)	N.A.
Demand 100%	Contrat <=25%	9 (5)	7 (2,8,9)	9 (1,2,3,4,5,6,7,8)	3 (1,2,6,7)
	25%< Contrat >=50%	5 (9)	7 (2,8)	9 (5)	3 (1,2,6,7)
	50%< Contrat >=75%	5 (9)	2 (7,8)	5 (9,4)	3 (1,2,6,7)
	Contrat >75%	5 (4,9)	2 (7,8,9)	5 (1,2,3,4,6,7,8,9)	N.A.
Demand 150%	Contrat <=25%	9 (5)	8 (2,7,9)	3 (6)	3 (1,2,6,7)
	25%< Contrat >=50%	9 (5)	8 (2,7)	3 (5,6,9)	3 (1,2,6,7)
	50%< Contrat >=75%	5 (9)	8 (2,7)	3 (5,6,9)	3 (1,2,6,7)
	Contrat >75%	5 (3,6,9)	8 (2,7,9)	3 (6)	N.A.

5.4.4 Penalty factor analysis

While experimenting different demand patterns gives interesting insights on which behaviours to adopt, it could be also interesting to modify the lateness penalties, contract bonuses and inventory holding costs in order to better understand their impact on the behaviour to adopt. When one or many of these variables are modified, the preferable team behaviour indeed changes. For example, a downstream planning strategy is known to imply a high degree of late deliveries to customers, mainly because the customers' demand is not used to plan production. When the lateness penalty is rather negligible, this strategy can be used. Otherwise, if the lateness penalty increases the situation can change. Figure 5.8 presents such an evolution, presenting the adjusted revenues curves for 100% demand, using a lateness penalty of 3.5% of product value per day instead of 1.5% (used in previous simulations). In this example, we can see that behaviour 3 considerably reduced its advantage over the other behaviours, compared to results presented in Figure 5.6 for a demand intensity of 100%. These behaviour performance changes are linked to the fact that any change in the system has an impact on the performance indicator. Simulation is interesting here because it is often not trivial to forecast the impact of each planning behaviour.

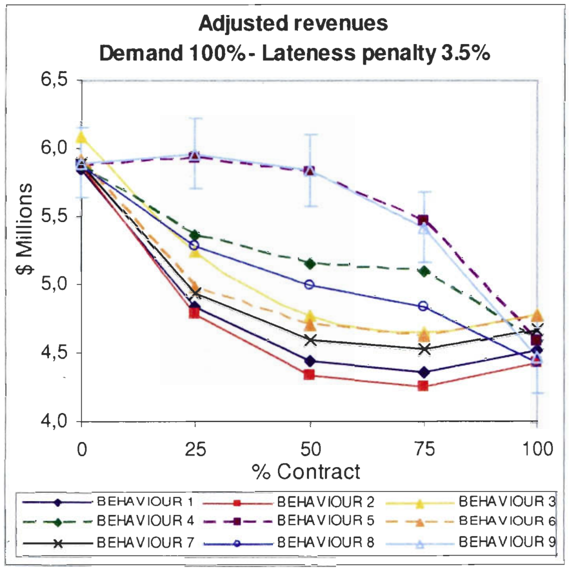

Figure 5.8. Performance for adjusted revenues with lateness penalty of 3.5%

5.4.5 Two-criteria analysis

While Figures 5.4 to 5.8 present an analysis of the preferable team behaviour considering a single performance indicator at the time, it is possible to analyze simultaneously the performance of many indicators. Often, there is no totally dominant behaviour for both performance indicators and multi-behaviour agents must make a selection, based on rules predefined by the system designer. This kind of analysis is particularly interesting when there is not a single performance indicator the planning agent must follow. One can argue that the adjusted revenues indicator must be prioritized over all others. This can be true in many situations, but in a long term relationship with customers, high lateness and poor spot delivery performance can lead to the loss of customers and reputation. Also, in the lumber industry, high levels of inventory can lead to losses due to the degradation of the material (insect infestation, wood crackling, mould, fire, etc.).

5.4.6 Potential gains

For the different environment conditions and performance indicators, it is possible to compare the performance results of the preferable team behaviour to worst team behaviour and the average performances of all team behaviours. This gives the maximum potential gain and the average expected. Table 5.4 presents the results for the different environmental conditions. As an example, for the adjusted revenues, at a demand intensity of 100% and a proportion of 50% of contract, we obtain a maximum potential gain of 7.8% and an average expected gain of 5.2% by using the preferable team behaviour. When the demand intensity increases to 150% (for the same contract proportion), the maximum potential gain and the expected gain rises respectively at 36.6% and 31.6%. Also, because the simulation covers a 30-day period, these potential gains are recurrent.

Table 5.4. Gains by selecting the best behaviours compared to the average results

Environment \ Indicator		Contract Lateness		Supply Chain Inventory		Estimated revenues		Spot Delivery	
		Max potential gain	Average expected gain	Max potential gain	Average expected gain	Max potential gain	Average expected gain	Max potential gain	Average expected gain
Demand 50%	0% Contract	N.A.	N.A.	12.6%	5.8%	1.8%	0.7%	3.5%	1.2%
	25% Contract	99.3%	98.6%	12.8%	6.1%	2.0%	0.8%	6.8%	2.3%
	50% Contract	92.0%	85.2%	12.5%	5.9%	2.0%	0.8%	13.3%	4.8%
	75% Contract	66.0%	46.3%	12.8%	6.2%	6.6%	0.8%	20.5%	6.8%
	100% Contract	28.0%	8.7%	12.0%	5.9%	1.6%	0.5%	N.A.	N.A.
Demand 100%	0% Contract	N.A.	N.A.	14.5%	7.0%	7.4%	5.1%	37.2%	13.7%
	25% Contract	98.6%	97.7%	14.2%	7.6%	7.6%	5.0%	34.4%	14.3%
	50% Contract	88.0%	81.3%	18.5%	9.2%	7.8%	5.2%	56.5%	23.4%
	75% Contract	65.8%	52.0%	17.2%	8.9%	7.8%	5.1%	74.6%	32.2%
	100% Contract	23.8%	15.9%	17.9%	8.2%	7.2%	4.9%	N.A.	N.A.
Demand 150%	0% Contract	N.A.	N.A.	16.0%	8.0%	33.9%	30.8%	14.8%	11.5%
	25% Contract	97.3%	95.8%	17.3%	9.9%	34.2%	31.1%	53.1%	26.2%
	50% Contract	88.2%	81.2%	19.0%	10.0%	36.6%	31.6%	82.7%	44.1%
	75% Contract	58.1%	41.9%	17.2%	9.5%	33.6%	30.1%	90.7%	50.6%
	100% Contract	27.1%	20.2%	19.6%	9.8%	33.0%	29.8%	N.A.	N.A.

These results give an insight into the potential gains for the supply chain's use of multi-behaviour agents to adapt to environmental changes. As the demand level rises, the possible gains grow dramatically, suggesting the importance of managing planning behaviours for under capacity situations. These benefits cannot be ignored, even more so in an industry such as the lumber industry where profits are made of thin margins. Following this idea, supply chain planning systems should strongly consider using different planning behaviours in order to adapt to the highly dynamic nature of supply chains.

Another way to analyze the simulation results is to compare different uses of planning behaviours in changing environments. Table 5.5 presents adjusted revenues for four periods of 30 days, where the demand intensity starts at 100% (period 1 and 2), then goes to 150% (period 3) and moves back to 100% (period 4). At the same time, the contract orders proportion varies from 50% (period 1) to 75% (period 2 and 3) and 100% (period 4). The idea was to verify the impact of changing behaviours or keeping the same behaviour over many periods. Five different approaches have been tested. The *best behaviour* approach is based on the use of the planning behaviour that offered the best performance during simulations for each specific set of environmental conditions. The *always behaviour X* approaches are about using always the same planning behaviour, by selecting one of the behaviours (9, 5 and 3) that showed the best results in one of the four periods and keeping it all the time. The *best late* approach is about selecting the best behaviour identified during simulations, but with a delay of one period, characterizing a slower reaction to changes. In this example, behaviour 9 is used in periods 1 and 2, behaviour 5 is used in period 3 and behaviour 3 is used in period 4.

Table 5.5. Potential adjusted revenues for dynamic environment changes (in million $)

	Period 1 Intensity 100% Contract 50%	Period 2 Intensity 100% Contract 75%	Period 3 Intensity 150% Contract 75%	Period 4 Intensity 100% Contract 100%	Result
Best behaviours	5.97	5.84	7.18	5.71	24.70
Always behaviour 9	5.97	5.83	6.26	5.46	23.52
Always behaviour 5	5.95	5.84	6.52	5.50	23.81
Always behaviour 3	5.62	5.61	7.18	5.71	24.12
Best late	5.97	5.83	6.52	5.71	24.03

These results show the advantage to the best behaviour for every environmental change in a dynamic context. Using the same planning behaviour over time gave inferior performances to using the best behaviours for each period. Also, the best late behaviour (a delay of one period for using the best behaviour) gave a superior performance to using the same behaviour over time for two of the three tests. Only the use of the best behaviours and behaviour 3 all the time offered better results. On the other hand, these results represent only the potential of adapting planning behaviours in changing environments, because results in each period have been obtained separately instead of in a rolling horizon. In other words, on-hand inventory at the end of a period has not been considered at the beginning of the other. More precise results could be obtained by running simulations in a rolling horizon, starting the next planning period with the exact final state of the last period.

5.5 Conclusion

Designers of planning systems often do not consider the possibilities of using different planning behaviours to deal with the dynamic aspect of business. This paper proposes an approach that breaks free from the hypothesis that planning must always be conducted the same way. By using multi-behaviour agents in an agent-based planning platform, the system designer can provide planning agents with the ability to adapt their planning behaviours according to changes in their environment.

In this paper, we presented a performance analysis of multi-behaviour agents in supply chain planning. Simulation results are presented from an application to the lumber supply chain. Various team behaviours have been tested in different environmental conditions and have presented different performance levels. We extended our proposition by presenting possible revenue gains by using the best team behaviour in every situation instead of using the same one all over the entire horizon. Preliminary results show a potential to increase supply chain performance. Multi-behaviour agents can be a powerful tool to reach appreciable gains when implemented in an agent-based supply chain planning system such as the FORAC experimental platform.

The next step intended in this research is to run simulations of adaptive planning behaviours over a rolling horizon. This would be necessary to have a clearer view of the level of possible gains of using multi-behaviour agents in changing environments. Also, it would be interesting to develop the learning ability of the multi-behaviour agent. Different learning technologies can be implemented and compared to help the agent to update its preference over time. This is very promising and could lead to an even more agile supply chain. Finally, anticipation and negotiation planning behaviours can be developed and simulated in order to exploit to the maximum all the multi-behaviour agent possibilities.

Chapter 6

Collaborative Agent-based Negotiation in Supply Chain Planning using Multi-behaviour Agents

In the third paper, we discuss the possibility of implementing negotiation behaviours in the simulations. We review the different kinds of automated negotiations and how they have been applied to supply chain planning. A generic protocol for adaptive and collaborative one-to-one negotiations is presented. Simulations of one-to-one negotiations between two planning agents are performed on the FORAC experimental agent-based platform, using the lumber supply chain study case. An advantage for the agents to change negotiation protocols depending on the demand environment is noticed. This paper is in correction to be submitted to the *European Journal of Industrial Engineering*. Pascal Forget is the first author, with Thibaud Monteiro, Sophie D'Amours and Jean-Marc Frayret as the co-authors.

Résumé

Pour travailler efficacement, les membres d'une chaîne d'approvisionnement doivent coordonner leurs actions. Lorsque la planification est distribuée plutôt que centralisée (comme c'est souvent le cas), il est nécessaire d'utiliser des protocoles de coordination spécifiques entre les différents partenaires pour planifier les activités d'une façon cohérente. Souvent, les membres doivent s'entendre mutuellement pour satisfaire leurs contraintes. La négociation peut être utilisée comme mécanisme de coordination pour trouver un compromis acceptable ou pour rechercher collectivement une solution coordonnée. Les systèmes de planification à base d'agents peuvent intégrer la négociation automatisée pour ajouter la capacité de négocier entre les partenaires. Alors que différents mécanismes de négociation (appelés ici comportements de négociation) peuvent être utilisés dans différentes situations, des agents de planification utilisant des habiletés de raisonnement par cas peuvent apprendre quel comportement doit être adopté sous des conditions spécifiques. Cet article propose d'étudier l'amélioration de la performance lorsque plusieurs comportements de négociation sont disponibles plutôt qu'un seul. Une revue de la négociation automatisée en général et spécifiquement adaptée à la planification de la chaîne d'approvisionnement est d'abord présentée, suivi ensuite par une analyse empirique à partir de simulations de différents comportements de négociation un à un. Les agents négociateurs ont un pouvoir de négociation équivalent et ils sont purement collaboratifs. Les comportements présentés sont basés sur des heuristiques de négociation et ils sont implantés dans une plateforme de planification à base d'agents, en utilisant des agents à comportements multiples. Les simulations sont basées sur un cas virtuel de la chaîne d'approvisionnement du bois d'œuvre.

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.

6.1 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. In a context like the supply chain production planning, 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 comprised of 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 for the development of 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, basic 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 universal 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 organized as follows: in Section 6.2, a general literature review is provided on automated negotiation, which characterizes the negotiation environment and reviews different negotiation methods. Section 6.3 presents a specific review on supply chain automated negotiations, distinguishing contributions addressing contract negotiations and production planning negotiations. Section 6.4 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 6.5, with an analysis of the preliminary results. A conclusion is presented in Section 6.6.

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.

6.2.1 Negotiation characteristics

There are various forms of automated negotiations, depending on the situation in which the negotiation partners are involved. *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 classes (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 & Schneeweiss, 2000; Fink, 2004; Jiao et al., 2006; Dudek & Statdler, 2005; Ito &

Salleh, 2000; Nagarajan & 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 & Vulkan, 1999; Oliviera, 2001; Arunachalam & 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 & 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 & 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 & Wilkenfeld, 1991; Oliveira & Rocha, 2001; Dworman & 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 reject the offer. Participants typically evaluate offers with single of multiple issues with a utility function. 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 varies 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 the 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 terms 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 need.

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.

6.2.2 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*, *argumentation-based negotiation*, *auctions* and *heuristics-based negotiation.*

6.2.2.1 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 & 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 against their opponent. Cachon & 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 coalitions and sharing profit among partners are two important topics of cooperative game theory and are presented in detail in Nagarajan & Sosic (2008).

A frequently mentioned drawback of game theoretical 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 immediately employed (Binmore & 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 these problems, 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 & Wilkenfeld (1991) and Binmore & 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.

6.2.2.2 Argumentation-based negotiation

In the game-theoretic approaches presented previously, agents cannot justify to their partner why they refuse an offer or what part of the offer was problematical. 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 of 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).

6.2.2.3 Auctions

Negotiation and auctions have traditionally been considered as different classes, with specific characteristics and applications. Traditional auctions 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.

6.2.2.4 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 is followed (in this case, customer satisfaction) and in a limited period of time, supply chain members search locally for a better arrangement, without looking for the "best" production plan possible.

6.3 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 & Sosic, 2008; Cachon & Lariviere, 2005), price agreement (Homburg & Schneeweiss, 2000), coalition formation (Oliveira and Rocha, 2001; Nagarajan & 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 on that specific topic.

While contract negotiations focus on defining terms of contracts, production planning issues can require supply chain partners to negotiate in order 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 & 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 iteratively adjust supply 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 this scheme closely approaches optimal results obtained by central coordination. Ertogral & Wu (2000) also 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). Xue et al. (2007) proposed an agent-based collaborative negotiation platform to improve effectiveness and efficiency in planning activities between decision-makers, applied to the construction supply chain

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 suppliers 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). MAGNET is 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 a 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 a negotiation-based framework for supply chain management where functional agents (such as 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 & Salleh (2000) proposed a blackboard-based negotiation approach 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 6.1 presents a positioning of different applications based on 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 6.1 synthesizes research on agent-based supply chain negotiation presented in this section.

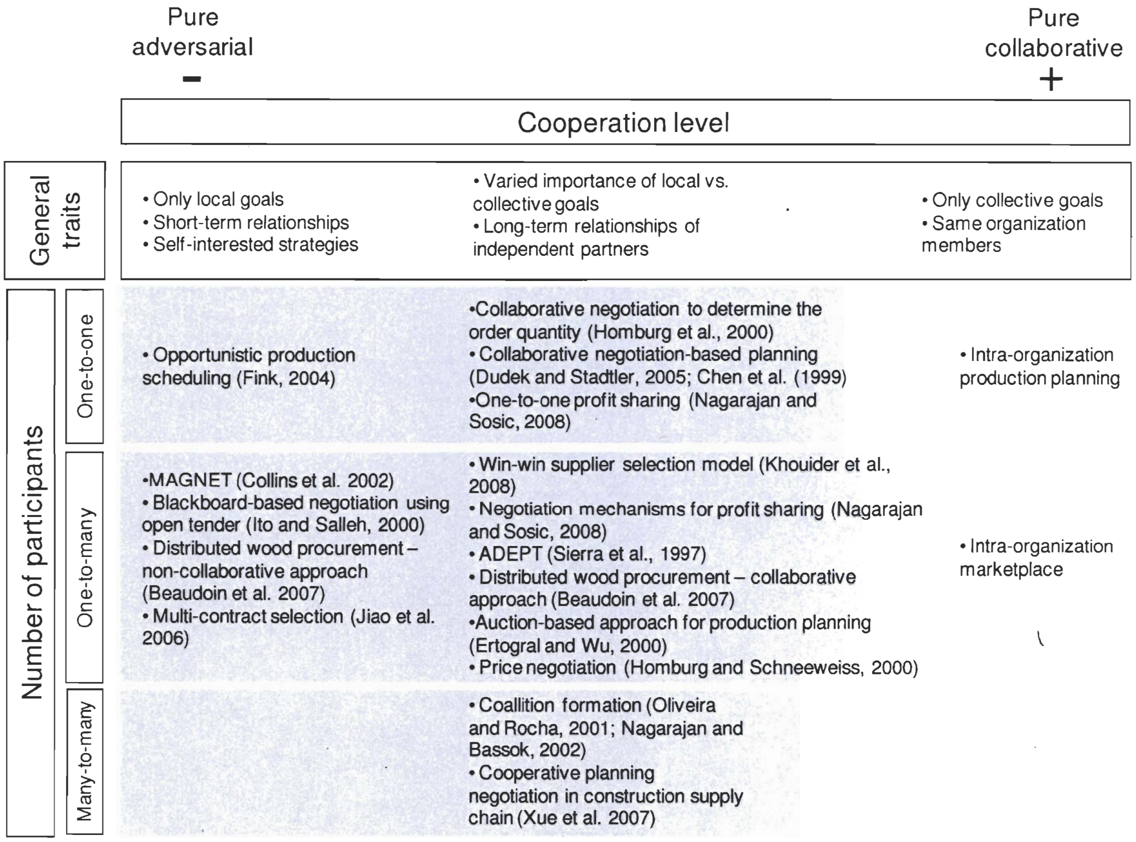

Figure 6.1. Supply chain negotiation applications positioning

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) compare 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 had to effectively coordinate their sourcing, procurement, production, and customer bidding decisions. Arunachalam & Sadeh (2005) present a review of different agent strategies used during the competition and discuss how this kind of competition-based research can be useful.

Table 6.1. 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

Confronted with a large array 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 adoption of different negotiation strategies in different environments between a buyer and a seller, depending on the time and resources available. Faratin (2000) compared different negotiation mechanisms on a service management application. He developed a meta-level deliberation mechanism that helped negotiation agents make a choice about which one to use for different environments.

We follow 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 the negotiation approach that 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.

6.4 Application context

6.4.1 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 has been used (Frayret et al., 2007). 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 6.2 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.

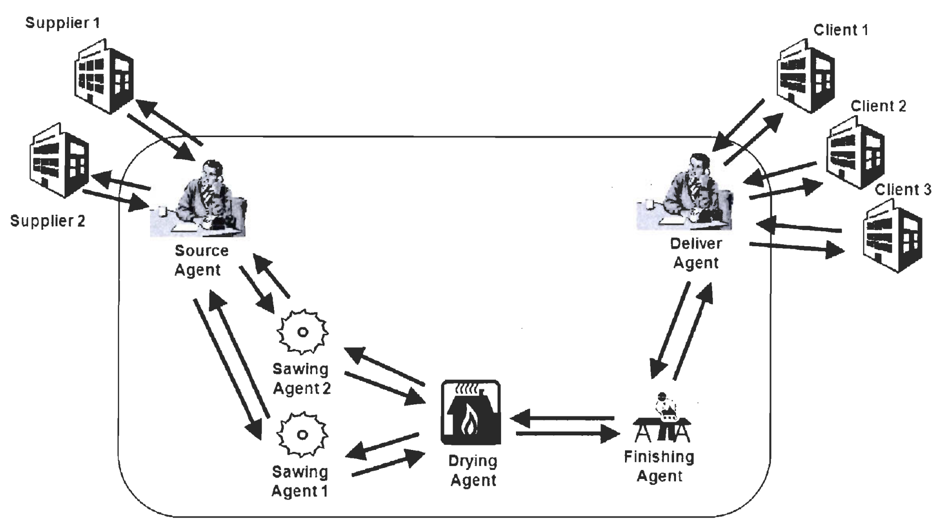

Figure 6.2. A supply chain configuration example from the agent-based planning platform

In this supply chain configuration, 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 (version

9.000). 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 (version 6.000). Finally, a MIP model was designed to address this finishing planning problem and is resolved using ILOG CPLEX (version 9.000). Details on the different models can be found in Gaudreault et al. (2008).

Because each agent is responsible for locally monitoring 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.

6.4.2 Multi-behaviour agent model

The multi-behaviour agent model (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 in this research are reactive. They present 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): *Direct Reaction*, *Reaction with Anticipation* and *Negotiation*. When faced with 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 TF 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 TFs) which use only local information with no feedback loop. Simulations have been made previously in order to test the impact of using multiple direct reaction behaviours in an application to the lumber supply chain (Forget et al., 2008c). Various team behaviours have been tested in different environmental conditions. This showed that different performance levels are reached according to the behaviour selected. This also presented possible revenue gains by using the best team behaviour in each situation instead of using the same one over the entire time horizon. Reaction with anticipation behaviours consists of more advanced forms of planning TFs 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 short, 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 this case an open loop feedback of its partner's decision model 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. (2008b).

This paper presents the results of an implementation of multi-behaviour agents in the FORAC agent-based planning platform for simulation. Using these agents, we can simulate different negotiation behaviours in various supply chain environments and take advantage of the agent's adaptability to increase the global performance.

6.4.3 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 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 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 dry. 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.

6.5 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. We considered four types of negotiation context: 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, we are faced with a collaborative one-to-many negotiation. When the negotiation occurs between agents whose local goal is dominant over the common good, such as a source agent and a supplier agent from two different companies, we have an adversarial one-to-one negotiation. When many supplier agents are involved, it is an adversarial one-to-many negotiation.

6.5.1 Negotiation process description

In this paper, we study the collaborative negotiation process between two different planning agents, sawing agent and drying agent, from the same company. The reader interested in adversarial negotiations between forest companies in a similar context is referred to Beaudoin (2007). 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 6.3.

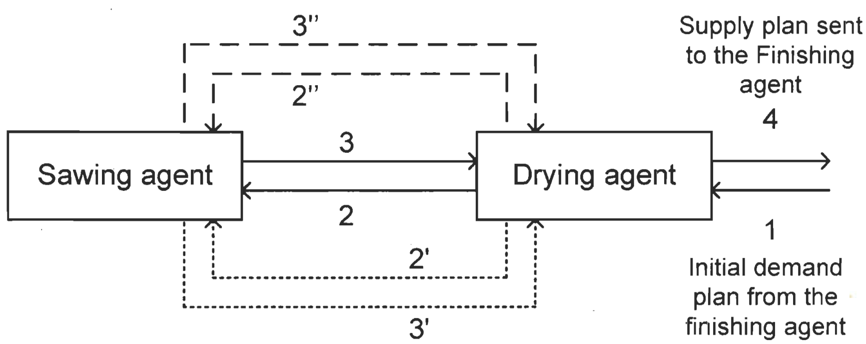

Figure 6.3. Negotiation framework

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 dimensions (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 words, 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 6.3.

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.

6.5.2 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 are the *Priority*, *Substitution* and *Lot sizing* behaviours. As mentioned previously, these behaviours will slightly modify 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.

6.5.2.1 Priority negotiation

Priority negotiation involves the modification of the delivery dates of certain demanded volumes. 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, but a different size, 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 spruce planned to be late for 15 days, and permutes it with a two millions FBM of 2x6 spruce 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.

6.5.2.2 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. At 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.

6.5.2.3 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 spruce 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.

6.5.3 Generalized negotiation protocol

The negotiation protocol used in these experiments is based on the one-to-one negotiation framework presented in Figure 6.3 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 6.4.

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, rejected or suitable for a compromise. The decision of searching for a compromise through negotiation is based on the use of a performance boundary. If the plan submitted to the drying agent is close to be acceptable (for example less than 5%), the drying agent triggers a negotiation process. By doing so, it analyzes the situation and selects the preferable negotiation behaviour to adopt (i.e., Priority, Substitution or Lot sizing). The choice of the preferable behaviour is based on the history of previous performances or simulation results. The agent stores this performance history in a knowledge matrix that is continually updated with new planning results. Using the selected behaviour, a new demand plan is generated by the drying agent and sent to the sawing agent. Upon reception, the sawing agent builds a new production plan and decides whether it is accepted, rejected 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.

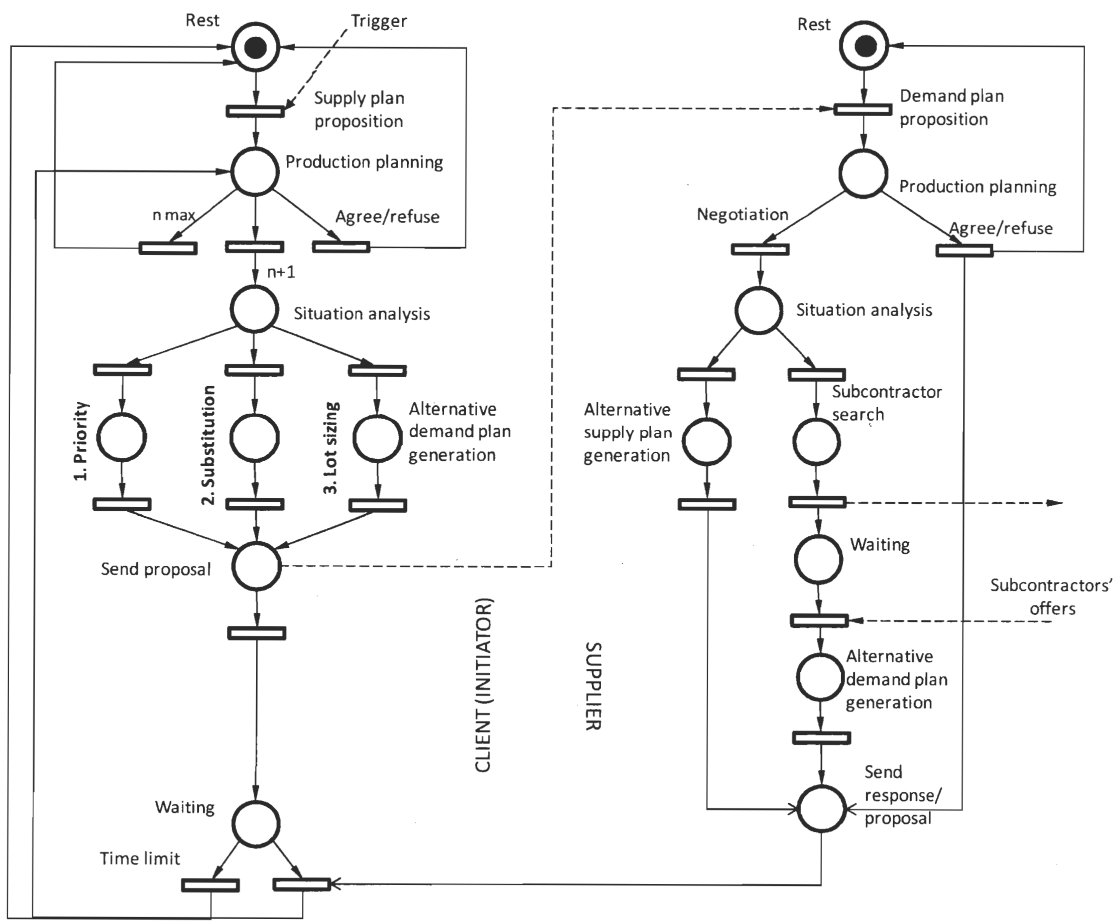

Figure 6.4. One-to-one generalized negotiation protocol

6.6 Experiments

Experiments of one-to-one negotiation behaviours between two multi-behaviour agents were performed using the planning platform configuration presented in Figure 6.2. 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 of 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 by using different demand plans and supply plans. 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 was changed successively at 90%, 100% and 110% of the total capacity of the supply chain. Demand plans were created to meet these various intensities. Then, these plans were modified to present contract proportions of 50% and 100%. Following this, six different demand plans were created. These plans were made of products of two species (spruce and fir) and three different dimensions (2x3, 2x4 and 2x6), over a 30-day horizon. Also, at the same moment, the supply intensity to the sawing agent was 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 was the delivery lateness; more specifically, the sum of volume of lumber (in FBM) planned to be delivered late per day. Each negotiation included three rounds, where a different change is proposed following the same negotiation behaviour.

For each new external client's demand plan sent to the drying agent, the platform planning process was fully completed and the lateness performance indicator was recorded, which represent the initial performance when no negotiation is involved. Then, the drying agent's demand plan was manually modified following one of the negotiation rules previously defined. This new demand plan acted as a counter-offer from the drying agent to the sawing agent. Upon the transmission of this plan to the sawing agent, the platform started a new planning process from this point and the performance indicator for the supply chain lateness was also recorded. For each negotiation behaviour used by the drying agent, three consecutive negotiation rounds (R1, R2 and R3) were simulated. In the second and third round, a different modification is made to the demand plan. In the end, a total of 60 planning simulations are performed, including the six initial planning results. This time, only the lateness indicator has been studied, because we considered this indicator as one of the most important in a highly competitive industry such as the lumber industry.

Table 6.2 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 colored in grey.

Table 6.2. 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	8.1
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	1.8	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 6.3 presents the lateness performance gain (in percentage) for the supply chain in using the preferable negotiation behaviour for a specific environment, when compared to the initial round, when no negotiation is started.

Table 6.3. Gain in percentage in using 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%

6.7 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 direct reaction and reaction with 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.

Chapter 7

Conclusion

This chapter presents a conclusion of this thesis. A summary is first proposed, outlining the achievements and contributions of this work. Then, different research opportunities are described, presenting various ways to continue the work begun. In this thesis, ideas have been proposed and experiments have been made, but a lot more can be done to concretize the experimental results into real performance gain for the industry. In these times of global competition and economic instability, this kind of technology seems to have the potential of making a difference between loss and profitability.

7.1 Summary

In order to stay competitive in this era of great changes for business, organizations must find ways to maintain a competitive advantage. This thesis offers an approach to increase the competitiveness of a supply chain by studying the collaborative adaptation planning using agent-based technology. More precisely, it proposes to use adaptive planning agents called multi-behaviour agents that can adopt different planning behaviours, or methodologies, according to what is preferable for the supply chain. These agents can learn by simulations which planning behaviour is favorable depending on the changes in the environment.

Different achievements were presented in this thesis. In order to verify the possible advantage of using adaptive agents to increase supply chain performance, a multi-behaviour agent model has been presented. With the ability to analyze the situation and learn the preferable planning behaviour, the agent can choose among known behaviours. Different behaviour protocols were presented as examples of planning variations. Then, an implementation of multi-behaviours agents was realized on the FORAC agent-based planning platform, using a study case in the lumber supply chain. By varying demand characteristics and agent reaction behaviours, experiments showed that the best results are not obtained with the same planning behaviour, but with the planning behaviour most adapted to the environment. Possible gain estimations for the supply chain gave examples of the advantages of using such adaptive planning agents in a supply chain planning system. Finally, collaborative negotiation behaviours were experimented with multi-behaviour agents. Different negotiation behaviour protocols were presented for one-to-one situations, when a compromise must be found between two agents. One-to-one negotiation simulations showed that it is suitable to change negotiation behaviour depending on the environment.

A limit of this thesis is the preliminary nature of the experimental results presented. Simulation of different planning behaviours in various conditions can give an idea of possible performance, but even with a very good modelling of processes, clients and suppliers, it remains an approximation of a real adaptive behaviour in a real-time situation. In order to go deeper and verify more precisely the hypothesis of the thesis, it will be necessary to simulate multi-behaviour agents in situations where environmental conditions are changing and agents must dynamically choose which behaviour to select and, from period to period, analyze the new conditions and adapt their behaviours accordingly.

7.2 Research opportunities

This thesis opens the way to some research opportunities. The work presented here was only a beginning, raising new questions and possibilities. These opportunities are divided into four types: experiments, behaviour coordination, learning ability and one-to-many negotiations.

7.2.1 Experiments

The multi-behaviour agent model introduced in Chapter 3 includes three categories of planning behaviours. While the thesis presents experiments of reaction and negotiation behaviours, little work has been done on anticipation behaviours. It would be interesting to experiment the impact of using different anticipation models of supply chain agents, more or less complex, and compare them to other behaviours. Different anticipation behaviours must be developed to give agents the possibility of creating their own production plan using a model of their partner's decision model, instead of directly negotiating or not using any outside information as in reaction planning. This idea build on previous work conducted in the NetMan project (Frayret, 2004).

Also, while Chapters 4 and 5 presented simulations of two different kinds of behaviours, reaction and negotiation behaviours, the natural following step would be to compare directly all these planning behaviours in the same situations. The idea behind the multi-behaviour agent model is to give the possibility of using a variety of behaviours in different situations. It would be interesting to simulate them on the same implementation. With anticipation behaviours available, multi-behaviour agents could be implemented to their full potential.

While this thesis presented performance of planning behaviours when a new demand order is received, it could be extended to a wide variety of changes. Many reasons can push planning agents to replan, other than predictable events. Supply variations (e.g. from bad weather, transportation delay) and production perturbations (e.g. power outage, machine breakdown, absenteeism, wrong product produced) can have a major impact on an organization and, ultimately, on the supply chain. Such changes could be simulated in order to find the best planning behaviours for all situations.

7.2.2 Behaviour coordination

This thesis presented simulations where various team behaviours were compared. Multi-behaviour agents can learn which behaviour is preferable in many situations. Indeed, the agent can change its behaviour when a new state is reached in its environment, but such fast response could generate instability in the supply chain. Because team behaviours have been simulated, all agents have to change at the same time, following a precise arrangement of behaviours for everyone. This raises the need for a coordination mechanism to insure that all agents adapt their behaviour at a specific frequency.

Various approaches can be tested, such as using a clock or a team leader. Depending on the frequency of changes in the environment, different performances can be reached. More simulations could help find the preferable approach for different environment stability levels.

7.2.3 Learning ability

While the agent has, as discussed in the thesis, the ability to use a certain level of learning (some would see it more as a memory structure) to choose the preferable planning behaviour by simulation, it would be interesting to investigate the various learning approaches presented in the literature and verify their respective advantages and disadvantageous. Researchers present various agent-based learning implementations and it could be possible to compare the results obtained by our implementation. Also, it would be possible to analyze the impact of the number of simulations to learn the best behaviours to adopt.

Agent-based learning approaches (also called machine learning) can be divided into three main approaches: inductive learning, analytic learning and learning on the fly. Using inductive learning, the agent builds a rule based on training examples and can update this rule with new examples. Examples of techniques used are decision tree learning, instance-based learning (or case-based learning), bayesian learning, neural network learning and genetic algorithms. In analytic learning, the agent builds a rule based on training examples and theoretical rules previously known. A technique generally used is the explanation-based learning. Finally, the learning on the fly approach is the more informal approach, where the agent, instead of referring to a training example, is directly put into action and learns with oncoming events. A technique employed in the literature is reinforcement learning, where the agent learns which reward is associated with which action, without trying to build a precise rule.

Simulations such as those presented in this thesis are interesting to allow agents to use offline learning, which means information is collected when the system is disconnected from the real world. A different and complementary learning approach is online learning, where the agent learns from its experience in real planning situations. It would be interesting to study the implication of such learning abilities and how the agent could still experiment with non-preferable behaviours.

7.2.4 Negotiation

In Chapter 6, one-to-one collaborative negotiation behaviours were presented. In supply chains, it may occur that negotiations involve more than two members. Moreover, negotiations may be adversarial. For example, a client can have two different suppliers and want to negotiate with both of them at the same time. Adversarial negotiations are common when both parties are from different organizations. In order to include these types of negotiations into the multi-behaviour agent model, new negotiation protocols must be developed and different negotiation behaviours can be identified. By their nature, adversarial and one-to-many negotiations are very different from negotiation approaches presented in this thesis and necessitate new developments. Then, the simulation of these new negotiation behaviours would give a more complete view of negotiation possibilities for supply chain planning.

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