



CIRRELT

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

Interuniversity Research Centre
on Enterprise Networks, Logistics and Transportation

Performance Analysis of Multi- Behaviour Agents for Supply Chain Planning

Pascal Forget
Sophie D'Amours
Jean-Marc Frayret
Jonathan Gaudreault

August 2008

CIRRELT-2008-43

Bureaux de Montréal :

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

Bureaux de Québec :

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

www.cirrelt.ca

Performance Analysis of Multi-Behaviour Agents for Supply Chain Planning

Pascal Forget^{1,2,*}, Sophie D'Amours^{1,2}, Jean-Marc Frayret^{1,3}, Jonathan Gaudreault^{1,2}

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

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

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

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 follows 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 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 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. The performance analysis shows that advanced planning systems can take advantage of using multiple planning processes, because of the dynamic context of supply chains.

Keywords. Collaborative supply chain planning, agent-based planning systems, agent-based technology, advanced planning systems, simulation.

Acknowledgements. This work was funded by the FORAC Research Consortium and the Natural Sciences and Engineering Research Council of Canada (NSERC).

Results and views expressed in this publication are the sole responsibility of the authors and do not necessarily reflect those of CIRRELT.

Les résultats et opinions contenus dans cette publication ne reflètent pas nécessairement la position du CIRRELT et n'engagent pas sa responsabilité.

* Corresponding author: Pascal.Forget@cirrelt.ca

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

© Copyright Forget, D'Amours, Frayret, Gaudreault and CIRRELT, 2008

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 centers 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 term 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 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. 2008a). 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 2 provides a literature review on supply chain planning and agent related subjects. In Section 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 4, a performance analysis is presented. Finally, Section 5 concludes and provides an overview of intended future work.

2. Literature Review

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 (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. 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., 2006a). Among these projects, Montreuil (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 its 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 3.1.

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 centers is essential because decisions concerning production planning are interdependent and have an impact on partners (Moyaux et al.,

2006a). These interdependencies need to be managed, which requires the building of coordination mechanisms to maintain a certain level of coherence between the different decision centers. 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., 2001; Shen et al., 2006). 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 centers. 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.

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. (2008a) 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 (Shen et al., 2001; Frayret et al., 2004; Moyaux et al., 2006a, Schneeweiss, 2003). These categories are identified as *Reaction*, *Anticipation* and *Negotiation*. The reaction behaviours are simple sequences of planning tasks (or planning task flow) 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 task flows involving feedback loops to find an acceptable compromise for both negotiating agents. Figure 1 presents the multi-behaviour agent model.

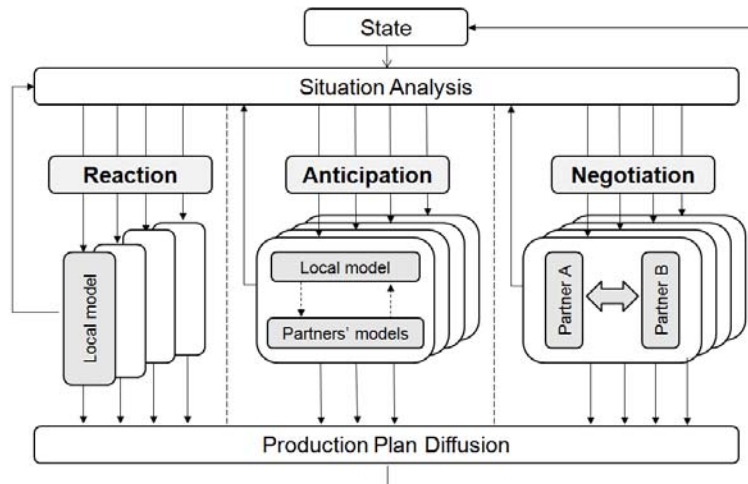


Figure 1. Multi-behaviour agent model

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 task flow and source of the perturbation. Researchers have presented several approaches to select the best task flow 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. (2008a). 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.

2.4 Learning in Supply Chain Planning

Adaptive agents in supply chain show many promising features. However, linking behaviours and supply chain performance with environmental conditions can be a difficult task. The main reason is that most changes in manufacturing environments are not predictable in advance (Shen et al., 2006). This raises the need for agents that cannot only adapt but also learn (Weiss and Sen, 1996). Agents then are able to recognize and analyze the current situation and apply the most appropriate behaviour instead of trying each of them, one at the time. Alonso et al. (2001) argue that learning is the most crucial characteristic of intelligent agent systems.

Many researchers have investigated learning agents, from defining fundamental issues of intelligent learning agents, (Schleiffer, 2005) to designing learning techniques for multi-agent systems (Alonso et al., 2001; Weiss and Sen, 1996). Shen et al. (2000) present a research review related to the enhancement of agent-based manufacturing systems through learning, including the use of learning in a more general manufacturing context. Among them, mediator agents in the agent-based architecture

MetaMorph (Maturana et al., 1999) use two learning mechanisms, *learning from history* and *learning from future*, in order to enhance the manufacturing system's performance and responsiveness. Crawford and Veloso (2007) recently studied how agents can learn to negotiate strategically to reach better performance in agent-based meeting scheduling. To create adaptive and learning agents, Fox et al. (2000) use the Markov decision processes in conversation protocols. Each action included in the protocol has a probability to cause a transition to a determined state. From obtained results, the agent updates probabilities, which changes agent behaviour over time. In a case where multiple agents cooperate and coordinate their actions, they can learn together how to solve a joint task and maximize their utility: it is called cooperative multi-agent learning. Panait and Luke (2005) present a complete review of this topic, including team learning and concurrent learning. Basically, team learning involves a single agent learning for an entire group, specifying the set of behaviours for every member, while concurrent learning describes the use of multiple agents, where each one is responsible for a certain learning space. Multi-behaviour agents use team learning to learn which planning behaviour to use in various situations.

3. Simulation methodology

Using agent-based technology, simulation experiments have been undertaken to verify if 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.

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 centers 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 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 center 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.

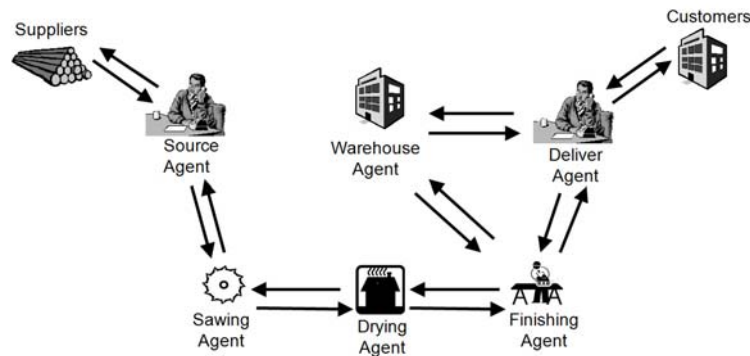


Figure 2. Supply chain example from the FORAC planning platform

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., 2006). Finally, a MIP model was designed to address this 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)

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 centers, 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 center, corresponding to approximately one week of production at full capacity.

More precisely, the sawing production center 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 center is 233 million FBM (Foot Board Measure) per year when the most efficient processes are used. The drying production center 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 center uses one line, working 7 days per week, at 16 hours per day. Its maximum capacity is 219 million FBM per year. Table 1 presents the production center details.

Table 1. Production centers 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

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.

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 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).

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: spot orders with priority over the contract orders, contract orders with 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. 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. Table 2 resumes the variables.

Table 2. Optimization variables

Planning logics		
Scheduling strategy	Priority	Penalty
Just-In-Time Forward	Priority on spot Priority on contract Equal priority spot/contract	Penalty BO Equal penalty inventory/BO

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 3 presents the coordination mechanisms between the three production planning agents.

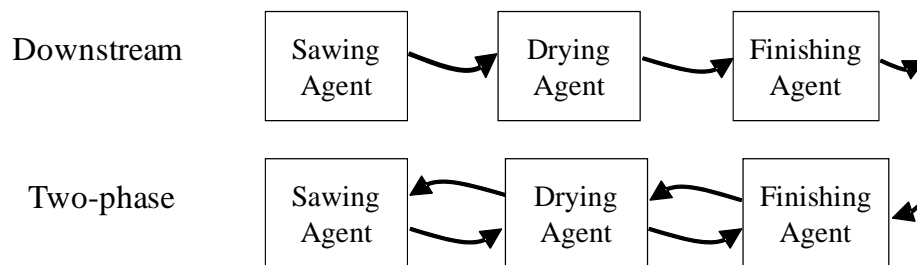


Figure 3. Coordination mechanisms

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 3). The three optimization variables presented in the last section have been applied to a different agent: the planning algorithm 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 3. Team behaviours used in experiments

Team behaviour	Drying Agent Scheduling Strategy	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

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 (Foot Board Measure) 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.

4. Performance analysis

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 4-7 present the 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.

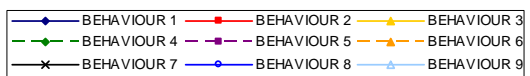
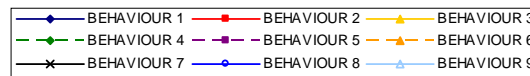
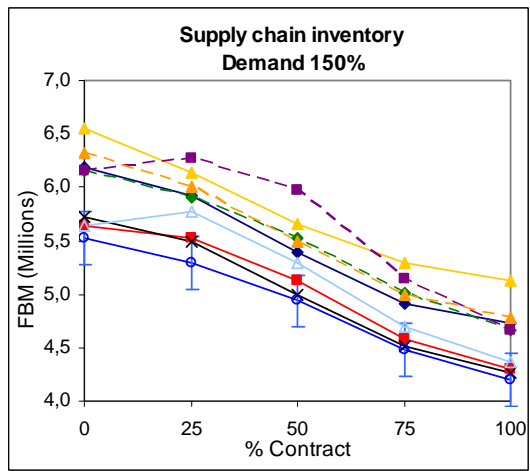
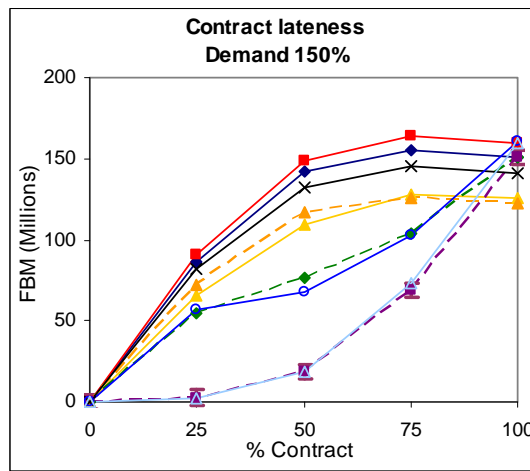
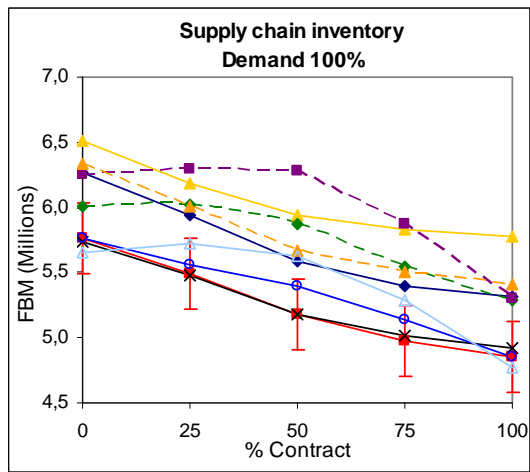
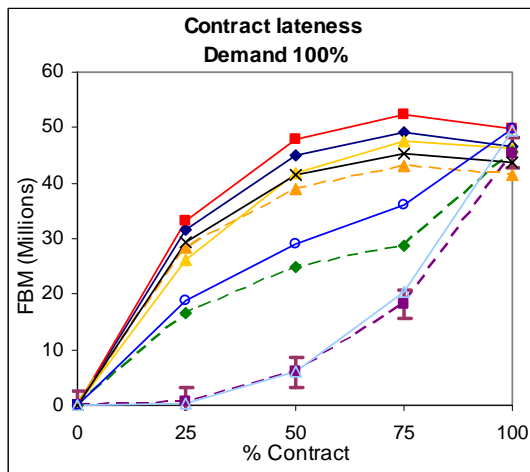
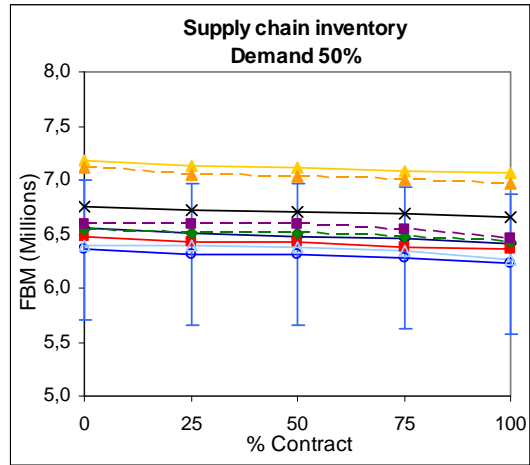
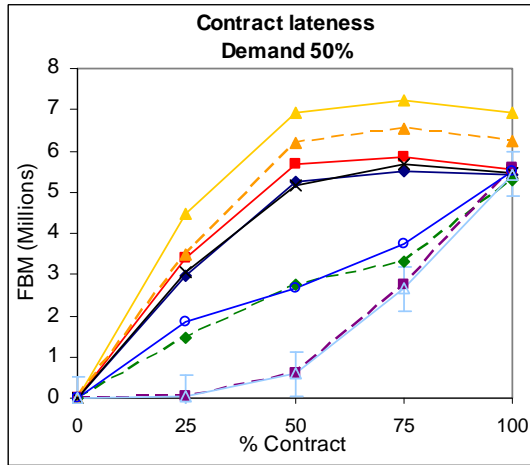


Figure 4. Performance for contract lateness

Figure 5. Performance for average inventory

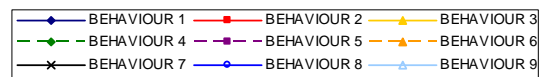
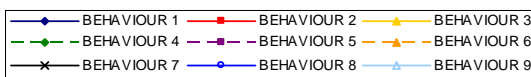
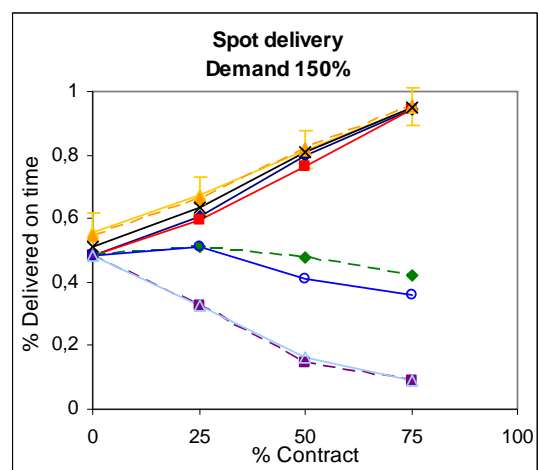
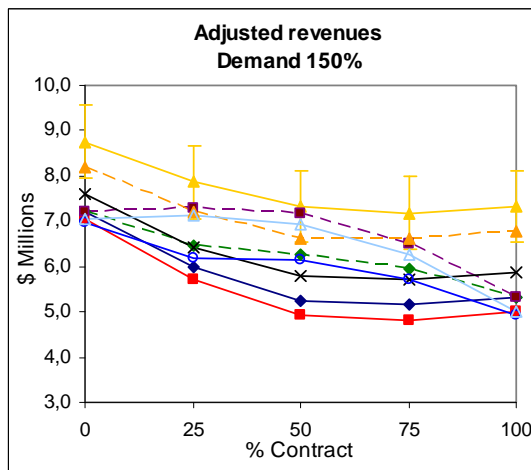
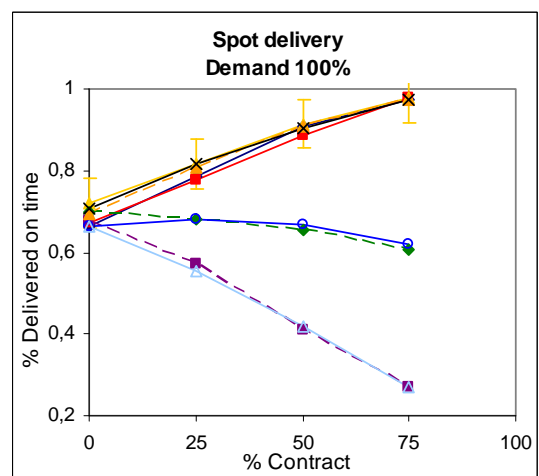
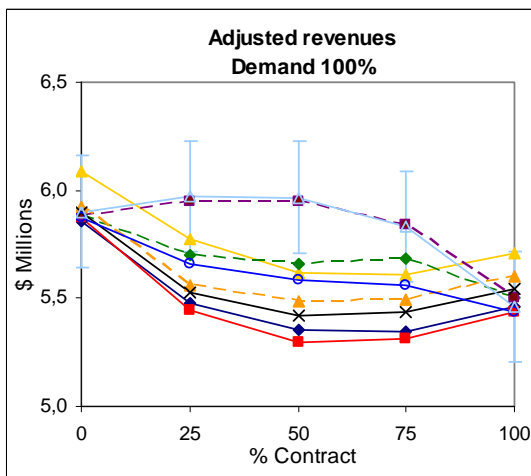
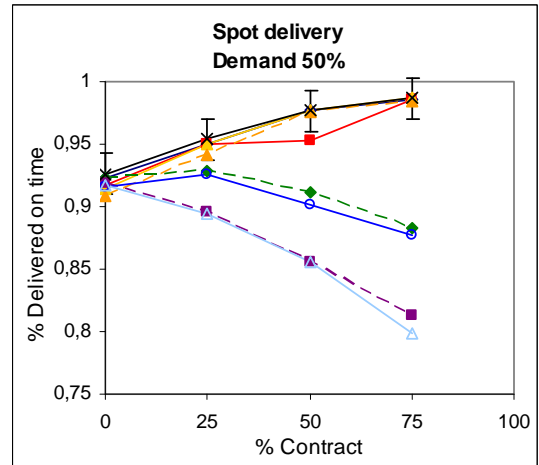
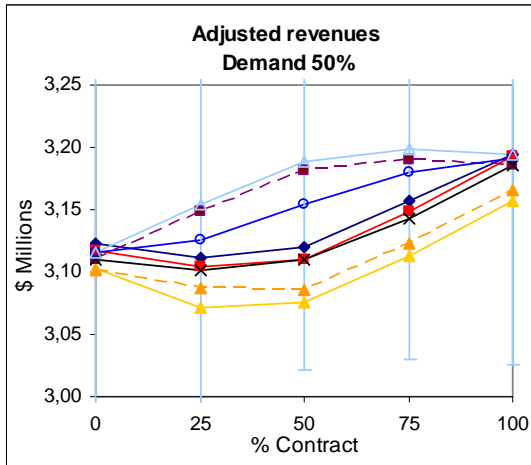


Figure 6. Performance for adjusted revenues

Figure 7. Performance for spot delivery

In Figure 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 (especially for 100% and 150% demand), behaviour 6 offers the best results. In Figure 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 4 seem to perform better most of the time. Figure 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 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 a behaviour performs better for a specific situation, a hypothesis can be proposed. For example, in the adjusted revenues curves (Figure 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 merely every product can be sold (in high demand intensity).

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 4-7) 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 and 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 and 6 may decrease (or increase) from the results obtained here from four replications by going through more replications.

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 4 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 4. 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.

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 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 8 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.

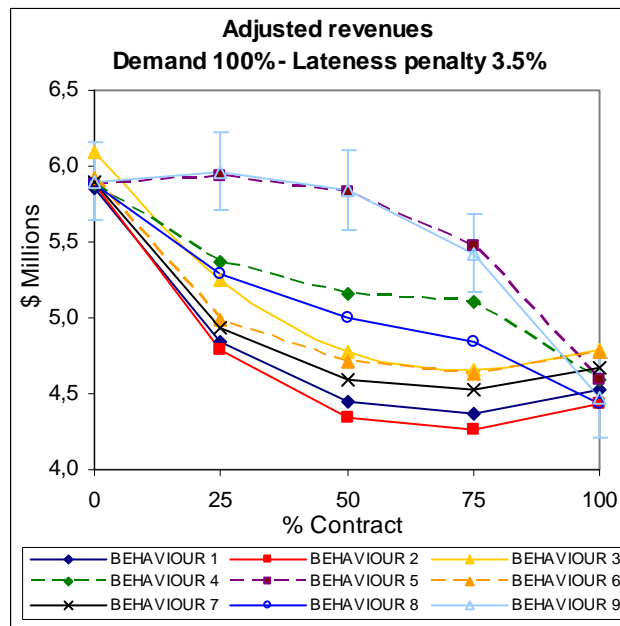


Figure 8. Performance for adjusted revenues with lateness penalty of 3.5%

4.5 Two-criteria analysis

While Figures 4 to 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.).

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 with worst team behaviour and the average performances of all team behaviours. This gives the maximum potential gain and the average expected. Table 5 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.

These results give an, the possible gains grow dramatically, suggesting the importance of managing planning behaviours 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 for under capacity situations. These benefits cannot be ignored, even more 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.

Table 5. Gains to select the best behaviours compared to the average results

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
Environment									
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.

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 profit gains by using the best team behaviour in every situation instead of using the same one all over the entire horizon. Preliminary

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 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.

Acknowledgement

This work was funded by the FORAC Research Consortium and the Natural Sciences and Engineering Research Council of Canada (NSERC).

References

- Alonso, E., D'Inverno, M., Kudenko, D., Luck, M. & Noble, J. (2001). Learning in multi-agent systems. *Knowledge Engineering Review*, Vol. 16, No. 3, 277-284
- Alvarez, E. (2007). Multi-plant production scheduling in SMEs. *Robotics and Computer-Integrated Manufacturing*, Vol. 23, No. 6, 608-613
- Aytug, H., Lawley, M.A., McKay, K., Mohan, S. & Uzsoy, R. (2005). Executing production schedules in the face of uncertainties: A review and some future directions. *European Journal of Operational Research*, Vol. 161, 86-110
- Bussmann, S., Jennings, N.R. & Wooldridge M. (2004). *Multiagent Systems for manufacturing Control: A Design Methodology*, Springer-Verlag , ISBN: 978-3-540-20924-9
- Caridi, M. & Cavalieri, S. (2004). Multi-agent systems in production planning and control: an overview. *Knowledge Information Systems*, Vol. 15, No. 2, 106-118
- Chen, Y., Peng, Y., Finin, T., Labrou, Y., Cost, S., Chu, B., Sun, R. & Willhelm, B. (1999) A negotiation-based multi-agent system for supply chain management, *Workshop on supply chain management, Autonomous Agents '99*, Seattle, USA
- Crawford, E. & Veloso, M. (2007). An experts approach to strategy selection in multiagent meeting scheduling. *Journal Autonomous Agents and Multi-Agent Systems*, Vol. 15, No. 1, 5-28
- Dudek, G. & Stadtler, H. (2005). Negotiation-based collaborative planning between supply chains partners. *European Journal of Operational Research*, Vol. 163, 668-687

- Forget, P., D'Amours, S. & Frayret, J.M. (2008a). Multi-Behaviour Agent Model for Planning in Supply Chains: An Application to the Lumber Industry, *Robotics and Computer-Integrated Manufacturing*, Vol. 24, 664–679
- Forget, P., D'Amours, S. & Frayret, J.M. (2008b). Design of Multi-Behaviour Agent for Supply Chain Planning: An Application to the Lumber Industry, In *Supply Chain: Theory and Application*, I-TECH Education and Publishing, Vienna, Austria, p. 551-568
- Fox, M.S., Barbuceanu, M. & Teigen, R. (2000). Agent-Oriented Supply-Chain Management. *International Journal of Flexible Manufacturing Systems*, Vol. 12, 165-188
- Frayret, J.M., D'Amours, S. & Montreuil, B. (2004). Coordination and Control in Distributed and Agent-Based Manufacturing Systems. *Production Planning and Control*, Vol. 15, No. 1, 42-54
- Frayret, J.M., D'Amours, S., Rousseau, A., Harvey, S. & Gaudreault, J. (2007). Agent-based Supply Chain Planning in the Forest Products Industry. *International Journal of Flexible Manufacturing Systems*, Vol. 19, no. 4, 358-391
- Gaudreault, J., Frayret, J.M., Rousseau, A. & D'amours, S. (2006). *Integrated planning and scheduling in a divergent production system with co production*. Working Paper DT-2006-JMF-1, CENTOR, Université Laval, Québec, Canada
- Jeng, J.J., Ettl, M., & Chung, J.Y. (2006). Commitment Based Sense-and-Respond Framework for Manufacturing Supply Chain, In: *Studies in Computational Intelligence (SCI)*, Chaib-draa, B. & Muller, J.P., (Eds.), Vol. 28, 395-417, Springer-Verlag, ISBN: 3-540-33875-6, Berlin
- Jiao, J., You, X. & Kumar, A. (2006). An agent-based framework for collaborative negotiation in the global manufacturing supply chain network. *Robotics and Computer-Integrated Manufacturing*, Vol. 22, 239-255
- Lemieux S., D'Amours S., Frayret J.-M. & Gaudreault, J. (2008). Integration d'outils APS dans une simulation multi-agent : une application à l'industrie du bois d'œuvre, in Proceedings of the 7th International Conference on Modeling and Simulation (MOSIM 08), Paris, France
- Marik, V., Pechoucek, M. & Stepankova, O. (2001). Social Knowledge in Multi-agent Systems, In: *Multi-Agent Systems and Applications*, M. Luck et al. (Eds): ACAI 2001, LNAI 2086, p. 211-245, Springer
- Maturana, F., Shen, W. & Norrie, D.H. (1999). MetaMorph: an adaptive agent-based architecture for intelligent manufacturing. *International Journal of Production Research*, Vol. 37, No. 10, 2159-2173, ISSN: 0020-7543/99
- Monteiro, T., Roy, D. & Anciaux, D. (2007). Multi-site coordination using a multi-agent system. *Computers in industry*, Vol. 58, 367-377
- Montreuil, B., Frayret, J.M. & D'Amours, S. (2000). A Strategic Framework for Networked Manufacturing. *Computers in Industry*, Vol. 42, 299-317
- Moyaux, T., Chaib-draa, B. & D'Amours, S. (2006a). Supply Chain Management and Multiagent Systems: An Overview. In: *Studies in Computational Intelligence (SCI)*, Chaib-draa, B. & Muller, J.P., (Eds.), Vol. 28, p. 1-27, Springer-Verlag, ISBN: 3-540-33875-6, Berlin
- Muller J.P. (1997). *The Design of Intelligent Agents: A Layered Approach*, Springer, New York.
- Panait, L. & Luke, S. (2005). Cooperative Multi-Agent Learning: The State of the Art. *Autonomous Agents and Multi-Agent Systems*, Vol. 11, 387–434
- Pechoucek, M., Vokrinek, J. & Becvar, P. (2005). ExPlanTech: Multiagent Support for Manufacturing Decision Making. *IEEE Intelligent Systems*, Vol. 20, No. 1, 67-74
- Schleiffer, R. (2005). An intelligent agent model. *European Journal of Operational Research*, Vol. 166, No. 3, 666–693
- Schneeweiss, C. (2003). *Distributed Decision Making*, Springer-Verlag, New York

- Shen, W., Maturana, F. & Norrie, D.H. (2000). Enhancing the performance of an agent-based manufacturing system through learning and forecasting. *Journal of Intelligent Manufacturing*, Vol. 11, No. 4, 365-380
- Shen, W., Norrie, D.H. & Barthes, J.P. (2001). *Multiagent Systems for Concurrent Intelligent Design and Manufacturing*, Taylor and Francis, ISBN, London, UK
- Shen, W., Hao, Q., Yoon, H.J. & Norrie, D.H. (2006). Applications of agent-based systems in intelligent manufacturing: an updated review. *Advanced Engineering Informatics*, Vol. 20, 415-431
- Stephens, S. (2000). The Supply Chain Council and the Supply Chain Operations Reference (SCOR) model: Integrating processes, performance measurements, technology and best practice. *Logistics Spectrum*, Vol. 34, No. 3, 16-18
- Weiss, G. & Sen, J. (1996). *Adaptation and Learning in Multi-Agent Systems*, LNAI 1042, Springer, Berlin