7[e] Conférence Internationale de MOdélisation et SIMulation - MOSIM'08 - du 31 mars au 2 avril 2008 – Paris- France
« Modélisation, Optimisation et Simulation des Systèmes : Communication, Coopération et Coordination.».

MOTIVATIONS FOR MULTI-BEHAVIOR AGENTS IN SUPPLY CHAIN PLANNING

P. FORGET, S. D'AMOURS, J. GAUDREAULT

FOR@C, Université Laval
Département de génie mécanique
Québec, (Québec) Canada, G1K 7P4
{pascal.forget, sophie.damours}@cirrelt.ca
jonathan.gaudreault@forac.ulaval.ca

J.-M. FRAYRET

FOR@C, École Polytechnique de Montréal
2500, chemin de Polytechnique
Montréal, (Québec) Canada, H3T 1J4
jean-marc.frayret@polymtl.ca

ABSTRACT: *In today's industrial context, competitiveness is closely associated to supply chain performance. Coordination between production partners is essential in supply chains to deliver products on time to final clients. As perturbations occur all the time, production centers have to react quickly to correct deviances and create new plans, while coordinating changes with partners. Agent-based technology provides a natural approach to model supply chain networks and describe specialized planning agents. To coordinate and optimize their production plan, agents use heuristics in order to reach feasible global solutions. In a dynamic environment it is extremely difficult to correctly specify the heuristic parameters a priori, at the time of their design and prior to their use. The solution proposed here is to give agents the opportunity to change these parameters, modifying their planning behaviors following the environmental conditions met. Using simulation, agents can identify optimal team behaviors for the supply chain in different situations. This paper explains the methodology followed to experiment multi-behavior agents and presents results from an application to the lumber supply chain.*

KEY WORDS: *Supply chain planning, simulation, agent-based planning, agent architecture, lumber industry.*

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 looked to reengineer their organizational processes and business practices and adopt supply chain management best practices. An aspect studied by many researchers recently is supply chain sales and operations planning, which deals with the management of client orders through the supply chain. Each partner involved must decide quantities and production dates, and allocate resources for each product needed, with respect to production capacities and transportation delays. Coordination between production partners is essential in such a context in order to deliver products on time to final clients. As perturbations occur all the time in such complex system, production centers have to react quickly to correct deviances and create new plans, while coordinating changes with partners.

At the structural level, centralized approaches handle supply chain planning and coordination with difficulty, mainly because of the complexity of such problems and the challenges of sharing private information between partners. Decentralized approaches are now being considered to overcome these problems, giving different partners the responsibility to locally plan their production and using coordination schemes and communication capabilities to insure coherent supply chain behavior. Agent-based technology provides a natural approach to model supply chain networks and describe specialized planning agents. On the other hand, decentralized approaches are generally sub-optimal. Heuristics are used by agents to coordinate and optimize their production plan in order to reach feasible global solutions. Because a local change in a plan can impact other partners, a coordination mechanism must be used to insure that every partner is informed of the change and can make their own changes if necessary.

An agent-based planning platform can be used to plan production for the entire supply chain, reacting automatically to perturbations and interacting with other agents to build feasible plans. Also, it can be used to simulate changes in the supply chain, such as different configurations, planning heuristics and coordination mechanisms.

Most of the time, system designers or production planners select a planning heuristic at design time, choosing what they believe to be the best decision for their specific application. The main problem is that the heuristic may not be adapted to further perturbations or environmental conditions the planning agents will face in a production context. Usually, these local algorithms used by agents can be parameterized on several levels (such as objectives, penalties, etc.), creating a variety of planning behaviors for an agent. We call a local planning behavior any planning strategy used by an agent to construct a production plan. A global planning behavior, or team behavior, is the combinational result of all local behaviors demonstrated in the supply chain. The task to set behavior parameters for every agent composing the supply chain is complex because all these setting are interdependent. In a dynamic environment it is extremely difficult, and sometimes even impossible, to correctly specify these parameters a priori, at the time of their design and prior to their use (Weiss, 2003).

Our main argument is that it is preferable not to choose a specific behavior for each agent at design time, but to develop agents possessing different planning behaviors. We term them *multi-behavior agents*. Confronted with a perturbation, an agent can dynamically change the planning and coordination mechanisms and, ultimately, increase supply chain performance through improved coordination. The idea is not to handle every single perturbation (there will be always be a need for human interventions), but to automate certain perturbations with effective known responses. With the possibility to experiment different behaviors and observe their impact on the supply chain, agents can learn which behavior is optimal for the supply chain in different situations.

This paper presents the methodology followed to experiment multi-behavior agents and some results from an application to the lumber supply chain. Section 2 provides a literature review on agent-based supply chain planning, coordination in supply chain and adaptive agent-based planning. Section 3 presents the research context of these experiments, including a description of the agent-based planning platform used for the implementation, the multi-behavior agent conceptual model and the industrial base case used for experiments. In Section 4, we present results from the implementation of these agents to the lumber supply chain. Finally, section 5 presents a conclusion and provides an overview of intended future work.

2. LITERATURE REVIEW

In this literature review, distributed supply chain planning approaches are first reviewed and agent-based planning is presented as a particularly interesting paradigm to manage supply chain planning. Next, in order to create a coherent environment, coordination mechanisms used in these approaches are presented, including negotiation between partners. Because agent-based planning systems can be made of a variety of agent types, a closer look at functional agent mechanisms is then made by investigating adaptive planning agent architectures.

2.1 Distributed Supply Chain Planning

Traditionally, centralized planning systems have been used for production planning in a single company. Offering a complete view of the production activities, they usually use optimization algorithms to find the best production planning solutions. In a distributed context like supply chains, where different partners work together to deliver goods to final customers, planning problems become rapidly too complex 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. In centralized systems, this typically leads to incomplete information and sometimes infeasible plans.

Different 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) and many resolving approaches have been applied, including integer programming, priority dispatching rules, heuristics (Alvarez, 2007) and constraint programming. Another trend in supply chain operational planning has resulted in the development of agent-based planning systems. Agent-based systems focus on implementing individual and social behaviors in a distributed context, using notions like autonomy, reactivity and goal-directed reasoning (Bussmann et al., 2004). They 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 best decision according to the situation and its goals, in order to carry out their part of the planning task (Marik et al., 2001).

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., 2005; Moyaux et al., 2006). Among these projects, Montreuil (Montreuil et al., 2000) presented a NetMan application, which is an operation system for networked manufacturing organizations that aims to provide a collaborative approach to operations planning. 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 the 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., 2005) presents an architecture combining agent-based technology and operation research-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. More details will be given of this platform in section 3.

2.2 Coordination in Supply Chains

As discussed previously, distributed planning provides clear advantages over centralized planning for supply chains, but represents a major challenge for coordinating the independent planning centers in order to build coherent and efficient production plans. In fact, 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., 2006). These interdependencies need to be managed, which requires building coordination mechanisms to keep a certain degree of coherence between the different decision centers (Frayret et al., 2004). These coordination mechanisms are in fact sets of rules that partners use to choose their own planning activities. Different categories of coordination mechanisms have been proposed for distributed systems, but can be summarized in five basic categories: third party coordination, coordination by mutual adjustment, coordination by standardization, mediated coordination and coordination by reactive behaviors (Shen et al., 2001). A new classification has been proposed (Frayret et al., 2004), which tries to overcome certain limits of previous classifications, including a distinction made between coordination before and during activities.

Negotiation is a common supply chain coordination approach, as a part of the mutual adjustment category. Jiao (Jiao et al., 2006) identifies negotiation as 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 (Dudek & 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 (Jiao et al., 2006) presented an agent-based framework that enables multi-contract negotiation and coordination of multiple negotiation processes in a supply chain. Monteiro (Monteiro et al., 2007) proposes 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 to limit the negotiation process and facilitate cooperation between production centers. Chen (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 a specific coordination and optimization mechanism to face a perturbation and develop new production plans, they can be insufficient in dynamic environments. Many complex and unpredictable situations require planning agents to adapt their behavior to their environment and change the coordination and optimization mechanism used. This leads to the need to design and implement highly adaptive multi-behavior agents.

2.3 Adaptive Agent-based Planning

When the planning environment shows a high level of variability and perturbation, common to a supply chain context, planning agents are asked to create or review production plans continually. In some situations, it could be advantageous for agents to adapt their planning behavior and use different coordination and optimization mechanisms. Such adaptive planning requires developing new kind of agents. Different adaptive agent models have been proposed in the literature, some of them specifically designed to improve supply chain performance.

One of the best known is the InteRRaP architecture (Muller, 1996). This layer-based agent model provides an interesting approach to react and deliberate when confronted with perturbations, using different capability levels. The agent can build action plans, depending if 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 supply chain management system. The ABS is geared to handle perturbations 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 unexpected events. Another adaptive agent model is the tri-base acquaintance model (3bA) (Marik et al., 2001). It provides the possibility of dealing with perturbations in a global perspective instead of resolving problems from a local perspective. This is accomplished by using information about other agents without the need of a central facilitator. Theses 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 roles of system coordinators and encapsulate various mediation behaviors (or strategies) to break decision deadlocks. Jeng (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 perturbations, using multiple decision agents. An application to the microelectronic supply chain is presented.

These agent architectures all offer the possibility of adapting their behavior when a certain situation occurs. Some of them know beforehand which behavior must be used for each situation, while other agents successively try different alternatives. The multi-behavior agent model is inspired by these architectures, possessing alternative behaviors for different situations and using learning abilities to link successful behaviors to situations.

3. RESEARCH CONTEXT

3.1 Agent-based Planning Platform

With the purpose of developing a new operation management approach for the lumber supply chain, the FOR@C Research Consortium has developed an experimental Internet-based planning platform built on an agent-based architecture for advanced planning and scheduling (Frayret et al., 2005). This platform allows the different production centers to independently plan and correct deviance in line with their own needs, while maintaining feasibility and coordination. By distributing planning decisions among specialized planning agents using adapted optimization tools, the platform increases supply chain reactivity and performance. More than a planning tool, this platform can also be used to simulate different supply chain configurations and coordination mechanisms.

The agent-based architecture presented is based on the 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 planning unit, including external exchanges with suppliers and customers. Planning units divide activities among specialized production planning agents: a sawing agent, a drying agent and a finishing agent, since each of these planning problems are quite different in terms of the way the process and the set-up are conducted. Each of these agents is responsible for supporting the planning of its production center 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. The validation of these developments was carried out with the collaboration of a Canadian lumber company.

Implementation of multi-behavior agents in the platform is simple since every agent is loosely coupled with others. Each agent can be removed, replaced or modified with a minimum of manipulations. It becomes easy to modify agent's behaviors on the fly and observe performance in simulations.

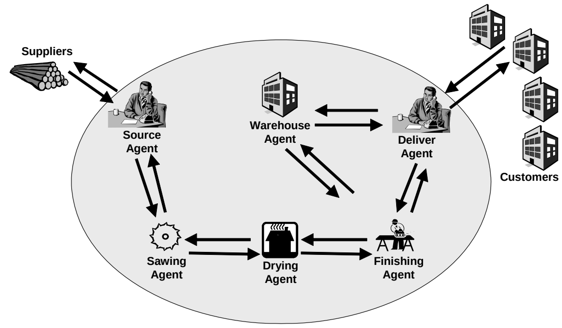

Fig. 2. Example of a planning unit from FOR@C experimental platform

3.2 Multi-behavior Agent Model

The multi-behavior agent model presents three basic behavior categories, inspired by the coordination mechanisms found in the literature (Shen et al., 2001; Frayret et al., 2004; Moyaux et al., 2006). They are identified as *Reaction*, *Anticipation* and *Negotiation*. Each of these categories includes different planning behavior variations, from which the agent has to choose. While mono-behavior agents construct plans using the same planning strategy continuously, multi-behavior agents can adopt different planning behaviors, depending on the environment. Multiple behaviors can be designed and added in order to create adapted response to the environment. Figure 3 presents the multi-behavior agent model.

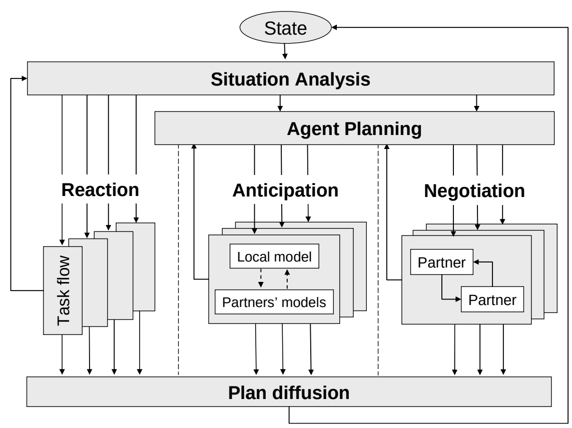

Fig. 3. Multi-behavior agent model

Because the agent is not controlled by a central supply chain planning system, it is free to decide which action it will perform, using its own preferences. From a new state in the environment, the agent first starts the *Situation Analysis* phase. An analysis of the agent environment is performed in order to determine if a reactive behavior or a deliberative behavior must be selected. Reactive behaviors use no new information during processing. The agent uses its own knowledge and local goals to respond to a perturbation. A large variety of task flows or algorithms can be available, some of them taking a considerable amount of time but leading to optimal solutions, others finding acceptable (but not optimal) solutions in a very short period of time.

For more complex situation, deliberative behaviors must be adopted. The *Agent Planning* phase is then started. The agent deliberates to decide which planning behavior it should adopt, using different selection criteria, such as available time, chance of success of a particular task flow, source of the perturbation and local goals. 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). This model uses a rule-based reasoning approach with learning abilities.

Two kinds of deliberative behavior categories have been identified: Anticipation and Negotiation. Anticipation behaviors consist in using partners' models in addition to the agent's own local model. Basically, it concerns integrating information about partners into its planning behavior. Collaboration between planning partners through anticipation has been studied in hierarchical relation types to improve decision making (Schneeweiss & Zimmer, 2004). Anticipation in supply chain planning can be interesting in situations where communication is limited or time is constrained. For example, a drying agent can use an internal model of its partner, the finishing agent, to supply it with alternative products, if the required ones are not available in time.

Negotiation behaviors involve some forms of exchange with partners during planning. This may take the form of proposal and counter proposal (e.g. Contract Net, alternative demand and supply plans). 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.

When the agent planning phase is ended, the next phase is the execution of the task flow, which is mainly the allocation of resources (machine, labor, etc.) to specific production tasks. Using a pre-determined algorithm, a production plan is built, creating demand plans for suppliers and supply plans for clients. The last phase is the *Plan diffusion* which distributes operation plans to all interested actors in the environment, including other planning agents and production staff related to the agent.

3.3 Industrial base case

In order to use the agent-based planning platform and experiment multi-behavior agents, it was necessary to set an industrial base case. 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 production centers in term 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 the final client, corresponding to different lengths and quality of wood pieces. An initial inventory has been determined for each production center, corresponding to approximately one week of production at full capacity.

Demand orders from clients are generated by a probabilistic demand generator. This generator creates random demand, according to predetermined settings such as distribution curves, minimum/maximum limits and seasonality. Supply from the forest is considered unlimited, since all demand from the sawing agent is completely fulfilled.

4. RESULTS

4.1 Identification of design factors

To simplify the current application, we focused our efforts by considering a common perturbation, which is a new purchase order from a client. Impacts from this perturbation can vary greatly depending on the environment of the agents. In this case, we identified two different design factors describing the demand environment: (1) demand type (spot or contract) proportion and (2) demand intensity. In demand type, we distinguish a spot demand (one-time order, irregular frequency) with contract demand (regular demand from a contract client, including a premium bonus). A late spot demand is considered lost because the client usually changes supplier. A late contract demand is not lost, but a penalty for each day is charged. The demand intensity represents the percentage of production capacity used. For a nominal demand intensity of 100%, which approximately represents the production unit capacity, different intensity can be considered, such as 50% and 150%.

Other factors from the demand environment can be used (but have not been applied here) such as order intensity over total demand and client priority. Order intensity denotes the importance of the last order over all orders. For example, an order can represent less than 1% of the next month's production, which can have a minor impact on production planning. Finally, client priority represents the importance given to a specific client over another, which can give clues about which order to prioritize and which can be late.

In order to respond to this perturbation, different planning behaviors have been identified. Two planning algorithms were used, which are the Just-in-Time (JIT) algorithm and the forward planning algorithm. JIT is about planning orders at the latest possible date without being late, while forward planning plans order as soon as possible. Different planning options related to these two algorithms were available to give different solution: priority on spot orders, priority on contract orders, equal priority for spot and contract, strong penalty for back orders (BO) and equal penalty for inventory and BO. Table 2 presents the different planning options identified in this application. An agent must choose an algorithm, a priority option and a penalty option, creating a specific planning logic. Each of these logics is used as different design factors.

Planning logic		
Algorithms	**Priority options**	**Penalty options**
Just-In-Time (JIT) Forward planning	Priority on contract Priority on spot Equal priority contract/spot	Penalty back orders (BO) Equal penalty inventory/BO

Table 2. Planning logics available to agents

Another way to change supply chain behavior is to modify the coordination strategy between agents. Here, three coordination strategies are identified: downstream planning, upstream planning, two-phase planning, complete planning loop and truncated planning loop. Downstream planning (1) is characterized by plan coordination from the bottom of the supply chain, which is generally used in the lumber industry. In this case, the products harvested in the forest dictate what will be processed in the supply chain. In upstream planning (2), agents plan their operations one after the other, beginning with the agent that is closest to the final customer. This presupposes that each agent is able to satisfy the demand of its customer agent. This mechanism was not used in the present application, mainly because of the difficulty to have good results in a highly dynamic environment such as the lumber industry. Two-phase planning (3) is a coordination mechanism combining both upstream and downstream planning. This approach involves a hierarchy of subproblems that implicates each agent twice (except the raw material supplier). 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).

Combining these design factors, we identified nine different team behaviors (see table 3). These behaviors represent the different levels of factors used in our experiments. The priority option was applied to the deliver agent only, which had the possibility to put planning priority on different kinds of demand (contract or spot). Coordination mechanisms were applied to the entire supply chain. This selection of team behavior was based on the experience of managers and researchers, but may not represent the best behaviors available.

	Planning logic			Coordination strategies
#	**Algorithms**	**Priority options**	**Penalty options**	
1	JIT	Contract	Back orders	Two-phase
2	Forward	Contract	Back orders	Two-phase
3	JIT	Contract	Back orders	Dowstream
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

Table 3. Team behaviors used in experiments

To analyze the different planning behaviors over the supply chain, different performance indicators are used. These can be various, such as supply chain profit, supply chain inventory and level of service to final clients. Depending on the choice of a specific indicator, the best team behavior may be different. In certain environmental situations, a specific behavior can dominate others for all indicators, but in another situation the same behavior can show poor results. Here, results are analyzed regarding to a profit indicator, which is base on the revenues generated by the sell of products to final clients, minus inventory holding costs, minus lateness penalty. This indicator is partial since it does not include production costs but is sufficient to compare planning behaviors.

4.2 Experiments

In each experiment planning agents have to prepare a production plan for the 30 next days, knowing the incoming orders in that time horizon. Using each team behavior alternatively, the supply chain was confronted with a combination of demand intensity (100%, 50% and 150%) and contract demand proportion (0%, 25%, 50%, 75% and 100%). A penalty cost is associated with lateness of contract demand (1.5% for backorder per day) and a premium bonus is given for the fulfilled contract demand (5%). A daily inventory holding cost of 0.5% of the market value is charged. A total of four replications of the same design factors have been executed. For every replication, a new 30-day demand plan is generated and used as a final customer demand. The objective is to find different optimal team behaviors for different states of the environment.

From these experiments, different graphics were drawn to observe the evolution of the behaviors' performance. Figure 4 illustrates some results in terms of profit for the supply chain, for 100% demand. As we see, depending on the percentage of contracts the best behavior switches. From 0% demand to approximately 15% and from approximately 85% to 100%, behavior 3 offers the highest profit. On the other hand, from 15% to 85%, behavior 9 (closely followed by behavior 6) shows a better performance.

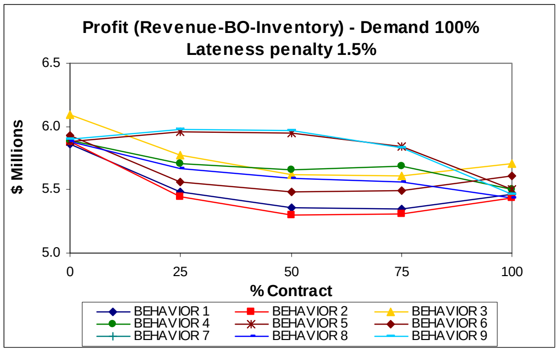

Fig. 4. Profit curves for a 100% demand

For the different levels of factors and performance indicators used, it is possible to identify the best performance and compare it to the average performance offered by all behaviors. This gives the average gain obtained by using the best behavior. Table 4 presents such analysis for a 100% demand. In this case, for the profit performance indicator, using the best behavior gives an average gain of 3.0%, 5.3%, 6.7%, 4.9% and 3.5% for respectively 0%, 25%, 50%, 75% and 100% of contract demand.

Following these results, planning agents can decide together to adopt a specific team behavior because it showed to be optimal for the supply chain. This remains true for a totally collaborative supply chain, but if agents are competitive, they may choose other behaviors to increase local profits, even if this can degrade the supply chain performance.

While figure 4 present an analysis of the best behavior considering a single performance indicator (i.e. profit), these experiments permit to analyze the performance of many criteria simultaneously. Figure 5 presents a graph where the different behaviors are compared to average lateness (X-axis) and average inventory (Y-axis). Because no behavior is dominant for both indicators, the multi-behavior agent can make a choice, based on a rule predefined by the system designer.

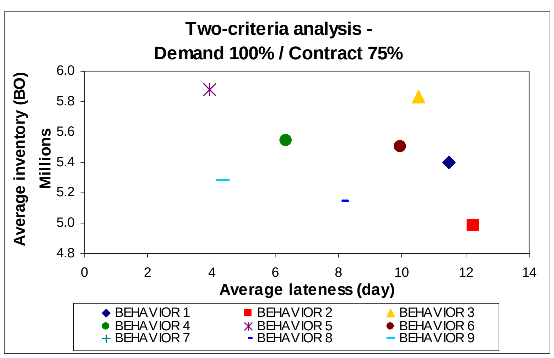

Fig. 5. Performance analysis for two indicators

While modifying demand environment in experiments give interesting information on which behavior to adopt, the same thing applies to lateness penalty, contract bonus and holding costs. When one or many of these variables are modified, the best planning behavior can change. For example, a downstream planning strategy, like behavior 3, is known to have high level of lateness to the final client, mainly because the client's demand is not used to select production. When the lateness penalty is low, this strategy can be used. Otherwise, when lateness penalty gets higher, situation can change. Figure 6 presents such evolution, presenting the profit curves for a 100% demand, using this time a lateness penalty of 3.5% of product value per day instead of 1.5%. In this example, we can see that behavior 3 reduced considerably its advantage over the other behaviors, compared to results presented in figure 4.

4.2 Simulation over a rolling horizon

Work is still on-going to realize test simulations over a rolling horizon. The idea is to change the behavior anytime during the planning horizon when a perturbation occurs and have an impact on the planning environment. By adopting the best behavior at each perturbation, the supply chain can reach the best performance. The black line in Figure 7 shows the potential profit that could be generated by adopting always the best behavior, instead of preferring a single behavior.

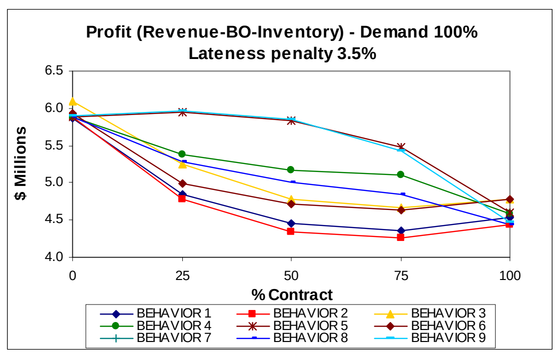

Fig. 6. Profit curves for a 100% demand with lateness penalty of 3.5%

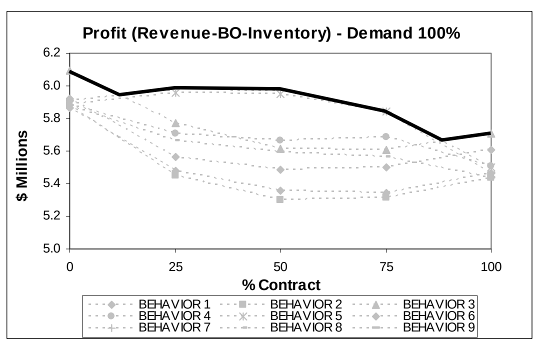

Fig. 7. Adopting the best behavior for maximum profit

Figure 8 gives an example of a simulation for a planning agent confronted to perturbations. The best team behavior identified from experiments is used at each perturbation. In this example, an agent faces a change in the proportion of contract/spot demand. From 0% contract, it first changes to 50% and later 100%. In the case the performance indicator is the profit, we change the planning behavior following information from the profit curves presented in figure 7. This lead to adopting behavior 3 for the first plan, behavior 9 for the second plan and adopting back behavior 3 for the third plan. The performance of this simulation over a rolling horizon can be compared to a plan where a singly planning behavior is used, attesting the motivations to use multi-behavior agents.

		0% Contract	25% Contract	50% Contract	75% Contract	100% Contract
Lateness (BO)	Average gain ($)	N.A.	$19,032,836	$24,078,413	$18,777,704	$5,390,051
	Percentage gain (%)	N.A.	97.6%	80.3%	50.8%	11.5%
Inventory	Average gain ($)	$411,525	$425,534	$517,740	$465,241	$429,767
	Percentage gain (%)	6.8%	7.2%	9.1%	8.5%	8.3%
Profit	Average gain ($)	$179,118	$299,794	$374,618	$274,271	$190,804
	Percentage gain (%)	3.0%	5.3%	6.7%	4.9%	3.5%
Spot performance	Average gain (%)	4.3%	9.5%	17.3%	23.8%	N.A.
	Percentage gain (%)	6.4%	13.2%	23.3%	32.2%	N.A.

Table 4. Gains to select the best behaviors for a 100% demand

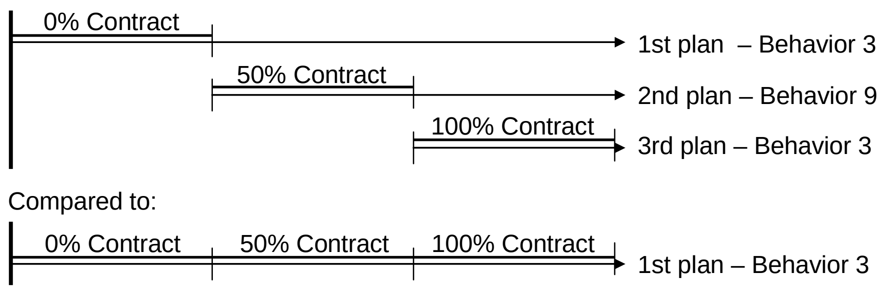

Fig. 8. Example of a simulation for a change in contract proportion

5. CONCLUSION AND FUTURE WORK

When using multi-behavior agents in an agent-based planning platform, the system designer gives planning agents the possibility to change their planning behavior according to change in the environment, instead of planning with the same strategy over time. Preliminary results show a potential to increase supply chain performance. Supply chain planning agent model which use the advantage of reactivity, anticipation and negotiation, such as multi-behavior agents, can be a powerful tool to reach appreciated gains when implemented in an agent-based supply chain planning system such as the FOR@C experimental platform.

Future work is intended to continue this research, starting with the completion of simulations over rolling horizon and the implementation of multi-behavior agents for on-line planning. Several features have been simplified for the application presented in this paper. Experiments were conducted using only reaction behaviors, with a unique perturbation (new demand order). Also, the base case used in this application included a single planning unit. The next application will be extended to multiple planning units, leading to a more complex but realistic supply chain. It will be interesting to develop anticipation and negotiation behaviors, and simulate to compare them to previous behaviors.

Another important feature that must be studied is the synchronization of the behaviors of all agents. Indeed, multi-behavior agents can recognize situations and adapt their behavior, but in order to avoid multiple behavior changes, it may be necessary to use a synchronization agent. Finally, it will be of great interest to increase research efforts on learning. A multi-behavior agent geared with learning abilities would be able to update its knowledge of the best behaviors by running new experiments over time. This is highly promising and could lead to an even more agile and performing supply chain.

REFERENCES

Alvarez, E., 2007. Multi-plant production scheduling in SMEs. Robotics and Computer-Integrated Manufacturing, Vol. 23, No. 6, p. 608-613

Aytug, H., M.A. Lawley, K. McKay, S. Mohan and R. Uzsoy 2005. Executing production schedules in the face of uncertainties: A review and some future directions. European Journal of Operational Research, Vol. 161, p. 86-110

Bussmann, S., N.R. Jennings and M. Wooldridge, 2004. Multiagent Systems for manufacturing Control: A Design Methodology, Springer-Verlag

Caridi, M. and S. Cavalieri, 2004. Multi-agent systems in production planning and control: an overview. Knowledge Information Systems, Vol. 15, No. 2, p. 106-118

Chen, Y., Y. Peng, T. Finin, Y. Labrou, S. Cost, B. Chu, R. Sun and B. Willhelm, 1999. A negotiation-based multi-agent system for supply chain management, Workshop on supply chain management, Autonomous Agents '99, Seattle, USA

Dudek, G. and H. Stadtler, 2005. Negotiation-based collaborative planning between supply chains partners. European Journal of Operational Research, Vol. 163, p. 668-687

Forget, P., S. D'Amours and J.M. Frayret, 2008. Multi-Behavior Agent Model for Planning in Supply Chains: An Application to the Lumber Industry, Robotics and Computer Integrated Manufacturing (accepted paper)

Fox, M.S., M. Barbuceanu and R. Teigen, 2000. Agent-Oriented Supply-Chain Management. Int J Flex Manuf Sys, Vol. 12, p. 165-188

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

Frayret, J.M., S. D'Amours, A. Rousseau, J. Gaudreault and S. Harvey, 2008. Agent-Based Supply Chain Planning In The Forest Products Industry, International Journal of Flexible Manufacturing Systems (accepted paper)

Jeng, J.J., M. Ettl and J.Y. Chung, 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, p. 395-417, Springer-Verlag, Berlin

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

Marik, V., M. Pechoucek and O. Stepankova, 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., W. Shen and D.H. Norrie, 1999. MetaMorph: an adaptive agent-based architecture for intelligent manufacturing. Int. J. Prod. Res., Vol. 37, No. 10, pp. 2159-2173

Monteiro, T., D. Roy and D. Anciaux, 2007. Multi-site coordination using a multi-agent system. Computers in industry, Vol. 58, p. 367-377

Montreuil, B., J.M. Frayret and S. D'Amours, 2000. A Strategic Framework for Networked Manufacturing. Computers in Industry, Vol. 42, p. 299-317

Moyaux, T., B. Chaib-draa and S. D'Amours, 2006. 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, Berlin

Muller J.P., 1996. The Design of Intelligent Agents: A Layered Approach, In: Artificial Intelligence (LNAI 1177), Springer

Pechoucek, M., J. Vokrinek and P. Becvar, 2005. ExPlanTech: Multiagent Support for Manufacturing Decision Making. IEEE Intelligent Systems, Vol. 20, No. 1, p. 67-74

Schneeweiss, C. and K. Zimmer, 2004. Hierarchical coordination mechanisms within the supply chain. European Journal of Operational Research, Vol. 153, p. 687-703

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

Shen, W., Q. Hao, H.J. Yoon and D.H. Norrie, 2006. Applications of agent-based systems in intelligent manufacturing: an updated review. Advanced Engineering Informatics, Vol. 20, p. 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, p. 16-18

Weiss G., 2003. Multiagent Systems: A Modern Approach to Distributed Artificial Intelligence, The MIT Press, Massachusetts