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Design of Multi-Behavior Agents for Supply Chain Planning: An Application to the Lumber Industry

Pascal Forget , Sophie D'Amours, Jean-Marc Frayret and Jonathan Gaudreault
*Universite Laval, FORAC Research Consortium
 Canada*

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, using coordination schemes 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.

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

Source: Supply Chain, Theory and Applications, Book edited by: Vedran Kordic, ISBN 978-3-902613-22-6, pp. 558, February 2008, I-Tech Education and Publishing, Vienna, Austria

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 settings 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.

This chapter presents a framework to design such agents, to help identify perturbations, propose planning behaviors, and how to use experiment and simulation to adopt the best behavior for specific situations. Section 2 provides a literature review on agent-based supply chain planning, coordination in supply chain, adaptive agent-based planning and learning agents. Section 3 presents the proposed framework to design multi-behavior agents, explaining how different planning behaviors can be identified, compared and introduced in an agent-based planning system. In Section 4, we give results from an application of the framework to the lumber supply chain. Finally, section 5 presents a conclusion and provides an overview of intended future work.

The North American lumber industry represents a perfect context for this proposal. In fact, this industry is highly distributed, with many production units geographically dispersed, interacting in all activity levels, using a variety of specific planning processes. What makes this industry interesting for research is the large amount of stochastic perturbations in many aspects of the supply chain, mainly due to the highly heterogeneous aspect of the resource, uncertain process output, production of co-products and by-products, price variation in the spot market demand, resulting in a variation in commodity markets all inducing a very complex planning activity.

2. Literature review

In order to understand the research context of this chapter, this literature review covers the literature from organizational approaches to more functional approaches. 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 agile planning agent architectures. Finally, a specific agent characteristic is investigated, which is the ability to learn.

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. 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 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. More advanced agents compile the performance of past experiences and learn from it: these are the learning agents. 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.

2.4 Learning in supply chain planning

Multi-behavior agents in supply chain show many promising features. However, linking behaviors with environmental conditions can be a hard task, even for experienced system designers. The main reason is that most changes and perturbations in manufacturing environments are not predictable in advance (Shen et al., 2006). Environmental conditions can change so that what was preferable at the design time is not anymore. This raises the need for agents that can not only adapt but also learn (Weiss & Sen, 1996). Agents then have the possibility of recognizing situations and applying the best behavior instead of trying each of them one at the time. Alonso (Alonso et al., 2001) argues that learning is the most crucial characteristic of intelligent agent systems.

Many researchers have been investigating learning agents, from defining fundamental issues of intelligent learning agents (Schleiffer, 2005) to describing major learning techniques for multi-agents systems (Alonso et al., 2001; Weiss & Sen, 1996). Shen (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 (Crawford & Veloso, 2007) recently studied how agents can learn to negotiate strategically to reach

better performance. To create adaptive and learning agents, Fox (Fox et al., 2000) uses 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 change agent behavior over time.

In a case where multiple agents must cooperate and coordinate their actions, they can learn together how to maximize their global performance; it is called cooperative multi-agent learning. Panait (Panait & Luke, 2005) presents a complete review on this topic, including team learning and concurrent learning. Basically, team learning involves a single agent learning for an entire group, specifying the set of behaviors for every member, while concurrent learning describes the use of multiple agents, where each one is responsible for a certain learning space.

3. Behavior design framework

This section presents a framework to design multi-behavior agents, using a multi-behavior agent conceptual model. The basic steps are described to give a design guideline, including the identification of the environment characteristics (perturbations) which require the adoption of a new behavior, the description of different behaviors available to react to perturbations, experiments to identify the best behaviors for different situations, simulations for continuous adaptation and finally, implementation and continuous learning.

3.1 Identification of perturbations

In a highly dependent network of entities, when activities are tightly planned, perturbations can have important impacts throughout the supply chain. For example, a major mechanical breakdown in a strategic third-tier supplier can reduce supply availability for several days, which can trigger a cascade of perturbations within the supply chain, translating into a delay for the final client. Another example is a quick change in demand pattern. When such changes happen, every local production plan and demand plan exchanged between partners must be updated. If it is not done in a very short period of time, inventories will pile-up, money will be wasted and the client will be unsatisfied. The first step in the methodology is to identify a maximum number of perturbations that show an impact on production plans. Table 1 presents examples of perturbation in the lumber industry and their related impact, obtained during interviews with decision takers. Inspired by Davis (Davis, 1993), perturbations have been classified into three categories: demand, execution and supply. Each of these renders current production plan inadequate. In order to correct this deviation and retrieve a feasible plan, agents must take action to change production plans.

For each perturbation, it is necessary to identify environmental conditions that would change the intensity of the impact on the supply chain. An environmental condition is any identifiable state that may change the kind of response needed. For example, a minor mechanical breakdown will not have the same impact depending on the level of use. This information represents the planning environment that agents must analyze to make decisions concerning their actions.

Perturbations	Impacts
Demand Variation	
Changes in product price	Changes in demand plan
New purchase order	Changes in demand plan
Execution Variation	
Out of stock	Execution delay
Strike	Execution delay
Resignation	Execution delay
absenteeism	Execution delay
Power outage	Execution stopped
Minor mechanical breakdowns (few hours)	Execution stopped
Major mechanical breakdowns (few days)	Execution stopped
Corrective maintenance	Execution delay
Stocks lost, misplaced	Execution delay
Resource different as expected	Changes in supply
Machining time longer	Execution delay
Wrong product produced	Changes in supply
Out of transport (lack of trucks, wagons)	Delivery delay
Supply Variation	
Political disorders (environmentalists, etc.)	Execution stopped
Bad weather	Execution delayed or stopped
Resource production different from forecast	Changes in supply
Transportation delay	Execution delayed or stopped

Table 1. Examples of perturbations

3.2 Identification of planning behaviors

The second step is to identify possible planning behaviors available to agents to respond to the perturbations previously identified. Different behaviors can be specific for specialized agents, while others can be more generic, all leading to far different performances depending on perturbations and environmental conditions. We distinguish two kinds of planning behaviors, which are optimization behaviors and a coordination behavior. The former characterizes different planning optimization algorithms and heuristics available for the planning problems. Various optimization algorithms have been applied to production planning and are available in the literature, such as JIT, forward planning and FIFO (first in first out). Also, different research heuristics can be used, like branch-and-bound, tabu search and genetic algorithms. The latter refers to mechanisms used to coordinate plans between partners. It can concern changing the order of planning actions between partners or the type of rule used to exchange information.

This step identifies planning behaviors, without associating them to any specific perturbations. All different behaviors must be identified, even those which at first sight seems less effective.

3.3 Team learning experiments

The complexity of supply chains makes it very difficult to identify which agent behavior is favorable for different environmental situations. Using learning abilities, agent designers do

not need to make initial decisions on linking behaviors to situations. Agents experiment with different environment situations, adopt different planning behaviors and observe the results. The third step is the team learning experiments, where agents experiment with different planning behaviors together and gather information on obtained performances. The objective of this learning process is to test all combinations of planning behaviors for every agent, in all environmental conditions. Each of these combinations creates a different team behavior. Performances from all team behaviors are gathered for each environmental condition toward different performance indicators (ex. maximizing profit, minimizing inventory, minimizing lateness, etc.). Results from these experiments are put in a knowledge matrix indicating to the agent the best planning behavior available for specific environmental conditions.

Such experiments must be realized following a clear strategy of experimentation. This includes the number of replications, the order of experimental trials, randomization restriction and the type of statistical analysis to check the validity of the results. The reader is invited to refer to Montgomery (Montgomery, 2005) for further details.

3.4 Test simulation

The next step is to use knowledge matrix previously built from team experiments to run simulations over a rolling horizon. Instead of using a fixed planning horizon with the same behavior corresponding to a specific perturbation, multiple perturbations can be observed and behavior changes can be applied. This more realistic approach enables the possibility of comparing the performances of an agent switching behaviors when it is necessary, to an agent keeping the same behavior. Again, a strategy of experimentation must be designed and results must be verified with proper statistical analysis.

The execution of these simulation runs verifies assumptions made previously by the team learning experiments. Agents can update their knowledge and become more accurate when responding to perturbations. Work is currently in progress to gather data from these simulations and verify the performance increase.

3.5 Implementation and continuous learning

The last step of the framework is the implementation of behaviors in a production context and the use of multi-behavior agents for on-line planning of production activities. In order to continuously check planning performance of behaviors for specific environmental conditions, continuous learning represents an interesting approach. Periodically team learning experiments can be executed and agents can modify designed relations according to new results. Multi-behavior agents geared with learning abilities would be able to update their preferences.

4. Results

An application has been developed to test the proposed framework for the lumber industry. In this section, the application context is first described, including the agent-based planning platform used to implement the agents, the multi-behavior agent model followed to coordinate the different behaviors and the industrial base case used for experiments and

simulation. Then, details of the framework application are given for each step, as well as the obtained results.

4.1 Application context

4.1.1 Agent-based planning platform

With the purpose of developing a new operation management approach for 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., 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.

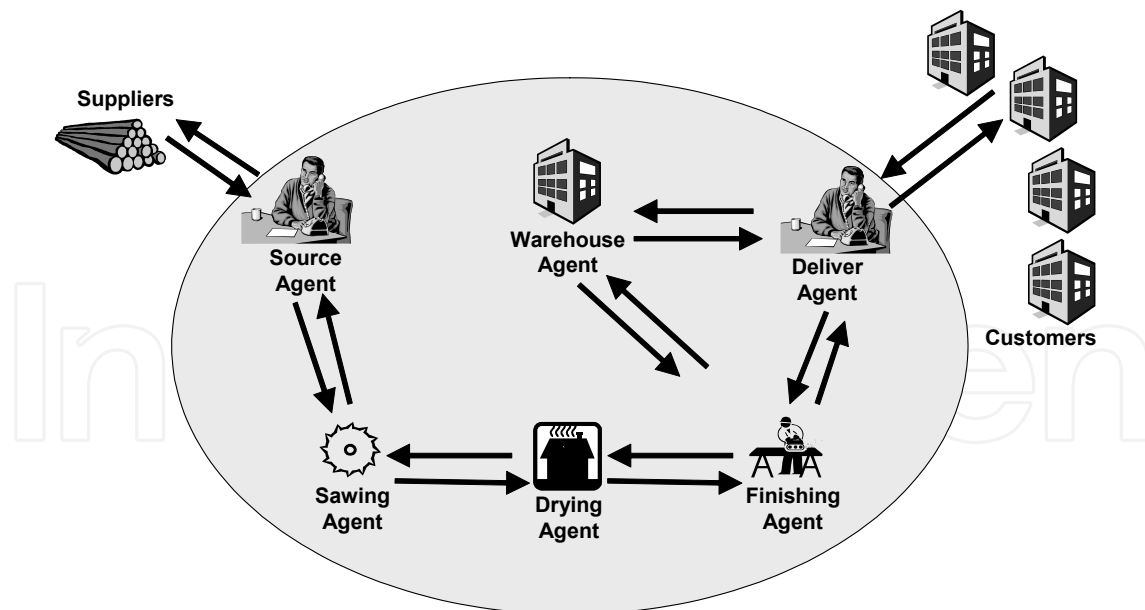


Figure 2. Example of a planning unit from the FORAC experimental platform

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.

4.1.2 Multi-behavior agent model

The framework presented in the previous section is a guideline to design multi-behavior agents based on the multi-behavior agent model. These multi-behavior agents can replace or enhance any existing planning agents in the experimental platform. In order to specify how works a multi-behavior agent, a descriptive model has been proposed (Forget et al., 2006) and a brief description is presented here.

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.

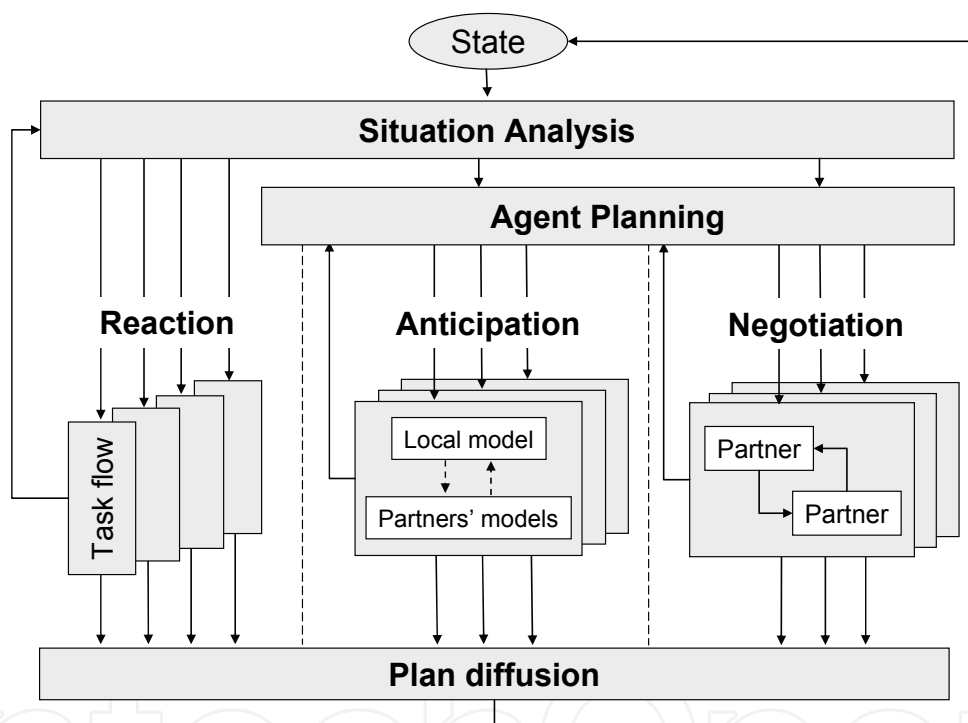


Figure 3. Multi-behavior agent model

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.

If more deliberative behaviors must be adopted the *Agent Planning* phase is 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 behaviors have been identified, Anticipation and Negotiation behaviors. 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.

4.1.3 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.

4.2 Framework application

Following the steps described in section 3, we first identified major disturbances that need to be handled in a planning context. Table 1 previously presented the results of our

investigation. 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 environmental conditions: (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 environmental conditions 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.

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

Table 2. Planning logic available to agents

Another way to change supply chain behavior is to modify the coordination strategy between agents. Here, five 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). If some capacity is left unused, agents can decide to plan other products by using on-hand inventory. When informed of the supply granted by its supplier, the initial agent has to revise its production plan in order to account for supply constraints.

Also, coordination between partners can be modified by intervening in the sequence of information exchanges. The complete planning loop (4) is referred to as an exchange of plans involving each partner successively, receiving demand plans from immediate customers and transmitting requirement plans to suppliers. The truncated planning loop (5) is similar to the complete loop but skips one or several partners in the communication sequence. This is particularly interesting when a specific production center represents a bottleneck and needs to be planned before other production centers. In this application, the drying unit is an important bottle neck in the supply chain. Figure 4 presents these different coordination strategies.

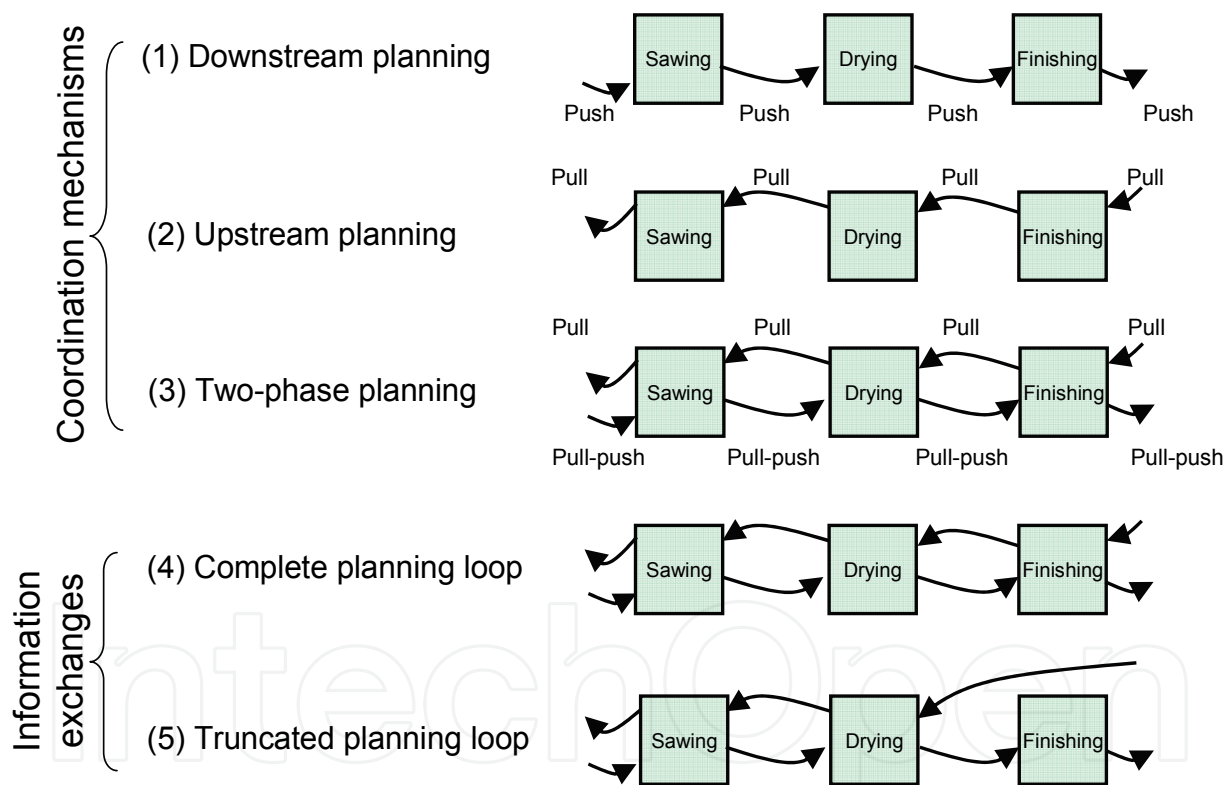


Figure. 4. Coordination strategies and information exchanges

During the team experiments phase, we identified five different planning behavior combinations, leading to five team behaviors. 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 and information exchange changes 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. Table 3 present the team behaviors used in our experiments, which were set for demonstration purposes.

To analyze the different planning behaviors over the supply chain, different performance indicators are used. These can be various, such as maximizing supply chain profit, minimizing inventory and maximizing level of service. 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 were analyzed regarding two different performance indicators, which are supply chain inventory and back orders.

#	Planning logic			Coordination strategies	
	Algorithms	Priority options	Penalty options	Coordination mechanisms	Information exchange
1	JIT	Contract	Back orders	Two-phase	Complete loop
2	Forward planning	Contract	Back orders	Two-phase	Complete loop
3	JIT	Contract	Back orders	Dowstream	Complete loop
4	JIT	No priority	Back orders	Two-phase	Complete loop
5	JIT	Spot	Back orders	Two-phase	Complete loop

Table 3. Team behaviors used in experiments

Basically, 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. From these experiments, different graphics were drawn to observe the evolution of the behaviors' performance with supply chain goals. Figures 4 and 5 present a sample of obtained results, showing the evolution of the performance for the different planning behaviors, under different environmental conditions. Figure 4 illustrates the results in terms of average inventory for the entire supply chain, for 50% demand (left graph) and 150% demand (right graph). For this specific performance indicator, it is not possible to identify a dominant planning behavior. Behavior 5 performs better in a context of 50% demand, while behaviors 1 and 4 seem to perform well for 150% demand. In these results, behavior 3 was removed from the figure because it was offering very poor results.

Figure 5 presents another example, showing the evolution of the average lateness (per board foot) for contract demand, again for 50% demand and 150% demand. This time, behaviors 1 and 2 appear very close to each other as the best behavior to adopt. In the case where lateness is a performance indicator, either behavior would be an acceptable choice. But if both minimizing lateness and minimizing inventory are indicators of equal importance (when multiple indicators are used), a different decision can emerge by analyzing results from figure 4 and figure 5. One would prefer behavior 1 as behavior 2 demonstrates poor performance in regard to inventory level. Table 4 presents the best planning behavior for the selected combination of environmental conditions and performance indicators. When two behaviors are suggested, none of these has proven to be significantly better.

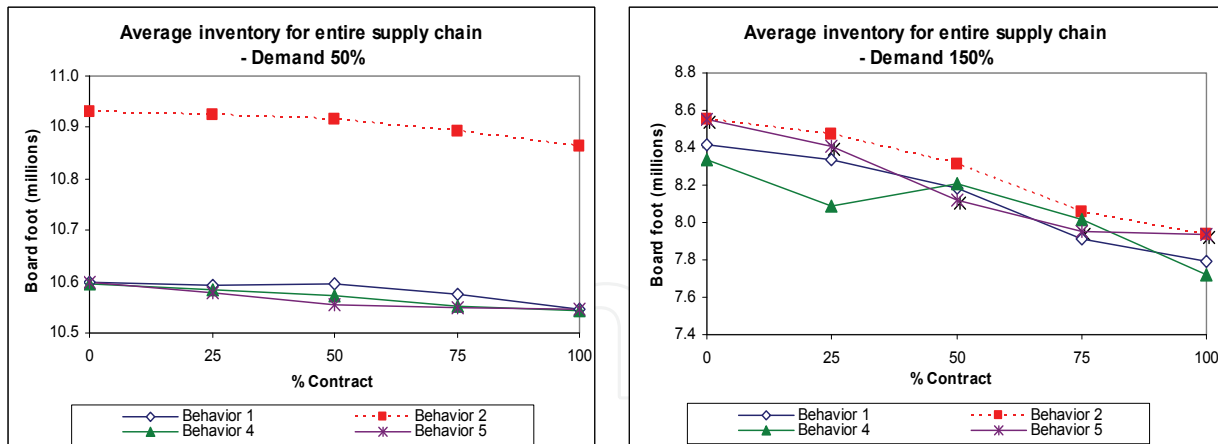


Figure 4. Average inventory for four planning behaviors

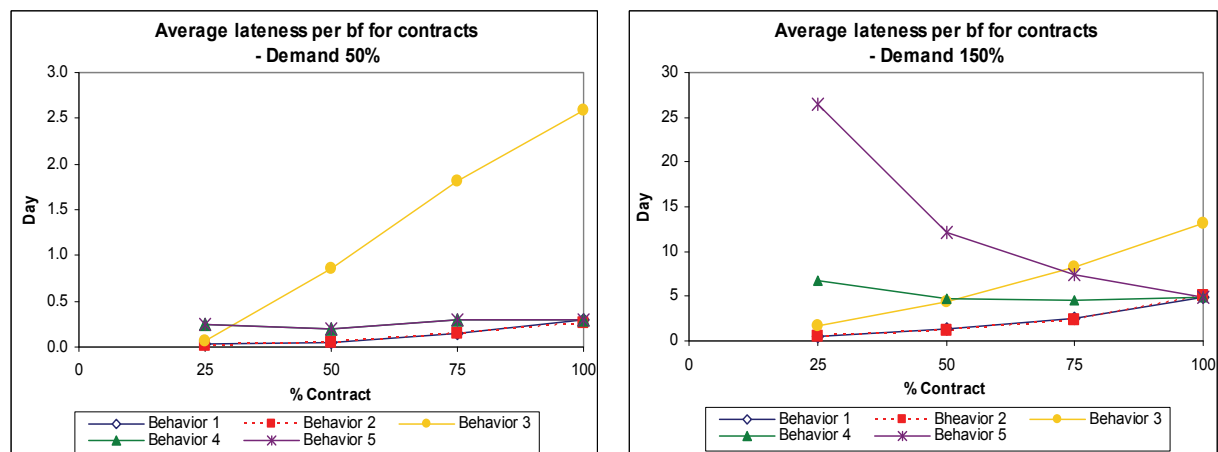


Figure 5. Average lateness for five planning behaviors

Environment		Objectives	Maximize supply chain profit	Minimize inventory	Minimize BO	Maximize sum of local profits
Demand 50%	Contract <=25%		5	5	1-2	1
	25%< Contract <=75%		5	4	1-2	1
	Contract >75%		5	5	2	1
Demand 100%	Contract <=25%		2	4	1-2	2
	25%< Contract <=75%		2	5	2	2
	Contract >75%		2	5	1	2
Demand 150%	Contract <=25%		5	4	1-2	4
	25%< Contract <=75%		5	1	1-2	4
	Contract >75%		1-5	5	1	4

Table 4. Knowledge matrix built from experiments

Work is still on-going to realize test simulations over a rolling horizon. Figure 6 gives an example of a simulation for a planning agent confronted to perturbations, here with three successive demand intensities. The best team behavior identified from experiments is used with each perturbation. In this example, behavior 1 is associated to 50% demand, behavior 2

with 100% demand and behavior 4 with 150% demand. Results are then compared to a simulation where only one behavior is used instead of different.

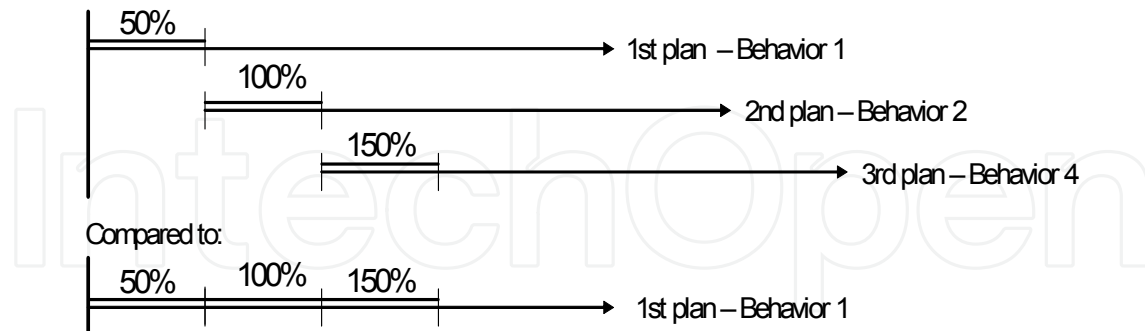


Figure 6. Example of a simulation for a demand increase

5. Conclusion and future work

This chapter proposes a framework to design multi-behavior agents in a supply chain agent-based planning system. The basic steps are described to give a design framework, including (1) the identification of environment characteristics which require a change of behavior, (2) the description of the different planning behaviors available to the agent, (3) an experiment methodology, (4) a test simulation phase and (5) an on-line implementation with continuous learning. An application from the lumber industry has been tested on an agent-based planning platform and results are presented.

By following this design framework for multi-behavior agents, the planning system designer gives a system's 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, depending on an agent's local and global goals. Supply chain planning agent models which use the advantage of reactivity, utility evaluation, 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 current simulations, the implementation of multi-behavior agents for on-line planning and the development of the on-line learning ability. Several features have been simplified in the application of the design framework presented in this chapter. 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.

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Traditionally supply chain management has meant factories, assembly lines, warehouses, transportation vehicles, and time sheets. Modern supply chain management is a highly complex, multidimensional problem set with virtually endless number of variables for optimization. An Internet enabled supply chain may have just-in-time delivery, precise inventory visibility, and up-to-the-minute distribution-tracking capabilities. Technology advances have enabled supply chains to become strategic weapons that can help avoid disasters, lower costs, and make money. From internal enterprise processes to external business transactions with suppliers, transporters, channels and end-users marks the wide range of challenges researchers have to handle. The aim of this book is at revealing and illustrating this diversity in terms of scientific and theoretical fundamentals, prevailing concepts as well as current practical applications.

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University Campus STeP Ri
Slavka Krautzeka 83/A
51000 Rijeka, Croatia
Phone: +385 (51) 770 447
Fax: +385 (51) 686 166
www.intechopen.com

InTech China

Unit 405, Office Block, Hotel Equatorial Shanghai
No.65, Yan An Road (West), Shanghai, 200040, China
中国上海市延安西路65号上海国际贵都大饭店办公楼405单元
Phone: +86-21-62489820
Fax: +86-21-62489821

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