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Abstract. This paper investigates the robustness of different tactical planning and control policies for a softwood supply chain using an agent-based environment that simulates a distributed APS (advanced planning and scheduling) system and its corresponding supply chain operations. Simulations were modelled using a novel agent-based methodology combined with a robust experimental design approach and an industrial dataset obtained from two companies in Québec, Canada. Experimental results provide insights about the dynamic relations among factors related to control levels, planning methods and planning horizon lengths. In addition, they give indications on how to obtain an optimum robust configuration of these parameters so as to minimize the impact of uncertainties related to supply, manufacturing and demand.

Keywords. Supply chain management, tactical planning, softwood lumber industry, agent-based simulation, robust design.

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1. Introduction

The softwood lumber supply chain in Canada is going through of the most difficult times in its history. It is under great pressure and is compelled to respond to a new set of market requirements in terms of lower operational costs and improved service levels. It is also faced with a set of new supply and manufacturing constraints, such as reduced cutting rights and aging machinery, which impact productivity.

To improve its business performance and re-establish its market position, academics and practitioners are trying to identify different tactics for this industry sector. Influenced by strategic planning, supply chain tactics define mid-term plans constraining how operations will be planned and executed. We know from practice that implementing an efficient and effective supply chain tactic is a difficult task since it includes many parameters, possible interactions among them and several uncertainties that disturb supply chain performance. As well, it is known that testing different planning and control tactics in practice can be quite costly and sometimes infeasible.

In order to respond to these needs, we are performing simulation studies in the domain of the softwood lumber industry to help better understand how certain relevant planning and control tactical policies contribute to the performance of the entire supply chain. In addition, we have investigated how these policies should be adjusted to obtain a robust system taking into consideration environmental uncertainties related to demand unpredictability, supply instability and manufacturing variability. The selected policies are control levels, planning methods and planning horizons. In this study the viewpoints of both customers and the company are analyzed through specific performance indicators.

With the goal of performing realistic experiments, we employed a novel advanced supply chain planning system called the FORAC experimental planning platform. It is able to mimic complex supply chain behaviours through agent-based planning and simulation. Our research is based on a case study inspired by two real lumber companies, providing a realistic test case that represents an industrial-scale situation. The whole of the modelling effort followed an agent-based modelling methodology, combined with a robust experimentation design approach.

Despite the fact that both results and methodology are validated for the lumber industry, we strongly believe that other industry sectors (e.g., food and chemical industries) can benefit from this approach and from the experience gained from this case, mainly those that have important stochastic behaviours in terms of supply, demand and manufacturing operations, as well as those having divergent production processes.

This paper is organized as follows. Section 2 presents a literature review in the domain and Section 3 introduces the FORAC experimental planning platform. Next, Section 4 explains the simulation problem. Section 5 details the methodology employed to model and implement the case. Section 6 explains how the experiments were specified, while Section 7 details how all parameters of the experiments were designed and implemented in the simulation platform. Section 8 presents and discusses the statistics of the case. Finally, Section 9 outlines some final remarks and conclusions.

2. Literature Review

Supply chain planning basically covers three decision levels: strategic planning, tactical planning and operational planning. Named hierarchical production planning by Hax & Meal (1973), this is a typical approach carried out in many research papers until today (Thomas et al. 2008).

Strategic planning reflects long-term and broad-based decisions to support the mission, vision and objectives of an organization, such as supply chain network design. Tactical planning defines general 'rules-of-the-game', such as production and distribution lot sizes, inventory safety stock levels, production levels, capacity levels, staffing levels, funding levels, and so forth, to achieve the intermediate goals and objectives in order to support the organization's strategic plan. Tactical plans and policies are used as planning constraints at the operational level. Operational level is basically related to decisions of floor managers for the day-to-day operations, detailing specific actions that lead to the achievement of tactical objectives. Operational plans are more detailed than strategic and tactical plans and cover a shorter time horizon (APICS 2008). In this paper, we are interested in exploring the tactical level.

The literature on supply chain modelling and simulation at the tactical level is vast and covers many problems and several different solution approaches. Traditionally, mathematical programming methods are employed. Ouhimmou et al. (2008) propose a supply chain tactical planning problem for a furniture company to define manufacturing and logistics policies that will allow the company to have competitive service levels at minimum costs. They employed a mixed-integer programming model and heuristics to solve it, using data from an industrial case. Comelli et al. (2008) propose an approach to synchronize financial and physical flows in supply chains at tactical level, allowing for budgeting in production planning with APS (advanced planning and scheduling) tools. Thomas et al. (2008) present a procedure for tactical supply chain planning based on mathematical programming to produce stable master production schedules following a robust reference plan policy generated through sales and operations planning procedures. Based on the known MIT's Beer Game, von Lanzenauer & Pilz-Glombik (2002) propose a mixed-integer programming model to support tactical decision level covering ordering, producing and transportation. They compare analytical results obtained from their model with human decision making, indicating that significant gains can be obtained through the use of analytical models. The reader is referred to Comelli et al. (2006) for a literature review on models for supply chain tactical planning, mainly related to lot sizing problems.

Landeghem & Vanmaele (2002) highlight the limitation of tactical planning approaches in the literature, as well as in the APS sector, to deal with uncertainties. Uncertainty and robustness are normally treated through a combination of mathematical modelling with simulation techniques, such as Monte Carlo simulation, scenario-based simulation, sensitivity analysis and, sometimes, discrete-event simulation. For example, Landeghem & Vanmaele (2002) developed a tactical planning method embedded with a Monte Carlo simulation approach for the assessment of uncertainties in supply chains. Genin et al. (2007) compare three tactical planning approaches so as to evaluate which one is the most robust. Supply chain plans were generated through traditional mathematical planning models, and perturbations were introduced through random demand generation to evaluate the total cost of the plans and service levels. Beaudoin et al. (2007) employ a tactical planning approach for wood procurement planning. They developed a mathematical deterministic model (mixed-integer programming), which does not address robustness explicitly, but employs a set of mechanisms to assess a posteriori several alternative plans.

Van Eck (2003) explains that traditional approaches for coping with uncertainties are limited, and Stadtler (2005) argues that management of uncertainties is a significant limitation for conventional APS systems. The most important reasons are probably related to the reactiveness of the approach and the complexity of creating these solutions. A more pro-active approach is needed to find solutions which are less sensitive to the uncertainties of parameters. A way of doing this is to include uncertainties in the model itself so that the algorithms could attempt to reduce variability (Van Eck 2003). Many efforts have been made to overcome this drawback, such as the emergence of APS employing stochastic programming. This technique puts together models for optimum resource allocation as well as models of randomness to produce a robust decision-making approach.

For example, Sodhi (2005) demonstrates how stochastic modelling can be useful in a tactical supply chain planning context for a particular electronics company. As mentioned by the author, the work is only a starting point in developing model-aided processes to manage risk. Despite their potential, at tactical and operational levels, the sizes of stochastic programming models problems may still be hard to solve, especially in APS contexts. Genin et al. (2007) explain that stochastic programming is an interesting approach, but it still does not succeed in solving real-size problems. The problem is the growth of the model size when several scenarios are evaluated in a multi-period model. Some recent works now demonstrate that real-scale problems can be considered tractable in some cases, such as the one for the sawmill industry from Kazemi et al. (2008).

Our work employs a different methodology from the field of artificial intelligence, known as the multi-agent approach. It is one of most recent models for advanced supply chain planning. In this case, agent-based modelling is used to encapsulate one or more supply chain optimization models together with the main elements from discrete-event simulation (occurrence of uncertain events over time); to develop what is called d-APS (distributed-APS) systems, according to Santa-Eulalia et al. (2008). These systems possess four main advantages over traditional approaches. First of all, their distributed characteristic facilitates modelling heterogeneous planning domains of different supply chain partners, allowing for complex interaction schemas to be created so that a compromise between local and global solutions can be found. Second, they are able to exhibit intelligent behaviours, which are integrated into their management applications. Inspired from distributed artificial intelligence, d-APS systems demonstrate decision autonomy and proactive abilities and are able to learn from their previous experiences. Third, uncertainties are naturally modelled in agents' behaviours due to their ability to incorporate discrete-event simulation mechanisms. Finally, these systems provide a very powerful simulation environment for testing different supply chain planning concepts, methods, tools, and technologies.

Since the 90s, several agent-based approaches explicitly mention the use of optimization procedures or finite capacity planning models to perform supply chain planning. For example, Swaminathan et al. (1998) provide a supply chain modelling framework containing a library of modular and reusable software components that represents different kinds of supply chain agents, their constituent control elements and their interaction protocols. Sauter et al. (1999) propose an architecture, called ANTS (Agent Network for Task Scheduling), that consists of a supply chain planning system composed of agents inspired by human intuition and insect colonies. Sadeh et al. (1999) put forward an agent architecture called MASCOT (Multi-Agent Supply Chain cOordination Tool) for coordinated supply chain planning and scheduling across the entire supply chain. Montreuil et al. (2000) introduce the NetMAN approach, which is a network-oriented organizational concept where a manufacturing business dynamically organizes its operations by configuring and activating a distributed network composed of interdependent responsible manufacturing centres. Gjerdrum et al. (2001) present multi-agents incorporating mathematical programming for the manufacturing components, to form a platform where simulations can be performed for demand-driven supply chain networks. Baumgaertel & John (2003) present an agent-based simulation architecture for supply networks, incorporating APS components and using finite domain constraint technology. As for us, we employ the d-APS called the FORAC experimental planning platform, described by Frayret et al. (2007), which is agent-based and encompasses concepts of autonomy and cooperation to deal with distributed decision making problems that naturally reside in supply chains. To our knowledge, this is the first and only d-APS system capable of capturing business scenarios for the forest products industry. According to Azevedo et al. (2004), despite the fact that the agent-based approach is particularly interesting for tactical problems, there are few applications for more tactical and less structured problems in enterprise networks. Many of the multi-agent approaches found in the literature are oriented to specific applications of an operational nature. The FORAC experimental planning platform is specifically useful for simulations at the tactical decision level, as demonstrated by Cid-Yanez et al. (2008). This platform is explained in the following.

3. FORAC Experimental Planning Platform

In the FORAC experimental planning platform, a set of planning agents, using advanced planning tools based on operations research technology, individually produce operational plans. Agents collectively interact with each other to carry out functionalities that synchronize their plans across the network to create a feasible operational schedule and enhance global performance. Some planning agents have been developed to represent an internal supply chain. Figure 1 depicts the agents implemented for the present case study.

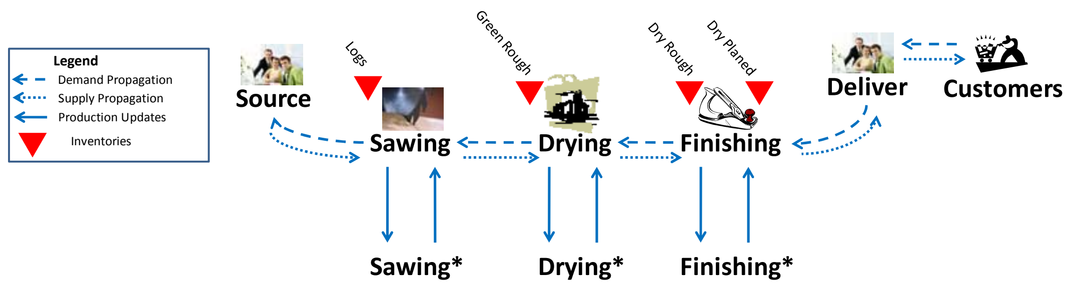

Figure 1: Implemented agents for the case study.

The agents implemented are: deliver agent (manages all relationships with the business unit's external customers and fulfils all commitments with them); three agents (sawing, drying and finishing) responsible for carrying out production planning functions, each one being in charge of a part of the overall planning functions by means of specialized planning capabilities; source agent (manages the relationship with all the business units' suppliers, forwarding procurement needs to the right suppliers), customer agent (generates the demand for products and evaluates supply chain offers). In addition, each agent responsible for production planning has a counterpart agent responsible for executing the production plan (sawing*, drying* and finishing*), referred to as execution agents.

Figure 1 can be understood through its flow of materials: logs are sawn into green rough lumber, which are transformed into dry rough lumber, and finally transformed into dry planed lumber during the finishing process. Arrows represent the basic planning and control process. Essentially, this process is divided into five basic steps:

1) Production update: before starting a planning cycle, all planning agents update their inventory level states. In fact, all execution agents (sawing*, drying* and finishing*) receive the last planned inventory for the current period from the planning agents (sawing, drying and finishing). The execution agents perform perturbations on the inventory level to represent the stochastic behaviour of the execution system and send the perturbed information back to their respective planning agents. This perturbation in the execution system can be seen as an aggregated representation of what happens on the shop floor, i.e., a set of uncertainties that make the manufacturing system have a stochastic output, which is ultimately reflected in the physical inventory level of the supply chain;

2) Demand propagation: with the planned inventory updated, all agents are ready to perform operations planning. The first planning cycle is called demand propagation because the customer demand is transmitted across the whole supply chain. First, the deliver agent receives customers' orders for finished products (dry planed lumber) and sends this demand to the finishing agent. If no products are available in stock, the finishing agent will perform an infinite capacity planning for this demand and will send its requirements in terms of dry rough lumber to the drying agent. The drying agent now performs its planning operations using also an infinite capacity planning logic, and its requirements in terms of green rough lumber will be sent to the sawing agent. Following this, sawing executes an infinite capacity planning process to generate its needs of logs, which are transmitted to the source agent. The source agent will confirm

with sawing whether all requirements will be sent on time. Now, the supply propagation starts;

3) Supply propagation: based on the supply offer from the source agent, sawing now performs finite capacity planning in a way that respects the demand from drying in terms of green rough lumber (pull planning approach), and respects its own limitation in terms of production capacity. In addition, sawing tries to identify whether it still has some available capacity to perform a push planning approach. If there are resources with available capacity, sawing allocates more production based on a price list to maximize the throughput value, meaning that it makes a complementary plan to occupy the additional capacity with products of high market prices. The sawing plan containing products to answer drying demands and products to occupy the exceeding capacity is finally sent to drying. Drying, in return, uses the same planning logic (first a pull and after a push planning logic) and sends an offer to the finishing agent. Finishing performs the same planning approach and sends an offer to the deliver agent. Deliver send its offer to the customer agent. In summary, the general idea of supply propagation is to perform finite capacity planning, where part of the capacity can be used to fulfil orders (pull approach) and part of it to push products to customers so as to better occupy capacity.

4) Demand acceptation: the customer agent receives offers from deliver and evaluates whether they satisfy all its needs. Part of this offer can be accepted by the customer and part can be rejected, for example because it will not arrive at the desired time. This information is sent to the deliver agent. Now, as part of the demand is not necessary anymore, deliver will send the adjusted demand for the finishing in the form of a new demand propagation step with fewer product

volumes. This new demand will be propagated backwards to the source agent. Next, from source this demand will be forwarded in the form of a supply propagation step up to the deliver agent. During the demand propagation, all planning agents will have more available capacity to be occupied with high market price products. The planning cycle finishes here.

5) Time advancement: due to the fact that the FORAC platform uses the rolling horizon approach, after the end of a planning cycle involving these four steps, the simulation time moves ahead for the next planning period. In this case, the next planning period is the next "replanning date", which is delimited by the control level (replanning frequency). It can vary within any time period, from a day to several months, and it depends on the interest of the supply chain planner. The planning cycle (i.e., the above-mentioned four steps) is repeated at each replanning date until the end of the simulation horizon.

These five steps represent the basic logic of operations planning. Some mechanisms useful for simulation during these five steps are detailed hereafter.

Perturbations in the platform are performed through a traditional random number generation approach. As a lot of data was needed a fast and flexible generator was employed. The selected uniform number generator was the Mersenne Twister (Matsumoto & Nishimura 1998), which provides random numbers for a considerably long period without slowing down the algorithm. The transformation of the random numbers into random variables follows a simple method for discretizing the density function of the probability distribution desired. Simulation analysts can select different probability distribution functions, such as normal, exponential or triangular. More details about number generation are found in Lemieux et al. (2008).

Another important issue is how agents perform their planning activities. Both demand propagation and supply propagation for each agent are geared up with specialized optimization models. They are depicted in Table 1 in terms of objective functions, processes, planning parameters and optimization methods, according to Frayret et al. (2007) and Lemieux et al. (2008).

Table 1: Planning engines for each agent.

	Sawing Agent	Drying Agent	Finishing Agent
Objective: Demand Propagation	Minimize lateness	Minimize lateness	Minimize lateness
Objective: Supply Propagation	Maximize production value	Maximize production value	Maximize production value
Processes features	Divergent product flow; coproduction; alternative process selection; only compatible processes can be executed within the same production shift	Divergent product flow; coproduction; alternative process selection	Divergent product flow; coproduction; alternative process selection; only compatible processes can be executed within the same production shift
Planning parameters	Machine capacity calendar; frozen jobs; maximum sales per product; inventory costs; raw products costs	Machine capacity calendar; frozen jobs; operations cost	Machine capacity calendar; frozen jobs; exploitation mode in the solution tree (for the optimization method – see next line); minimum production lead-time per family
Optimization method	Mixed Integer Programming	Constraint programming	Heuristic

The planning approaches described in Table 1 are radically different with regard to their nature, as explained by Frayret et al. (2007). In sawing, for both demand and supply propagations, planning activities are designed to identify the right mix of log type in order to control the overall divergent production process. What changes for the demand and supply propagations are their objective functions and constraints. Drying, on the other hand, is batch-oriented and tries to find simultaneously the best type of green rough lumber to allocate to the dryers and the best drying process to implement. The optimization model of this agent is described thoroughly in Gaudreault et al. (2006). In this approach, what is interesting is that it tries to find a feasible solution in a short time, but if more time is available, it will try to find a better one using a search algorithm through the solution tree. Finishing employs a heuristic approach to find out what rough dry lumber type will be used and how much it should be planed considering setup time. For more details on how planning engines work, the reader is referred to Frayret et al. (2007).

Another issue concerning simulation functioning is the time advance mechanism used to manage all of these uncertain events and planning activities. We opted for a central simulation clock, which aims at guaranteeing that all agents are synchronized so that none of them are late or in advance. In this case, all agents use the same simulation clock instead of each having its own clock. This was used to simplify the time management effort. The general functioning logic is simple. The simulator has a list of all agents participating in the simulation and their corresponding state, which can be "busy" or "standby". When at least one agent is busy (sometimes more than one could be working in parallel), time advances in real-time. When all agents are on standby, time advances according to the simulation list. This means that the simulator looks for the next action to be accomplished and advances the simulation time to the realization moment of this action. Next, the simulator asks the concerned agent to perform this action. As the case here is set to perform planning activities for each replanning date (as will be discussed later), the simulation always advances to the next replanning moment. This central clock management mechanism implies that when an agent needs to perform a new action, it adds this action (with its respective time of occurrence) in the simulation list. This action can be triggered immediately or later, depending on its time of occurrence.

Finally, it is important to give details about the data set employed for this case. In order to create a complete case for this simulation study, most data were obtained from two industrial partners, both softwood lumber producers. When no data were available, we used expert people (researchers or practitioners from the industry) and also expert systems (basically Optitek©) to estimate lacking figures. For example, due to the heterogeneous nature of the raw material (trees), it is hard to predict the output (lumber volume) of the wood transformation process. Optitek© can be used to simulate this possibility (Zhang & Tong 2005).

Lemieux et al. (2008) explain the main characteristics of the proposed supply chain, including products, processors, capacities, and processes. A process defines how an operation is performed and what input is required for a particular operation. For example, in sawing operations, a process is an association of log and cutting patterns, consuming inputs (a group of logs) and producing outputs (green rough lumber, sawdust, chips) using a certain resource (a processor, i.e. a sawing line in this case). Every time an agent performs planning activities, it has to allocate one process to a processor, and this decision depends on general manufacturing conditions, such as demand, capacity availability, etc.

The FORAC experimental planning platform and its industrial data set were used to help us answer some simulation questions, as explained next.

4. Simulation Problem

In this study we are interested in understanding the impact of alternative tactical policies related to the control level, planning horizon and planning method.

The control level represents the frequency at which one updates information about inventory levels, supply quantities from vendors and demand requested by clients. This control notion proposes to link the planning process to the execution of the operations. When it is time to perform an update, the planning system triggers a “replanning process”, i.e., it updates all system information and it plans again all operations for the current planning horizon. In the case of the FORAC experimental planning platform's execution agents, all manufacturing perturbations are captured at the inventory level in order to represent the stochasticity of the production process. As all manufacturing uncertainties (machine breakdowns, unpredictable production yields, etc.) will ultimately impact on the planned inventory level, this represents an aggregate manner to introduce manufacturing perturbations for analysis at the tactical decision level. It is important to note that perturbations occurring today will impact future planning and execution processes, i.e. uncertain events are accumulated over time. In addition, uncertainties are propagated across the supply chain, meaning that events at the sawing level will later disturb drying and finishing. The planning agents employed here are designed to cope with these perturbations by adjusting their plans at each replanning period.

The second factor, the planning horizon, represents the amount of future time that will be considered when preparing a plan. The way these plans are calculated depends on the planning method employed. The planning method stands for the approach (or algorithm) used to produce a plan. A set of algorithms exist and, for example, traditional softwood lumber industries employ a classical forward planning method, which is performed by humans. By using this method, all operations are planned for the earliest moments (i.e., the first available time slot) with respect to the delivery date. A more complicated method would include other planning criteria. For instance, the "urgency-directed forward planning" is also based on a traditional forward planning scheme, but it employs an additional criterion to select which job will be planned first. This criterion is the "urgency" of the customer order, which can take into consideration the remaining time before the due date.

Thus, the present study aims to guide us in answering the following research questions:

1) Do the control level, planning horizon and planning method really contribute to supply chain performance?

2) Does one policy influence the others, i.e., do they interact?

3) What are the optimum planning horizons, planning methods and control levels to be implemented to minimize the impact of uncertainties in this supply chain?

Analyses have to consider the company's and customer's points of view. This means that we will have to select KPI (key performance indicators) representing both aspects.

The following section explains how we will approach this simulation problem.

5. Methodology

In order to translate our simulation problem into simulation requirements and then into a simulation environment (in this case the FORAC experimental planning platform) we used the methodology schematized in Figure 2.

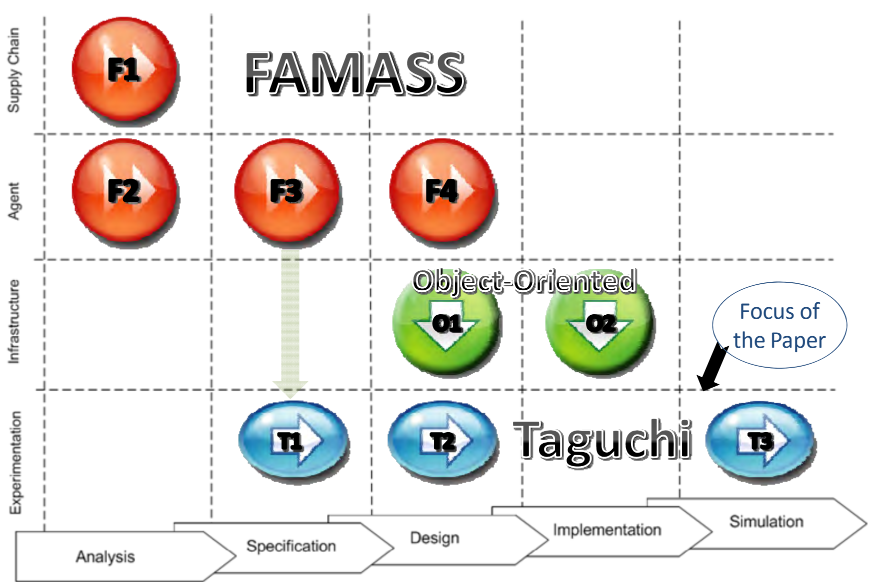

Figure 2: Modelling methodology employed for the case.

As one can see in Figure 2, we organized the whole modelling process according to two mains aspects (Santa-Eulalia et al. 2008): “the modelling view” (vertical axis) and the “methodological phases” of the development process (horizontal axis). The modelling view comprises four main issues: supply chain (refers to the supply chain planning problem without thinking in terms of agents); agent (the supply chain domain problem is translated into an agent-based view); infrastructure (refers to a specific model in order to define how an agent system can be supported by computing resources, e.g., integrating infrastructure, and hardware); experimentation (refers to models guiding the design of experiments, i.e., how to manipulate factors to have the desired responses for the simulation).

As for the methodological phases (horizontal axis), the framework adheres to the methodology for simulation of distributed systems developed by Galland et al. (2003), which comprises the following phases: analysis (abstract description of the modelled system containing the simulation requirements); specification (translation of the information derived from the analysis into a formal model); design (creating a data-processing model that describes in more detail the specification model); implementation (translation of the model resulting from the design phase into a specific software platform); simulation (use of the simulation model by customers according to a set of experimental plans).

In the grid of Figure 2, three basic methodological approaches were employed together. First, the FAMASS (*F*ORAC *A*rchitecture for *M*odelling *A*gent-based *S*imulation for *S*upply chain planning), based on the premises of Santa-Eulalia et al. (2008) and Santa-Eulalia (2009), covers the supply chain and agent level. At *F*1, we model the supply chain planning problem by using a distributed decision logic. During *F*2, these models are converted into agent-based simulation requirements, capturing the social and individual aspects of the multi-agent system. These agent-based requirements are specified in *F*3, and then the system is designed in *F*4. *F3* and *F4* are inspired from Labarthe et al. (2007). The object-oriented approach in Figure 2 was used to create models detailing how the system has to be coded. First, at *O*1 we model the main classes to be implemented and the manner in which they synchronize messages with other classes, as well as with system infrastructure (databases, etc.). At the *O*2, the FORAC experimental planning platform is implemented using C++, the Microsoft .NET© C# language and, in order to put into operation the optimization mechanisms, we employed the Ilog OPL Studio© (which includes Cplex© and Solver©).

The focus of the present paper is on the third methodological approach, schematized in Figure 2 and inspired by the Taguchi Robust Design (Taguchi 2005). We performed in *T*1 the experimental design, manipulating factors and levels, interactions, responses, and uncertainties through orthogonal arrays, so that scenarios are specified and quantities of runs and replications are defined. At *T*2, we detailed these parameters by deciding how they would be configured in the system (e.g., modelling stochastic perturbations to represent the desired uncertainties). Finally, at *T*3 we executed all simulation runs and analyzed the simulation data through the statistical approaches proposed by Taguchi (Taguchi 2005).

Why we decided to employ an approach based on Taguchi Robust Design, as well as how we performed the three corresponding steps (*T*1, *T*2 and *T*3) are explained next.

5.1 Taguchi Robust Design

Despite the fact that simulation is a powerful tool for investigating the different behaviours of a given system (i.e., “what if” question), it does not provide a solution for optimizing a system (i.e., “what’s best”), while keeping robustness in mind. To address this problem, we employed an optimization-oriented experimental design to determine the optimum region for the combination of the system parameters. To design the experiments and analyze data, we employ the Taguchi Robust Design Methodology (Taguchi 2005).

The Taguchi approach was used in several studies in the area of supply chain management for studying optimal regions. For example, Genin et al. (2007) evaluate the robustness of multi-facilities tactical planning using a linear programming model coupled with a simulation model for a steel tubes supply chain. Shang et al. (2004) used Taguchi’s method for optimizing service levels and total costs using factors related to supply chain capacity, delayed differentiation approaches and cooperation strategies under uncertainties related to demand and inventory holding costs. Veza et al. (2003) applied Taguchi’s robust design for optimizing total costs of the system and backorders of a TV set supply chain. Grubić & Veza (2004) used exactly the same approach in a generic supply chain. Kleijnen et al. (2002) applied Taguchi’s view (not its statistical methods) in a case study for the mobile communications industry at Ericsson in Sweden.

This indicates that Taguchi’s approach for designing robust experiments has proven to be of great value. Shang et al. (2004) explain that other optimization-oriented experimental design methods can be used (solely or combined with Taguchi), especially RSM (Response Surface Methodology). The problem underlying RSM approaches is that they cannot optimize qualitative variables, such as the planning method. One of Taguchi's main drawbacks is that it does not fully take interaction factors into account, due to limitations in the linear graph of the orthogonal arrays. But, if the experimenter has reasons to believe that first order interactions (i.e., one-to-one factor interactions) are strong, this approach is of great applicability (Montgomery 1991).

The methodology can be summarized as three basic steps:

- *T1. Specifying the experiments*: before performing *F*1, the FAMASS approach provides us with general guidance for the classical experimental design, helping analysts to identify factors, levels, interactions and responses. Initially, by performing a screening approach, important factors are selected, as well as their respective levels. In addition, the simulation analysts have to consider whether interactions between these factors exist or not. Factors can be controllable (policy factors) and/or uncontrollable (noise factors, which managers have no control over, but that can be manipulated during the experiments). During the FAMASS phase, simulation analysts also have to select certain responses, i.e. KPI, to be used during the experiments. Based on the information provided by the FAMASS approach, we need to define at *T1* the orthogonal arrays to be used for the inner (controllable factors) and outer array (noise factors). These arrays will guide the simulation preparation, organizing factor levels for each experiment, quantities of simulation runs and replications.

- *T2. Designing experimental parameters*: in this phase we detail the simulation parameters defined in *T*1. First, one has to define how factors and their respective levels have to be operationalized. For example, if factor levels require different stochastic number generation approaches, one has to decide how they will be modelled. The same problems arise for uncertainties. For example, it would be important at this moment to decide how perturbations on the shop floor operations should be represented. Finally, how KPI are calculated and gathered is also discussed at *T*2.

- *T3. Collecting and analyzing data*: at this phase, one executes the experiments, i.e. a set of simulations is run in order to gather the selected KPI. After the simulation execution, data analysis is performed using an adapted version of the analysis of variance (ANOVA) approach, which guides analysts to identify the most influential factors, possible interactions between factors and to define the optimal configuration for control factors. In addition, plots are used to define the optimum region. Finally, the last step is to perform a confirmatory experiment, which allows verifying whether the optimal configuration is reliable for a given confidence interval.

The next subsection explains how this methodology is used for the softwood lumber case study.

6. Specifying the Experiments (T1)

Shang et al. (2004) suggest that a typical supply chain consists of *n*-vector controllable parameters, θ, and *m*-vector uncontrollable parameters, ξ. The performance of the supply chain can be expressed as $V_{sc}(\theta, \xi)$. Since $V_{sc}(\theta, \xi)$ depends on θ and ξ to optimize the supply chain one needs to find arg max $V_{sc}(\theta, \xi)$. Thus, this simulation experiment aims to identify the optimal θ^*:

$$V_{sc}(\theta^*, \xi) = \arg\max V_{sc}(\theta, \xi) \qquad [1]$$

In the present simulation study, the controllable factors are $\theta = \{c, h, m\}$, where

- $c \in$ {7 days, 14 days, 21 days} represents the control level that simulation analysts can test.
- $h \in$ {21 days, 42 days, 63 days} represents the planning horizon duration.
- $m \in$ {forward planning, urgency-directed forward planning} represents the planning method used.

This provides us with three controllable factors. Two of them have three levels and one has two levels. As we also believe that all these factors may interact, we test whether all first order interactions are present, i.e. c x h, c x m and h x m. When interactions exist, the effect of one factor depends on the level of other factors.

Despite the fact that noise factors are not controlled by managers in the real world, they can be in a simulation experiment. According to Davis (1993), a supply chain is under uncertainty of supply, manufacturing process and demand. By testing these three uncertainties, it is possible to determine the best setting of the controllable factors to minimize negative impacts on the supply chain performance. The uncertainties considered in this experiment are $\xi = \{s, m, d\}$, where:

- $s \in$ {profile 1, profile 2} represents the supply uncertainty.
- $p \in$ {low perturbation, high perturbation} represents manufacturing uncertainties.
- $d \in$ {optimist, pessimist} represents the demand uncertainty.

This provides us with three noise factors on two levels each. It is important to explain that *s* and *d* are determinist uncertainties. On the other hand, manufacturing uncertainties are of a stochastic nature in our model. In the following section we will provide more details on how these uncertainties were determined.

Finally, in terms of responses of the experiments, two KPI were selected, backorders (*B*) and daily average inventory (*I*). *B* is of great relevance for measuring customer satisfaction, while *I* is related to the company's point of view.

In an attempt to organize all these modelling decisions in a simple diagram, the simulation experiment is summarized in Figure 3 using a fishbone diagram.

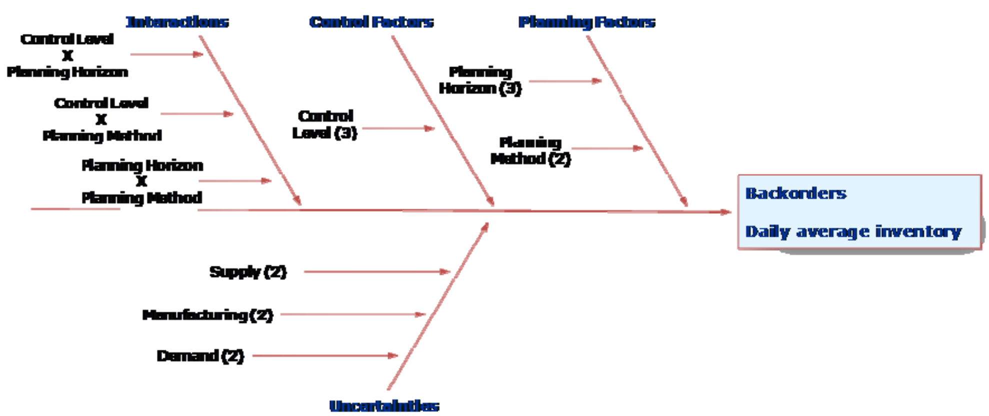

Figure 3: Experimental definitions.

Figure 3 indicates that the two KPI selected (backorders and daily average inventories) are influenced by factors related to the control system (control level) and planning system (planning horizon and planning method). In addition, as one factor can potentiate the others, interactions among these factors are to be tested. The diagram also indicates that the system is influenced by three uncertainties related to supply, manufacturing and demand.

Thus, based on the experimental definitions shown in Figure 3, we performed the experimental design using orthogonal arrays. Taguchi developed orthogonal arrays, linear graphs and triangular tables to provide the maximum amount of information with the lowest quantity of trials. Using Taguchi's orthogonal arrays logic, we selected the L_{27} design for the controllable factors. This orthogonal array is useful for 3 to 13 controllable factors and can be used to capture interactions as well. It provides 13 columns for the factors and interactions and 27 lines for the possible combination of factors, creating 27 experimental scenarios. This array was used with a mixed-levels approach, since two factors have three possible levels and one factor can assume only two levels. We could employ a more cost-effective inner array (e.g., L_{18}), but this would limit our study in terms of interactions analysis. As we are interested in knowing whether our factors interact with each other and how, L_{27} provides a good compromise. As for the outer array, we used a L_4 which is indicated for three two-level factors. The outer array will provide guidance for having four replications. The total number of experiments is 108.

This kind of experiment is very often a terminating simulation (Shang et al. 2004), which starts at a prescribed initial state in time (in our case, January 1), and terminates when the system reaches a prescribed terminal state or time (in our case, six months, or June 30). The simulation results reflect a planning horizon that is sufficiently broad to cover several replanning periods at the tactical level, traditionally varying from one to three months.

The following section explains how each simulation parameter was set.

7. Designing Experimental Parameters (T2)

In this section we explain how to configure experimental parameters, notably how uncertainties and KPI are modelled.

Two determinist supply profiles *s* exist. The first represents a situation where we provide the supply chain system with a higher distribution of logs favouring high-priced products, i.e. 2x6 end products. On the contrary, profile 2 provides the supply chain system with tree logs of a higher distribution of lower price end products (2x3 and 2x4 lumber products). This represents a situation where we are not always sure about the kind of supply that will be available to the company.

As for manufacturing uncertainties *m*, two possible stochastic levels were selected. The first represents a situation where the manufacturing system is better controlled (low perturbations); while the other refers to a manufacturing system less controlled (high perturbations). In the selected situation, the probability *P* of having a "low perturbation" is twice the probability of having a "bigger perturbation":

$$P(\text{"}\textit{High Perturbation}\text{"}) = 2\,P(\text{"}\textit{Low Perturbation}\text{"}) \qquad [2]$$

For both cases we employed a triangular distribution function with parameters *a*, *b*, *c*, where:

$$P(a \leq \textit{inventory} \leq \mathrm{c}) = 4\,P(c \leq \textit{inventory} \leq b) \qquad [3]$$

The impact of a manufacturing perturbation in this case is captured at the inventory level. The model aims at representing a real situation of manufacturing perturbation, where the probability of having inventory under the planned levels (due to machine breakdown, raw material problems, absenteeism etc.) is higher than having inventory over the planned levels. In this case, we choose a factor of 4. In addition, the perturbed inventory depends on the control level introduced in the manufacturing system. When inventory updates occur at a frequency of 21 days, the inventory level will include the accumulated perturbations for each of the previous 21 days. On the other hand, if a shorter updating frequency is used, say 7 days, only a third of the perturbations are counted when the inventory is updated. Thus, we considered that the probability *P* of occurrences of the manufacturing uncertainty is given by:

$$P(\text{“}control\ level = 14\ days\text{”}) = 2\,P(\text{“}control\ level = 7\ days\text{”}) \qquad [4]$$

$$P(\text{“}control\ level = 21\ days\text{”}) = 3\,P(\text{“}control\ level = 7\ days\text{”}) \qquad [5]$$

As for demand uncertainty *d*, two basic market situations were chosen. Based on the demand forecast, we created an optimistic demand representing 110% of the forecast, as well as a pessimistic demand representing 90% of the forecast. The forecasted demand for this case was generated in accordance with the supply chain capacity so that the capacity is filled to slightly over 100%. In addition, to respect the demand seasonal profile from the real world, we applied a sigmoidal seasonality factor for each product.

Finally, in terms of responses of the experiments, two KPI were selected, backorders (*B*) and daily average inventory (*I*), which are calculated as follows[1]:

$$B(days) = \sum_{p \in finished\_products} \left(late\_orders_p(bfm) * late\_days / total\_orders_p(bfm) \right) \qquad [6]$$

$$I(bfm/days) = \sum_{p \in finished\_products} \left(inventory\_each\_day_p(bfm) / planning\_horizon(days) \right) \qquad [7]$$

Note that both KPI are calculated for the products $p \in$ {finished products} to evaluate the performance of the entire supply chain. Three product families were

1 “bfm” (board feet measurement) is a common unit of measurement used in the lumber or timber domain, which represents 144 cubic inches of wood (1 foot x 1 foot x 1 inch).

selected, representing the most common products of this supply chain, i.e. 2x3, 2x4 and 2x6 lumber products.

These experimental designs guide us to create a set of simulation models in the FORAC experimental planning platform. Before using these models for simulation purposes, we performed several verification and validation steps to guarantee their reliability. During the verification steps, we checked if the results of the models could be considered logical. For example, we tested much higher uncertainties, compared with those proposed here, to verify how the planning system reacts. As for the validation tests, we compared the results of some preliminary experiments with planning results of the companies used as reference. The validation was conducted during over 18 months of close collaboration with the planning manager and his team. Outputs from the model were therefore validated in both an industrial context and a changing environment.

8. Collecting and Analyzing Data (T3)

We ran the 108 proposed experiments and gathered both B_{ij} and I_{ij} (scenario *i* and replication *j*). To analyze the data, we employed the Signal-To-Noise (SN) ratio measurement, as proposed by Taguchi. Signal represents the average value of responses and corresponds to the desired component. Noise is a measure of variability and represents the undesirable component. The largest SN ratio, measured in dB, gives the best setting. A larger SN indicates that the target (signal) is respected with a reduced dispersion of noise. The SN ratio is applied for B_{ij} and I_{ij}. Both backorder and daily average inventory have to be minimized, thus the appropriate Taguchi approach is the "smaller-is-better", calculated as follows:

$$SN_i(B_i) = -10 \cdot \log_{10}\left(\frac{1}{N_i}\sum_{j=1}^{N_i} B_{i,j}^2\right) \qquad [8]$$

$$SN_i(I_i) = -10 \cdot \log_{10}\left(\frac{1}{N_i}\sum_{j=1}^{N_i} I_{i,j}^2\right) \qquad [9]$$

Where, i represents the experiment number, j the replication (trial) number and N_i the number of trials for the experiment i, i.e. $\{a, b, c, d\}$. Taguchi's method analyzes the experimental results (after SN transformation) through ANOVA (analysis of variance), plots and summary measures. This allows determining which controllable factors are significant, whether factors interactions are present, as well as the optimal level for each factor. The software employed for performing these analyses is Optimum®. The SN ratio is applied for B_{ij} and I_{ij}, presented in Table 2 and the ANOVA for the experiments is presented in Table 3 and Table 4. The contribution of all factors and interactions is summarized in Figure 4.

Table 2: SN ratios for B_{ij} (in days) and I_{ij} (in bfm).

Experiment	B_{i1}	B_{i2}	B_{i3}	B_{i4}	I_{i1}	I_{i2}	I_{i3}	I_{i4}
1	0.092	0.262	0.217	0.234	250 314.50	271 969.70	314 426.80	420 602.70
2	0.329	0.454	0.394	0.219	208 088.80	227 162.04	371 697.70	158 488.20
3	0.334	0.258	0.289	0.146	401 686.60	174 794.08	732 363.30	773 137.10
4	0.209	0.256	0.334	0.175	381 497.60	245 196.48	269 675.30	638 233.40
5	0.219	0.368	0.338	0.268	661 180.60	168 444.51	335 023.40	112 306.90
6	0.214	0.238	0.270	0.234	437 088.30	99 125.43	265 602.60	1 261 063.00
7	0.201	0.288	0.442	0.223	228 438.00	331 501.70	120 508.30	176 862.30
8	0.289	0.369	0.333	0.193	357 918.30	393 301.09	375 651.70	387 715.00
9	0.202	0.231	0.222	0.228	805 320.10	310 277.74	656 375.00	876 689.80
10	0.313	0.530	0.534	0.656	276 090.30	432 133.87	225 652.10	769 648.80
11	0.447	0.394	0.697	0.574	437 692.10	186 522.27	212 584.80	389 742.30
12	0.620	0.332	0.594	0.717	513 701.10	511 222.40	150 799.50	582 472.40
13	0.537	0.557	0.692	0.651	383 118.90	339 387.51	628 090.60	360 660.80
14	0.557	0.323	0.712	0.601	392 304.40	204 577.88	222 496.50	484 860.10
15	0.454	0.399	0.446	0.687	295 233.40	229 246.97	323 578.20	478 322.30
16	0.445	0.470	0.641	0.340	580 496.40	375 471.21	179 963.50	257 489.90
17	0.574	0.551	0.624	0.447	181 006.80	237 834.66	551 386.10	434 396.60
18	0.370	0.475	0.557	0.746	592 438.70	168 292.81	188 276.50	2 674 379.00
19	1.999	1.527	2.133	2.325	569 874.80	150 470.88	72 786.93	161 817.70
20	1.650	1.242	1.781	2.364	1 123 301.00	1 803 871.25	313 188.70	1 263 710.00
21	0.908	0.630	1.772	2.012	473 377.90	249 512.59	113 630.10	316 860.30
22	1.995	1.870	2.104	2.404	458 685.10	337 507.82	156 754.90	324 274.40
23	2.145	1.733	1.967	1.942	845 836.40	2 191 214.54	108 060.20	476 611.80
24	1.764	2.749	2.080	1.238	992 909.60	235 369.80	1 684 962.00	164 338.40
25	1.888	1.994	2.085	2.192	291 074.40	309 170.51	130 402.40	472 616.10
26	1.799	2.066	1.849	2.067	489 798.30	182 270.73	226 413.70	208 221.50
27	1.730	2.046	1.919	2.408	369 338.50	308 601.90	225 657.90	339 285.20

Table 3: ANOVA for backorders (B_{ij}).

	Controllable Factors and Interactions	Contribution (%)	Probability of F (%)	F	Pooling
1	Control Level	97.7644	100.0000	875.3431	
2	Planning Horizon				X
3	Control Level x Planning Horizon				X
4	Planning Method	0.1990	95.4041	4.5602	
5	Control Level x Planning Method	0.5363	98.9169	5.7968	
6	Planning Horizon x Planning Method	0.0466	73.3119	1.4172	
	Error	1.4536			

Table 4: ANOVA for the daily average inventory (I_{ij}).

	Controllable Factors and Interactions	Contribution (%)	Probability of F (%)	F	Pooling
1	Control Level	0.9744	79.3747	1.7708	
2	Planning Horizon	2.3982	91.1471	2.8973	
3	Control Level x Planning Horizon	18.126	99.8712	8.1699	
4	Planning Method				X
5	Control Level x Planning Method	39.7672	99.9995	32.4604	
6	Planning Horizon x Planning Method	22.3018	99.9887	18.6433	
	Error	16.4325			

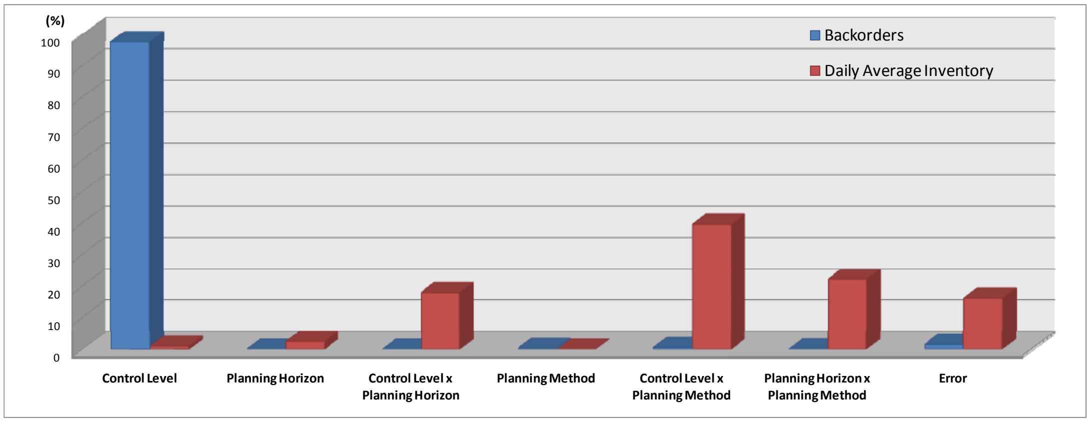

Figure 4: Contribution of all factors and interactions.

Figure 4 leads us to believe that the Control Level can be considered almost as the unique source of backorder variation, representing more than 97% of the contribution, with a confidence of 100%, while the remaining factors and interactions have little influence (less than 1% each, with at least 73% of confidence). Note that we performed pooling for the Planning Horizon and for the interaction Control Level and Planning Horizon, since they have a negligible influence on the performance. Consequently their variations were incorporated into the error category. Also, from this table we conclude that the experimental error is responsible for a small amount of variation, lower than 1.5%. This indicates that only approximately 1.5% of the variation cannot be explained by the model. This raises the importance of the Control Level for backorders, since we know from practice that when control is performed more frequently, all interferences from the modelled uncertainties are reduced. Hence, more time to recover from any problems engendered by these uncertainties is available, avoiding backorders.

The situation is not as clear for the daily average inventory. Table 4 points out that the controllable factors have little influence when configured solely. The most important factor is the planning horizon, which contributes approximately for only 2.4% of the variations, at 99% of confidence. The Control Level, in opposition to the backorder point of view, contributes to no more than 1%, with a confidence of almost 80%. Due to its negligible contribution, the Planning Method was pooled into the error. However, this second analysis leads us to understand that these controllable factors have a considerably large effect when configured together, due to the fact that interactions play an important role from the point of view of the daily average inventory. For example, with almost 100% of confidence, we can affirm that the interaction Control Level and Planning Method roughly contributes to 40% of the variations; that the interaction between the Planning Horizon and the Planning Method influences more than 22% of the inventory variations; and that the interaction between Control Level and the Planning Horizon has a contribution higher than 18%. Briefly, interactions are responsible for more than 80% of the variation.

Although this appears to be quite interesting, we would like to draw attention to the fact that the ANOVA for the daily average inventory indicates that about 16% of the variation cannot be explained by the controllable factors in question and their corresponding main interactions. Possibly these variations are related to the unique achievable second order interaction (i.e., among Control Level, Planning Horizon and Planning Method). This interaction is not evaluated here due to the limitations of the Taguchi approach, as discussed previously. In addition, many variations were introduced into the system through uncertainties related to supply, manufacturing, and demand.

Despite this limitation, interestingly, this second analysis indicates that if one desires to reduce inventories, we cannot consider only one isolated factor. Instead, a set of factors has to be taken into account at the same time due to the fact that one can potentiate others.

In order to define the optimum combination of factors, we provided an effect graph in Figure 5 and a set of interaction graphs in Figure 6 and Figure 7.

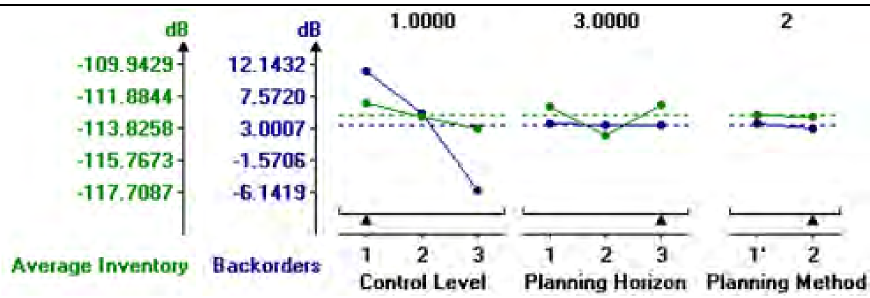

Figure 5: The plot for SN ratio for backorders and daily average inventory.

Figure 5 illustrates the graphs of effect for three relevant controllable factors in terms of backorders and daily average inventory. As we opted to prioritize customer service, we start with the most relevant factor for backorders. Because the objective of the Taguchi approach is to maximize the SN ratio, we can conclude that the best Control Level is seven days for both KPI (level 1). This is quite logical since tighter control makes it possible to detect problems earlier in the supply chain, thus avoiding backorders for example. The slopes of both curves also indicate that the control level is much more relevant for backorders than for the daily average inventory, and that we can improve supply chain performance by improving the frequency of the control level performed.

The analysis of the impact of the control level on the supply chain performance indicates to us possible interesting gains, as shown in Table 5.

Table 5: Possible gains by reconfiguring the control level.

Control Level	Average B_{ij} (days)	Average I_{ij} (bfm/days)
7 days	0,27	394 436,89
14 days	0,54	429 210,33
21 days	1,90	503 938,29

Table 5 indicates that the most frequent control level can provide important performance gains, i.e. up to 255% in terms of backorder and up to 17% in terms of daily average inventory.

In terms of planning horizons, by investigating Figure 5, it is obvious that no influence exists for the backorders because the curve is almost a horizontal line, so little could be done to improve the daily average inventory by changing the planning horizon exclusively. Consequently, we cannot select the optimum planning horizon by means of the main effect graphs because its interactions need to be studied first. Finally, the effects graph for the planning method indicates that it is not a relevant factor to be analyzed in isolation. Similarly, we would have to review interactions if we want to find an optimal configuration.

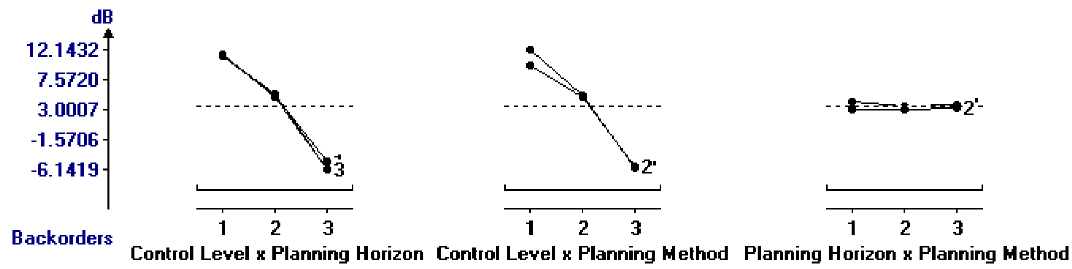

Figure 6: SN ratio for backorders: three possible interactions.

The three interactions curves in Figure 6 are not totally parallel, but neither do they have intersection points. This indicates that little or no interactions are present for the backorder analysis, confirming the ANOVA of Table 3. These curves are of no help in deciding the optimum for the planning horizon and planning method. It will be necessary to employ interaction graphs for the daily average inventory, as depicted in Figure 7.

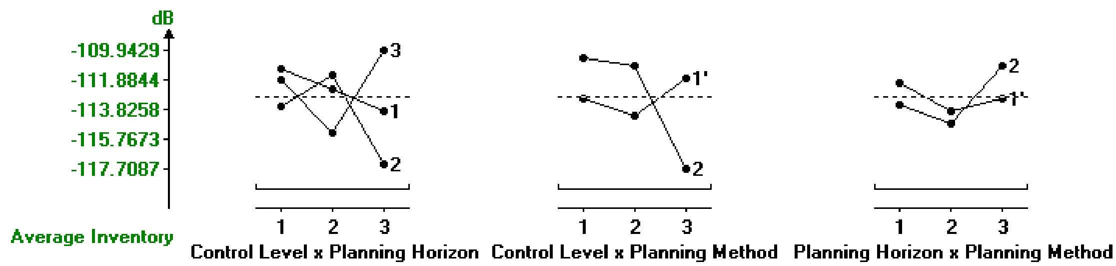

Figure 7: SN ratio for daily average inventory: three possible interactions.

Figure 7 helps us conclude that strong interactions are certainly present because all curves have intersections with their pairs. By analyzing the interaction “control level x planning horizon”, it is possible to see that, when control level is set to 1 (as decided previously), planning horizon 1 (21 days) and 3 (63 days) have high SN ratios, while the planning horizon number 2 (14 days) has a low SN ratio. We decided to select the planning horizon of 63 days to favour larger planning horizons so as to anticipate long term demand. The best planning method can now be determined by inspecting the remaining interaction graphs. When inspecting the interaction "control level x planning method", and since we previously determined that the optimum control level is seven days (level 1), we can say that the best control method to be used is the second one, i.e. the "urgency-directed forward planning". In the interaction "planning horizon x planning method" the best planning method is also the second one when the planning horizon is the third one.

Therefore, the optimum θ^* is {c = 7 days, h = 63 days, m = urgency-directed forward planning}. Next, we performed a confirmatory experiment to verify whether conclusions adhere to a selected confidence interval. According to the number of replications chosen and the risk of rejection selected, we determine the resulting confidence interval. With two replications and a risk of rejection of 1%, one can verify that the optimal setting is confirmed for both backorders and daily average inventory for confidence intervals of $8.6604 \text{ dB} \leq B \leq 12.2370 \text{ dB}$ and $-112.1908 \text{ dB} \leq I \leq -104.3074 \text{ dB}$.

Finally, in order to perform a preliminary statistical test to verify the presence of a second order factor interaction for the daily average inventory, we selected part of the simulation results of the 108 experiments performed before constructing a full-factorial design analysis, because it is the best experimental design to analyze interactions. In this case, to have a full-factorial matrix, we reduced the experimental region of the Taguchi design. We selected only two control levels (the extreme cases, i.e. 7 days and 21 days), two planning horizons (21 days and 63 days), and the two original planning methods. This reduced the original matrix to 32 experiments, instead of 108. Results of this full-factorial design analysis using the software SAS® indicates that a possible second order interaction has a p value of 0.0013, meaning that we have appreciable evidence of this effect, with a F = 13.1548 > 4.0467, suggesting that this effect is significant. The problem with this analysis is that its R^2 is only 54.13%, indicating that only half of the variations are explained by the model. Despite the fact that we have evidence to believe that a second order interaction exists, this preliminary study suggests that further experiments will be necessary to confirm it with more certainty.

9. Conclusions

This paper demonstrates the possibility and the relevance of testing supply chain tactics prior to their implementation through simulations performed in a d-APS system for the softwood lumber industry. To implement supply chain tactics is not a simple task, since it involves many parameters to be tested under several different supply chain uncertainties. By testing some policies through agent-based experiments, supply chain analysts can obtain reliable knowledge about new ways of creating value, without large investments. This ability is particularly important in rapidly changing and uncertain environments, where new ideas can be tested before committing more resources to them. In this sense, a d-APS system, notably the FORAC experimental planning platform, supported by our simulation modelling methodology, has shown great potential. It represents a realistic environment for sophisticated simulations in the selected industry sector, in which a set of agents mimicking supply chain units interact with each other and make intelligent decisions, considering both local and global supply chain objectives and constraints under typical business uncertainties.

In terms of simulation results for the lumber industry, perhaps the most important findings concern how to improve service levels to customers. The first analysis leads us to understand that supply chain control levels play quite a relevant role in defining robust service levels, while the supply chain planning horizon and method do not contribute significantly in this context. We identified that the more frequently control is performed, the more efficient the supply chain will be. In addition, from the supply chain inventory level point of view, we verified that the tactical rules related to control levels, planning horizon and planning methods have to be configured together if one desires to maximize their contribution for a robust supply chain system capable of coping with uncertainties from the business environment.

Due to the methodological limitations of the Taguchi experimental design, the second analysis (daily average inventory) is not able to explain about 16% of the variations in terms of inventory levels. We believe that most of this variation can be related to second order interaction among all the tactical policies selected for this study. Further experiments, together with other methodological approaches, will be necessary to refine these findings and confirm this hypothesis. Moreover, it is important to note that the validation experiments were done only for the experimental region delimited by the characteristics of this study, i.e., the region covered by different factor levels. This can limit the generalization of these experiments for a larger experimental region. For generalizing this experiment, one can perform more simulations, including adding more factors, levels, and uncertainties; as long as other experimental design methodologies can be applied, such as the RSM approach.

Finally, it is important to note that, despite the fact that both results and methodology are validated for a softwood lumber case, the authors strongly believe that other industry sectors would benefit from this approach and from the experience gained from the statistical results discussed, mainly those that have important stochastic behaviours in terms of supply, demand and manufacturing operations, as well as those having a divergent production process, like the softwood lumber industry.

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References

APICS, 2008. APICS: The Association of Operations Management - Online Dictionary. Available at: www.apics.org.

Azevedo, A. et al., 2004. An advanced agent-based order planning system for dynamic networked enterprises. *Production Planning & Control*, 15(2), 133–144.

Baumgaertel, H. & John, U., 2003. Combining agent-based supply net simulation and constraint technology for highly efficient simulation of supply networks using APS systems. In *2003 Winter Simulation Conference*.

Beaudoin, D., LeBel, L. & Frayret, J., 2007. Tactical supply chain planning in the forest products industry through optimization and scenario-based analysis. *Canadian Journal of Forest Research*, 37(2007), 128-140.

Cid-Yanez, F., J.-M., F. & Léger, F., 2008. Evaluation of push and pull strategies in lumber production: an agent-based approach. *International Journal of Production Research*, In press.

Comelli, M., Gourgand, M. & Lemoine, D., 2006. A review of tactical planning models. In *2006 International Conference on Service Systems and Service Management*. pp. 594-600.

Comelli, M., Féniès, P. & Tchernev, N., 2008. A combined financial and physical flows evaluation for logistic process and tactical production planning: Application in a company supply chain. *International Journal of Production Economics*, 112(1), 77-95.

Davis, T., 1993. Effective supply chain management. *Sloan Management Review*, 3(4), 35-46.

Frayret, J. et al., 2007. Agent-based supply-chain planning in the forest products industry. *International Journal of Flexible Manufacturing Systems*, 19(4), 358-391.

Galland, S. et al., 2003. MAMA-S: an introduction to a methodological approach for the simulation of distributed industrial systems. *International Journal of Production Economics*, 85, 11–31.

Gaudreault, J. et al., 2006. Integrated planning and scheduling in a divergent production system with co production. *Working paper CIRRELT DT-2006-JMF-1*. Available at: www.cirrelt.ca.

Genin, P., Thomas, A. & Lamouri, S., 2007. How to manage robust tactical planning with an APS (Advanced Planning Systems). *Journal of Intelligent Manufacturing*, 18, 209-221.

Gjerdrum, J., Shah, N. & Papageorgiou, L.G., 2001. A combined optimization and agent-based approach to supply chain modelling and performance assessment. *Production Planning and Control*, 12, 81-88.

Grubić, T. & Veza, I., 2004. Supply chain design with the use of Taguchi method.

Hax, A.C. & Meal, H.C., 1973. *Hierarchical integration of production planning and scheduling*, Massachusetts Institute of Technology (MIT), Sloan School of Management. Available at: http://ideas.repec.org/p/mit/sloanp/1868.html [Accessed October 2, 2009].

Kazemi, M., Ait-Kadi, D. & Nour El Fath, M., 2008. Robust production planning in a manufacturing environment with random yield: A case in sawmill production planning. Available at: www.cirrelt.ca.

Kleijnen, J., Bettonvil, B. & Persson, F., 2003. Robust solutions for supply chain management: Simulation and risk analysis. *robustness_KLICT_1*. Available at: http://www.atoapps.nl/klictware/docs/HR-178/Robust%20solutions%20for%20supply%20chain%20management.pdf.

Labarthe, O. et al., 2007. Toward a methodological framework for agent-based modelling and simulation of supply chain in a mass customization context. *Simulation Modelling Practice and Theory*, 15(2), 113-136.

Landeghem, H. & Vanmaele, H., 2002. Robust planning: a new paradigm for demand chain planning. *Journal of Operations Management*, 20(2002), 769-783.

von Lanzenauer, C.H. & Pilz-Glombik, K., 2002. Coordinating supply chain decisions: an optimization model. *OR Spectrum*, 24(1), 59-78.

Lemieux, S., D'Amours, S. & Frayret, J., 2008. Agent-based simulation to anticipate impacts of tactical supply chain decisions in the lumber industry. *FORAC Working Paper*. Available at: www.forac.ulaval.ca.

Lemieux, S. et al., 2008. Intégration d'outils APS dans une simulation multiagent : une application à l'industrie du bois d'oeuvre. In *MOSIM'08 - 7ème Conférence Francophone de Modélisation et Simulation*. Paris.

Matsumoto, M. & Nishimura, T., 1998. Mersenne twister: a 623-dimensionally equidistributed uniform pseudo-random number generator. *ACM Trans. Model. Comput. Simul.*, 8(1), 3-30.

Montgomery, D., 1991. *Design and analysis of experiments*, New York: John Woley & Sons.

Montreuil, B., Frayret, J. & D'Amours, S., 2000. A strategic framework for networked manufacturing. *Comput. Ind.*, 42(2-3), 299-317.

Ouhimmou, M. et al., 2008. Furniture supply chain tactical planning optimization using a time decomposition approach. *European Journal of Operational Research*, 189(3), 952-970.

Sadeh, N.M. et al., 1999. MASCOT: an agent-based architecture for coordinated mixed-initiative supply chain planning and scheduling. In *Agents'99 Workshop 'Agent-based ecision-support for managing the Interned-enabled supply-chain', Agents 99*. Seattle, pp. 133–138.

Santa-Eulalia, L., 2009. *Agent-based simulations for advanced supply chain planning: a methodological framework for requirements analysis and deployment*. Ph.D. Thesis. Université Laval, Faculté des Sciences et Génie.

Santa-Eulalia, L., D'Amours, S. & Frayret, J., 2008. Essay on conceptual modelling, analysis and illustration of agent-based simulations for distributed supply chain planning. *INFOR Information Systems and Operations Research Journal*, 46(2), 97-116.

Sauter, J.A., Parunak, H. & Goic, G., 1999. ANTS in the supply chain. In *Agents'99 Workshop Agent-based decision-support for managing the Interned-enabled supply-chain*. Seattle.

Shang, J., Li, S. & Tadikamalla, P., 2004. Operational design of a supply chain system using the Taguchi method, response surface methodology, simulation, and optimization. *international Journal of Production Research*, 42(18), 3823-3849.

Sodhi, M., 2005. Managing demand risk in tactical supply chain planning for a global consumer electronics company. *Production and Operations Management*, 14(1), 69-79.

Stadtler, H., 2005. Supply chain management and advanced planning - basics, overview and challenges. *European Journal of Operational Research*, 163(2005), 575-588.

Swaminathan, J., Smith, S. & Sadeh, N., 1998. Modelling supply chain dynamics: a multiagent approach. *Decision Sciences*, 29(3), 607-632.

Taguchi, G., 2005. *Taguchi's quality engineering handbook*, New Jersey: John Woley & Sons.

Thomas, A., Genin, P. & Lamouri, S., 2008. Mathematical Programming Approaches for Stable Tactical and Operational Planning in Supply Chain and APS Context. *Journal of Decision Systems*, 17(3), 425-455.

Van Eck, M., 2003. Advanced planning and scheduling: is logistics everything? *Working Paper, Vrije Universiteit Amsterdam*.

Veza, I., Grubic, T. & Bilic, B., 2003. Application of robust design in a supply chain design process. *International Journal of Simulation Modelling*, 2(3), 78-88.

Zhang, S. & Tong, Q., 2005. Modelling lumber recovery in relation to selected tree characteristics in jack pine using sawing simulator Optitek. *Annals of Forest Science*, 62(3), 219-228.