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Agent-based Simulation for Distributed Supply Chain Planning: Conceptual Modeling, Analysis and Illustration

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Abstract. Recent developments in supply chain planning have emerged from the field of agent technology and distributed decision making. Although several attempts have been made to exploit agent technology to design supply chain simulation tools, the integration of simulation with these distributed supply chain planning tools still remain to be addressed. This paper aims at investigating this aspect of supply chain planning through the use of theoretical contributions found in the field of simulation, systems theory and distributed decision making. More specifically, this paper proposes an analysis of the several uses of simulation in a supply chain context, both from the decision maker and the academic point of views. A theoretical illustrative case is finally presented in the lumber supply chain.

Keywords. agent-based simulation, advanced planning and scheduling, lumber supply chain.

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1. Introduction

Advanced Planning and Scheduling (APS) systems are largely considered as being the state-of-the-art solutions for production and supply chain (SC) planning. Despite their significant contribution to planning and scheduling of complex manufacturing systems, researchers and practitioners are currently facing research gaps in this domain ([10], [19]). In this paper we will approach two of them.

The first gap concerns the evolution of centralized, monolithic and hierarchical planning approaches compared to decentralized and collaborative ones. Centralized approaches can indeed be suitable within a local planning domain (e.g., an enterprise or a factory). However, they are considered inadequate to cover more complex and realistic situations with respect to the consideration of partners' plans. To overcome this limitation a set of approaches have been developed and tested. Specially, research developments in agent-based technology have shown great potential. In this case, decentralized models produce distributed plans which are coordinated by collaborative agents acting together to form a supply chain planning system [7].

The second gap concerns how APS systems can cope with uncertainty in a dynamic world. Considering the uncertain nature of the business environment, robustness and risk assessment play an important role. In order to manage uncertainty, simulation is seen as one of the most promising approaches in SC planning [9]. In current commercial APS systems, the potential of simulation is limited to runs of deterministic "what-if" tests of possible plans, in which a few exceptional situations can be tested in a "copied" version of the APS. If greater sophistication is needed, integration to other simulation systems may be required. Again, agent-based technologies appear as an interesting option for modeling distributed uncertain environments. Moreover, this technology allows for more flexible experiments than traditional simulation techniques.

Since the 90s, several agent-based approaches for manufacturing and SCs have been proposed in order to address these gaps [3]. Although there have been many relevant advances in this field, the potential of agent-based simulation in the domain of advanced planning & scheduling systems in a distributed context has still not been properly discussed in the literature. This paper aims at investigating this gap by exploring the potential use of simulation in distributed supply chain planning, as well as proposing some high-level modeling constructs for defining simulation problems that capture the distributed and stochastic behaviours of supply chains using agents.

In order to do so, our research approach consists in a systematic study of some fundamental works from the literature in the following areas: simulation [22], theory of complex systems [12], theory of distributed decision-making [18], and simulation methodology for distributed industrial systems ([37], [38]). These research areas and they respective works were selected because we believe that they are essential to understand our research problem. Anchored in these works, we propose some conceptual models to explore the potential use of simulation in a supply chain planning context. In order to illustrate our discussion, a theoretical case is presented as a proof-of-concept model in the lumber SC using a supply chain planning system specialized in the Canadian forest products industry and developed by the FOR@C Research Consortium.

This paper is organized as follows: section 2 discusses the concept of supply chain planning systems; section 3 defines how the concept of simulation can be employed in this context; also, this section proposes some conceptual modeling constructs; section 4 presents a theoretical illustrative case; and finally section 5 provides the conclusion and future steps.

2. Distributed Supply Chain Planning

This section defines and explains what a supply chain planning system is and why agents can be seen as an interesting modeling approach.

First, we have to understand what exactly an APS is. APS are computer supported planning systems for SCs. They are typically hierarchical production planning systems ([8], [20]). These systems employ operations research (OR) and primarily mathematical programming and meta-heuristics, in order to carry out integrated finite-capacity planning and scheduling, covering strategic, tactical and operational planning levels, for procurement, production, distribution and sales ([7], [20]). Although SC Management (SCM) refers to the coordination of operations, processes and distribution throughout the SC, few APS, if any, have the ability to cross organizational borders in order to properly address this purpose.

Software agents, on the other hand, are autonomous entities that sense their environment and carry out actions on it. They can communicate with one another and follow their own agenda to achieve their goals [26]. They are often used to model SCs because both can be considered as networks of distributed and cooperative entities aiming at solving problems together.

Several research developments propose approaches to distribute decisions across the SC using agent technology. For example, the pioneering work of Fox et al. [6] followed by others Parunak [16], Swaminathan [24], Strader et al. [23] and Montreuil et al. [14] just to mention a few, have led to some significant advances through the identification of fundamental entities for modeling SCs. However, the notion of APS systems is not explicitly addressed in most works. For instance, in many cases optimization routines are not explored clearly. More recently, APS have been explicitly addressed by some authors ([2], [13]). In Lendermann and McGinnis [13], traditional APS systems are integrated to distributed simulations which are encapsulated as federates, while in Baumgaertel and John [2] agents directly implement a distributed APS logic and their simulation capabilities.

Most work in this area are concerned with supply chain planning systems. Such a system can be defined as a distributed advanced planning and scheduling system (d-APS) that models the supply chain as a set of semi-autonomous and collaborative entities acting together to coordinate their decentralized plans. The concept of d-APS goes further than classic APS, as they allow for additional capabilities, such as the utilization of negotiation and artificial intelligence mechanisms to coordinate SC planning.

Agents can be seen as an interesting modeling construct for this kind of distributed SC planning logic, although a SC is considered a complex system [25]. Modeling a complex system can be challenging and we will explain why agents can be relevant.

According to Le Moigne [12], there are nine different comprehension levels for modeling a complex system, such as a SC. They are: 1) the phenomenon is identifiable: modellers have a minimum perception and identify the system as just a “closed set”; 2) the phenomenon is active: the closed set, seen as a “black box”, simply takes inputs and transforms them into outputs; 3) the phenomenon is controlled: the system has a simple internal mechanism for regulation, that is, a feedback control system; 4) the phenomenon has complex artefacts for regulation: as an evolution of the 3rd level, the system is able to get informed about its own behaviour for more complex regulations; that is, the system is auto-controlled through something as internal “nerves” used for communication and auto-control; 5) the system has cognitive capacity: capable of producing information, the system is now able to treat it and make decisions concerning its own behaviour; 6) the phenomenon has a memory system: more than using instantaneous information, as a thermostat does, the memory is an information system used to take more complex decisions; 7) the system is able to coordinate numerous decisions over time: not only one decision; 8) the system has an imagination capacity: for performing self-conception and to change its own design; 9) the system has finalization capacity: the system itself can “decide on its decision” so as it can infer that no more decisions will be necessary and terminate itself. These levels are accumulative, that is, modeling a system at the 6th level means that the preceding levels are also considered in the model.

Different modeling approaches can capture different complexity levels. For example, OR is a very good approach for modeling the 1st and 2nd levels, but OR was not conceived for modeling feedback control, as the 3rd level proposes. On the other hand, agents abstract real-life entities (as decision-makers and organizations) in a way that captures more complex SC behaviours, perhaps as the domain emerged from the distributed artificial intelligence field. In this case, agents can model the 3rd and 4th levels because they are conceived for monitoring their environment and acting upon it in a reactive or even proactive way. In addition, agents may model 5th and 6th levels because they can encapsulate complex cognitive capacities which employ various knowledge bases for decision-making. Also, due to its very distributed nature and its social abilities, agents are able to coordinate numerous decisions over time, which means that the 7th level can be modeled as well. For us, the 8th and 9th level are inherently suitable to real life agents, i.e. human beings, and the existing modeling approaches can still not capture their complexity.

Agents and OR form an interesting partnership to address supply chain planning problems. OR models and methods are encapsulated by agents representing distributed organizations in a SC. These models and methods stands for the cognitive capacity of agents, i.e., the decision-making ability of each organization in a SC. Each agent makes local decisions employing its cognition and collectively interacts with one another in order to arrive at global decisions. An agent’s social ability can be understood as a kind of meta-heuristic coordinating several OR tools in a way that allows complex social behaviours such as negotiations and collaboration. Thus, agents can be seen as a general framework for representing SC entities where different advanced planning tools can be plugged together and collaborate. This creates an attractive environment for performing experiments in the domain of SC planning.

Figure 1 schematizes this concept. Agent n encapsulates an APS tool dedicated to a specific planning domain n (e.g., a product assembler) while Agent $n+1$ encapsulates specialized APS for the planning domain $n+1$ (e.g., a distributor). Agent n interacts with $n+1$ exchanging information or negotiating. Also, the assembler interacts with a set of suppliers and the distributor cooperates with

a set of customers. Each agent has its own specialized APS tool that can provide solutions to its own planning problem. The whole SC planning takes place when all agents interact with one another collaboratively in order to reconcile their local plans with the global plan for the entire SC.

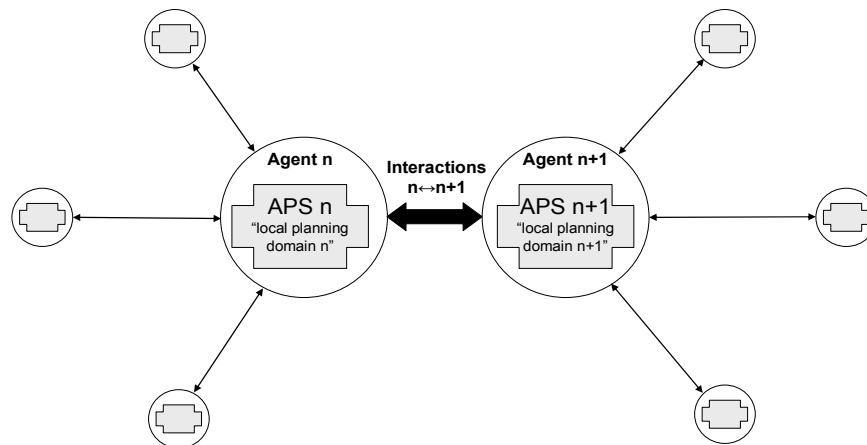


Figure 1: Distributed APS.

Even given the potential benefits of this technology, agents in manufacturing and SC planning are in its infancy [3]. Most of the known work in this domain presents limitations. To our knowledge it lacks, among others: a formal understanding of what is simulation in the context of supply chain planning; which simulation possibilities can be explored; and how to define simulation experiments for supporting the distributed planning and coordination of SCs. The remaining sections present our insight concerning these points.

3. Simulation and Distributed Supply Chain Planning

This section puts the notion of simulation into context and explores its potential. First, subsection 3.1 defines the wide concept of simulation. After, section 3.2 presents the scope of simulation in this context; then, subsection 3.3 discusses what kinds of simulation possibilities are possible. Subsection 3.4 proposes a conceptual model for identifying the simulation problem in SC, while, subsection 3.5 explains how one can translate these problems into a distributed model for supporting supply chain planning simulations. Next, sub-section 3.6 goes further in the notion of distribution and discusses how the simulation can be used to anticipate the impacts of distributed decision levels. Finally, section 3.7 discusses these ideas in methodological terms so as one can understand how the proposed conceptual models can be employed when creating supply chain planning simulations.

3.1 Simulation Definition

The notion of experimentation has been gaining considerable attention in recent years. Economists coined the meaningful term “experimental economy” and they pointed out the experimentation capacity is of great importance for companies or even nations to become and stay competitive. For example, it is widely believed that, “companies will have to look at their initiatives as “experiments,” attempts to find their way through a maze of uncertainty” [28]. Dominique Foray [29] states that we are actually moving toward the experimental economy in which experiments

with new solutions, technologies and approaches will become the normal state of affairs. Experimenting allows for the generation of reliable knowledge about new ways of creating value. This is particularly important in rapidly-changing and uncertain environments, where new ideas can be tested before committing more resources to them.

The term experimentation stands for the large notion of conducting tests of ideas under controlled conditions. The term “simulation” employed here can be understood as a synonym for “experiment”. The classical definitions of simulation refer to it as a “numerical exercise of a model” for the inputs to observe how output measures of performance are affected by these inputs [27]. Here, it is a generic and wider label for traditional simulation. It also includes more simple tests in which no mathematical simulation techniques (e.g., event-based simulations, system dynamics or game theory) are employed, as when testing prototypes, executing pilot projects or performing role-play games. It covers the idea of conducting tests and investigations also in real systems, not only in “virtual” systems, as will be discussed in the next sub-section. Many scholars and managers intuitively employ the term simulation as a more global concept and this common sense definition is largely used inside companies and in the literature of diverse domains. We prefer to adopt the term simulation so as to not disagree with this common sense utilization.

Due to the volatility of the planning environment, simulation can be an interesting approach in the APS domain, as discussed in the next sub-sections.

3.2 Simulation Scopes

According to Petrovic [30], dealing with uncertainty is an important issue in SC. Different sources of uncertainty exist in a SC, originating from suppliers, production and customers [4]. These uncertainties create a complex planning environment in which decision makers have to analyze different decision alternatives before implementing a given decision.

The management of uncertainties is a significant limitation of APS systems [19]. Many efforts have been made to overcome this drawback. For example, there is today an emergence of APS employing stochastic programming. This technique involves the design of resource allocation models taking explicitly into account the randomness of the decision making context. It is a powerful approach where the expected result is optimized according to statistical information about the decision parameters and the expected outputs. For example, Santoro et al. [40] present a stochastic programming approach for solving strategic SC design problems of realistic scales where a huge numbers of scenarios are modeled and analysed. However, due to the large number of scenario to consider, stochastic programming models are usually large and difficult to solve. It is even more complex to solve at the tactical and operational levels where models are generally multi-period.

Along the same line, simulation can be used in a SCM context to manage uncertainty [9]. It allows for scenarios analysis in stochastic and complex contexts. However, the use of simulation in the context of supply chain planning systems still remains to be investigated by academics and such complex tools still need to be developed. In order to investigate this domain, we first exploit Serman’s work on simulation [22]. In brief, the author explains that the objective of a simulation is to streamline the learning process. Based on this idea, Figure 2 represents a general understanding

of the simulation scopes in the context of supply chain planning. Three basic learning processes are presented: “intuitive learning” which naturally occurs when a decision-maker interacts with the real world and learns from reality; “formal learning”, in which the learning process is formalized through models or maps rather than occurring intuitively; “formal learning via simulation” in which the formalization is done through simulation models.

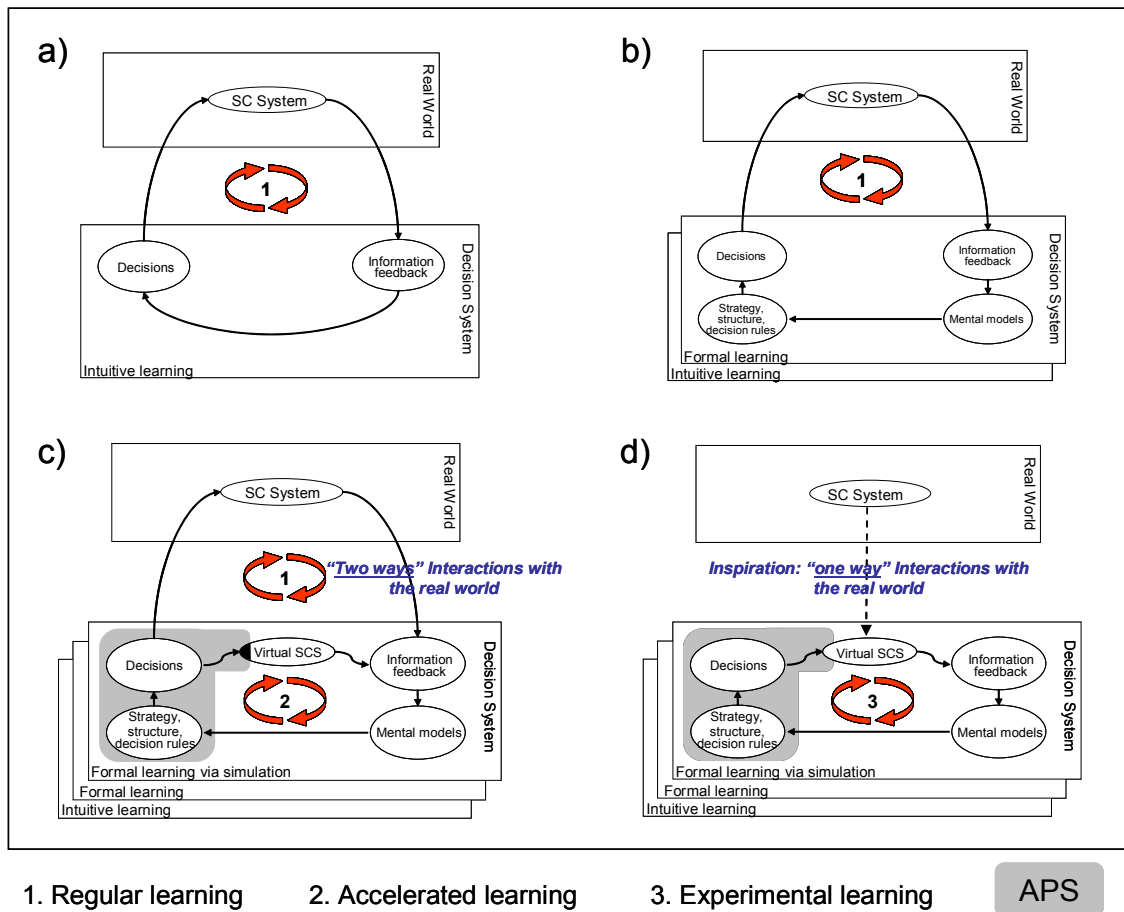


Figure 2: The learning processes.

Both “intuitive” and “formal” learning occurs through what is called a single learning loop (loop 1). Figure 2a) presents this loop, that can be seen as a “regular learning” process, in which the decision system (i.e., generally a human decision-maker) learns based on his/her experience with the real world. More precisely, the decision-maker, based on his own free will, decides to put the results of his learning into practice in the real world (the SC system – SCS). This produces some effects on the real world, which can be captured by the decision-maker’s information system, which in turn closes the feedback loop.

Next, the difference in Figure 2b) from Figure 2a) is the fact that feedback is “formally” used to change the decision-maker’s mental models, who can then design new goals and new decision rules, strategies and structures. In this case, information is manipulated through formal maps. Both processes (“intuitive” and “formal”) employ the regular learning mechanism that is, learning loop 1.

This “regular” learning process presents a set of limitations. For example, decision makers can make inferences about the consequences of their decision rules in unknown contexts. Or, the learning process can be considered extremely time consuming due to system complexity. In these cases, decision-makers can test their decision rules in a virtual world (Figure 2c) to streamline the leaning process.

Hence, in Figure 2c) the virtual world is composed of formal simulation models (e.g., physical models, role-play, and computer simulations), forming a relevant environment for decision-makers to conduct experiments. The simulation environment stimulates reflective thoughts in a way to break with established concepts. Such a virtual world may be necessary for effective learning in dynamically complex situations. This forms a double learning loop (loop 2), in which time and space can be compressed, actions can be repeated under the same or different conditions (or one can stop the action to analyze it), and one can study risky decisions without disrupting the real world. It is an accelerated learning process. In fact, an effective learning involves continuous experimentation in both the virtual world and real world (loop 1 and 2), as can be noted in Figure 2c.

In this framework, APS systems embed simultaneously “strategies, structures and rules”, as well as the decisions themselves. The latter is related to basic APS functionality (decision support system) and the former are important prerequisites to any decision process. Strategies, structures and decision rules are represented through APS mathematical models (objective functions, variables, constraints and parameters). In addition, APS may also include some basic “what-if” simulation capabilities, which are part of the virtual world (Figure 2c). This kind of simulation represents only one simulation possibility in virtual worlds, as mentioned in section 1.

The simulation functionality can be expanded to cover more possibilities. For example, Santa-Eulalia et al. [17], Labarthe et al. [11] and Swaminathan [24], among others, propose agent-based discrete-event simulation models for SC planning. In a different way, Moyaux [15] deals with simulations based on game theory and agent models to analyze the bullwhip effect across SCs. Kleijnen and Persson [10] employ Monte Carlo simulation together with traditional Design of Experiments and meta models for analyzing the robustness of a SC configuration. The work of Strader et al. [23] integrates system dynamics-based simulation and discrete agent-based modeling for studying order fulfillment and supplier evaluation policies in SCs. These are a few examples showing the potential of SC simulation. As it will be discussed later, it is possible to model different aspects of a SC system by means of agent-based simulation models, in order to leverage the potential of APS systems.

Figure 2d) presents an experimental learning loop (loop 3), which can be used for research activities (e.g., academic studies). In Figure 2a), b) and c), the real world inspires the creation of the virtual world and the decision-makers continuous interacting with the real world (loop 1) to implement decisions tested in the loop 2 or to gather more information (a “two ways interaction”, as seen in the Figure 2c)). Instead, in the learning loop 3 the only interaction between the real and virtual worlds is the inspirations that modellers employ when creating the virtual world (a “one way interaction”, as seen in the Figure 2d)). After, experimentation can be done in the virtual world without direct connection in the real world. This can be useful when the disconnection with reality does not impose problems to the analyst as he/she is more interested in conceptual aspects rather

than in practical ones. As a consequence, complex simulation models can be developed without requiring detailed information about the real world problems, what can burden theoretical studies.

These leaning loops allow experimenters to mainly perform three kinds of simulation, as it will be discussed in the next sub-section.

3.3 Simulation Uses

Based on the proposed learning loops, we suggest that three kinds of simulation are possible:

i) Simulation for Decision-Making: it refers to the use of simulation techniques to assist the decision-making process. In this case, prior to the implementation, the decision-maker tests one or several possible decisions in a real environment (loop 1) and/or in virtual environment (loop 2) for comprehension and comparison purposes. For example, Kleijnen and Persson [10] propose a simulation method for assessing three different SC designs at Ericsson in Sweden. In order to select the best design, they tested these scenarios by varying diverse factors for evaluating the SC robustness, i.e., the ability to handle changes in those factors without changing the SC design;

ii) Simulation for Technology Evaluation: instead of using the simulation to support organisational decisions, this simulation possibility employs the learning loop 3 for evaluating different supply chain planning technologies. In this case, as agents are very flexible, the d-APS tool is seen as a test-bench for new technological approaches. Basically, one can test technology in terms of:

(a) Agent cognitive capacity – i.e., the APS tool being employed, defining planning algorithms and methods. For example, the work of Gaudreault et al. [31] proposes different planning approaches (APS tools) for a softwood lumber SC. They use different models and algorithms (based on mixed integer programming and on constraint programming) in an agent-based planning system. The quality of solutions and computation time for three planning tools are evaluated;

(b) Agent behaviour – internal and social behaviour of the agents. For example, the work of Forget et al. [32] proposes a multi-behaviour agent model employing different decision-making approaches in the context a supply chain planning system. Agent's behaviour can vary from totally reactive employing only technical competencies (e.g., APS tools) to a cognitive agent employing complex collaborative competencies with learning abilities. They propose a simulation schema where when the system reaches a new state, each agent evaluates the situation and can select the appropriate behaviour;

(c) Agent middleware and network – which manages the interaction of different applications across different platforms. For example, the work of Gain et al. [33] perform simulation tests to compare two middleware approaches, namely the Runtime Infrastructure (RTI) of the High Level Architecture (HLA) and a tailor-made alternative approach in which a distributed simulation is implemented by a parallel and distributed discrete event simulation technology based on an extended asynchronous simulation protocol. The authors compare two issues (interoperability and performance) and tests were done using a semiconductor SC model.

iii) Simulation for Education: based on the learning loop 3, it refers to the use of simulation as a means to support training and education. Olhanger & Persson [39] report on the learning effects of

using simulations for investigating the behaviour of different production and inventory control methods in manufacturing within student projects. They demonstrated that the use of simulation provided a fast and accurate feedback loop for the students. Perhaps the most well-known simulation approach for this situation is Business Games (BG). BG are interactive experiments that allow managers to operate business situations within a simulated world. It is useful to model and simulate human behaviour, which is quite difficult compared to technological processes. These games are mainly used for educational purposes (e.g., to teach managers about the bullwhip effect across a SC – as with the famous Beer Game), but they are used in research as well (e.g., to study the confidence that managers have in their decisions). In this case, “human agents”, instead of software agents, interact with each other. For example, Holweg and Bicheno [34] describe a participative simulation model to demonstrate SC dynamics. It includes various levels of management from companies along the same SC, including directors, planners, schedulers, and was also used to train graduate level entry staff. Another interesting example of the beer game is presented by Van Horne and Marier [35]. It is called the Quebec Wood Supply Chain Game and uses the model of the classical Beer Game in the forest products industry, and can be played on the Internet. One interesting approach for education and training is the use of supply chain planning systems employing software agents together with human agents. The work of Dobson et al. [36] explores agent-based strategy games for decision training, but to our knowledge, this possibility is still not widely explored in the literature of SCM.

Among the three possibilities, perhaps the simulation for decision-making is the most common approach in the literature and will be the focus of our remaining sub-sections.

These three kinds of simulation require a virtual environment. Thus, the question that now arises is what exactly the virtual world can capture in order to perform simulations in a supply chain planning context, and why using agents can be advantageous. Therefore, sub-section 3.4 defines what a simulation problem is and sub-section 3.5 discusses how a simulation can be translated into a distributed agent-based system.

3.4 Simulation Problem

In order to understand what a virtual SC world can capture, this sub-section introduces the concepts of object and object environment. A virtual SCS aims at describing the behaviour of a given object (e.g., the SC, a facility, a relationship) under pre-defined environmental conditions (e.g., market conditions, material procurement limitations) in order to streamline the learning process related to SC planning (Figure 3).

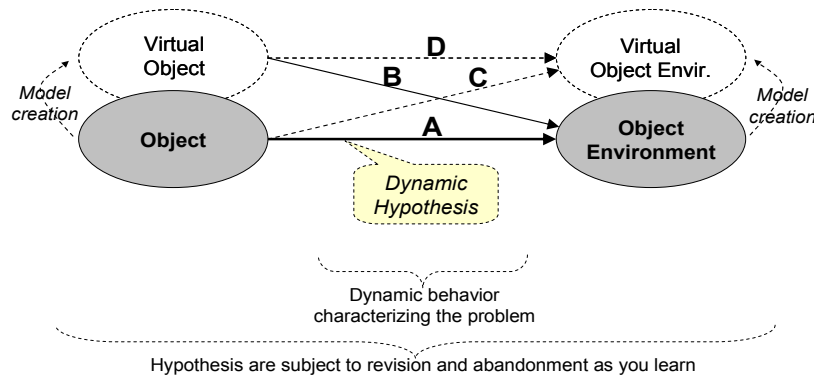


Figure 3: Defining the simulation problem.

In Figure 3 the grey ellipse on the left represents the object, which is anything that one desires to study. The grey ellipse on the right represents the object environment, which is a set of surrounding conditions that involves the object under study. Normally, the analyst desires to experiment with an object in some object environment because he suspects that the object has some predefined behaviour (i.e., some dynamic hypotheses about its behaviour). The analyst wants to validate or refute these hypotheses. For example, by believing that one key supplier is not able to support great demand variability one may perform experiments to analyze the robustness of supplier performance. In this case, the supplier is the “object”, different demand patterns form the “object environment” and the supposition that the supplier is not prepared to absorb great demand variability represents the “dynamic hypothesis”.

As depicted in Figure 3, both object and object environment can be either real or virtual. The object and the object environment can be used for experimentation as they are. The virtual object and the virtual object environment are usually created as simplified copies of the real world with which one can experiment. The utilization of a real object and a real object environment represents the learning loop 1. In many situations decision-makers use virtual objects and/or virtual object environment in order to streamline the learning process (loop 2 or 3). In this case, the experiment is conducted in a virtual world.

Basically, four combinations of objects and object environments are possible (see Figure 3): A) real object and real object environment, when performing real world experiments (e.g., when implementing a pilot project); B) virtual object and real object environment (e.g., when implementing a system prototype under real business conditions); C) real object and virtual object environment (e.g., the classical beer game where real objects composed of decision-makers – humans - are introduced in a fictitious SC order propagation system); D) virtual object and virtual object environment, which is the most common situation in computer-based SC simulation (e.g., the classical beer game is widely tested by means of system dynamics models, where both the object and the environment are virtual).

All three possible simulation possibilities exist in the context of SC planning. They allow for the accomplishment of the three learning loops. But the question that arises now is what exactly can be classified as an object and environment.

3.5 Distributed Simulation Environment

In order to understand which type of object and object environment exist and which kind of relationships they can establish, we employ one known framework from the literature to found our idea and to propose a conceptual schema.

Based on Le Moigne [12] work on complex systems, Figure 4 depicts four sub-systems that compose any complex system: i) Decision system (DS): is a system responsible for making managerial choices – in SCM, decisions are usually subdivided into strategic, tactical and operational levels (e.g., a manager or an AP system); ii) Information system (IS): is a system that includes groups of procedures, people and machines to collect, process, store and disseminate information from all companies’ sub-systems (e.g., an ERP system or an accountant); iii) Operating system (OS): is a set of planned activities involving many human and physical resources to perform various actions, allowing the SC system to function and to produce its outcomes, i.e. products and/or services (e.g., manual operators and CNC machines); iv) System Environment¹ (E): represents the sum of the existing surrounding conditions and forces by which the other sub-systems are influenced (e.g., economic, climatic, political, technological and competitive conditions that can influence the demand, raw material availabilities, production capacities etc. in a SC). These sub-systems interact with each other. All DS, IS and OS may simply represent an internal SC (e.g., only one company with all its production sites and distribution centers) or part of a given SC (e.g., the Original Equipment Manufacturer, its first tier suppliers and its first tier clients) or even the whole SC (e.g., from the source of raw-material to the final consumer).

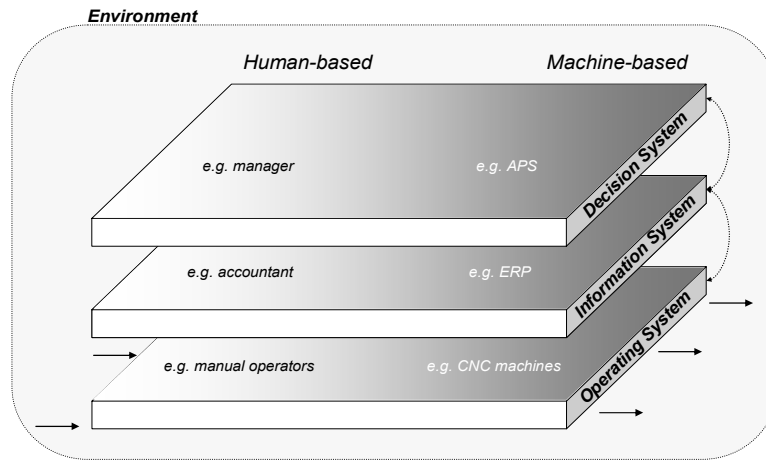


Figure 4: Complex SC.

As suggested by Figure 4, each layer can be seen as a continuum between human-based and machine-based elements. On the left side, managers, accountants and manual operators are examples of pure human-based DS, IS and OS respectively, while APS, ERP and CNC machines are examples of pure machine-based. In reality, most of the activities in a SC are done by both machines and humans.

¹ Note that here it is important to distinguish the “system environment” (E) from the “object environment”. The former represents involving conditions where the SC system exists, while the latter represents inclosing conditions where the object to be simulated operates.

Using the framework, it is possible to identify the potential conditions that constitute the object and the object environment. Actually, both object and object environment can be an entire sub-system (DS, IS, OS and E) or simply a small part of it, or even a combination of sub-systems and their parts. This allows for a set of flexible simulation possibilities. For instance, using an APS system, one may want to evaluate the behaviour of a new SC capacity profile (e.g., by eliminating a third work shift in some SC business units) under different demand patterns. In this simple example, the decision-maker hypothesis is that capacity utilization can be improved without disrupting the SC system even when demand changes. The object is the SC capacity profile and the object environment is the demand patterns. In order to do so, a firm may use its APS system to make some “what-if” tests. In this case, the “cloned” version of the APS for “what-if” purposes stands for the decision system and the demand represents the environment. In order to perform further tests, the decision-maker may desire to implement a given decision in a simulation model of the operating system using the discrete-event approach. By testing the impact of the decision in the OS, the analyst can better understand whether this decision will disturb the production execution or not. In this second setting, the object environment is represented by both E and OS. This case exemplifies the relationship D for the learning loop 2.

By using this modeling framework, one can capture different uncertainties in an APS domain. For instance, at the E level one can analyze uncertainties related to demand, supply or product prices. At IS uncertainty can be studied for its information quality (e.g., time, quantity and completeness). At OS one can examine the stochastic behaviour of transformation, transport and material handling.

Having seen what the object and object environment could be, we can now discuss how they can be distributed and how they can relate with each other.

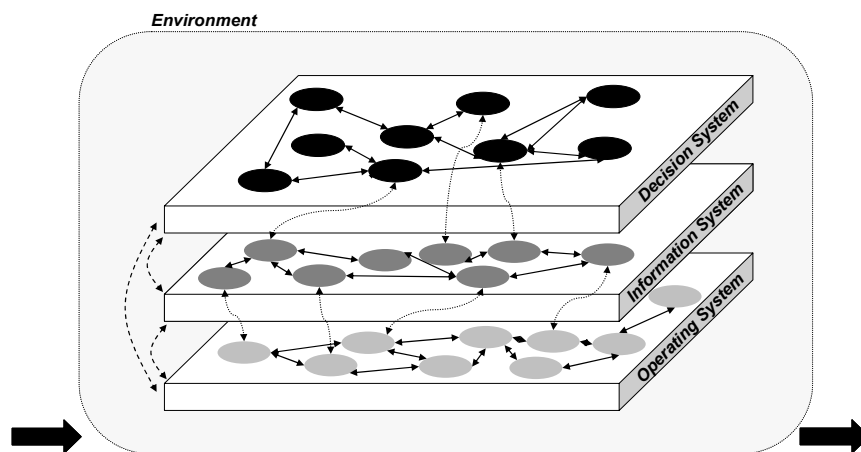


Figure 5: Problem distribution.

Figure 5 shows that for each SC sub-system a set of entities may exist. Each entity can establish relationships to other entities in the same sub-system, and/or to other entities from different sub-systems. Because agent-based supply chain planning involves several autonomous entities working together to coordinate their decentralized plans, therefore the DS necessarily accounts for multiple interacting entities. Additionally, the other sub-systems may implement diverse entities to represent their detailed behaviours. For example, machines, cells, facilities may represent the OS of a given

SC. They can interact with one another (e.g., exchanging orders and materials) and they may also interact with other sub-systems.

Now, it is important to understand one relevant concept. In supply chain planning simulation, the DS sub-system is involved because an APS is a decision-support system. The next sub-section will approach the potential of the supply chain planning systems in anticipating the impact of the decisions at the DS level on the other levels.

3.6 Distributed Decision Levels

Due to the integrated characteristics of SC problems, decisions cannot be studied in isolation. Decision at one level (e.g., strategic) will impact on other decision levels (e.g., tactical and operational), and decisions from a component of the DS will influence the behaviour of the other sub-systems.

Any test performed by means of simulation can be seen as an attempt to anticipate the impact of some tentative decision (a SC configuration, a plan, a rule, a protocol, etc.). Anticipating a decision's impacts allows the decision-maker to learn about possible results it may cause on the whole SCS. Under the light of Schneeweiss' approach [18], a known work on distributed decision-making, this anticipation can be represented as in Figure 6.

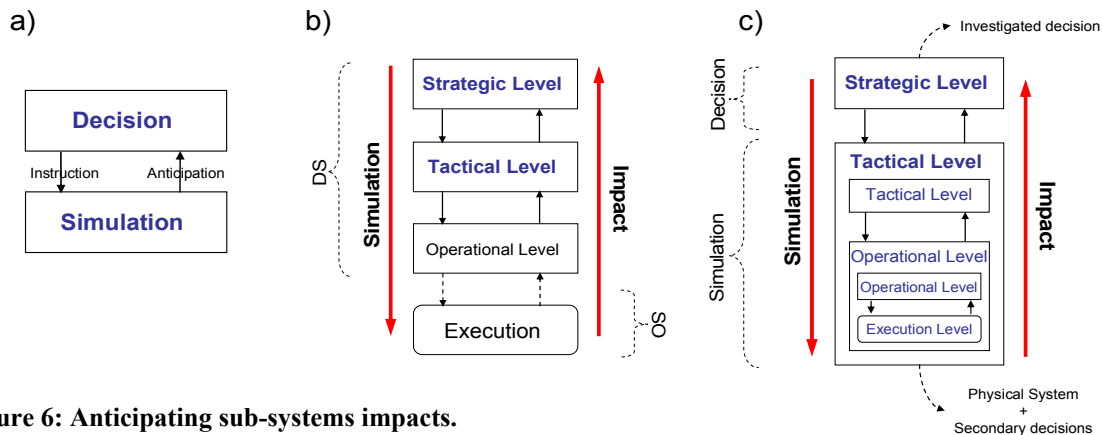


Figure 6: Anticipating sub-systems impacts.

Figure 6a) suggests that any simulation model is an anticipation of a given decision. Comparing to the initial model from Figure 2, the simulation can be seen as a virtual SCS and the instruction-anticipation can be seen as the feedback loop 2.

The potential of APS simulation resides in its ability to anticipate the impact of different decision levels and the behaviour of different sub-systems. Figure 6b) represents the case where the impact of a decision at the strategic level can be anticipated at the tactical level and so on. The impact of higher level decisions can be studied at lower decision levels. Also, Figure 6b) indicates that any decision at the DS can be tested at the OS concerning whether the decision can be implemented or not.

In the Figure 6c) we provide a more complex example. Suppose that a decision-maker needs to analyze a strategic decision of expanding a distribution network. The new tentative configuration of the distribution network represents the object that is investigated. The decision-maker wants to test

this object under different environmental conditions at the operational level, that is, he wants to execute some plans and schedules for the OS system in order to verify whether this strategic decision can be operationalized or not. In this case, the supply chain planning system will have to simulate some “secondary decisions” (tactical and operational) in order to simulate the desired orders for the “physical system”. In order to do so, a supply chain planning system properly configured can be used to produce plans at tactical levels and schedules at operational levels. Later, it can dispatch orders at OS, which will perform discrete-event simulations in order to know how these orders may behave operationally.

In order to understand how the proposed modeling constructs can be articulated to capture these SC characteristics, next sub-section discusses our ideas in the context of a modeling methodology.

3.7 Simulation Methodology

The proposed modeling constructs are intended to identify the simulation problem, setting its objectives and defining a high-level abstract model of the simulation problem. Banks et al. [1] explain that this early phase is a period of discovery and the initial statement of the problem may be somewhat nebulous, what may burden the modeling work. Therefore, it is a crucial step and our work suggests some guidelines for it.

We can understand these guidelines according to the methodological approach for simulation of distributed industrial systems proposed by Galland et al. [37]. Their methodology is based on systemic and multi-agent concepts and it defines a life-cycle of models with five major phases (Figure 7): i) analysis: an abstract description of the modeled system containing the simulation requirements; ii) specification: the translation of the information derived from the analysis into a formal model; iii) design: definition of a structural organisation of agents, as for example simulation agents and facilitator agents; iv) implementation: translation of the model resulting from the design to a specific software platform, as ARENA®; and v) experimentation: when the customer uses the simulation model on a set of experimental plans. The authors propose formal method for the specification, design and implementation phases, but the analysis phase is not tackled by them. They mention that this phase is complex and there is as yet no consensus within the community.

This paper contributes to the advancement of knowledge by proposing constructs for the definition of a supply chain simulation problem during the analysis phase. The initial nine steps of the analysis phase are represented in Figure 7.

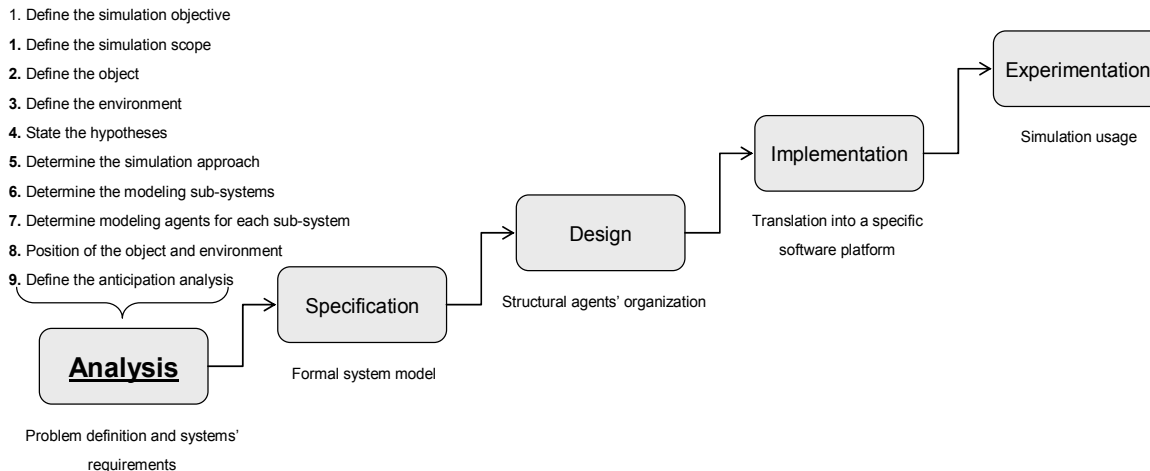


Figure 7: Modeling methodologies.

According to Galland [38] and Galland et al. [37], apart from the problem definition and simulation objectives, other elements of the analysis phase may be considered for the abstract description of the modeled system. Some examples are: all information which seems necessary to the implementation of a simulation process (e.g., description of the physical infrastructures, management policies, etc.), a list of experiment plans and the definition of the performance indicators for the simulation. As the objective of the present work is to position the potential use of simulation in a supply chain planning context, these elements are not considered here and might be subject of future publications.

In order to exemplify the whole discussion, the next section presents an illustrative case.

4. Illustrative Case

The proposed conceptual models will be theoretically illustrated using a supply chain planning system currently under development by the FOR@C Research Consortium. This system, called the FOR@C Experimental Planning Platform, is agent-based and encompasses concepts of autonomy and cooperation to deal with distributed decision-making problem that naturally resides in SC.

Basically, it addresses two relevant issues to provide a decision and planning tool for the forest products industry: i) capacity to plan and coordinate operations across the SC and ii) capacity to analyze the dynamics and performance of different SC scenarios by means of simulation [7]. These two issues are schematized in Figure 8.

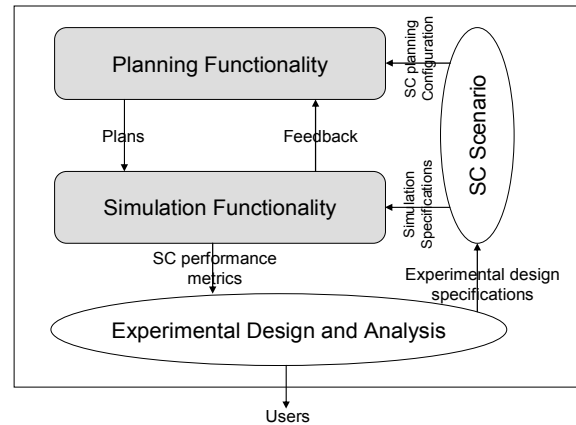


Figure 8: Overview of the FOR@C Planning platform [7].

4.1 The Planning Functionality

In this planning platform, a set of planning agents, geared up with advanced planning tools based on operations research technology, individually produce operations plans. These agents collectively interact with each other in order to carry out functionalities that synchronize their plans across the network to find enhanced global performance. Some planning agents have been developed to represent a business unit, i.e., an internal SC where all production units are owned by the same company. The following agents are responsible for the operational planning:

- Deliver agent (*De*): manages all relationships with the business unit's external customers and fulfils all commitments with them;
- Make agents: several make agents are 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. Currently, there are three make agents. Sawing (*Sa*), drying (*Dr*) and finishing (*Fi*) agents represent three different production units;
- Source agent (*So*): manages the relationship with all the business units' suppliers, forwarding procurement needs to the right suppliers.

This functional deployment is inspired by the SCOR model [21], and by the application presented in Fox et al. [5]. In addition, this platform involves the development of:

- **Plan agent** (*Pl*): is a tactical planning agent providing production and procurement policies (in the form of aggregated production guidelines) for all make agents;
- **Warehouse agent** (*Wa*): is responsible for inventory planning of final products at the warehouse level.

These planning agents represent the DS (from Figure 4). Next sub-section discusses how they can be used to create the simulation functionality shown in Figure 8.

4.2 The Simulation Functionality

In this specific implementation, simulation functionality has been added over the planning functionality to simulate objects outside the decision layer. In order to create our simulation functionality, the proposed planning agents are configured to create the distributed decision system. Then, for each of these planning agents, a simulation agent is created to model the manufacturing/logistic sub-system controlled by the planning agent (see Figure 9). These simulation agents have the responsibility to simulate plan execution.

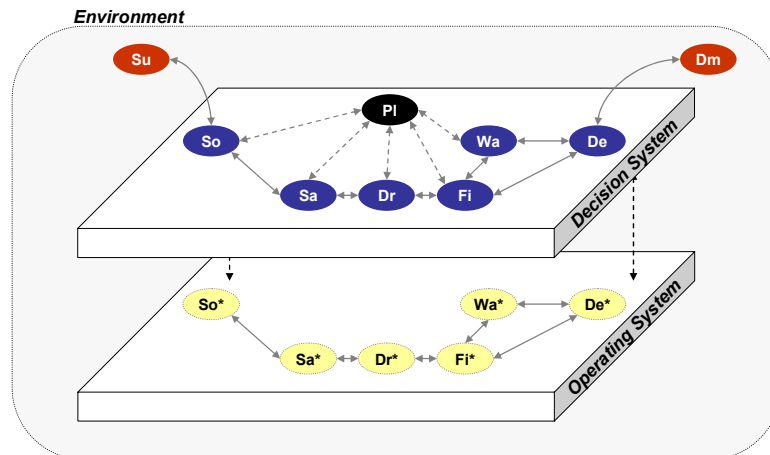


Figure 9: The simulation environment.

As noted in Figure 9, for each DS agent (apart from Plan Agent - *Pl*), a corresponding OS agent (marked with an “*”) is implemented (*So**, *Sa**, *Dr**, *Fi**, *Wa** and *De**). They are responsible for performing agent-based discrete-event simulation representing the stochastic behaviour of the SC physical system. Their functioning is based on the instructions sent by DS, i.e., production orders.

Additionally, two extra simulation agents are implemented to compose the outside environment. They are the demand agent (*Dm*) and the supply agent (*Su*). *Dm* is responsible to generate demand to delivery agent (*De*), i.e. generating customer orders so as the planning agents are able to perform planning activities to satisfy customer requirements. *Dm* has a stochastic behaviour in a way to represent demand uncertainties. *Su* is in charge of making quantities of raw materials available for source agent (*So*), i.e., representing the fluctuation of suppliers’ capacity. In this case, all environmental conditions are represented by only two agents.

The proposed model allows the implementation of decentralized stochastic behaviours all along the SC, as follows:

- At the E level, the *Dm* agent may implement stochastic behaviours in terms of “customer order arrival time”, “customer order delivery time”, “order quantity” and “product prices elasticity”. Similarly, the *Su* agent may implement stochastic behaviours of “supply order delivery time” and “supply order volume”;
- At the DS level, the planning agents may have embedded “stochastic optimization procedures” so as plan’s results may slightly differ even when same planning conditions are considered;

- At the OS level, i.e., the virtual physical system, the Sa* agent may implement uncertainty in terms of “production lead time” and the “distribution outputs of the process of disassembling logs into lumbers”. Dr* and Fi* agents may implement stochastic “production lead-times”.

Demand, product prices and the process of disassembling trees into logs are very stochastic in the lumber industry. Therefore, they are very important parameters in this sector and are of great utility in the proposed simulation model.

In order to carry out the simulation, each agent must communicate with other agents whenever necessary to maintain proper logical relationships between them. At the DS level agents have to negotiate with each other in order to synchronize their plans. On the other hand, at the OS level communication is used to maintain the correct time-ordering of actions, i.e., to synchronize the operation of the OS agents in different production units. In addition, the E agents continuously send environmental messages for the DS sub-system. Finally, the DS and OS can interact continuously for re-planning.

4.3 Analysis Examples

In this illustrative case, different simulation alternatives are possible. Three examples are presented hereafter to illustrate all possible simulation uses (Figure 10): i) Simulation for Decision-Making, ii) Simulation for Technology Evaluation, and iii) Simulation for Education.

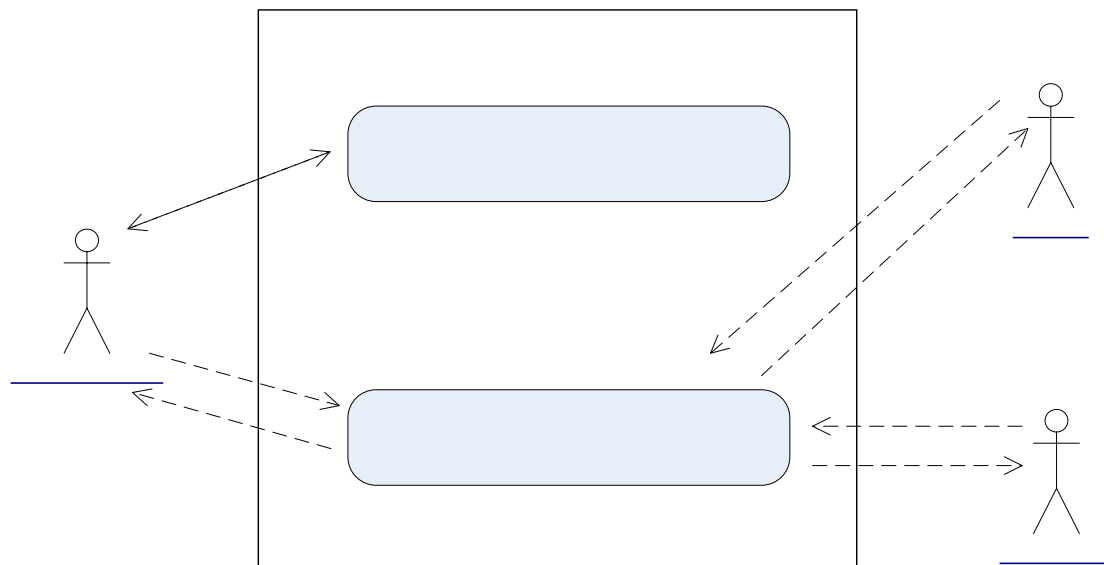


Figure 10: Examples for the three simulation possibilities.

i) Simulation for Decision-Making: first, as shown in Figure 10-(i), this simulation concerns a decision-maker who exploits the planning functionality to support his/her decisions, and the simulation functionality to evaluate the impacts of decision alternatives in an advanced what-if approach. We are here specifically interested in the relationship between the decision-maker and the simulation functionality.

For example, consider the case where one decision-maker desires to test different decoupling point positions in a lumber SC. He first wants to position it at the finishing level, after at the drying level and finally at the sawing level. By doing so, he wants to test the hypothesis that delivery performance can be improved when the decoupling point migrates from Finishing to Sawing, while maintaining similar costs. This can be obtained even when demand, supply and production are uncertain. The best configuration will be then implemented in a real SC.

Therefore, in order to test these scenarios, the decision maker first (1) configures the platform with the three possible scenarios. Once simulation runs have been carried out to test these scenarios, the decision maker can compare and analyse their performance indicators (2) to make a decision or decide to go further with the simulation.

In order to test this strategic analysis, Table 1 summarizes the 10 steps proposed in Figure 7b).

Design Steps	Design choices	Descriptions
<i>1. Define the simulation objective</i>	Decision-making simulation	The decision-maker desires to test three decoupling points positions prior to its implementation
<i>2. Define the simulation scope</i>	Accelerated learning	The “accelerated learning” (learning loop 2, Figure 2d) refers to learning about the potential gain due to a strategic change in the SC structure by identifying the cost and the delivery performance improvements of various SC configurations. After, the best configuration will be implemented
<i>3. Define the object</i>	SC configuration	As the analyst desires to test different decoupling point positions across the lumber SC, the objects under investigation (according to Figure 3’s model) are the “SC configurations”
<i>4. Define the object environment</i>	Demand, production and supply	The analyst expects to have better delivery performance even when demand, production and supply can be uncertain. Consequently, the environment (according to Figure 3’s model) can be defined as including different “demand patterns”, “production rates” and “supply patterns”
<i>5. State the hypotheses</i>	Superior delivery performance	Improved delivery performance if the decoupling point is positioned downstream
<i>6. Determine the simulation approach</i>	Virtual object and virtual environment (option D in Figure 3)	Both the object and the environment are virtually implemented, because we are employing the learning loop 3
<i>7. Determine the modeling sub-systems</i>	Environment, decision system and operating system	The proposed simulation objective is to test different tentative strategic decisions (at the “decision system” layer) concerning the object under different conditions related to the “environment” (demand) and to the “operating system” (physical production)
<i>8. Determine modeling agents for each sub-system</i>	All agents from Figure 9	For the “environment”, we have the “demand” and the “supply” agents. For the “decision system”, we have all planning and scheduling agents. Finally, the “operating system” is modeled by all agents representing the physical system, according to Figure 9. In a first simulation of the proposed model, a particular version of the operating system has been simulated with dummy agents, which were “cloned” versions from the decision system’ agents

<i>9. Position of the object and environment</i>	Object at the DS; Environment at E and OS	The tentative strategic decision is configured in a supply chain planning system representing the decision system. Environmental conditions are given by the uncertainty in the E (demand and supply patterns) and by the OS (production rates)
<i>10. Define the anticipation analysis</i>	Done according to Figure 6c).	The investigated strategic decision (decoupling point repositioning) will anticipate some secondary decisions (tactical and operational ones) and finally the physical system behaviour

Table 1: Problem formulation and conceptualization for the example (i)

ii) Simulation for Technology Evaluation: the second possibility in Figure 10-(ii) represents a researcher who wants to test two different algorithms for a given planning agent, within the same planning context, in order to compare them and make a recommendation.

For example, consider the case of a researcher who needs to test an alternative planning algorithm for the drying agent, which is currently the bottleneck of the overall planning process. The performance of this agent is obviously relevant for the SC planning process. Therefore, in order to improve its performance, the researcher developed a new algorithm and wants to compare it to the current one in terms of two performance measures, quality of solution and computation time. The researcher believes that the new algorithm will perform better for different problem sizes in terms of quantity of products to be planned, number of drying machines and planning horizon extents. Thus, the researcher first (1) implements each algorithm in the platform and runs the simulation. Once the performance is known (2), the researcher can use the results to publish its work or make a recommendation.

Table 2 summarizes the 10 steps for this example.

Design Steps	Design choices	Descriptions
<i>1. Define the simulation objective</i>	Technology evaluation	The researcher desires to test two algorithms for the drying agent
<i>2. Define the simulation scope</i>	Experimental learning	Refers to learning about the potential gain due to the new algorithm
<i>3. Define the object</i>	Agent planning capacity	The analyst changes the agent planning capacity by introducing a new algorithm
<i>4. Define the object environment</i>	Problem sizes	The researcher expects to have better performance even when quantity of products to be planned, number of drying machines and planning horizon extents change
<i>5. State the hypotheses</i>	Superior performance of the new algorithm	Improved performance in terms of quality of solution and computation time for the new algorithm even for different problem sizes
<i>6. Determine the simulation approach</i>	Virtual object and virtual environment	Both the object and the environment are virtually implemented (learning loop 3)
<i>7. Determine the modeling sub-systems</i>	Decision system	The proposed simulation objective is to test different algorithms at the “decision system” layer
<i>8. Determine modeling agents for each sub-system</i>	All agents from the decision system in Figure 9	All planning and scheduling agents in the “decision system”
<i>9. Position of the object and environment</i>	Both at the decision system	The different algorithm are implemented in the decision system, as well all parameters concerning the problem sizes

10. Define the anticipation analysis	Cognitive capacity of the drying agent	The investigated supply chain planning system anticipates some possible cognitive capacity of the drying agent
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Table 2: Problem formulation and conceptualization for the example (ii)

The advantage of performing this kind of simulation for the algorithm being tested is the fact that it is evaluated under complex and realistic network situations, where the SC partners are allowed to interact with each other and local and global analysis are possible.

iii) Simulation for Education: finally, the third simulation possibility deals with a student who wants to learn more about decoupling point repositioning and its effects on SC performance.

In order to do so, previously prepared by an instructor, the student can exploit three simulations that can be run with the supply chain planning system (Figure 10-(iii)-(1)). During the execution of the simulation, the student is able to see the dynamic of each configuration in a pre-emptive manner as he/she can stop the simulation at any time to analyse and compare the various situations. Such a tool is thus an educative tool as it provides a certain level of practical experience within a theoretical educative context.

In our example, the proposed three simulations are the configuration of the decoupling point at the finishing level, after at the drying level and finally at the sawing level, as done in the example (i) for decision making simulation. In this case, the same performance indicators and hypothesis are adopted. Although the simulation is similar to the example (i), the simulation objective and the simulation scope are different. The objective is “educational simulation” and the scope is “experimental learning”. The other eight points in Table 1 are the same. Another difference from the example (i) is related to the quantity of simulations required. As the example (i) refers to decision making, simulation precision is an important issue. In this case, a larger quantity of simulation can be required in order to obtain the desired confidence interval for the estimated performance measures. In the case (ii), precision could be less relevant if one simply wants to demonstrate that the decoupling point can influence the SC performance. Thus, in this case it can be necessary less simulation executions.

5. Final Remarks

In this paper we discuss the potential of agent-based simulation in the domain of supply chain planning. In addition, we propose some conceptual modeling constructs which aims to explore how agent-based simulation can be employed in the context of distributed SC planning. The proposed conceptual modeling constructs defines some high level building-blocks and it is the first step towards a complete framework that can assist decision-makers to understand, design and implement practical simulations in supply chain planning systems.

Undoubtedly, it is a difficult undertaking and important questions still remain not completely addressed. At the moment, ongoing work is being done on the development of: a dedicated methodology for simulation in supply chain planning, a detailed and formal version of the analysis phase and a general system architecture for supply chain planning.

The supply chain planning system of the illustrative case is under real advanced tests for validation purposes with an international forest products company for its planning environment and, also, under some initial tests for its simulation environment. Improved versions of these ideas with a first version of a more complete framework are to be published shortly.

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