ABSTRACT

Agent-based technology and its applications in multi-agent systems are a set of tools used in many sectors, including manufacturing, services, logistics, and health care, to model and study the dynamics, resilience, and self-organization of complex systems, as well as to design prescriptive decision support systems. Agent-based technology encompasses various techniques from distributed artificial intelligence and is sometime used in conjunction with operations research to model and simulate how system components behave and interact. These techniques are also used to assess the impact of regulations and organizational constraints on the ability of systems to self-organize and adapt to changes. Because this technology can model a wide range of behaviours, including reactive, proactive/planning, and learning, as well as interaction mechanisms such as competition and collaboration, agent-based technology has been used in many applications in the forest sector and the forest products industry, ranging from ecosystem simulation, territorial planning, fire management, and operations management to supply chain management. This paper proposes a survey of these applications and identifies how agent technology is used to develop advanced tools to achieve a better understanding of the biological, social, and economic dynamics of forest ecosystems, as well as to improve decision-making in territorial planning, land use, and production and transportation operations management.

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MULTI-AGENT SYSTEM APPLICATIONS IN THE FOREST PRODUCTS INDUSTRY

INTRODUCTION

The study of the complex patterns of interactions between and within the natural, organizational, social, and economic ecosystems of the forest sector is going through a radical change with the development and implementation of agent-based technology. Agent-based technology is used to model and simulate the dynamics of complex systems where several (decision-making) entities interact either directly, through information or signal exchanges or virtual proximity, or indirectly, through a shared data structure or a representation of their virtual environment. These virtual interactions can be biological in nature (e.g., predator/prey, virus/individual, ant/colony), social (e.g., acquaintance, professional relationship), economic (e.g., supplier/customer, competitor), or logistic (e.g., product/machine, product/bill-of-material). They can be modelled individually, while their collective occurrences and changes over time can be studied in various contexts or scenarios. Part of such complex systems of interactions can also be invented by a designer to create a distributed process from which emerges a normative or prescriptive behaviour.

The forest sector is a rich domain of study, which includes several complex interacting systems. The modelling and analysis of these systems provides a vast opportunity for the development and application of such a versatile technology. This paper proposes a review of specific applications of agent-based technology in the forest sector and in the forest products industry in particular. This review paper is organized as follows. The following section introduces the concepts of agent and multi-agent system and discusses the appropriateness of this modelling paradigm to the forest sector. Next, the methodology of the review process is presented, followed by descriptions of various MAS applications. After this, some of the challenges and issues related to the use and implementation of these applications are discussed, and the final section presents conclusions.

APPROPRIATENESS OF AGENT-BASED MODELLING FOR THE FOREST SECTOR

Multi-agent systems (MAS) are an application of agent-based technology. They have evolved within the field of distributed artificial intelligence (DAI), which views the process of creating intelligence differently than the mainstream of artificial intelligence (AI) research. MAS involve many different technological paradigms and models, which are used to create intelligence as an emerging characteristic of the complex interactions of small, specialized software entities. Because this basic principle also underlies social, organizational, and ecosystem intelligences, MAS has naturally been used to model and simulate social and group behaviours, organizational processes, and biological and economic ecosystems.

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Agents and MAS

MAS technology aims to create general and specialized behavioural and interaction models and to implement these models into distributed (or not) and interacting computer programs called agents. The design of such models follows certain guidelines that characterize agents, as first introduced by Wooldridge and Jennings (1995).

The fundamental characteristic of software agents is their ability to sense (i.e., have an internal perception of) their environment and to react (i.e., perform actions) in an autonomous manner (i.e., without the intervention of a human user) to changes in their environment. Therefore, agents are called situated, reactive, and autonomous. The definition of their environment and their specific perception of it is part of the system design process. These can be limited to specific computer parameters, variables, or states, which may include shared data repositories, legacy information systems, and messages sent by other agents. They can also extend to sensory information from the real world through, for example, data acquisition from sensor networks. Some agents are even designed to sense human users’ preferences and intentions through computer graphical user interfaces (GUIs) to act as an assistant. These agents are referred to as interface agents. Once agents have a perception of their environment, whether it be quantitative measures, state parameters, or beliefs about the state of this environment, agents must be able to process this information to react. To implement this function, many agent models have been proposed. Some agents exhibit only simple reactive behaviours, which involve obeying fixed rules or performing programmed sequences of actions. In the domain of spatial modelling, models of cellular automata can be seen as a simple application of MAS based on reactive agents, in which the agents are cells in a multi-dimensional grid, exchanging information (i.e., about their finite set of possible states) with their neighbours (i.e., other cells) and reacting to changes in their state according to fixed rules (which may be stochastic or deterministic). Other applications may be found in the simulation of natural systems such as flocks of birds or ant colonies, or in artificial systems, such as a manufacturing facility composed, for instance, of product agents, order agents, and resource agents interacting together according to fixed mathematical rules to find an efficient production schedule.

Other agents, however, exhibit more complex behaviour through some form of planning process. These proactive agents can plan their own course of action using their perception of the state of their environment and by applying AI planning algorithms with the objective of achieving certain goals (e.g., reaching a specific internal state or fulfilling commitments with other agents) or of maximizing some utility function. When their actions are planned, these intelligent agents act according to their plans to change the state of their environment. Intelligent agents may also have the ability to learn through some form of reinforcement learning or other learning techniques to adapt their behaviour over time so as to improve the effectiveness of their actions.

Another characteristic of agents, which is specific to the case of MAS, concerns their ability to communicate with other agents. This social ability may be implemented through some form of message passing or through a shared data repository (e.g., a blackboard). Again, simple agents may only be able to interpret specific types of formatted messages, signals, or data, while more advanced agents may be able to use and understand (i.e., process the semantics of) specific communication languages or to choose among several interaction protocols to communicate with others in different situations.

A MAS is therefore a collection of software agents that have specific, generally heterogeneous, views of their environment, are capable of more or less intelligent behaviour to react to changes in their environment, with different control responsibilities and relationships with other agents (e.g., hierarchical, interactions over decision variables or their own internal state, and are able to interact with other agents according to particular information exchange mechanisms. MAS have been used in many different domains to simulate complex systems, such as decision support tools for distributed decision problems, or even as a means to integrate software applications and business processes. The interested reader is referred to Monostori, Vancza, and Kumara (2006) for an in-depth presentation of the concepts of agent and MAS, with an emphasis on manufacturing applications, to Shen, Hao, Yoon, and Norrie (2006) for a review of manufacturing applications of MAS, and to Bousquet and Le Page (2004) for a review of MAS applications in ecosystem management.

Appropriateness of agent-based modelling in the forest sector

The use of MAS implies the adoption of the agent-based modelling paradigm. This paradigm implies the agentification of the system to model. In other words, the system is modelled as a collection of agents that perceive their environment and that can take action to change it. Such a modelling process can result in a high-level representation of the system (e.g., with agents representing organizational units in a supply chain) or, on the contrary, a very detailed view of the system (e.g., with agents representing individual organisms in an ecosystem). Therefore, the modelling and analysis of the interactions within and at the interfaces of natural, organizational, social, and economic ecosystems is appropriate for agent-based modelling because:

1. living beings (down to their cells), organizations and their functions (down to their products, processes, and processors), and social entities can naturally be represented as agents;
2. the heterogeneity of behaviours observed in natural, organizational, economic, and social systems can be modelled using different classes of agents;
3. the individual physiological and biological interactions of agents, their behaviours, and their decision processes...
can be modelled discretely;

(4) the natural environment is a form of shared data repository that can take the form of a geo-referenced database or grid in which agents can move, and through which the impacts of any actions (e.g., agent reproduction or mortality, predation, pheromone deposit, harvesting, fuel wood collection) by any agent can be perceived and can have repercussions on other agents’ ability to perform actions;

(5) the ability of organizations and individuals to adapt to new situations and to learn from history can be modelled using agents that can adapt and change their behaviour over time;

(6) the ability of organizations and individuals to collaborate with each other to define a course of action jointly and their complex patterns of interactions and control architectures (e.g., hierarchies) can be similarly modelled discretely using agents that can interact with each other, plan together, or control the actions of others;

(7) the ability of organizations and individuals to self-organize and to adapt collectively to new situations can also be modelled using agents that can create coalitions and can even be self-determined (i.e., possess the ability to change their own purpose according to the state of their environment);

(8) the specific responsibilities and information access of organizations and individuals can be modelled using agents that have disjoint decision domains and different information visibilities to model information asymmetry;

(9) advanced operations research decision-support tools and legacy information systems (e.g., advanced planning and scheduling systems, ERP, wildfire simulators, forest growth simulators) used in industry and in government agencies can be incorporated or encapsulated in agents and used in conjunction with other agents’ functions.

Although this domain is well adapted to the agent-based modelling paradigm, this process is not straightforward and remains a challenging task for model designers and analysts. This process is briefly overviewed later in this article. The next section presents the methodology used to review the applications of MAS in the forest sector and the forest products industry.

**METHODOLOGY OF THE LITERATURE REVIEW**

The methodology used to carry out this review relied on a systematic search using the Compendex and Web of Knowledge databases. The search was limited to peer-reviewed articles published in international journals. All queries were defined to contain the term “agent-based” in any of the fields of the databases. This term was preferred to the more inclusive term “agent” to avoid publications related to non-computerized agents such as infectious or biological agents. Next, three specific queries were defined by adding the terms “forest,” “wood,” and “timber” respectively in any of the fields of the two databases. To the set of publications obtained using these six queries, some restrictions were imposed to avoid publications that are not related, directly or indirectly, to the forest products industry, such as publications related to general ecosystem modelling and simulation. Although this theme is rather well developed, only publications directly related to forest ecosystems and their potential impact on the forest economy were therefore selected.

This search identified a relatively short list of relevant papers, which was then augmented by the author’s personal experience in this domain and by the known research projects of various research groups. These publications were then classified and analyzed according to their domain of application, their simulation platform, the types of agents used, the simulation dynamic, and their general type of use. This analysis of the literature was completed with a discussion of some of the issues and challenges in agent-based modelling in the forest sector.

**DOMAINS OF MAS APPLICATIONS IN THE FOREST SECTOR**

In the surveyed literature, several different applications of MAS were identified and classified. The framework used to classify these applications is an extension of the forest products value chain, from forest to market, and covers many different academic domains, including ecology, territorial planning, forest operations, industrial engineering, and supply chain management.

**Forest ecosystem**

Forest growth and health is an important concern for the forest products industry, which aims to create a balance between resource inventories, harvesting operations, and market demand. Therefore, foresters must simultaneously understand the ability of forest ecosystems to meet market demand and how this ability is affected by naturally occurring forest health issues such as insect outbreaks as well as its growth capability. Agent-based modelling and simulation of natural ecosystems is an extensive field of research and applications development. This review focuses on applications dedicated to the study of the natural forest ecosystem’s ability to supply wood and timber to the forest products industry.

One particular type of applications dominates in this context. The study of insect outbreaks, which directly affects the forest ecosystem’s ability to produce wood, is well suited to the use of agent-based simulation, which can model individual insects or sub-populations of insects and their interactions with their environment. Babin-Fenske and Anand (2011) used a spatial agent-based simulation model using NetLogo to simulate the population dynamics of forest tent caterpillars and to study the impact of various rates of fecundity and mortality on forest defoliation. In this model, the forest is modelled as a collection of cells that are randomly visited by sub-populations of insects, from which the insects gain energy to reproduce. Along the same line, Fahse and Heurich (2011)
developed a spatial agent-based simulation model to study the conditions that influence the development and spread of bark beetle outbreaks. In this application, the authors developed a model that takes into account individual trees (i.e., a cell in a grid), while beetles are modelled at the population level. Similarly, Perez and Dragićević (2010, 2011) developed a spatial agent-based simulation tool using the Repast Simphony platform integrated with a GIS tool to study the dynamics of mountain pine beetle outbreaks in British Columbia. This simulation model involves the modelling of individual trees and beetles to simulate the impact of an outbreak on individual trees and landscapes.

**Territorial and Land-Use Planning**

The dynamics of forest ecosystems and their ability to provide wood and timber products can also be studied in a territorial planning context. Here, the objective is not to study the dynamics of the interactions between living organisms within the forest ecosystem, but rather to study the interactions between the natural, social, and economic ecosystems. More specifically, the goal of such studies is to achieve a better understanding of the causal relationships between territorial planning decisions or governance policies and forest growth and health. This domain of application covers many different land-use planning contexts.

Purnomo, Mendoza, Prabhu, and Yasmi (2005) proposed an agent-based simulation tool to study the impact of multi-stakeholder decision-making in the context of forest management. This model was later extended and presented by Purnomo and Guizol (2006), who proposed a model that integrates the natural, social and economic ecosystems to study the co-management of forest resources and the use of policies to avoid illegal logging and forest degradation, to foster planting, and to analyze the impact of such policies on poverty in Malaysia.

Similarly, Evans and Kelley (2008) used agent-based simulation to study the interactions between forest regrowth and harvesting policies. The objective of the authors was to identify landowners' management strategies that led to particular landscape outcomes at specific points in time. Along this line, Monticino, Acevedo, Callcott, Cogdill, and Lindquist (2007) studied, on the one hand, the interactions between individual land-use decisions and public policies within the forest ecosystem to understand better the conditions that lead to long-term forest sustainability. On the other hand, these authors investigated the interaction between the various social and economic stakeholders in a county. Similarly, Moreno, Quintero, Alans, Barros, Davila, et al. (2007) proposed an agent-based model to study the impacts of land-use and agricultural policies on deforestation in Venezuela. In this model, settler agents deforest and grow crops, while lumber concessionaire agents plan and execute forest operations, which are in turn regulated by government agents according to different sets of policies. The environmental impacts of these decisions are analyzed using a cellular automata model of the environment. Bithell and Brasington (2009) pursued this approach further by adding to the social and forest ecosystems a 3D model of the soil characteristics and ground hydrology dynamics to analyze the influence of rainfall cycles and land-use decisions on forest development and the sustainability of farming practices.

In the model proposed by Bone and Dragićević (2010), the authors integrated an advanced learning capability into an agent-based model initially presented in Bone and Dragićević (2009). In this model, forest company agents are designed to maximize their profits by optimizing their harvesting operations plans, while considering the potential to cooperate with a conservationist agent whose objective is to protect species habitat. Using reinforcement learning algorithms, the forest company agents have the ability to learn, within each simulation run, the value of the stands to harvest according to their goals and their propensity to collaborate with the conservationist agent.

In a very different context, Christensen, Rayamaji, and Meilby (2009) studied the impact of fuel wood collection for cooking and heating in local communities on the biodiversity associated with dead wood. In the proposed agent-based simulation, household agents living in different settlements are modelled to visit the local forest and to collect loads of dead wood in a cell-based representation of the forest. Their goal is to minimize their effort in terms of walking distance and time to collect wood. Once all agents have collected a load, the biodiversity level and the time needed to collect more wood are adjusted according to statistical functions. Next, the agents can collect another load. This simulation tool is used to study the impact of various levels of fuel wood extraction and to assess the repercussion of road development on biodiversity.

Kelley and Evans (2011) used agent-based simulation in a comparative analysis of portfolio and single-output land-use approaches with respect to their impacts on forest size and fragmentation. Portfolio land-use approaches enable forest owners to mitigate their risk and to improve their capacity to meet market needs by a multitude of different land-use and labor-allocation decisions. These decisions are simulated by agents that can make labor and activity decisions for each land cell according to different decision rules.

Finally, for a different type of use, Simon and Etienne (2010) proposed an interactive simulation tool, referred to as a companion model, which enables real-life farmers and forest land owners collectively to take on the role of forest administrators by sharing management policies and by assessing the impacts of their decisions on alternative forest management plans. In this context, the agent-based simulation provides a shared representation of the current management context, while providing several views of alternative forest management scenarios.

These contributions from the literature propose simulation applications of MAS. However, other contributions propose very different types of applications. One of these types is the integration of distributed and heterogeneous information systems and data...
sources. In the domain of territorial and land-use planning, Nute, Potter, Maier, Wang, Twery et al. (2004) proposed a high-level agent-based software architecture to integrate heterogeneous simulation and optimization tools to support forest management decisions. These tools include vegetation and forest growth simulation models, wildlife models, and a GIS as well as user interfaces. In this MAS application, intelligent agents developed in Prolog encapsulate the use of these tools by automatically carrying out simulations and analyses according to the user’s views and tentative management plans and by providing reports. Agents do not interact directly with each other. They post tasks to be done, as well as their reports, on a blackboard. Agents can process task requirements and manage their own resources to carry out these tasks for the user.

Wildfire management and risk mitigation

Wildfire management is one domain where MAS is used to design decision support systems. The management of wildfire can be addressed either in terms of risk mitigation through land-use management and risk assessment, or in terms of firefighting strategy planning. In a context of land-use management and risk assessment, Maille and Espinacé (2011) used agent-based simulation to model and study the discontinuous urbanization space dynamics of local territories taking into account the risk of wildfire. Social agents and temporary geographical agents are collectively modelled to simulate the spatial changes through transaction decisions (i.e., exchange of parcels) and geographical decisions (i.e., modifying a parcel’s shape). A fire simulator is used to assess the risk of fire.

When a wildfire must be stopped or its impacts limited, a fire-fighting strategy must be devised. This decision process requires the coordination of actions by several resources, taking into account terrain, fuel type, and wind characteristics. Sahli and Moulin (2009) proposed a multi-agent geo-simulation approach to support this decision-making process. In this decision support system, certain agents are linked to an object in the real environment, for example, through a sensor web or a firefighter’s personal digital assistant (PDA), to relay live information about the status of a resource or the location of a fire. Using this information, actor agents (also called pathfinder agents) can devise the best course of action over time, taking into account the simulated progression of the fire. This progression is simulated using a cellular automata-based model referred to as Prometheus. When information is updated, actions are re-planned by pathfinder agents to propose a new course of action.

As has been seen previously in the domain of territorial and land-use planning, a wildfire management application proposed by Jaber, Guarnieri, and Wybo (2001) used MAS in a context of information systems integration and presented a high-level agent-based software architecture for the integration of different decision support tools to prevent and fight wildfires. In this integrated application, agents also encapsulate legacy systems and decision support tools such as GIS databases, early detection systems, monitoring and forecasting systems, and risk assessment. However, this system differs from that proposed by Nute, Potter, Maier, Wang, Twery, et al. (2004) because agents can communicate with each other directly using a specific language to cooperate with each other and to support the user’s decision-making process. To do this, intelligent software agents must first have an internal representation of the system’s capabilities and the functions they encapsulate. They must also have a simple representation of the functions supported by other agents. Using this knowledge along with the task requirements, agents interact directly to carry out the decision-support tasks collectively.

Forest operations and procurement planning

To be efficient, forest companies must understand the relationship between resource availability, mill operations, and market demand to schedule harvesting operations. In the case of shared resources, such as in a public forest, forest companies also must understand their dependencies with forest operations and how these dependencies impact their profitability to plan efficient joint operations. Several applications of MAS have been proposed to address such issues.

For instance, Schwab, Maness, Bull, and Roberts (2009) used agent-based simulation as a decision support system (DSS) for strategic planning to assess the impact of variations in resource inventories and demand on forest product sector economic viability. In this simulation, agents represent autonomous economic entities (e.g., forest companies) that simultaneously interact with their market and with their supply base. The ability of these agents to make strategic decisions over time is implemented through the design of intelligent agents that can adjust their behaviour from a behaviour driven by past successes (i.e., based on reinforcement learning), to a behaviour driven by beliefs and expectations. Next, strategic decision-making for production planning is implemented using an integrated optimization tool. Along the same line, stumpage fees are determined by simulating an auction process, and a reserve price to sell the product is adjusted at each period by taking into account several factors, including production cost and past market price. By modelling initial market price levels (e.g., resulting from a low level of housing starts in the U.S. market) and timber availability in the context of natural disturbances (e.g., salvage harvesting due to mountain pine beetle infestation), the authors were able to assess the impact of various demand configurations and to propose scenarios.

In a different context, Beaudoin, Frayret, and LeBel (2010) used a simple agent-based simulation model with two forest company agents to study the impact of collaboration in various market set-ups in the context of wood procurement on public land. In this simulation, the two company agents are responsible for developing a collective harvesting plan for a heterogeneous...
set of forest stands while maximizing their own profit. Such a simulation tool enabled the authors to study how collaboration through financial incentives can benefit both agents by allowing them to harvest initially unprofitable stands under poor market conditions and thereby increase their profit.

In a similar context, a project within the FORAC Consortium has studied the impacts of various negotiation strategies in an auction-based wood procurement system. In this project, forest company agents were designed to learn from previous auction rounds and adjust their bids in a first-price sealed-bid auction. Such a simulation can also be used to study different marketing scenarios with respect to auctioned lot sizes, auction frequency, and the nature (e.g., species mix) of lots.

**Mill operations**

Computer simulations were used in manufacturing long before agent-based technology. Both dynamic and discrete-event system simulations are widely used in manufacturing to analyze system configuration scenarios or to assess system design performance in various demand and resource availability contexts. Agent-based technology introduces a set of new techniques to simulate more accurately the behaviours and interactions of self-organized manufacturing systems where decisions result from a collective or emerging process. In the Canadian forest products industry, operations simulation has played an important role in the design of production systems, particularly in the softwood and hardwood sawmill industries. Several specific simulation tools, from discrete-event simulation to true-shape log sawing simulators, have been used for a number of years to support the optimization of lumber production. Finite-element simulation tools have also been developed to understand better the dynamics of moisture during wood drying.

However, the use of agent-based technology to simulate the detailed transformation operations of wood products has not yet been reported in the literature. Nevertheless, a project within the Canadian NSERC VCO network proposes to develop such a tool to simulate hardwood log handling, classification, and inventory management operations to optimize sawmill operations and ultimately to improve the production yield of secondary transformation operations (e.g., hardwood floor production, furniture manufacturing). This project is being carried out in collaboration with FPInnovations and aims to assess the performance of various log classification schemes. This agent-based simulation involves log agents, loader agents, and a production agent. In the same research group, another agent-based simulation will be developed to simulate various schemes for coordinating saving operations within a softwood sawmill. Such a simulation tool is required to simulate and improve the coordination of the distributed and currently independent machine optimizers throughout the facility.

**Supply chain operations planning**

The use of MAS in supply-chain operations planning is generally oriented toward two main goals. The first concerns the use of agent-based techniques to design efficient supply-chain coordination tools in the form of distributed advanced planning and scheduling systems. Because a supply chain is a naturally distributed decision-making system, the use of MAS seems particularly appropriate. The second and complementary goal concerns the study and analysis of the performance of various contexts of information exchange and coordination mechanisms in supply chains. The interested reader is referred to Frayret (2009) for a general multi-disciplinary review of supply-chain operations coordination.

In the forest products industry, Moyaux, Chaib-Draa, and D’Amours (2007) used a multi-agent simulation of a simple forest value chain, which includes wood procurement from the forest, softwood lumber production and distribution, and pulp and paper production. The authors proposed and evaluated several information exchange mechanisms between forest company agents. The authors also proposed a series of experiments involving several information exchange strategies and mechanisms and assessed their performance as well as their ability to lead to a Nash equilibrium for all partners.

Along the same line, Frayret, D’Amours, Rousseau, Harvey, and Gaudreault (2007) proposed an open agent-based supply-chain planning platform, which enables heterogeneous facility agents to use various behavioural models and advanced planning tools to coordinate operations planning across several facilities. This planning tool is equipped with simulated demand and procurement agents to assess the performance of several joint planning configurations and mechanisms and has been used in many studies. For instance, Cid Yañez, Frayret, Léger, and Rousseau (2009) described an analysis of various configurations of the decoupling point within a sawmill complex that includes a sawing agent, a lumber drying agent, and a finishing agent. Gaudreault, Forget, Frayret, Rousseau, Lemieux, et al. (2010) presented the various optimizations tools used in this simulation platform as well as a performance analysis of several simple coordination mechanisms. Along the same line, Gaudreault, Frayret, and Pesant (2009) proposed an advanced supply-chain planning coordination mechanism based on a constraint propagation technique. Similarly, Forget, D’Amours, and Frayret (2008) proposed a multi-behavioural agent framework that enables agents to adapt their local planning process configuration according to the situation.

**Timber and wood product marketing**

MAS propose various coordination and interaction mechanisms to model various forms of complex systems, ranging from competitive to collaborative settings. Market mechanisms in particular have been studied, developed, and implemented in many contexts ranging from the modelling and simulation of financial markets (see Samanidou, Zschischang, Stauffer, and Lux
of agent technology and the challenges involved in using this technology.

**Usefulness of MAS**

MAS are used in many domains, including social sciences, ecology, decision sciences, health-care organization, manufacturing, and logistics. Although they address very different problems, these applications are generally developed for a small number of different types of use. For instance, complex systems simulation and decision support are certainly the two most frequent types of use. Both involve the development of models. On the one hand, complex systems simulation applications involve the development of descriptive models, which aim to reproduce the behaviour of an existing system or a system-to-be and to show how this system could work in various scenarios and contexts. On the other hand, decision-support applications involve the development of normative models which aim to prescribe a “norm” of how the system should work, such as a set of decisions, an operations plan, or a resource configuration.

**Multi-Agent Coordination of Distributed Decisions:** A different type of use of MAS exploits directly the ability of agents to coordinate decision-making. More specifically, this functionality enables decision support system designers to create and implement distributed decision-support tools that can coordinate their local decision optimization activities through some form of information sharing (Cid Yáñez, Frayret, Léger, and Rousseau, 2009), market mechanisms, commitment/decommitment, constraint propagation (Gaudreault, Frayret, and Pesant, 2009), or other forms of distributed algorithm (see Frayret (2009) for a general review). In other words, from the users’ perspective, local decision-support systems directly process information about the local system state, but also communicate with other decision-support systems outside the organization to share information, to assess scenarios jointly, or to implement, in a transparent manner, a distributed decision optimization process. In this type of application, intelligent agents can be used, as in Forget, D’Amours, and Frayret (2008), to design a joint planning process that is highly adaptable to changing planning situations. This general type of use has been particularly studied in the forest supply chain by the FORAC Consortium at Laval University in Quebec, Canada. However, these advanced coordination techniques could also be used in other multi-stakeholder...
decision contexts, such as territorial and land-use planning, in which the mutual dependencies among the stakeholders’ decision problems and the contradictions between their planning objectives could be assessed and trade-offs could be found in a transparent manner through their interacting local agents, as proposed by Beaudoin, Frayret, and LeBel (2010).

**Multi-Agent Integration of Information Systems and Decision Tools:** This type of use exploits MAS to integrate informal or complex decision processes and information systems in cases where either there is no clear sequence of processes to carry out to solve a problem, or else there is a complex series of processes and information systems with precedence constraints and business rules. This is particularly the case in territorial and land-use planning (Nute, Potter, Mai, Wang, Twery, et al., 2004) and wildfire management (Jaber, Guarnieri, and Wybo, 2001). These decision processes need to use many different information systems and data sources and to analyze many scenarios with respect to their outcome, their constraints, and their impacts at many levels (e.g., natural ecosystems, economic and social welfare). These decision processes can either be characterized as informal decision processes, because the outcomes at each step strongly condition the next step to be performed, or as complex decision processes, because each step requires the use of many information systems and decision tools in a specific sequence. These decision-making contexts can therefore be supported by software agents that can carry the burden of exploiting information systems, data sources, and decision support systems (i.e., not just invoking functions) to make the overall decision process easier and to focus users’ attention on the processes of information interpretation, analysis, and final decision-making that are more complex or unethical to automate.

**Multi-Agent On-Line Trading and Inter-Organizational Business Process Integration:** Lastly, another type of use concerns the use of MAS to support one-line transactions between trading partners and to integrate business processes between organizations. In the context of the forest products industry, Gerber and Klusch (2002) proposed an agent-based architecture that provides, on the one hand, a continuous computer-supported process of information exchange, trading, and bidding among buyers and sellers of wood and timber products. On the other hand, this architecture provides a computer-supported integration of business processes within each forest products company and also supports on-line transactions with other forest products companies.

**Issues and Challenges of Agent-Based Applications**

As discussed in previous sections, agent-based applications are relevant in many sectors and for different types of use. However, their implementation and use reveal several challenges and issues which need to be addressed. The following sections present and discuss some of these issues and challenges.

**Nature and Reliability of Multi-Agent Simulation:** The first topic discussed here concerns the nature of the results and analyses that can be obtained using multi-agent simulations. As Batty and Torrens (2005) explained, complex system simulation models contain stochastic parameters, which are usually inferred from empirical data analysis. This means that various combinations of their possible values can lead to several outcomes that are all possible. Therefore, as pointed out by Brown, Aspinall, and Bennett (2006), complex system simulation models cannot be used as predictive tools. However, their results can be used to infer the likelihood of occurrence of certain types of outcomes and to achieve a better understanding of the dynamics and the general impacts of specific system design scenarios, as well as to analyze the sensitivity of the model to certain parameters.

The second topic concerns the reliability of the results obtained from agent-based simulations. This aspect is directly related to the process of calibrating and validating the models. Brown, Page, Riolo, et al. (2005) discussed validation challenges in the particular case of agent-based spatial models. Here, the classical validation approach involves analyzing and comparing data from simulation runs with empirical data collected directly from the actual system. This validation approach can be carried out using several sets of data at different points in time to assess the ability of the model to reproduce a specific path of evolution. Evans and Kelley (2008) discussed the value and the burden of such a process and raised the question of what is the best simulation model: the model that ends with the last observed data point, or the model that achieves the smallest deviation from observed values over time. Bouquet and Le Page (2004) also mentioned that validation can be performed using rigorous representations of the models, from which mathematical properties can be derived and analyzed, or using other models, such as differential equations, that can be mathematically solved and based on which a comparative analysis can be performed. The authors also mention the possibility of assessing the relevance of the hypotheses upon which the model is built in terms of agents’ behaviour and interactions, using an experimental approach or role-playing games. Küppers and Lenhard (2005) also pointed out that stakeholders’ agreement with the simulation results may provide sufficient validation of the models insofar as the purpose of the model has been served.

**Agent-Based Modelling and Description:** Another important issue in the implementation of MAS applications is model design and description. Agent-based modelling (ABM) starts with an analysis of the requirements of the problem at hand and finishes with a complete specification of the roles, functionalities, and interactions between the different components of the model (i.e., the agents), their environment and perceptions, and the control mechanisms (i.e., how the modelled system will be controlled by its users). This process involves many challenges, which
<table>
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<tr>
<th>Reference</th>
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<th>Agents (environment scale)</th>
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<tbody>
<tr>
<td>Babin-Fenske and Anand (2011)</td>
<td>Forest ecosystem (insect outbreak)</td>
<td>NetLogo</td>
<td>Sub-population of insects and forest cells (large geographical scale)</td>
<td>Agents representing populations of insects move from a cell to another and gain energy to reproduce</td>
</tr>
<tr>
<td>Fahse and Heurich (2011)</td>
<td>Forest ecosystem (insect outbreak)</td>
<td>(ODD model description standard)</td>
<td>Sub-population of insects and individual trees (stand scale)</td>
<td>Insects agents move from a tree to another and communicate through pheromones</td>
</tr>
<tr>
<td>Perez and Dragičević (2010, 2011)</td>
<td>Forest ecosystem (insect outbreak)</td>
<td>Repast Simphony, Java, and ArcGIS</td>
<td>Individual beetles and trees (landscape)</td>
<td>Beetle agents move from tree to tree according to a random displacement function and rules to control population</td>
</tr>
<tr>
<td>Evans and Kelley (2008)</td>
<td>Territorial planning (landscape management)</td>
<td>-</td>
<td>Landowners and owned land cells (landscape)</td>
<td>Landowner agents observe the state of the land cells and make decisions</td>
</tr>
<tr>
<td>Kelley and Evans (2011)</td>
<td>Land-use planning (landscape management)</td>
<td>-</td>
<td>Landowners and owned land cells (landscape)</td>
<td>Land owner agents make labour allocation decisions at the cell and parcel levels</td>
</tr>
<tr>
<td>Purnomo, Mendoza, Prabhu, et al. (2005)</td>
<td>Land-use planning (landscape management)</td>
<td>CORMAS (Common Pool Resources and Multi-Agent System)</td>
<td>Local communities, governments, and forest companies (forest stakeholders)</td>
<td>The forest company agent plans forest operations; the government agents regulate and approve plans</td>
</tr>
<tr>
<td>Purnomo and Guizol (2006)</td>
<td>Land-use planning (landscape management)</td>
<td>CORMAS (Common Pool Resources and Multi-Agent System)</td>
<td>Smallholders, forest management authority, forest companies, and brokers (forest stakeholders)</td>
<td>Agents adopt roles and interaction modes when acting in social groups involved in forest management, tree growing, and tree and wood trading</td>
</tr>
<tr>
<td>Christensen, Rayamajhi, and Meilby (2009)</td>
<td>Land-use planning (conservation strategy planning)</td>
<td>-</td>
<td>Household agents (forest level)</td>
<td>Household agents collect dead wood one after the other while minimizing effort; when wood is collected, biodiversity and the time needed to collect more wood are impacted</td>
</tr>
<tr>
<td>Monticino, Acevedo, Callicott, et al. (2007)</td>
<td>Land-use planning (landscape management)</td>
<td>-</td>
<td>Landowner agents, land developer agent, home owner agents, government agents (county)</td>
<td>Each class of agent can perform specific actions and follows its specific decision model, which represents its values</td>
</tr>
<tr>
<td>Moreno, Quintero, Ablan, et al. (2007)</td>
<td>Land-use planning (landscape management)</td>
<td>Galatea for the agents and SpaSim (for the cellular automata model), Java</td>
<td>Settlers, government, lumber concessionaires (forest level)</td>
<td>Social agents interact and make decisions which impact a cellular-automata simulation of the natural system</td>
</tr>
<tr>
<td>Bithell and Brasington (2009)</td>
<td>Land-use planning (landscape management)</td>
<td>Ad-hoc development in C++ (ODD model description standard)</td>
<td>Individual (decision-making) agents, tree (passive) agents</td>
<td>Individual agents make land-use decisions, which are influenced by land hydrology, which is in turn influenced by land use and terrain characteristics</td>
</tr>
<tr>
<td>Simon and Etienne (2010)</td>
<td>Land-use planning (landscape management)</td>
<td>CORMAS (Common Pool Resources and Multi-Agent System), cellular automata model of land and forest</td>
<td>Farmer agents, government agent (forest and farm land)</td>
<td>Farmer agents make decisions with respect to their production objectives (including breeding and firewood harvesting); the government agent regulates</td>
</tr>
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<tr>
<td>Bone and Dragićević (2009)</td>
<td>Land-use planning (forest management)</td>
<td>Repast, Python, and ArcGIS (integrated with Agent Analyst)</td>
<td>Timber agents and government agent (forest level)</td>
<td>Timber agents make harvesting decisions based on allowable cut level, timber price, harvest cost, and road proximity</td>
</tr>
<tr>
<td>Bone and Dragićević (2010)</td>
<td>Land-use planning (forest management)</td>
<td>Repast, Python, and ArcGIS (integrated with Agent Analyst)</td>
<td>Forest company agents, conservationist agent, government agent (forest level)</td>
<td>Forest company agents select stands that maximize their value (adjusting progressively their strategy); those that cooperate with the conservationist agent accept to adjust their choice to minimize wildlife impact</td>
</tr>
<tr>
<td>Maillé and Espinace (2011)</td>
<td>Land-use planning (urbanization)</td>
<td>Tilab JADE multi-agent platform and ad hoc development in JAVA</td>
<td>Social agents (owners, buyers, entrepreneurs, manager, surveyor), geographic agents (parcel, building...) (suburban level)</td>
<td>Social agents negotiate to exchange parcels; they trigger geographical agents to optimize land structure according to commands; risk of fire is assessed using a spatial simulator</td>
</tr>
<tr>
<td>Nute, Potter, Maier, et al. (2004)</td>
<td>Land-use planning (forest management)</td>
<td>Ad hoc development in C++ and Prolog around a blackboard architecture (MS Access database)</td>
<td>Function agents, such as goal analysis, interface, GIS, simulation, report generation (forest level)</td>
<td>Agents communicate through a blackboard (BB); tasks to be done are posted on the BB; an agent that can perform the task can do it and erase it; if another task must be performed, an agent can post a new task</td>
</tr>
<tr>
<td>Sahli and Moulin (2009)</td>
<td>Fire management</td>
<td>MAGS (multi-agent geo-simulation) platform applied to fire-fighting</td>
<td>Passive physical objects agents (e.g., fire, lake), dozer tracking agents, actor agents (dozer) (forest level)</td>
<td>Object agents provide data; tracking agents provide data through sensor web; dozer agents decide what dozers should do to fight fire; a fire model provides fire behaviour</td>
</tr>
<tr>
<td>Jaber, Guarnieri and Wybo (2001)</td>
<td>Wildfire management</td>
<td>Legacy systems are developed in C, C++, Delphi, Pascal</td>
<td>Function agents, such as databases, early detection systems, monitoring and forecasting systems, risk assessment (forest level)</td>
<td>Agents communicate directly with each other; they have internal and external knowledge of all agents' capabilities and interact using a high-level communication language</td>
</tr>
<tr>
<td>Schwab, Maness, Bull, and Roberts (2009)</td>
<td>Forest operations and procurement planning (strategic planning)</td>
<td>Repast platform, Java, integrated with a GIS application</td>
<td>Forest company agent (province)</td>
<td>Forest company agents react to changes in resource availability and market conditions by making strategic and operation planning decisions to acquire logs and sell wood products on the market</td>
</tr>
<tr>
<td>Beaudoin, Frayret, Lebel, (2010)</td>
<td>Forest operations and procurement planning (enterprise collaboration)</td>
<td>Cplex for optimization and MS Excel</td>
<td>Forest companies (two companies having to plan operations together)</td>
<td>Forest companies share interactively needs and offers and optimize procurement operations using advanced planning tools</td>
</tr>
<tr>
<td>Moyaux, Chaib-Draa, and D’Amours (2007)</td>
<td>Supply chain coordination (information exchange)</td>
<td>-</td>
<td>Forest companies (supply chain with six companies)</td>
<td>Forest companies order and deliver goods according to specific behaviour</td>
</tr>
<tr>
<td>Frayret, D’Amours, Rousseau, et al. (2007)</td>
<td>Supply chain coordination (advanced supply chain planning)</td>
<td>Ad-hoc development in C# and Cplex</td>
<td>Facility (supply chain with three detailed facilities)</td>
<td>Facilities exchange demand and delivery information according to configurable mechanisms to emulate various modes of exchange</td>
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</tbody>
</table>
The most obvious challenge concerns the identification of agent candidates. The easy candidates are the parts of the system being modelled that have the fundamental characteristics of agents (i.e., situated, reactive, autonomous). These characteristics apply for example, to a beetle, a colony of beetles situated in a relatively limited and homogeneous area, a household, a community, or a forest company. Agent candidates can also take less obvious forms. For instance, Van Dyke Parunak, Baker and Clark (2001) proposed transient agents whose existence in the system is limited in time. These agents represent transactional objects, such as customer orders, production orders, or purchase orders, and carry out simple processes, such as initiating a product inquiry or triggering production. Therefore, before agent candidates can be identified, it is necessary to analyze the modelling requirements to know what aspects of the system being modelled are relevant to the problem and specific to the domain. For instance, agent-based modelling of ecosystems is different from agent-based modelling in manufacturing, logistics, or land-use management. Therefore, the use of specific analysis and modelling methods and a study of the appropriate literature can dramatically improve the relevance and credibility of the model. For instance, Santa-Eulalia, D’Amours and Frayret (2008, 2011) proposed the FAMASS method for the analysis of supply-chain planning simulation requirements to support model designers in identifying agent candidates and defining their planning capabilities. FAMASS proposes a systematic analysis of different dimensions of the supply-chain problem, as well as a systematic approach to designing specific components of the model. Along the same line, Komma, Jain, and Mehta (2011) addressed agent modelling for the design of multi-agent system applications in manufacturing using the JADE platform. In a different context, Etienne, Du Toit, and Pollard (2011) proposed the ARDI method for the modelling of a multi-stakeholder land-management problem. ARDI involves a participatory modelling approach, which was used in the design of the companion agent-based simulation model proposed by Simon and Etienne (2010). Along the same line, in the context of ecosystem model design, Grimm, Berger, Bastiansen, Elith, Ginot, et al. (2006) introduced the ODD protocol for the design of ecosystem model components. These approaches have been applied to various domains, such as supply chain coordination, product marketing, and planning agents.

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<tbody>
<tr>
<td>Cid Yáñez, Frayret, Léger, and Rousseau (2009)</td>
<td>Supply chain coordination (decoupling point position)</td>
<td>Ad-hoc development in C# and Cplex</td>
<td>Facility (supply chain with three detailed facilities)</td>
<td>Facilities exchange demand and delivery information according to various decoupling point strategies</td>
</tr>
<tr>
<td>Gaudreault, Frayret, and Pesant (2009)</td>
<td>Supply chain coordination (collective planning)</td>
<td>Ad-hoc development in C# and Cplex</td>
<td>Facility (supply chain with three detailed facilities)</td>
<td>Facilities exchange demand and delivery information according to an advanced collaborative planning scheme</td>
</tr>
<tr>
<td>Gaudreault, Forget, Frayret, et al. (2010)</td>
<td>Supply chain coordination (advanced supply chain planning)</td>
<td>Ad-hoc development in C# and Cplex</td>
<td>Facility (supply chain with three detailed facilities)</td>
<td>Facilities exchange demand and delivery information according to simple mechanisms</td>
</tr>
<tr>
<td>Forget, D’Amours, and Frayret (2008)</td>
<td>Supply chain coordination (advanced supply chain planning)</td>
<td>Ad-hoc development in C# and Cplex</td>
<td>Facility (supply chain with three detailed facilities)</td>
<td>Facilities exchange demand and delivery information according to different configuration of planning behaviours</td>
</tr>
<tr>
<td>Gerber and Klusch (2002)</td>
<td>Timber and wood product marketing (e-commerce)</td>
<td>Ad-hoc development in Java (agent architecture is compliant with InteRRaP and FIPA)</td>
<td>Market actors are modelled using several agents, such as company, personal assistant, information management, and planning agents</td>
<td>The actors’ company agents interact with each other according to market mechanisms (e.g., auctions), and with its internal agents to carry out specific tasks and receive its users’ inputs</td>
</tr>
<tr>
<td>Gerber, Russ, and Klusch (2003)</td>
<td>Timber and wood product marketing (e-commerce)</td>
<td>Ad-hoc development in Java (agent architecture is compliant with InteRRaP and FIPA)</td>
<td>Market actors are modelled using several agents, such as company, personal assistant, information management, and planning agents</td>
<td>Extends Gerber and Klusch (2002) by proposing an advanced offer/demand matching algorithm</td>
</tr>
<tr>
<td>Maya Sopha, Klöckner, and Hertwich (2011)</td>
<td>Timber and wood product marketing (new product introduction)</td>
<td>Repast platform, Java (in an Eclipse environment)</td>
<td>Household agents (country level)</td>
<td>Household agents possess one of four investment strategies about heating technology; they may be influenced by other agents, prices, and incentives</td>
</tr>
</tbody>
</table>
advances in the model and the length of time that the model must cover. These factors have similar impacts on agents’ perception of their environment as well as on their behaviour. Whether the model is a discrete-event model (i.e., time advances from event to event, skipping the time between two events), a real-time model (i.e., time advances at the same speed as real time), or a period-based model (i.e., time advances from one period to the next), agents’ perception of changes in their environmental state, as well as the scope and impact of their actions on their environment, must be specified accordingly. Concerning the scope of the model, Evans and Kelley (2008) pointed out, in the context of a simulation involving social agents, that simulation runs over long periods may involve behavioural changes over time, as well as agent turnover, that must be addressed to reflect demographic and cultural changes.

**MAS Application Implementation:** The last point to be discussed here is the implementation challenge, from model specification to MAS application. This section provides only an introduction to certain model implementation challenges. The interested reader is referred to Railsback, Lytinen, and Jackson (2006) and Macal and North (2009) for a more detailed discussion on that subject.

MAS simulation applications can be developed within a complete generic development environment that provides a runtime environment (in which agents can be active), some kind of programming interface (to configure agents and their environment), and an interface for conducting and visualizing experiments (e.g., NetLogo, Repast, Swarm). Such environments make MAS simulation applications easier to implement for non-programming experts. Some of the applications reviewed previously use such platforms (see Table 2), including Repast and NetLogo. These platforms do not necessary require an extensive knowledge of computer science to implement a model because they use simple programming language (Repast, NetLogo) or point-and-click flowchart programming interfaces (Repast). However, these environments are powerful enough to implement a large variety of models. Repast enables system designers to implement specific agent functionalities using existing class libraries directly in Java, C#, or Python. Repast also includes a library for easy integration with ArcGIS to implement spatial simulations. In the context of natural resource simulation, CORMAS also provides a complete programming and experimentation environment with class libraries, but it requires substantial experience with SmallTalk. CORMAS includes specific libraries dedicated to natural resource modelling. However, unlike the two platforms mentioned earlier, it does not include a simple programming language.

MAS applications can also be developed using a development environment that does not necessarily provide all these integrated functions, such as JADE and Galatea, which are both based on Java and can work within a generic development environment (e.g., Eclipse, NetBeans). However, such an environment requires a more extensive knowledge of programming because agent functionalities are generally coded in libraries which provide the classes necessary to implement general MAS applications. Such an environment is flexible and efficient in terms of development because only specific agent behaviours and functionalities need to be implemented. Finally, some MAS applications are directly programmed in general-purpose development environments without the use of specific agent libraries. This mode of development is extremely flexible; however, it is not the most efficient because the basic functions of agents must be implemented from scratch.

**CONCLUSIONS**

Agent-based modelling and MAS applications provide tools to solve a variety of problems. This paper has presented a review of MAS applications in the forest sector and the forest products industry, ranging from simulation of natural, social, and economic ecosystems to the
development of advanced decision-support systems. MAS applications are particularly well adapted to system simulation and decision problems that are naturally distributed and in which several living, organizational, social, or economic entities interact. MAS applications entail modelling and implementation challenges that must be carefully addressed with appropriate methodologies and development environments if the results are to be useful.

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