Simulation and Evaluation of Coordination Mechanisms for a Decentralized Lumber Production System with Coproduction

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Abstract

Sawmilling activities in softwood mills (i.e., wood-sawing, drying, and finishing) cannot be efficiently planned at the operational level in a centralized manner because of the complexity of the production process. Sawmills plan their activities in a decentralized manner (although they try to coordinate them). Thus, specific mathematical models have been developed over the years to support planning for each activity. In the literature, these planning models are usually evaluated and tested independently, or connected using heuristics and evaluated for a fixed demand–planning horizon, assuming a known demand for the entire planning period. In this study, we simulate the use of planning models for decentralized sawmill production, but in a context where new orders arrive randomly and replanning is carried out periodically using a rolling horizon. We also simulated and evaluated different coordination mechanisms at the operational level, highlighting that previously published coordination mechanisms for decentralized planning of sawmilling operations may lead to a low order-fill rate when used in such a dynamic environment. We then propose a more advanced push–pull coordination mechanism based on the concept of *decoupling point,* revealing that this new mechanism may be more appropriate regarding the market characteristics considered in the study, while leading to a sales increase and reduced inventory. Actual numbers vary depending on specific market conditions.

Lumber production for softwood mills involves three main production stages: *sawing*, *drying,* and *finishing*. Many products are generated from a single raw material, so the process is known as *divergent* (from one log several products are obtained) with uncontrolled *coproduction,* which means that several products are produced at the same time (see Öner and Bilgic 2008) and each change made at a production stage affects the following phases. Sawing, drying, and finishing operations are typically planned using different models in a decentralized environment. Even though these three activities share the same goal, they may lack coherence because each unit is optimized independently (Gaudreault et al. 2010). This could explain why this industry often suffers from a low order-fill rate, high inventory, and significant lead time. Planning these operations using a centralized approach (based on a single coordinator responsible for establishing a centralized plan that must be followed by the planners of each subsystem) limits the specific operational details that can be taken into account (Gaudreault et al. 2010). Furthermore, Gaudreault et al. (2009) mentioned that centralized approaches cannot be used because of the complexity of the process involved, and highlighted the fact that there are not enough powerful computers able to process this data system. Thus, in order to keep the system decentralized (based on the fact that each unit is responsible for its own planning) while ensuring customer demand satisfaction, the lumber production process may be synchronized using efficient coordination mechanisms. These coordination mechanisms can be tools, agreements, and

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information that are used to ensure the coordination of the entire production process (Arshinder et al. 2011).

This research focuses on the coordination of these production stages in order to increase the volume of sales and decrease the average inventory. A simulation approach inspired from Dumetz et al. (2016) is proposed to simulate the entire softwood sawmilling production process at the operational level and evaluate the use of different coordination mechanisms, based on different order acceptance policies. The planning processes are further simulated by integrating mathematical optimization models for each processing activity.

In particular, two coordination mechanisms reported by Gaudreault et al. (2010) as being effective for the sawmilling industry are analyzed. In their original article, the authors evaluated these mechanisms using *static* data sets, namely a fixed planning horizon as well as a fixed and known demand (that is, a set of orders that is known in advance, before planning) for the whole planning horizon. Two mechanisms were already tested and showed good results in a particular context; therefore, we wanted to evaluate such coordination mechanisms with a more realistic dynamic order arrival process, which calls for periodic production replanning (rolling horizon) as well as the implementation of order acceptance policies (i.e., Available-to-Promise, Capable-to-Promise, and Stock). The environment is then considered to be dynamic because new orders arrive from one week to another and they must be taken into account. Results show that in this dynamic context, using the aforementioned mechanisms leads to poor performance, which may be explained by the high level of coproduction that affects coordination. A hybrid push–pull coordination mechanism, taking into account the decoupling point concept, is therefore proposed and evaluated. Simulation reveals that such a mechanism may lead to a higher order acceptance rate as well as a lower inventory. From an industrial point of view, this study provides information regarding how better coordination can be achieved in a decentralized production system with coproduction.

The remainder of this article is organized as follows. ''Preliminary Concepts'' introduces preliminary concepts about the North American lumber industry and coordination in supply chains and the coordination mechanisms evaluated. ''Assessing Coordination Mechanisms in a Dynamic Context'' describes the simulation framework needed to carry out the experiments and presents the experiments and the results. Finally, ''Conclusions'' concludes the article.

Preliminary Concepts

North American lumber industry

Softwood lumber production encompasses many particularities that distinguish it from other industries. Its production process is carried out following three main production stages (i.e., sawing, drying, and finishing), as illustrated in Figure 1. Logs come from different forest areas and are processed according to several cutting patterns (1). The mix of sawn lumber obtained at the exit of the first stage is of various lengths, thicknesses, and qualities. Next, these sawn pieces of lumber are grouped according to their physical characteristics and dried using high-capacity kilns (2). Lumber are then planed, trimmed, sorted at the finishing unit (3) and kept in stock until delivered to customers. Each production stage is therefore very different from the others by having its own particular production process. Furthermore, at each stage, an inventory of semifinished products is typically built to ensure the continuity of the process.

This process is also said to be *divergent*: from a single raw material, several final products are obtained, conversely to traditional manufacturing where the finished products are made from several products (Arnold et al. 2008). Moreover, many products are obtained at the same time and this cannot be avoided (*coproduction*). The characteristics of the logs and the cutting pattern used allow a certain control over this coproduction system (see Fig. 2 adapted from Wery et al. [2014]). Using one cutting pattern more than another, the sawn products are different. *Divergence* and *coproduction* make it then very difficult to know what log should be sawn, dried, and planed in order to fit with the demand. Furthermore, coproduction generates inventories for products that can be hard to sell or have less value. Figure 3 represents the section of a log. From this log several products can be obtained (2X3, 2X4, 2X6, . . .). If only product P1 (2X3) is in demand, other products are coproducts. Once produced, the company will need to wait until a demand comes from these specific products. Sawmills typically use historical data to forecast the expected quantities of various products that may be obtained from a specific class of logs, but still need to deal with customer orders every day.

Typically, the sawmilling industry takes into account the possible agreements and the demand forecast to create a production plan. In general, the production plan is for 4 weeks and the replanning is done weekly. When an order comes, the sawmill needs to accept or refuse the order depending on its inventory or its current and future production. The result is that it is difficult to plan the production at each stage without the use of large inventories of semifinished and finished products (Mendoza et al. 1991). The North American lumber system relies on a standardization process that defines strict dimensions and qualities, making lumber a commodity market. The situation is different in Europe, where most pieces are made to order according to specific characteristics. In this context, North American sawmills have adopted a push system described by the American Production & Inventory Control Society Operations Management Body of Knowledge (APICS DICTIONARY; Blackstone 2008, p. 49) as ''the production of items on a scheduled plan in advance of customer need.'' In this context, the revenue throughput is often the main indicator of a sawmill. The push system is then often associated with the making of a large inventory, considering their constraints such as supply volume, production capacity, etc., instead of taking into account the customer demand and producing *on order* (Simard et al. 2016).

A way to better respond to the demand is to plan the production stages using specialized models that take these particularities into consideration. Here are some examples of advanced tools at the operational level developed by researchers to deliver the right product to the right customer. Furthermore, Rönnqvist et al. (2015) listed 33 open problems related to operational research in forestry. They mentioned that problems can be very large and cannot be solved directly.

For the sawing operations, Maturana et al. (2010) presented several authors who have worked on the selection of the right cutting pattern to generate the highest volume

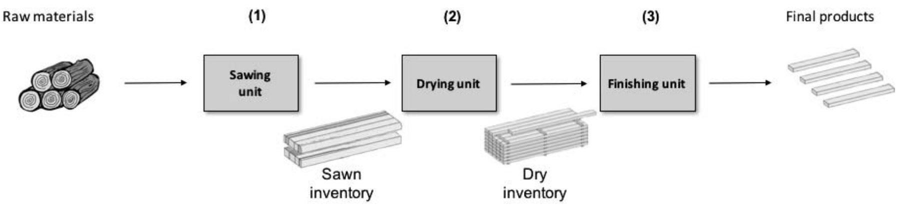

Figure 1.—Description of the lumber production process.

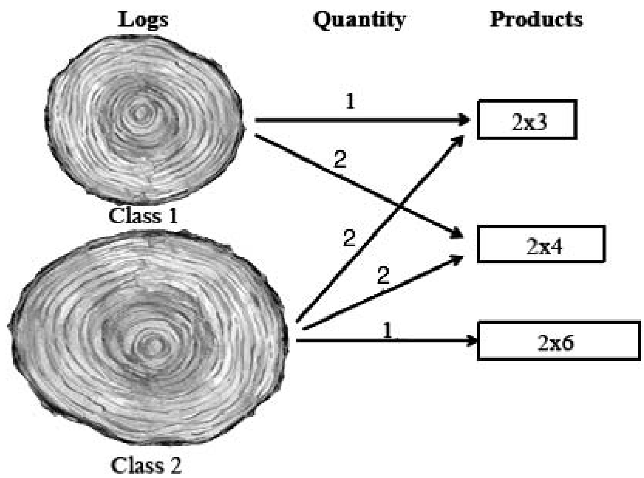

Figure 2.—Example of a production matrix (adapted from Wery et al. 2014).

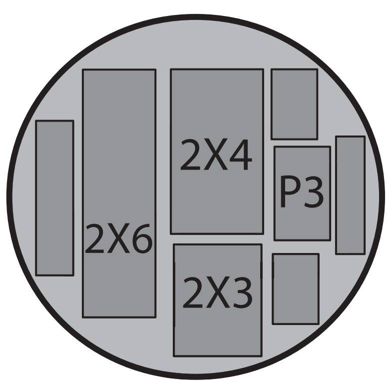

Figure 3.—Divergence and coproduction in the forestry sector.

and/or value: Occeña and Schmoldt (1996); Todoroki and Rönnqvist (1999); and Winn et al. (2004). Todoroki and Rönnqvist (2002) proposed a model that considers the optimization at the sawing operations according to general demand for sawn products. Maturana et al. (2010) compared two methods (an exact model and a heuristic approach) to select the best cutting patterns over a period of a few weeks in a sawmill, taking into account the demand for final products. The volume supplied is predetermined and there are no stochastic events in the business environment. Gaudreault et al. (2010) proposed a Mixed-Integer Programming (MIP) model to schedule the sawing operations in a sawmill. The goal was to maximize the production value and to minimize order lateness. Alvarez and Vera (2014) proposed a robust optimization method for tactical level planning of sawing operations (i.e., the main decision concerns the quantity of logs requested to satisfy the demand). They focused on uncertainty of the sawing process yield and they showed that computing robust solutions does not much deteriorate the objective-function value.

Concerning drying operations, Gascon et al. (1998) developed a heuristic approach to minimize order lateness for the lumber drying process. Aggarwal et al. (1992) developed an MIP to plan drying operations for the furniture industry. Their model also included the purchase of dry wood. Yaghubian et al. (2001) also developed a dry-kiln planning model, taking into account the possibility to buy dried wood or to dry it. The objective function was to satisfy the demand at the lowest cost. Gaudreault et al. (2010) proposed an MIP model to schedule the drying operations in a sawmill. The goal was to maximize the production value and to minimize order lateness. Marier et al. (2016) proposed an MIP planning model that dynamically generates load patterns during the drying planning process. This model is currently used in a few Canadian sawmills.

For the finishing operations, Gaudreault et al. (2010) introduced an MIP model to schedule the finishing operations in a sawmill. The goal is to maximize the production value and to minimize order lateness. Marier et al. (2014) adapted this model to plan the finishing operations in a sawmill while allowing a period-to-period production plan. The model requires the unit to be at 100 percent of its production capacity.

Even though all of these models can certainly be helpful for the forest products industry, there is still a need to coordinate the three main production stages and, as a result, to align the different production plans in order to ensure that the whole production system leads to global benefits, as introduced below.

Supply chain coordination

Coordinating an internal or external supply chain involves being able to manage dependencies between activities and efforts of each entity so as to achieve a common goal (Malone and Crowston 1994). Yesilbas and Lombard (2004) defined coordination as rules and procedures to ensure the operation of a group. Conversely, the lack of coordination in decentralized systems is associated with inaccurate forecasts, low capacity usage, excessive inventory, inadequate customer service, high inventory costs, increased customer response time, and low quality (Ramdas and Spekman 2000, Arshinder et al. 2008, Arshinder et al. 2011). To facilitate the coordination of decentralized systems, some mechanisms can therefore be implemented between various activities of the same company as well as between various companies of a supply chain.

At the interfirm level, Li and Wang (2007) proposed a review of these different coordination mechanisms for centralized and decentralized supply chains. Most common mechanisms concern the use of contracts (Cachon 2003), information sharing (Yu et al. 2001), joint decision-making (Turban et al. 2011), and cost–benefit sharing (McLaren et al. 2002, Audy et al. 2012, Elleuch 2013).

At the intrafirm level, coordination mechanisms typically focus on similar approaches. Muhl et al. (2003) showed the importance of coordination encompassing different jobs (i.e., several local optimizers) in the automotive industry. The study concerned an assembly line encompassing three units: the body assembly, the painting unit, and the final assembly. Each unit was optimized independently and various performance indicators were used to evaluate their efficiency. The idea was to vary the parameters of each local optimizer. Furthermore, in order to qualify and quantify quality of the overall flow in the entire final assembly plant, the authors developed a simulator of the production system combined with a weighted indicator system. The study showed the interest in considering the local optimizers (decentralized way) within a more global optimization approach (centralized way).

In the forest products industry, the particularities explained in the section ''North American lumber industry'' call for specific models. However, less attention has been paid concerning coordination (Ajayi 2016, Larsson et al. 2016). Rönnqvist et al. (2015) and Larsson et al. (2016) mentioned that coordination in the forest industry is a challenge and needs to be addressed. At the interfirm level, the forest-products supply chain still needs coordination efforts to continue expanding and becoming more profitable (Alam et al. 2014). Moyaux et al. (2003) showed that information sharing can reduce the bullwhip effect and increase the performance of the forest supply chain in terms of global costs. Lehoux et al. (2009) showed that the profits of two forest-products companies could be significantly improved via increased coordination and collaboration. Guajardo and Rönnqvist (2015) showed the benefits of a coalition between various actors for wood transportation. Alayet et al. (2016) proposed a centralized-production planning model at a tactical level for multiple forest companies in order to manage wood fiber freshness and ensure enough wood chip production.

At the intrafirm level, Gaudreault et al. (2010) studied the problems of intracoordination and proposed a planning model for each stage of the lumber production process. These models, mentioned in the section ''North American lumber industry,'' were coordinated using the following mechanisms at the operational level: *Two-phase planning* mechanism and *Bottleneck-first*. The following subsections explain the mechanisms in detail because they will be part of the coordination mechanisms tested in our simulation.

Two-phase planning.—When using the two-phase planning mechanism (see Fig. 4), two phases are executed. Customer demand is first tentatively propagated from one production stage to the other, beginning with the phase that is closest to the customer (i.e., finishing). A tentative plan is made by this unit, taking into account the customer demand (1), but without any supply constraint (infinite supply). This allows computing the *ideal* supply needed by this unit. It becomes the demand that will be transferred to the next unit (i.e., drying) (2), etc. The sawing unit (3) plans its operations according to its real supply and the demand it received from the drying unit. Drying then produces its real production plan according to the real supply it got from the sawing unit (4). This generates the supply used by the finishing unit to plan its production (5).

Bottleneck-first planning.—In this second mechanism, defined as bottleneck-first planning (Fig. 5), the customer demand is transferred directly to the bottleneck unit (i.e., the drying unit, as in most North American sawmills). This approach derives from Goldratt et al. (1992). In this context, the drying unit must have information about finishing processes and its available capacity in order to plan its own operations according to the demand for finished products. Production planning then occurs as in the two-phase planning mechanism.

Evaluation of coordination mechanisms.—The previous mechanisms were evaluated in Gaudreault et al. (2010), using real data such as production processes, products, orders, inventory, prices, various costs, supply, and capacities from a Canadian lumber company. Data were extracted from the enterprise resource planning (ERP) system of a partner company. Using an agent-based simulation platform, they evaluated these coordination mechanisms according to the number of late deliveries. Gaudreault et al. (2010) know in advance (before planning) all exact demand–orders for the whole fixed-planning horizon. They plan according to this demand and then analyze the quality of this plan. There are no orders arrivals, rolling horizon, or any simulation at all involved in their study. The authors showed that over a fixed period of 60 days, the bottleneck-first planning mechanism obtained the best results in terms of on-time delivered orders for a bottleneck located at the drying stage.

In our study, we use a rolling horizon. We simulate the arrival of new orders that triggers a replanning process. Of course, that demand should be ''generated at some point.'' This is done using a probabilistic demand generator, but new orders are generated in real time (and thus, demand is not known in advance). Therefore, we can evaluate more accurately what the performance of a company using a given planning process–coordination mechanism would be than Gaudreault et al. (2010) were able to do.

Assessing Coordination Mechanisms in a Dynamic Context

To efficiently reflect the industry's reality, this article aims to simulate a lumber production system where orders are generated dynamically and periodic production replanning is carried on, as opposed to the fixed planning horizon and fixed demand context explored by Gaudreault et al. (2010). A rolling-horizon planning procedure is then used (Fig. 6), which corresponds to moving the planning forward to a new period taking into account new data.

To achieve this goal, the simulation model proposed by Dumetz et al. (2016) is adapted to the context under investigation, taking into account the decentralization aspects of the lumber production system (Fig. 7). This simulation model, which is responsible for the simulation of the processes of orders generation, orders acceptance or refusal, and orders delivery, was developed using Simio, a general-purpose programmable discrete-event simulation tool, and combined with a ''custom-built ERP,'' which uses mathematical models to generate a production plan for each lumber production stage. The ''custom-built ERP'' was created in order to keep the inventory value of the different

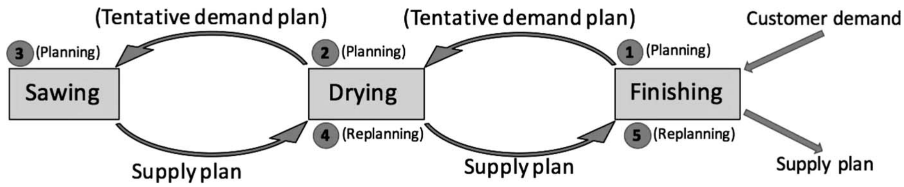

Figure 4.—Two-phase coordination mechanism.

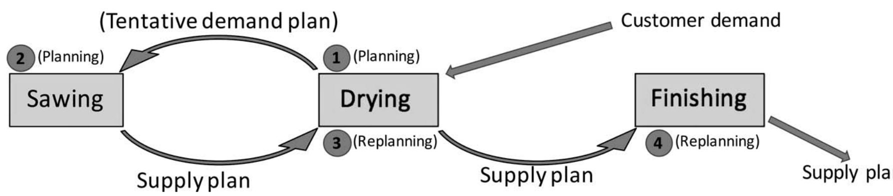

Figure 5.—Bottleneck-first coordination mechanism.

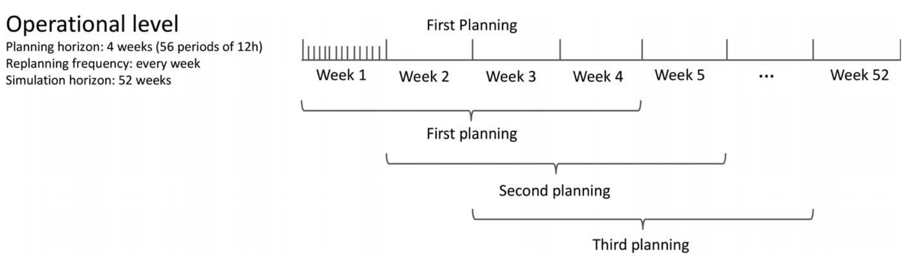

Figure 6.—Planning using a rolling horizon.

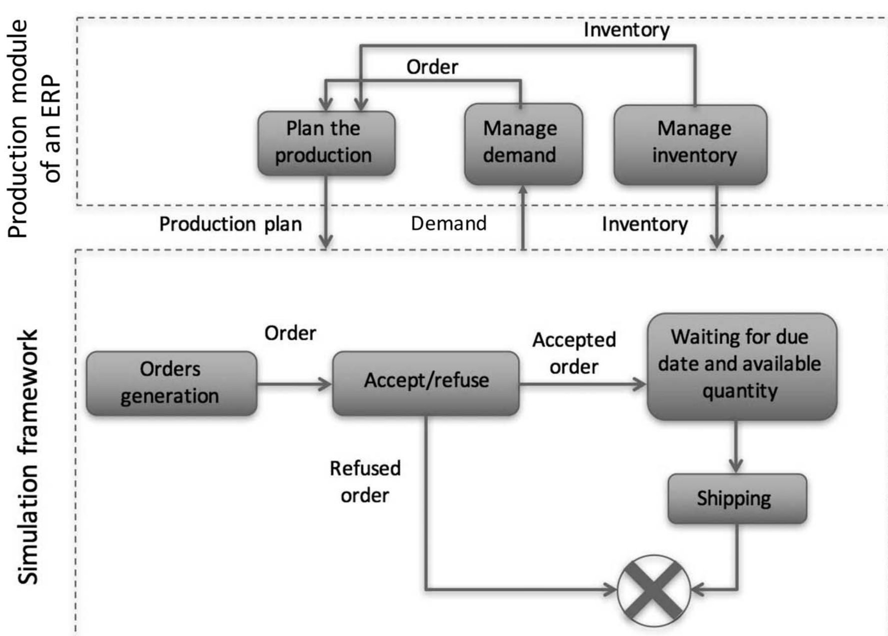

Figure 7.—Conceptual representation of the simulation framework adapted from Dumetz et al. (2016). ERP = enterprise resource planning.

products, the production plans of the different production stages, and the commitments. Using the simulation model, this ‘‘custom-built ERP’’ can call each of the different operational models to generate a new plan in real time. Simio is a well-recognized software used in various simulation areas because it provides analysis and randomness that are necessary for simulation studies.

Orders are often generated according to a Poisson distribution. The Poisson distribution is recognized to fit with order generation and was used by authors in the forest sector (Ben Ali et al. 2014, Marier et al. 2014). The parameters change according to the product in order to respect the quantity of each product received by the sawmill in one year. These orders are then accepted or refused according to a predetermined order-acceptance policy (e.g., *Available-to-promise* [ATP], *Capable-to-promise* [CTP], or *Stock* policy if the item is already in stock). Under ATP, defined by the APICS DICTIONARY (Blackstone 2008, p. 55) as ‘‘the uncommitted portion of a company’s inventory and planned production maintained in the master schedule to support customer order promising,’’ an order of size Q is accepted only if Q is smaller than or equal to the expected inventory, for every period of the planning horizon after the due date:

$$Q \leq I + \sum_{t=\text{now}}^{D-1} (P_t - E_t) - \max_{D \leq t \leq T} \left\{ \sum_{k=D}^{t} (E_k - P_k) \right\} \quad (1)$$

where D is the order due date, T is the simulation horizon, I is the current inventory, P_t is the production at period t, and E_t is the commitment at period t. Accepting an order using the ATP policy means that the order is accepted if the product is in stock or if the product will be produced before its due date. Using ATP and Stock policies, we only take into account the demand forecast that is based on the value market prices of the products.

When a CTP order-acceptance policy is used, it means that we try to first accept orders under ATP; if it is not possible, we try to modify the production plan in order to include the new orders. We also take into account the past commitments, using information contained in the ‘‘custom-built ERP.’’ An order accepted under CTP will then replace the production part that was used to produce the demand forecast in order to reach the maximal production capacity. Using CTP policy, we take the customer orders and the demand forecast (which is based on the value market prices of the products) into account in order to reach the maximal production capacity. When an order is accepted, the simulation model waits for the due date and the available quantity and then delivers the order.

In the original simulation model from Dumetz et al. (2016), the sawing, drying, and finishing units were considered as a single *blackbox* consuming raw material and producing final products. This was sufficient to highlight the impact of using various order-acceptance policies on the company’s performances. It was possible to see which policy is better than another. It was concluded that depending on the production parameter and the market context, the best policy to use was not always the most advanced policy (such as CTP). For example, depending on the market context and the production parameters of the sawmill, ATP can also outperform CTP in a high-demand market (see Dumetz et al. [2016] for more information). However, in real industrial context, such a centralized planning approach would not be feasible because of the complex relationship between each sawmilling activity. Therefore, we modified the model as follows in order to evaluate their interaction and the impact of different coordination mechanisms.

For each production unit (sawing, drying, and finishing), we used a specific model from the literature to optimize the production. At the sawing stage, we adapted a model from Marier et al. (2014) based on the sawing model from Gaudreault et al. (2010) to provide a period-by-period production plan, taking into account the raw material supply, the sawing capacity, and various cutting patterns. The sawing plan states which process is used, when it is used, and for how long, as well as how many sawn products are produced. Raw material is infinite, and the production is available 14 h/day, 7 days/wk. All cutting patterns have the same operational cost, but each product has a different expected market value. The planning horizon is 4 weeks and replanning occurs once per week. Figure 8 summarizes the input and the output of the model.

At the drying level, a kiln dryer can be represented as a huge container (defined by its length, height, and width) where bundles to be dried are assembled on a wagon and then pushed inside the kiln. We use an MIP–constraint hybrid planning model developed by Marier et al. (2016) to dynamically generate load patterns during the planning while taking into account the results from the sawing model, the physical constraints of the kilns, and various drying constraints such as the type of wood to dry. The drying plan states which wood bundle to dry, when and in which dryer, and how to load the kiln (loading pattern). The planning horizon is 4 weeks with replanning occurring once per week. Figure 9 summarizes the input and the output of the model.

At the finishing operation, we use a model adapted by Marier et al. (2014) from Gaudreault et al. (2010). This mixed-integer programming model tries to minimize order lateness and states the quantities of each product that should be planed for each production shift, as well as the finishing recipes to use. The planning horizon is 4 weeks, with replanning occurring once per week. The simulation framework exploited in this article allows us to integrate these three planning models in order to evaluate different coordination mechanisms for a decentralized lumber production system. Figure 10 summarizes the input and the output of the model.

The production stages are coordinated using the two-phase planning and bottleneck-first planning mechanisms (as described herein). For the purpose of comparison, we also simulate a straightforward ‘‘push approach.’’ We call it a ‘‘push approach’’ in reference to the push system that is described by the APICS DICTIONARY(Blackstone 2008, p. 49), which is a planning approach using the push system characteristics. We first planned sawing operations with the sole objective of maximizing production value. We then plan the drying stage based on the sawn products received, and finally plan the finishing operations (Fig. 11).

Experiments

Combining basic coordination mechanisms and order acceptance policies.—We tested different combinations of coordination mechanisms and order acceptance policies. Combinations depend on the characteristics of the order

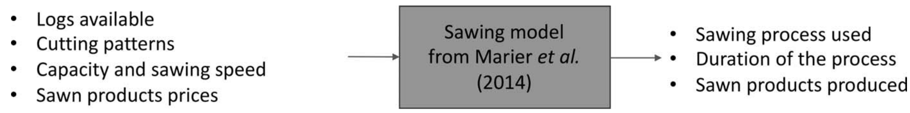

Figure 8.—Sawing model from Marier et al. (2014).

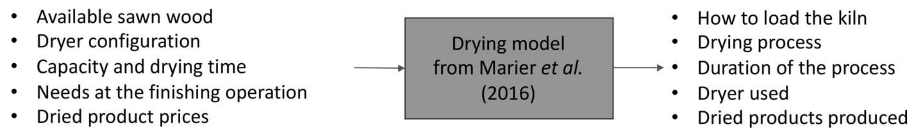

Figure 9.—Drying model from Marier et al. (2016).

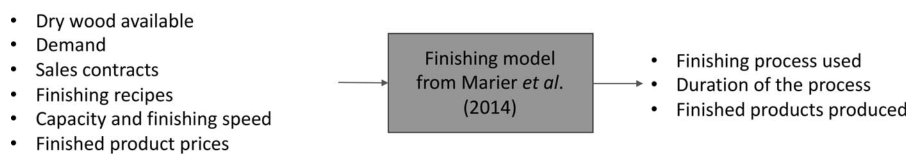

Figure 10.—Finishing model from Marier et al. (2014).

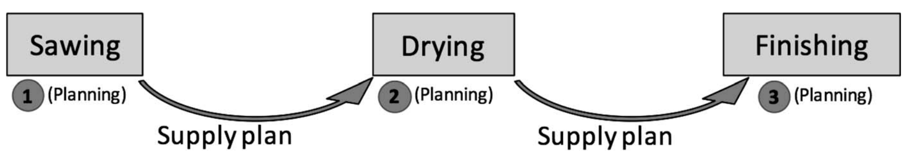

Figure 11.—Push planning system.

acceptance policy and the coordination mechanism. We listed all the existing combinations: three order acceptance policies and three coordination mechanisms (Table 1). We eliminated the ones that do not make sense (i.e., the ones for which order acceptance policies cannot be used with such coordination mechanisms).

Within Scenarios 1a and 1b, the push planning ''approach'' (Fig. 6) is used in combination with an ATP (1a) or a Stock (1b) order-acceptance policy. We recall that the push planning approach only takes into account the demand forecast (based on the value market price of the products) without any information concerning the customer demand; thus, it can only be combined with ATP or Stock, but not with CTP.

Within Scenarios 2 and 3, the two-phase planning and the bottleneck-first planning mechanisms are coupled to a CTP order-acceptance policy. For each received order, we check whether the current production plan would allow accepting the order. If not, production is tentatively replanned to check whether the order could be produced without violating previous commitments. We ran each scenario at 100 percent available capacity.

Table 1.—Scenarios of coordination mechanisms and order acceptance policies.

Scenario	Coordination mechanism	Order acceptance policies[a]
1a	Push planning system	ATP
1b	Push planning system	Stock
2	Two-phase planning	CTP
3	Bottleneck-first planning	CTP

[a] ATP = available-to-promise; CTP = capable-to-promise; Stock = the item is already in stock.

In order to compare and evaluate the mechanism's ability to coordinate the decentralized lumber-planning process, we measured the efficiency of the system in terms of sales and average inventory along the production process. In our simulation, the volume is the same for each order and each product. By assuming a given price per volume, the number of sales is proportional to the revenues. This volume could have been converted into dollars ($), but it led to the problem of determining which prices we were going to use because North American prices have doubled in recent years. It is the relative performance between the different approaches that is important. Consequently, we used the number of sales as a key performance indicator to compare each scenario.

The data used come from a North American sawmill's real production plan, although the size of the problem was reduced in order to ensure a verifiable experiment plan. Using a Pareto-inspired approach, we considered 10 products, representing approximately 80 percent of the total production volume over the year. We defined cutting patterns, drying processes, and stages of finishing recipes according to real patterns but adapted to fit only these 10 products. We did not extract incoming orders and delivery time from an actual database, but randomly generated them as in Ben Ali et al. (2014), using a Poisson distribution for the incoming orders and a triangular distribution (1, 2, 3 wk), respectively, for the delivery time required by the customer. Each scenario uses the same lead time. These distributions have been recognized as corresponding best to the reality. Each order consists of a single product with a fixed order quantity of 50,000 BFM (board-foot measure, which is the unit of measure used in North America). We chose this value because it is the quantity a fully-loaded truck can transport. The incoming orders-generation process is controlled by a parameter we called the *demand intensity*. This demand intensity corresponds to the amount of demand received during a year, and is expressed as the percentage of the maximal production capacity of the company. As an example, at a demand intensity of 100 percent, the volume of demand the company is expected to receive will be equal to its entire production capacity during one year. At 200 percent, it will be two times its entire production capacity during one year. By using this demand dynamic, it became possible to simulate the impact of facing a high-demand market versus a low-demand market.

The simulation horizon covered 1 year of production, each day being divided into two production shifts (periods) of 7 hours. We added a warm-up period of 1 year to the simulation horizon to reach the steady-state situation. Enough raw materials were available for the actual production capacity of the first activity (sawing).

We conducted 15 replications for each scenario, which allowed us to reach a significant confidence level (95%). Each replication had a computation time of 1.5 to 3 hours, depending on the demand intensity, for a total simulation time of 1,350 hours. We used and modified an existing simulation model from Dumetz et al. (2016), so we performed verification and validation stages using the same input data set as the previous model, and compared the results following Sargent (2013).

We can observe that the sales performance varied with demand intensity for all of the scenarios (Fig. 12). The higher the demand, the greater the performance. This can be explained by the fact that from one log, many different types of products are obtained (coproduction). That means for an order of a product P1, many other coproducts (e.g., products P2 and P3) are produced at the same time. As a result of coproduction, a mill requires high demand to be able to sell all the products. In such conditions, the number of sales increases as the demand intensity increases because demand exists also for the other products that are produced.

Results show that with the ‘‘push approach’’ (1a and 1b), the ATP policy leads to better performance than the Stock policy in terms of number of sales. In other words, it is beneficial to be able to sell a product based on the production planned. The bottleneck-first approach (Scenario 3) leads to better results than the two-phase planning mechanism (Scenario 2), as also was observed by Gaudreault et al. (2010). Two-phase planning and bottleneck-first planning mechanisms both outperform the ‘‘push approach’’ for small- and medium-demand intensities. At a low-demand intensity, using CTP is then better and more agile because CTP allows the possibility to adapt its production plan by adding the new order, versus ATP or stock where the production plan is the same, according to the demand forecast.

Here is a small example: a company produces five different products. According to the demand forecast that is based on the value market price, the three most valuable products are P1, P2, and P3. Using this information, at a low demand intensity, the sawmill will create P1, P2, and P3 most of the time. As soon as an order for P4 or P5 comes, accepting the order under ATP or Stock policies can be impossible because the plan only produces P1, P2, and P3, but very few P4 and P5. On the other hand, CTP will try to include this new order of P4 or P5 by modifying its production plan. That is the reason that CTP shows better performance at lower intensity. CTP is more agile. However, at a higher intensity, the coproduction products in a CTP approach will change very often because, when using CTP, we change the plan for every order. Then it is possible to accept an order for a product that is not ordered often. The production of this product can lead to other coproducts that can be hard to sell (by changing the plan, we also change the coproducts that are produced). Coproduction using ATP is always the same and will be sold when demand will be large enough. That is why ATP shows better

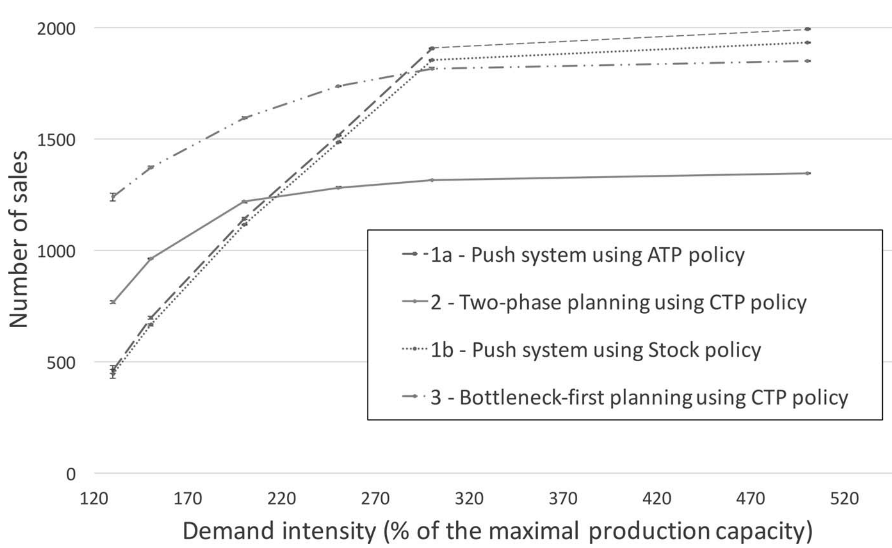

Figure 12.—Number of sales according to the demand intensity (push system, two-phase planning mechanism, and bottleneck-first planning mechanism, using Stock, ATP, and CTP order acceptance policies); confidence interval 95 percent. ATP is available-to-promise, CTP is capable-to-promise, and Stock indicates the item is already in stock.

performances at higher demand intensity. With the ‘‘push approach,’’ the mill is driven by the global market value and the plans are kept ‘‘as is.’’

Investigating a coordination mechanism mixing pull and push ‘‘approaches’’.—In order to minimize the effect observed in previous section, we then investigated a mechanism mixing ‘‘pull’’ and ‘‘push’’ approaches. As opposed to the push system, APICS DICTIONARY (Blackstone 2008, p. 50) describes the pull system as ‘‘the production of items only as demanded for use or to replace those taken for use.’’ The mechanism takes care of the decoupling point, defined by APICS DICTIONARY (Blackstone 2008, p. 48) as ‘‘the locations in the product structure or distribution network where inventory is placed to create independence between processes or entities.’’ A previous study investigates the impact of the location of the decoupling point on the capability to accept an order in the sawing industry (Cid Yáñez et al. 2009). However, in their work, only the planning process is simulated in a fixed horizon. In our study, we aim to simulate the planning process, the production process, and sales. We also use a rolling horizon with orders that are dynamically generated. For the case under study, coordinating the system based on this element involves using a push system to create inventory until the decoupling point and then using a pull system that takes into account the customer demand (see push–pull boundary in the APCIS DICTIONARY [Blackstone 2008, p. 50], that is, ‘‘the point at which one system ends and the other takes over’’). In the experiment, we assume that the decoupling point is associated with the drying stage. As a result, from raw material reception to the bottleneck (drying unit), we carried out the production planning using a ‘‘push approach,’’ where material is ‘‘pushed’’; whereas, for operations from the bottleneck to the finishing stage, we based the production planning on the bottleneck-first approach (thus taking into account the customer demand directly at the drying operation). Consequently, we used a ‘‘push approach’’ at the sawing unit and a ‘‘pull approach’’ at the drying and finishing unit. Our push–pull ‘‘approach’’ is then a planning approach using the push characteristics at the beginning of the process and pull characteristics at the end. Figure 13 illustrates this in a context where the drying unit is the bottleneck.

The simulation model and data sets used were the same as in the previous experiments, which allowed for the comparison of the impact of the new mechanism (Fig. 14) with the ones obtained from the other mechanisms tested in Scenarios 1a, 1b, and 3; and the number of sales is much greater than the ones obtained with Scenarios 1 and 3. In this case, the bottleneck is at the drying activity and we used a push system up to that point. At the drying activity, the customers' needs are taken directly into account, and we used a pull system at the drying and finishing activities. Using a push system at the sawing activity leads to a large inventory of sawn products that will be used at the drying stage. The drying plan then takes into account the customer needs, and this offers better results compared with other scenarios. For example, Scenario 3 is using the two-phase planning and bottleneck first, followed by an attempt to plan the sawing activity by taking into account the demand. Doing this results in a poor solution—it is very difficult to plan according to the demand because sawing is the first activity and it generates a great deal of coproduction. It can be very hard to obtain a good sawing plan that allows for drying and finishing to have the right product at the right time, which is the reason Scenario 4 outperforms Scenario 3. Furthermore, the new mechanism dominates the others for any demand intensity level. Of course, at a very high demand intensity, the number of sales for every scenario can be very close.

In the previous experiments, the production bottleneck was located at the drying unit, as is the case for most sawmills in North America. We now move the bottleneck to the finishing stage. To do that, we improve the capacity of the kiln dryer to be able to have the bottleneck at the finishing stage. As a counter example, we also test the situation where the decoupling point is kept at the drying unit (that means a push system until that point) although the finishing operation is still the bottleneck. As illustrated in Figure 15, better sales are obtained when the decoupling point is correctly positioned just before the bottleneck (finishing activity in this case). If the decoupling point remains before the drying activity, the number of sales is indeed lower because this is not the current bottleneck.

Impact of the coordination mechanism on the average inventory

Another aspect the decision-maker needs to consider is the average inventory level of sawn, dried, and finished products that may be produced. They represent a significant part of the total production cost while requiring significant storage space.

Figure 16 shows the average inventory MFBM (1,000 board-feet, the unit of measure for the volume of lumber used in North America) for a precise demand intensity (300%) for each type of product. We chose a demand intensity of 300 percent because at this demand intensity, the number of sales for all scenarios is almost equal (see Fig. 9). We recall that the demand intensity is the amount of orders received in 1 year, and express it as a percentage of

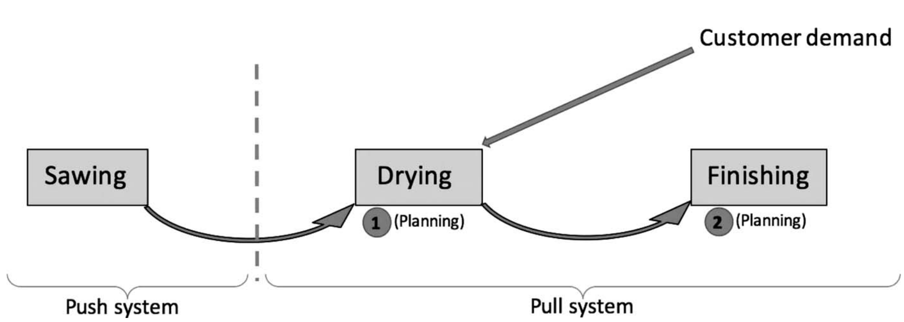

Figure 13.—Decoupling point before the drying stage.

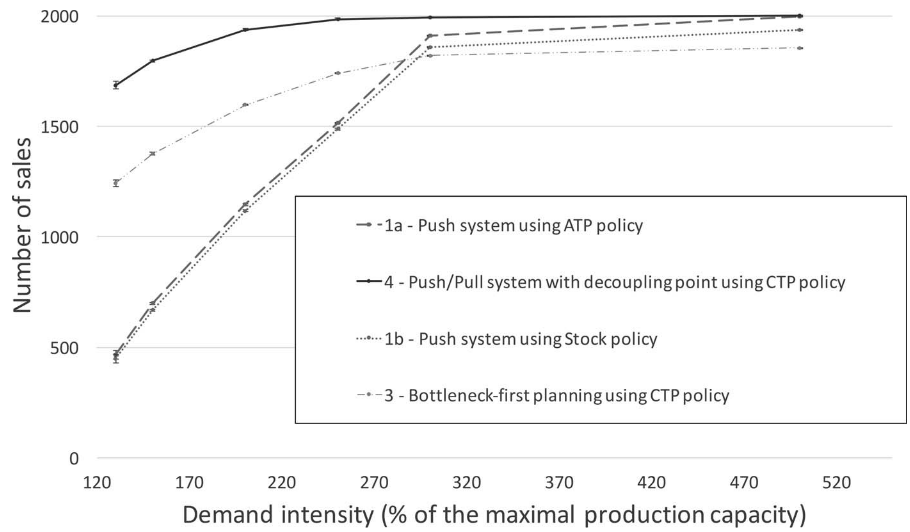

Figure 14.—Number of sales according to the demand intensity (push system, bottleneck first mechanism, push–pull system with decoupling point using Stock, ATP, and CTP order acceptance policies) when the bottleneck is at the drying activity; confidence interval 95 percent. ATP is available-to-promise, CTP is capable-to-promise, and Stock indicates the item is already in stock.

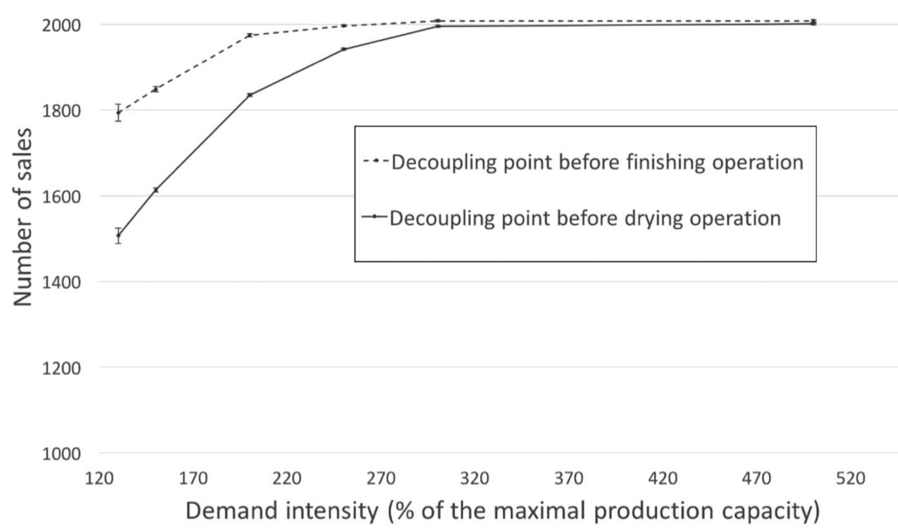

Figure 15.—Number of sales according to the demand intensity when the bottleneck is at the finishing unit; confidence interval 95 percent.

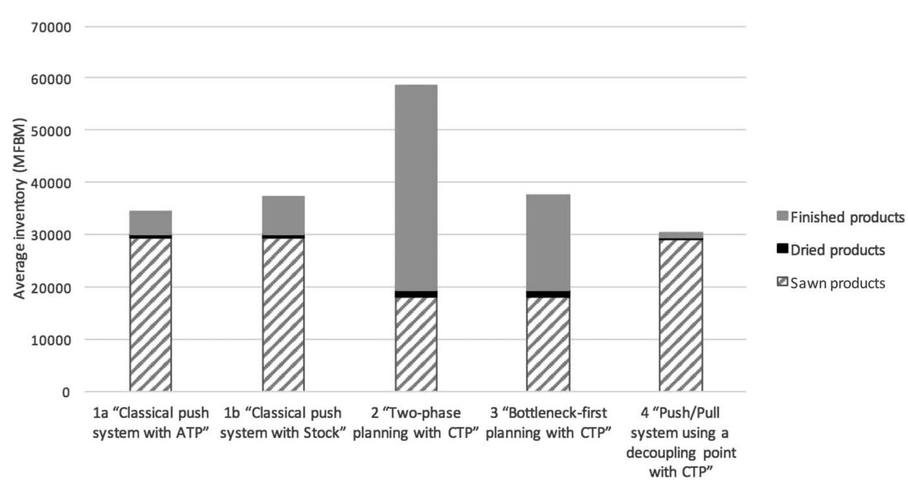

Figure 16.—Average inventory for each scenario for sawn products, dried products, and final products (demand intensity = 300% of the maximal production capacity) when the bottleneck is at the drying stage; confidence interval 95 percent. ATP = available-to-promise; CTP = capable-to-promise; Stock = the item is already in stock.

the maximal production capacity. Here, the bottleneck is located back at the drying stage and uses the same data set as in previous experiments.

Scenario 4 (push–pull system with decoupling point) presents the smallest total average inventory. The bottleneck stage can change its plan to better fit the demand, resulting in less inventory of finished products. Other products stay for a longer period in inventory.

The average inventory of sawn products is the same for Scenarios 1a, 1b, and 4. Indeed, in all these scenarios, the sawing operations are planned in the same manner. However, the difference in the average inventory for dried and finished products is significant. Scenarios 2 and 3 show larger inventory for finished products, caused by the coproducts obtained when replanning on demand, coupled with the lack of synchronization between drying and finishing (which is improved when introducing a decoupling point in Scenario 4).

We recall that those results are obtained for a demand intensity of 300 percent. Average inventory would be different for other demand intensities; however, we still conserve the same magnitude and the best scenario still remains Scenario 4. The intervals are not on the figure because it would be unreadable, but intervals concerning finish products and dried products between scenarios are statistically significant.

Conclusion

In this research, we simulated the operational planning of the lumber production process, an industry dealing with a high level of coproduction. The lumber production process involves three main production stages: *sawing*, *drying,* and *finishing,* that are planned in a decentralized manner. In order to ensure coordination, we tested and compared different coordination mechanisms between these production stages and evaluated their performances. We considered the market context (quantity of demand) and the production parameters (such as cutting patterns, drying and finishing characteristics, planning horizon, and replanning frequency) of a typical North American sawmill in the experiment, and used a rolling horizon with dynamically incoming orders. Coordination mechanisms known to be good in a ''static'' context appeared inefficient when facing a dynamic order-arrival process. Indeed, this is due to the coproduction phenomenon that is amplified when simulating in a dynamic environment; each time a new order arrives and is accepted, the process of generating a new wood product leads to the production of coproducts that may be difficult to sell or that may not be needed by the next production phases. We therefore proposed a hybrid push–pull coordination mechanism, which takes into consideration the decoupling point. Until the decoupling point, the material is ''pushed'' without taking into account the demand. After this decoupling point, the material is ''pulled'' by the demand. We showed that this new mechanism may be very profitable for any level of demand intensity, outperforming all the other approaches.

From an industrial point of view, this study provides information regarding how better coordination can be achieved in decentralized production systems with coproduction. As an example, to operate a sawmill, various production parameters should be taken into account, such as the order acceptance policies and planning frequency, as well as the coordination mechanism at the operational level. These coordination mechanisms are used to keep a good consistency between the three processes (sawing, drying, and finishing). In the actual industry, these choices are very difficult to make depending on the market context, and one can influence the choice of others. In this work, the model can simulate them in order to choose the right policy (order acceptance, planning frequency, coordination mechanism, etc.). The lumber industry is not the only industry where divergence and coproduction are important factors to take into account; the float-glass manufacturing (Taskin and Ünal 2009), oil (Pinto et al. 2000), and food industries (Ahumada and Villalobos 2009) are comparable examples.

In future work, it would be interesting to integrate a tactical planning level that could define production targets to follow over a long period of time, so as to provide the forest products industry with a complete tool to better plan and control its lumber production system.

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