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Abstract: Raw material heterogeneity, complex transformation processes, and divergent product flowsmake sawmilling operationsdifficult to manage. Most north-American lumber sawmillsapply a make-to-stock production strategy, some accepting/refusing orders according to available-to-promise (ATP) quantities, while a few uses more advanced approaches. This article introduces a simulation framework allowing comparing and evaluatingdifferentproduction planning strategies as well as order management strategies. A basic ERP system is also integrated into the framework (inventory management, lumber production planning algorithms, ATP and CTP calculation, etc). The user can configure the production planning and order management process, and evaluate how they will perform in various market contexts using the discrete event simulation model.

*Keywords:*Production planningstrategies,lumber, order management, simulation

## 1. INTRODUCTION

Sawmilling is a process difficult to manage. Raw material (log) comes from the forests and shows a great diversity in terms of wood quality, diameter, length, etc. The sawmill must take into account this heterogeneity while trying to maximize produced value and/or meet customer expectations. Satisfying demand is difficult for the following reasons. First, sawing generates many products at the same time (i.e., divergentprocess with co-production), which cannot be avoided (Weryet al. 2012).Many researchers have proposed models to optimize lumber production. However, companies do not necessarily know the best way to integrate these optimization models within their management processes.

This paper describes a simulation frameworkdeveloped to compare and evaluate different planningand order management strategies. Each strategy is defined by: the production planning models used, the size of the planning horizon, the re-planning frequency,and the order acceptation criteria (which can be based on stock levels, ATP, CTP, etc).

These strategies can be evaluated for different market conditions in order to answer questions such as: What control strategy should be used for this market? What should be the planning horizon and the planning interval to improve the financial performance of the company? If reducing the lead-time waspossible, what would be the rateof acceptance fornew orders? Should we re-schedule more often when business activities areincreased?

This paper is organized as follows: Section 2 presents a reviewof existing tools used to support the decision-making process for different stages of a lumber production system. Section 3 introducesthe simulation framework. Section 4 presentsa case study used to demonstrate how the framework can be used to compare different strategies.Very basic strategies are used in order to verify the model. In Section 5, results are presented and analysed.

## 2. BACKGROUND

Lumber production is a three phase manufacturing process. As described by Gaudreault et al. (2010), it involves three facilities. First, the sawing unit is responsbile forsawing logsinto green rough lumber according to different cutting patterns. At this step, produced lumber vary in quality (grade), length, and dimension. Then, the lumber must be dried using a kilnunit in order to reduce the moisture content. This step is necessary to use the lumber in construction industry (Wery et al. 2014). According to Yan et al. (2001), drying operation is crucial to ensure quality (by reducing biological damage, by increasing dimensional stability) while reducingtransportation cost. The final step is conducted by the planing unit to obtain the desiredsurface and thickness.

Many optimizationmodels have been developed to support decision makingprocess in the lumber industry.They lead to optimalor near-optimal solutions. The aim of this type of optimization is often to maximize value or minimize costs.

Marier(2011) and Marier et al.(2014) proposed a tactical MIP model integrating production (sawing, drying, finishing), sales, and distribution. A Sales and Operation Planning (S&OP)approach is usedto correlate sales, marketing, procurement, production, and finance, so as to create an annual plan that takes into consideration differentproduct families. A similar tactical planning model was proposed by Singer et al. (2007) for the Chilean sawmilling industry.

At the operational level, Gaudreault et al. (2010) proposed three MIP models that can be used to plan/schedule sawing, drying, and wood finishing (planing) operations. The

objective function allows maximizing production value and/or minimizing orders lateness.A basic coordination mechanism (heuristic) is provided to synchronize those plans. Improved coordination mechanisms are proposed in Gaudreault et al. (2009) and Gaudreault et al. (2012). A stochastic version of the sawing operations planning was developed by Kazemi-Zanjani et al. (2013). An improved version of the drying model was also proposed in Gaudreault et al. (2011).

Even though the previous optimization models show many benefits, they still involve many challenging issues such as how they should best be used by a specific company evolving in a specific market context. Each company/production unit should put in place an operation management system integrating (1) optimization models and algorithms; (2) business processes and policies.

To deal with this issue, discrete-event simulation can be used to test different scenarios and show how the different changes in the operating environment will impact the performance of the organization. Discrete-event simulation can be used in such context. For example, El Haouzi et al. (2008)used discrete-event simulation to compare different manufacturing systemin a company implementing Demand Flow Technology (Costanza J. 1996).In Abdel-Malek et al (2005), the authors compareddifferent supply chain outsourcing strategies. The key performance indicatorsused were the inventory levels and the total cost.

## 3. SIMULATIONFRAMEWORK

The framework presented here allows comparing and evaluating different planningand orders management strategies. Each strategy is defined by: the production planning models used, the size of the planning horizon, the re-planning frequency, and the order acceptation criteria (which can be based on stock levels, ATP, CTP, etc.).

These strategies can be evaluated for different market conditions (order arrival rate per product, order size, demand lead time, etc.)

A discrete event simulation model is developed using SIMIO. The user can therefore definescenarios visually (i.e. configure its operations management framework and market conditions). The simulation model is also connected to a basic ERP system (inventory management, lumber production, planning algorithms, ATP and CTP calculation, etc) we developed.

### *3.1-Simulation framework description*

A conceptual representation of the framework is provided in Figure 1.

For each product, orders are generated in (1) according to a given arrival rate. Following Ben Ali et al. (2014), orders in the lumber industry typically follow a Poisson distribution. Other distributions are provided to model the size of the order and the demand lead-time. This parameter corresponds to the time between the order arrival and the delivery date D (Tony Arnold et al. 2010).

Each ordercan be either accepted or rejected (2) according to a given policy. If the order is rejected, it leaves the system. If it is accepted, it waits until delivery date and material availability (3). The order is then shipped (4).

The ERP system is in charge of the planning production (a)

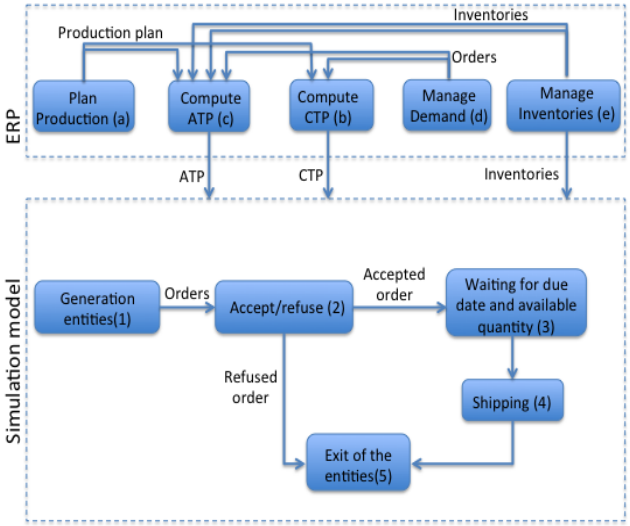


Figure 1: Conceptual representation of the framework

using a model from Marier et al. (2014). The ERP also offers services for computing volumes that are available to promise (ATP) (b) and capable to promise (CTP) (c), whilemanaging a list of accepted orders (d) and inventories (e).

The simulation model "calls" the ERP each timea planning is needed, a new order is accepted, or when ATP, CTP or inventory information is needed.

Parameters of the model specify the simulation horizon, the planning horizon, and the re-planning frequency. The user also needs to specify which policy should be used to accept/refuse an order. The order can be accepted based on current stocks, ATP, or CTP.

### *3.2-Order acceptation policies*

**Stock**: a tentative order of size *Q* is accepted if current inventory *I* minus the sum of commitments (accepted orders not delivered yet) is greater than or equal to *Q*.

**ATP:** an order is accepted if

Q ≤ Minimum foreseen stock after order due date

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

Where D is the order due date, T is the simulation horizon and I is the current inventory, Pt the production at period t and Et the commitment at period t.

**CTP:** When processing an order, a tentative production plan is computed in order to check if we can satisfy the new order without compromising the previously accepted orders.

**AcceptAll**: For study/comparison purpose, the model can also be configured to accept all orders.

## 4. EXPERIMENTS / MODEL VERIFICATION

The following experiment was carried out in order to perform model verification. We tested different scenarios (combination of order acceptation policies, market conditions, and planning parameters) for a case that was small enough for us to anticipate the results.

The simulation horizon covers a full year, each day being divided into 2 production shifts (periods) of 7 hours of work. We consider that enough raw materialsare available for the production of finished goods (i.e., infinite supply availability). Each order is for one single product and there are ten different products. The initial state of the model is as follow: the quantity available for each product is set between 50 and 200 MBFM. The starting quantity for each product was chosen to have a little inventory at the beginning of the simulation. Values are multiple of the order size and take into account the importance of each product (i.e., the number of sales of each product in one year).It is possible to have other starting values like previous commitments

Table 1 below shows the full factorial design. It defines parameters values for orders acceptation policy, production planning policy, and market conditions.

Table 1: Full factorial design

| | **Parameters** | **Level** | **Value** |
|---|---|---|---|
| *Orders acceptation policy* | Orders acceptation policy | 3 | Stock, ATP, AcceptAll |
| *Production planning policy* | Demand lead time | 2 | Randomtriangular( 1,2,3)<br>Randomtriangular( 0.5,1,2) |
| | Re-planning frequency | 3 | 1,2,3 weeks |
| | Planning horizon size | 5 | 1,1.5,2,3,4 weeks |
| *Marketconditions* | DemandIntensity[1] | 5 | 90, 100, 110, 130, 150 % |
| | Order Size | 1 | 50 MBFM (capacity of a full truck load) |

A total of 450 scenarios are defined. We needed 50replications to obtain a significant confidence interval (95%). The time needed to run one scenario considering the confidence interval was around 20 seconds, for a total of 150 hours of computation time.

Although *CTP* is supported by the framework, it is not part of the experiment/results as it was too computing intensive to provide results on time. When using *CTP*, one replication needs more than 30 minutes of computation time. That would have increase simulation time by approximately 187 days. However, we have access to a super computer (8000 processors) that will allow us to provide the results in the future.

## 5. RESULTS AND ANALYSIS

To analyse the results, some key performance indicators have been considered: the simulation model then allows choosing the scenario that may maximize accepted orders, maximize orders delivered on time, minimize inventory, or simply highlight different parameters where an interaction between them occurs.

### *5.1- Impact of the size of the planning horizon on the accepted volume of orders and inventory levels*

Figure 2 on the next page shows the impact of the planning horizon sizeon the total volume of ordersaccepted,as well as on the average inventory level. The parameters of the model are setfor a demand intensity corresponding to 130% of the production capacity, a triangular demand lead-time distribution (1,2,3), and a re-planning frequency of 1 week. We show results for *ATP*, *Stock*, and *AcceptAll* orders acceptation policies.

*AcceptAll* is utopic because accepted volume exceeds the total capacity while generating backorders. On the other hand, it defines an upper bound for the total volume of accepted orders and a lower bound for the inventory level. As for the policy where we accept orders based on *Stocks*, it is our lower bound for the total volume of accepted orders and our upper bound for inventory levels.

If we look at the volume of orders accepted for *ATP*, as expected,they are greater than for *Stock*. Volume of accepted orders for *ATP* increases with the size of the planning horizon (the smaller the horizon, the morewe need to refuse some orders because our production plan and ATP do not reach that point). In our specific case, with a cumulative lead time of 3 weeks and a re-planning frequency of 1 week, there would be no purpose having a planning horizon superior to 4 weeks since no order can be received after the fourth week (although industry often use a longer planning horizon to have a better visibility, as mentioned by Tony Arnold et al.,2010).This result was expected (see Vollman et al. 1997) and contributed to establish the validity of the simulation model.

Conversely, the inventory level associated to the *ATP* policy decreases when the size of the planning horizon increases, until we reach a planning horizon of four weeks. This result is also coherent.

[1]Demand intensity is a parameter we defined to express the total number of orders received as a percentage of the production capacity. It is used to define the arrival rate.

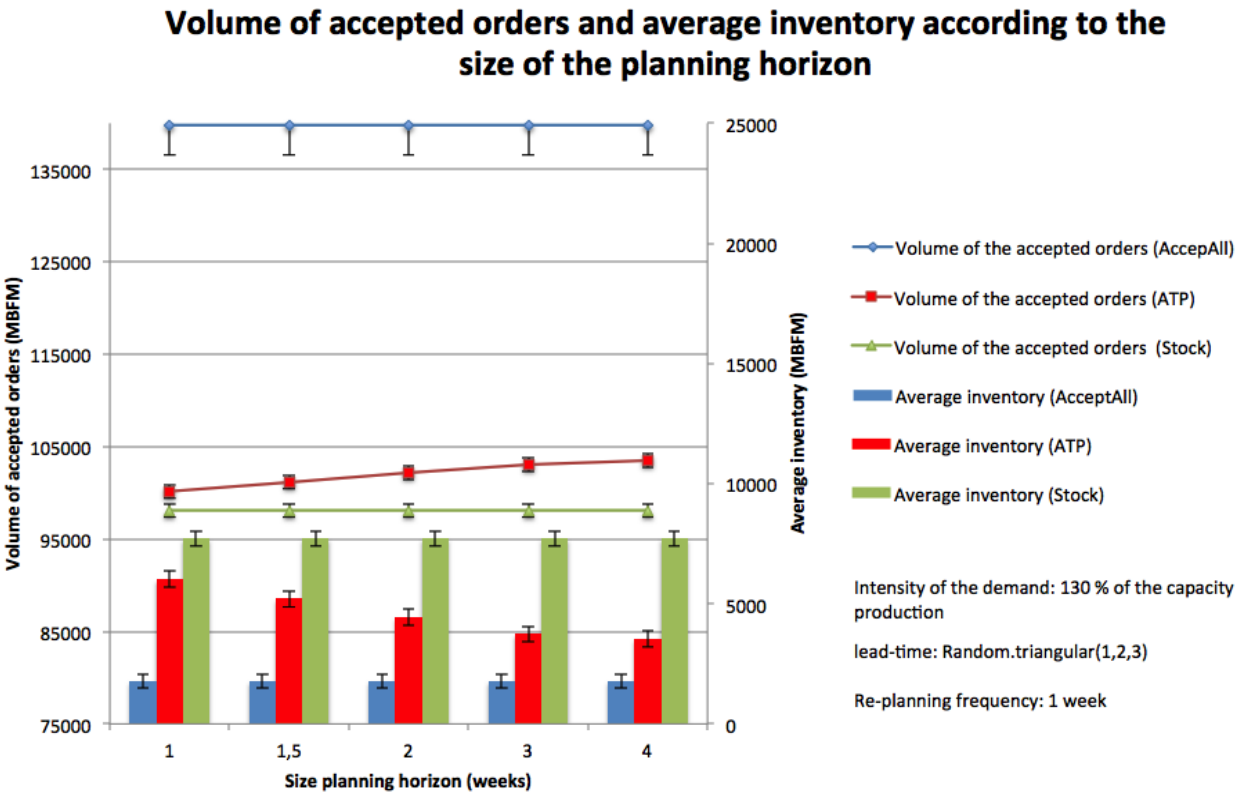


Figure 2: Impact of the size of the planning horizon

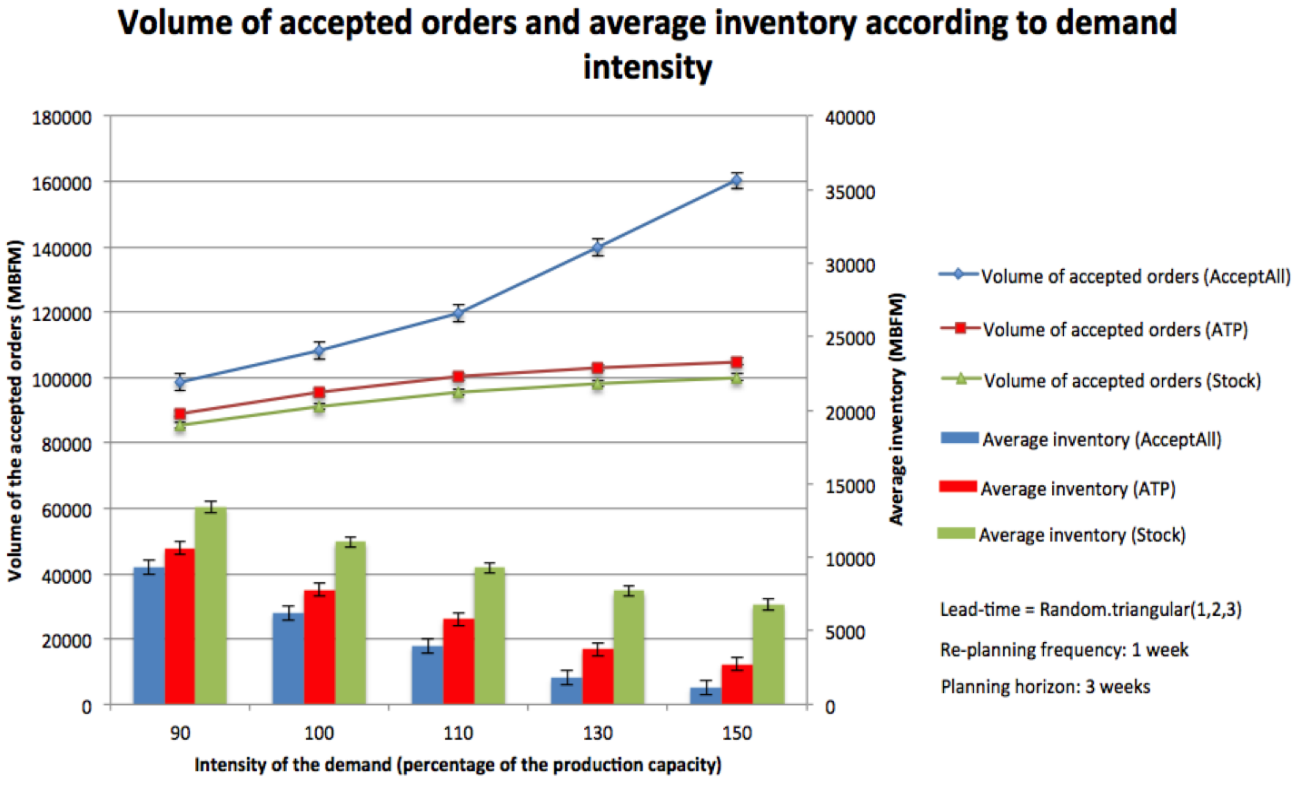


Figure 3: Impact of the demand intensity

Finally, we note that for the *ATP*policy, even thoughthe accepted volume is only slightly higher than the *Stock*policy (as the total production capacity remains the same), the reduction of the average inventory is significant (48,5% for a planning horizon of three weeks).

*5.2- Impact of the demand intensity*

We first recall that *demand intensity* is the total demand expressed as a percentage of the total production capacity. Figure 3 on the previous page shows the total volume of accepted orders and the average inventory according to the demand intensity.

As expected, the greater demand intensity is, the greater the total volume of accepted orderswill be. This is true until we reach a point where all the production can be sold. This pointis not represented in the figure;for the specific case reported, it was reachedat around 170% (the volume of accepted orders is then equalledto the global production capacity). An intensity of 100% of the production capacity would thus not be enough (due to the stochastic environment, demand for some specific products would be less than their production volumes; some orders would have due date outside the simulation horizon; too many orders could have the same due date, forcing the reject for some of them).

Regarding the average inventory level, the greater the intensity of demand is, the smaller the average inventory has to be. This is true for any policy. However, the greater the intensity is, the bigger is the difference between *ATPand* Stock policies.

We recall that *AcceptAll*policy may look attractive (less inventory and many orders accepted). However, there isa huge number of late deliveries and therefore the customer satisfaction is very poor. By comparison, on-time delivery reaches 39% for *AcceptAll*, against 100% for *Stock* strategy and *ATP*.

## 6. CONCLUSION

This article proposed a simulation frameworkto compare and evaluate different planning and order management strategies. It also encompasses a basic ERP system that covers inventory management, lumber production, planning algorithms, ATP and CTP calculation. The user can configure the production planning and order management process directly on the framework and then evaluate how they will perform in various market contexts. This tool could be used ina company as a decision-making tool by allowingchoosing the right production planning and ordering management strategies.

Even though this simulation model is at its first stage, the results of the experiments refer to recognized practicesin the literature(Vollman et al. 1997) andare verified.

In future work, this framework will be used as the backbone of a more complex study. The goal is to propose guidelines for more agile operations management driven by demand. We need to propose an operation management framework describing how to combine algorithms, humans, and decision processes in order to maximize the overall performance of the organization (business process reengineering).Some work to integrate a complete tactical planning, differentiate the operation planning (sawing, drying, planing) and have stochastic event in the production and supply, are underway. Therefore, the framework will allow simulating different coordination mechanisms between the tactical and operational planning level, as well as between the different departments (ex: raw material procurement, production and sales). The goal will be to recommend configurations adapted to different market conditions.

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