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Integrating Revenue Management and Sales and Operations Planning in a Make-To-Stock environment: Softwood lumber case study

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Abstract

Most research regarding revenue management in manufacturing has considered only a short-term planning horizon, assuming supply and production data exogenously given. Motivated by the case of the Canadian softwood lumber industry, this paper offers additionally a medium-term visibility for firms with limited capacity and faced with seasonal markets. We propose a demand management process for Make-To-Stock environments, integrating sales and operations planning (S&OP) and order promising based on revenue management concepts. Given heterogeneous customers, divergent product structure and multiple sourcing locations in a multi-period context, we first define a multi-level decision framework in order to support medium-term, short-term and real-time sales decisions in a way to maximize profits and to enhance the service level offered to high-priority customers. We further propose a mathematical formulation integrating an S&OP network model in the Canadian softwood lumber industry and an order promising model using nested booking limits. This new formulation allows reviewing previous order promising decisions while respecting sales commitments. A rolling horizon simulation is used to evaluate

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the performance of the proposed process in various demand scenarios and provides evidence that better performances can be achieved compared to common demand management practices by integrating S&OP and revenue management concepts.

KEYWORDS
Revenue management ; Sales and operations planning ; Demand management ; Rolling horizon simulation ; Softwood lumber industry.

1. Introduction

Revenue management (RM) techniques have received notable attention in manufacturing as a powerful tool for order promising in supply-constrained environment. Although it is a critical task, order promising focuses on maximizing short-term revenue, often ignoring the potential profit that can be obtained by anticipating mid-term demand. In contrast, sales and operations planning (S&OP) focuses on mid-term revenue and offers the possibility of taking advantage of demand and price fluctuations. Unfortunately, it seems that current studies and existing systems that dealt separately with RM or S&OP, hardly capture the needs of sales managers. In fact, the integration between RM and S&OP is not well understood either in theory or practice.

In this research, the integration of RM and S&OP is motivated by the case of most Canadian softwood lumber firms, which fight ferociously to be more competitive when facing a set of business challenges: economic pressures, high operating costs, convergent processes, heterogeneous customers, limited raw material availability and capacity, and seasonal market. Based on multiple meetings with softwood lumber managers from the Eastern Canadian region, we noted first the lack of synchronization between the different business units of the softwood supply chain due to divergent product structure (i.e. from one log, it is not possible to generate different products independently) and the highly heterogeneous nature of its raw material, and second the ingenuous manner in which orders are fulfilled.The objectives of this paper are i) to offer guidance for such firms by extending the existing research in demand management for Make-To-Stock (MTS) manufacturing systems in a way to maximize profits and enhance the service level offered to high-priority customers, and ii) to provide evidence to managers of the value of integrating S&OP and RM.

More precisely, our contributions are as follows: First, in order to support sales decisions that have to be taken at multiple planning levels and at different frequencies (real-time, short-term and mid-term sales decisions), we define a demand management process integrating S&OP and RM and considering differentiated demand segments, divergent production processes and multiple sourcing locations in a multi-period context. Second, we propose a mathematical model integrating an S&OP network model in the Canadian softwood lumber industry and an order promising model based on RM concepts. Our integrated model also offers the possibility of changing decisions of how confirmed orders have to be fulfilled as late as possible, which we called order reassignment. Third, we evaluate the demand management process performance with various demand scenarios via a rolling horizon simulation. We emphasize the benefits of integrating S&OP and RM concepts for softwood lumber manufacturers located in Eastern Canada, as compared to demand management common practices.

This paper is structured as follows: In Section 2, we restate the problem faced by Canadian softwood lumber firms and define the paper's positioning via an overview of recent studies about S&OP and RM applications in manufacturing context. Furthermore, in Section 3 we propose a demand management process for MTS environments, including S&OP at the tactical level and real-time order promising based on RM concepts at the operational/execution level . In Section 4, a tactical model and an order promising model are formulated as linear programs (LP) so that order assignment may be changed as late as possible, although the decision of accepting or refusing an order is instantaneous and definitive. A network perspective is considered. Afterward, the illustrative case, based on softwood lumber manufacturers located in Eastern Canada, and experiments that will be conducted are depicted in Section 5. In Section 6, we discuss the potential benefits of integrating S&OP and RM concepts and the managerial implications. Finally, concluding remarks are provided in Section 7.

2. Problem statement and related literature

In this section, we first state the problem faced by sales managers in Canadian softwood lumber firms. Then, we proceed with a literature review to describe the basis of S&OP and to analyze the current research state on RM in manufacturing context.

2.1. *Demand management problem in Canadian softwood lumber industry*

The softwood lumber industry is an important sector in the Canadian economy. It offers thousands of direct jobs and significant benefits supporting indirect jobs. This sector is also involved in the development of rural and remote communities in certain regions. Moreover, softwood lumber accounts for 20% of the value of Canadian forest product exports [1], destined for domestic and international markets.

During recent years, this industry has faced various trade and economic pressures (Dufour 2007), including Canada–US softwood lumber agreements and fluctuations in the Canada–US exchange rate, American anti-dumping, a rise in energy and raw material prices and the increased competition from Asiatic emerging countries. Within this context, softwood lumber companies try to remain profitable and to maintain positive profit margins.

A softwood lumber firm can be considered as an MTS environment as its activities are driven by forecasts. It is composed generally of multiple facilities including mills and distribution centers. Unlike traditional manufacturing industries (i.e. assembly) which have a convergent product structure, the softwood lumber industry has complex transformation processes with heterogeneous raw materials (great diversity in terms of wood quality, diameters, length, etc.), divergent product flows (generating many products at the same time) and radically different planning problems to be solved by each mill.

Since a high percentage of softwood lumber is used in the construction industry, demand for lumber decreases in October–November and reaches a seasonal low during the winter months of December–February. Then, it experiences strong seasonal and cyclical rise in the second and third quarters. Prices are expected to move higher going into the summer as demand increases. Thus, most seasonal fluctuations in soft-

1. Natural Resources Canada, Forest products, accessed on September 15, 2015, http://www.nrcan.gc.ca/forests/industry/13317

wood lumber prices can be explained by demand seasonality related to construction activities. Although most of the time sawmills operate at full capacity, products are not always available in stock at the right time to take advantage of price fluctuation for many reasons. First, there is almost no flexibility in raw material availability, depending on regulations of forestry activities and on the seasonal nature of harvesting operations, which limits the variation in the lumber sawing process. Second, production operations are complex since divergent processes force different products to be made dependently.

In this context, the dominant thinking currently in the Canadian lumber industry is to produce the maximum volume with the available resource. Production is oriented towards large batches to take advantage of economy of scale, resulting in large inventories, low flexibility and low agility. A case study of a medium Canadian lumber firm, presented in Marier et al. (2014), has shown that tactical planning such S&OP is important to take advantage of the cyclical nature of the softwood lumber industry. But in practice, S&OP is still not well understood by such firms.

Furthermore, a large portfolio of softwood lumber products is offered to heterogeneous customers, having different attitudes and priorities. Dealers and distributors for example, are more sensitive to price than to quality. Other customers, such as home improvement warehouse companies and housing component manufacturers, are willing to pay more for better products and better services. RM is then interesting as a means to prioritize them, especially since a softwood lumber firm generally operates in supply-constrained environment as raw material availability and capacity are bottlenecks. Consequently, all demand cannot always be fulfilled and the supply chain may offer fewer finished products than customer requests. So, sales managers are obliged to reject orders. Order promising based on RM concepts can support them to decide which orders should be rejected in anticipation of more valuable orders (Guhlich et al. 2015), not only if resources are not available.

While decisions of accepting or refusing an order have to be near instantaneous and definitive, 3000 orders can be received weekly for a medium Canadian softwood lumber company with three sawmills. Thus, sales managers are continuously confronted with the following decision problem: How can we synchronize mid-term, short-term and real-time sales decisions—that have to be taken at multiple planning levels and at different frequencies—in a way to maximize profits and enhance the service level offered to high-priority customers?

2.2. *Related literature*

2.2.1. Sales and operations planning (S&OP)

According to APICS Dictionary (2013), S&OP integrates all the business plans of a company (supply, production, sales, customers, marketing, R&D and finance) in general terms, facilitates coordination between the various functions, and supports strategic and business plans. Tuomikangas and Kaipia (2014) emphasize the tactical role of S&OP as a means of linking company strategy and operational planning based on academic and practitioner literature. The S&OP process acts as a continuous mechanism that supports cross-functional integration (Oliva and Watson 2011). Despite the conflicting incentives in firms, S&OP facilitates integrated supply chain planning and the involvement of all functions in every stage through a continuous criticism. Based on right information and effective planning procedures, a good performance can be achieved. S&OP can also support strategic decisions such as capacity decisions (Olhager et al. 2001). Moreover, S&OP supports integration between the supply chains of different companies and ensures scheduling control to reduce delays (Affonso et al. 2008). In an uncertain environment, S&OP aligns sales targets with resource availability. First, S&OP has an important role as a mediator in improving operational performance in production environments characterized by market incertitude (Olhager and Selldin 2007; Sodhi and Tang 2011; Feng et al. 2013). By simulating an S&OP model with a stochastic demand, Feng et al. (2010) have proven that the S&OP process reduces effects of forecast errors in a Make-To-Order environment. S&OP can also deal with order configuration uncertainty (Chen-Ritzo et al. 2010). In contrast to the problems covered in these studies, our concern is not with S&OP performance in different contexts, but with how S&OP can be integrated with RM concepts.

2.2.2. RM in production systems

Common studies in production systems have introduced RM concepts by different allocation mechanisms of the Available To Promise (ATP), which were summarized by Pibernik (2005). Standard ATP allocation mechanisms reject orders only if not enough resources are available, while in RM, due to the heterogeneity of customers, orders are also rejected in anticipation of more valuable orders (Guhlich et al. 2015). Regarding application of RM concepts in manufacturing context, two research streams can be distinguished. Within the first stream, the focus is on the implantation of allocation models in MTS context. A second stream has evolved from more advanced work on Assemble-To-Order (ATO) and Make-To-Order (MTO) environments, where both storable and non-storable resources are considered.

To the best of our knowledge, Meyr (2009) was the first to propose allocation models for *MTS environments*. He dealt with a deterministic demand and a known exogenous supply and developed a linear programming formulation composed of two stages: "ATP allocation" and "real-time ATP consumption". This research was expanded by Azevedo et al. (2016), who considers several mills and several products, while Meyr (2009) dealt with just one mill and one product. The assumption of a deterministic demand may not be applicable in some cases. So, Quante et al. (2009) considered demand uncertainty and proposed a dynamic programming formulation to take into account the impact of consumption decisions. They showed that allocation model with nested booking limits always achieved better profits, like the deterministic model of Meyr (2009). Unlike Quante et al. (2009) that assume that order reception period is the same as the due date, our analysis considers a stochastic lead time. Pibernik and Yadav (2009) also dealt with stochastic demand, but the framework proposed takes into account carry over between allocation planning and order promising. This research was expanded (Samii et al. 2011) to provide a formulation of a trade-off between the benefits of reserving inventories for high-priority customers and the negative impact that this will have on the overall system performance. These analyses were limited to a single period inventory reservation problem of one product and just two classes of customers, in contrast to our study which considers multiple demand classes, divergent product structure and multiple sourcing locations in a multi-period context.

Dynamic programming is often used by existing studies about RM in *ATO and MTO production systems* (Harris and Pinder 1995; Gao et al. 2012). Bid-price approaches are also commonly used as RM instruments for *MTO production systems* such as Spengler et al. (2007) and Volling et al. (2011), but these analyses used fixed planning horizons and a single plant case as opposed to the present paper in which a monthly replanning of several plants is considered over a year. Tsai and Wang (2009) is one of the first studies that considers more than one plant in an ATP mechanism for *ATO production system*. Recently, Guhlich et al. (2015) have developed a heuristic RM approach using bid prices for a manufacturer using an ATO production system and facing stochastic demand. Stochastic approaches, such as in the Guhlich et al. (2015) study, cannot be applied in our case since there is not enough data to model demand according to a known probability distribution.

All presented studies about RM application in production systems considered short-term planning horizon. Within this time horizon, capacity levels cannot be extended and a known exogenous supply is given. In particular, Azevedo et al. (2016) explained how RM concepts can be introduced in a MTS context such as the softwood lumber industry. However, the model that was proposed considered only a short-term planning horizon and clearly ignored the potential profit that can be obtained by anticipating mid-term demand. Our paper defines supply and production decisions as mid-term decision variables in a context of divergent processes. So, we offer the possibility of taking advantage of demand and price fluctuations. In fact, an integrated demand management process is proposed in order to synchronize S&OP mid-term decisions with short-term and real-time sales decisions taken according to RM concepts.

2.2.3. Order promising and medium term issues

Contrary to S&OP, order promising is a real-time problem. It is a critical task (Fleischmann and Meyr 2003), as it has impacts not only on company profitability and customer service level in the short, medium and long term, but also has significant influence on scheduling and execution of manufacturing and logistics activities (Pibernik and Yadav 2009). The relevance of integrating order promising with tactical planning tasks was exhibited in a built-to-order context by Volling and Spengler

(2011), which explicitly model order promising and master production scheduling as distinct, interdependent planning functions. Based on rolling horizons, the analysis revealed the capacity of the integrated system to capture the impact of production planning routines on the responsiveness and reliability of the order fulfillment system and, vice versa, that of order promising decisions on the performance of production planning. More complex transformation processes with heterogeneous raw materials and divergent product structure are considered in this paper. Besides, unlike our problem settings, the Volling and Spengler (2011) study is not concerned about market seasonality and order/customer differentiation. The study of Dansereau et al. (2014) is a demonstration that integrating RM concepts at the tactical level can help to achieve better returns by providing a better alignment of production with various market conditions. The model proposed explored the customer heterogeneity at the tactical level and optimized ATP quantities exclusively reserved to each customer segment. However, this is too rigid to be applied in practice. Our paper offers more flexibility by integrating a tactical model with RM using nested booking limits at real-time level and so higher-profitable segments can have access instantaneously to quantities reserved for lower-profitable segments. More flexibility is also guaranteed by operating in a rolling horizon environment and by changing decisions of how confirmed orders have to be fulfilled after receiving each order and after each tactical planning.

The interaction between order promising decisions based on RM and customer relationship management, which focuses on medium-term horizon, was discussed in the case study of Ovchinnikov et al. (2014). They developed a general dynamic model and showed that trade-offs need to be made to benefit from low-value customers. A similar point of view is discussed in our paper, based on S&OP decisions instead of customer relationship management considerations.

2.2.4. Order reassignment

The idea of order reassignment can be related to the idea of flexible products presented in Petrick et al. (2012) and Gönsch et al. (2014), in which the firm retains the right to specify later some of the details of a sold flexible product. In our case, decision postponement concerns the provenance from which an accepted order should be fulfilled.

3. Proposed demand management process

In this section, we describe the basic assumptions and the relevant decisions of the demand management process that we propose to support sales decision making in firms such as Canadian softwood lumber firms.

Assumption 1 (Customers): A company generally offers its products p to different markets m, which refer to customers from different geographical regions (Azevedo et al. 2016). Each market m can be split into customer segments g. Customer segmentation is a strategic task and a frequently applied tool in marketing science (Hofmann et al. 2013) to group the various types of customers and their behaviors and requirements, according to different criteria such as willingness to pay (Feng and Xiao 2000; Zhang et al. 2006; Li and Chen 2010), quality sensitivity (Xiaodong et al. 2007), lead times (Li and Chen 2010), etc. This can provide the company with comprehensive information about its customers in order to identify sales opportunities (e.g. focus on profitable or loyal segments), to meet customer expectations and to follow segment evolution over time.

Assumption 2 (Demand information and time structure): Sales and price forecasting are critical inputs of the S&OP process (Mentzer et al. 2007). New information about demand and prices can be periodically obtained. While disaggregated forecasts can be made for short-term horizon, medium-term forecasts are generally more dubious and aggregated. Forecasts aggregation (or disaggregation) can be applied to multiple dimensions simultaneously: product families or single products, customer markets/segments or individual customers, different periods of time, etc. For instance, considering a medium-term horizon composed of T weeks, new forecasts of market demands D_{pmt}^{max} and market prices α_{pmt} can periodically be available as shown in Figure 1.

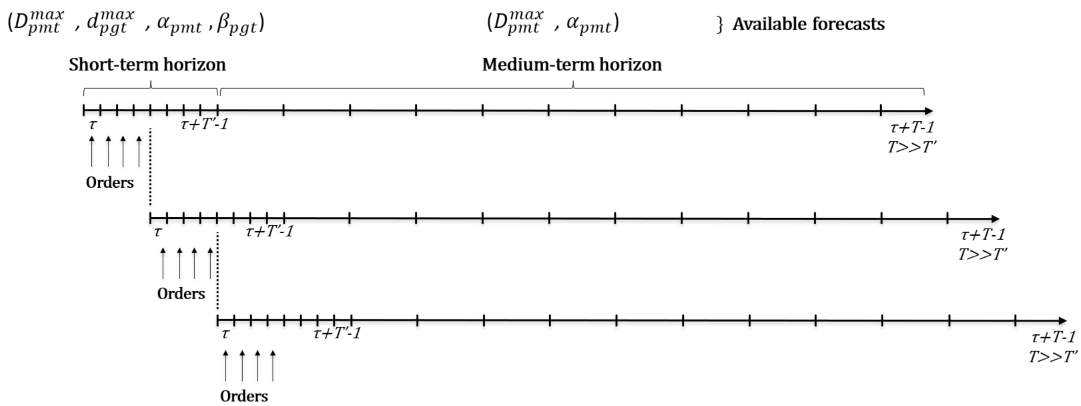

Figure 1.: Available forecasts for short-term and medium-term horizons

Weekly market forecasts for short-term periods (weeks from the first week τ to week $\tau + T^{'} - 1$, considering that the short-term horizon is composed of $T^{'}$ weeks as $T^{'} << T$) and monthly market forecasts for medium-term periods (months from week $\tau + T^{'}$ to week $\tau + T - 1$). Moreover, new weekly short-term forecasts of segment demands d_{pgt}^{max} and segment prices β_{pgt} can be available each month. S&OP process can be re-executed as soon as new forecasts are available.

Assumption 3 (Decisions): Based on assumptions 1 and 2, firms looking to integrate S&OP and order promising based on RM concepts have four principal decision-making stages as presented in Figure 2.

(1) S&OP: Considering market demand forecasts D_{pmt}^{max} and market prices forecasts α_{pmt}, contracts, sales commitments z_{pgt}^{sell} made in previous periods and current inventories i_{pn0} in each node n (a mill or a warehouse), we execute the S&OP every month over medium-term horizon (e.g. twelve months) to predetermine supply, production, transport plans and market sales V_{pnmt} for each product p expected to be sold from node n to market m at period t.

(2) Allocation planning: Based on weekly short-term segment demand forecasts d_{pgt}^{max} and segment prices forecasts β_{pgt}, we allocate short-term market sales V_{pnmt} to different customer segments over short-term horizon (e.g. eight weeks). Commitments z_{pgt}^{sell} to sell product p to segment g at period t, already made in previous periods, and weekly segment forecasts d_{pgt}^{max} respectively represent

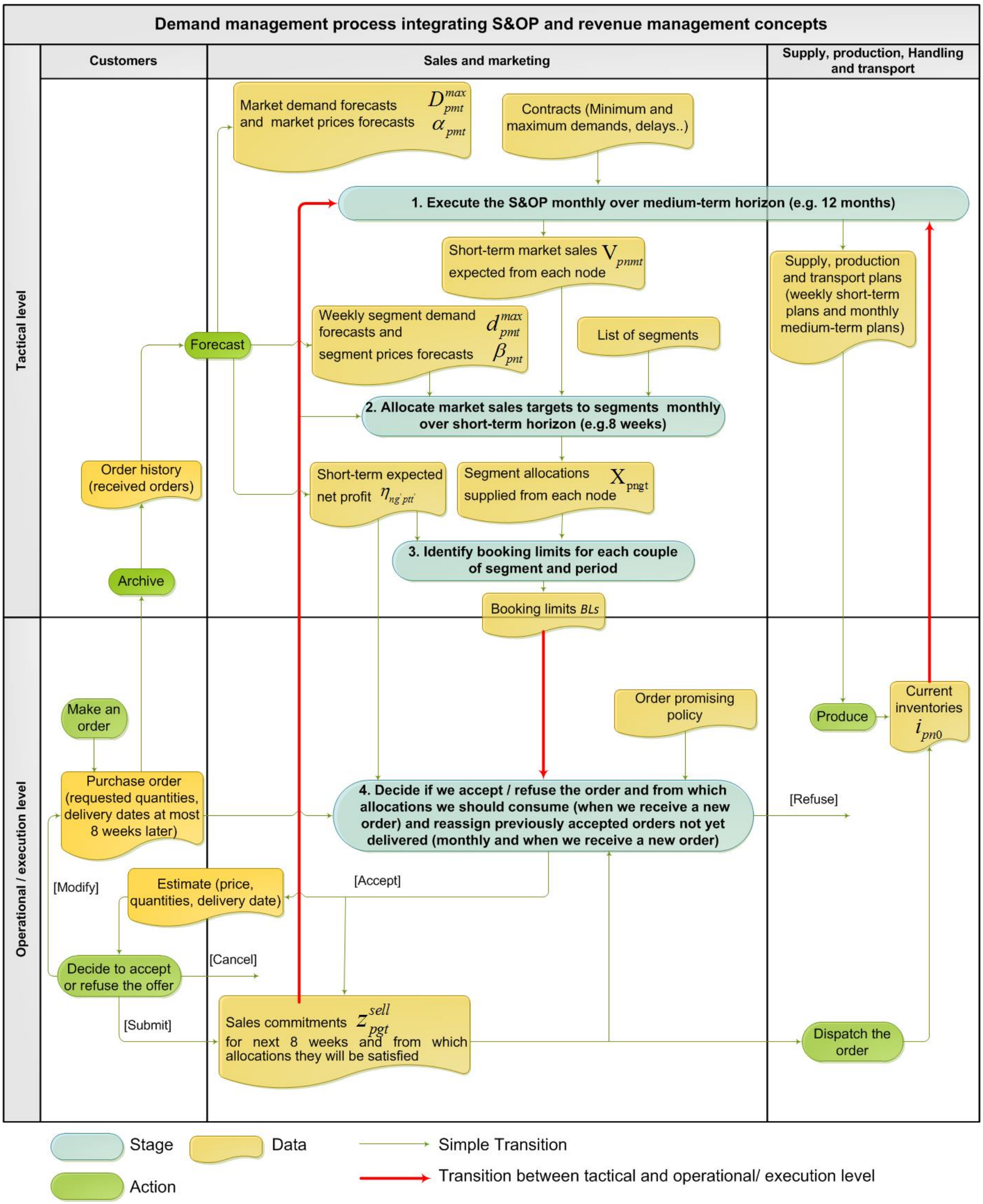

Figure 2.: Proposed demand management process

lower and upper bounds for segment allocations X_{pngt}(quantities of product p from node n allocated to segment g for period t). In industrial practices, S&OP and allocation planning are mostly planned by different teams. Nevertheless, it can be advantageous to simultaneously perform them as soon as we receive new forecasts (e.g. at the beginning of each month).

(3) Booking limits identification: Before making promises, we identify, for each segment $g^{'}$ and for each period $t^{'}$, from which allocations X_{pngt} we can consume by setting booking limits (BLs) for each combination of segment $g^{'}$ and period $t^{'}$, based on expected profit margin $\eta_{ng'ptt'}$ for selling a product p, available in node n at period t, to segment $g^{'}$ at period $t^{'}$ $(t \leq t^{'})$. This stage will be detailed more in Section 4.2.1.

(4) Real-time order promising and reassignment of orders to allocations: When we receive a new order, we have to decide if we accept or refuse the order and from which allocations X_{pngt} we should consume, considering BLs. We can also reassign previously accepted orders, not yet delivered. Moreover, order reassignment has to be done monthly after each tactical planning.

Figure 2 illustrates the proposed demand management process. In this graphical representation, we suppose that S&OP is planned over a medium-term horizon (e.g. 12 months) and that we can make commitments just for short-term horizon (e.g. 8 weeks). Demand set by contracts needs to be satisfied and is considered as hard constraints in the S&OP. This demand is included in incoming orders.

Assumption 4 (Orders): Orders are treated individually. Batch order processing approaches in a similar setting as presented in the current paper are considered in Meyr (2009). We also assume that the decision of accepting or refusing an order has to be instantaneous and definitive. However, order assignment to sourcing locations is temporary and may be changed. Partial fulfillment is not allowed, but an order can be fulfilled from different sourcing locations. Sequence of high and low priority orders is not considered since they are randomly received most of the time for the softwood lumber case, but can be examined in further research. Although the expected periodical demand is approximately known based on forecasts, the exact ordering quantity varies randomly.

4. Model formulation

Figure 3 illustrates a supply network of a multi-site softwood company. In such a MTS environment, a company has several nodes n ($n \in \mathbf{N}$), representing sawmills and warehouses. Nodes can be supplied by different sources s ($s \in \mathbf{S}$) and sell to various markets m ($m \in \mathbf{M}$) composed of differentiated segments g ($g \in \mathbf{G}$). Manufacturing plants are equipped with different types of resources e ($e \in \mathbf{E}$) enabling various activities a ($a \in \mathbf{A}$). A node n is supplied by sources $\mathbf{S}^n$ ($\mathbf{S}^n \in \mathbf{S}$) and can execute activities $\mathbf{A}^n$ ($\mathbf{A}^n \in \mathbf{A}$). An activity a refers to a drying, planing or sawing recipe, so that the activity level can define amounts of consumed inputs and generated outputs. $\mathbf{AP}^p$ ($\mathbf{AP}^p \in \mathbf{A}$) are activities generating product p ($p \in \mathbf{P}$), which can then be consumed by activities $\mathbf{AC}^p$ ($\mathbf{AC}^p \in \mathbf{A}$). Each product p can be transported on roads $(nn^{'}) \in \mathbf{Ro}^p$. The S&OP horizon is composed of T periods.

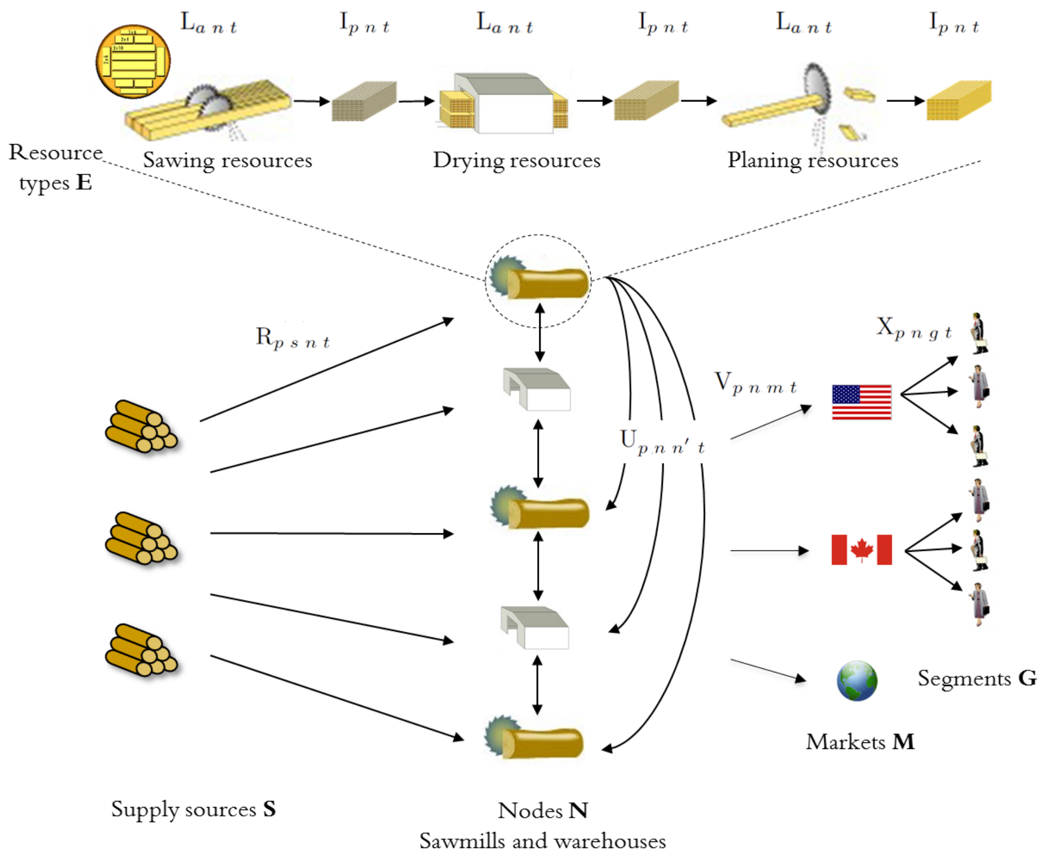

Figure 3.: Supply network of a multi-site softwood company

4.1. *Tactical model (Stages 1 and 2)*

At the beginning of each month, a tactical model simultaneously plans S&OP and allocation planning. An S&OP network model for softwood company was proposed by Marier et al. (2014). It makes decisions related to supply, production, handling, transportation and sales in order to optimize the total company profit margin over a fixed horizon composed of T periods. Sales decisions are set by customer markets. We extended the model of Marier et al. (2014) in order to:

— work with a rolling horizon planning: We made several adaptations so that at each new tactical planning execution, decisions of the previous plan are integrated,

— allow order reassignment while respecting previous sales commitments,

— incorporate the allocation planning (stage 2 in Figure 2): First, short-term sales decisions have to be allocated to different customer segments. Second, sales commitments and demand forecasts are set as lower and upper bounds for both market sales targets and segment allocations.

Tables 1, 2 and 3 present respectively sets, parameters and decision variables involved in the tactical model. Next, the objective function and constraints related to supply, transport, sales, inventory holding, production, flow balances, allocation and non-negativity will be depicted.

Table 1.: Sets

Sets	Description
$\mathbf{A}$	Activities a
$\mathbf{E}$	Resource types $e \in \mathbf{E}$ ={sawing, drying or planing resources}
$\mathbf{M}$	Markets m
$\mathbf{G}$	Customer segments g
$\mathbf{G}^m$	Customer segments g of the market m
$\mathbf{N}$	Nodes n(sawmills and warehouses)
$\mathbf{P}$	Raw materials and products p
$\mathbf{S}$	Supply sources s
$\mathbf{S}^n$	Sources s supplying node n ($\mathbf{S}^n \subseteq \mathbf{S}$)
$\mathbf{A}^n$	Activities executed in node n /$\mathbf{A}^n \subseteq \mathbf{A}$
$\mathbf{AC}^p$	Activities consuming product p / $\mathbf{AC}^p \subseteq \mathbf{A}$
$\mathbf{AP}^p$	Activities generating product p / $\mathbf{AP}^p \subseteq \mathbf{A}$
$\mathbf{Ro}$	Roads *(n, n')* $\in \mathbf{N} \times \mathbf{N} \cup \mathbf{M}$
$\mathbf{Ro}^p$	Roads *(n, n')* $\in \mathbf{Ro}$ allowing transport of product p ($\mathbf{Ro}^p \subseteq \mathbf{Ro}$)

Table 2.: Parameters

Parameters	Description	
Time		
τ	First period of the planning horizon	Index
T	Length of medium-term horizon	Week
T'	Length of short-term horizon	Week
Prices/Costs		
α_{pmt}	Selling price of product p to market m during period t	\$/Qty
β_{pgt}	Selling price of product p to segment g during period t	\$/Qty
c^{sup}_{snt}	Supply cost from source s to node n during period t (purchase + transport)	\$/Qty
c^{hol}_{pnt}	Holding cost of product p in node n during period t	\$/Qty
c^{pro}_{ant}	Production cost of activity $a \in \mathbf{A}^n$ during period t	\$
$c^{tra}_{pnn't}$	Transportation cost of product p on road $(n, n^{'}) \in \mathbf{Ro}^p$ during period t	\$/Qty
Supply		
λ^{min}_{pst}, λ^{max}_{pst}	Minimum [maximum] supply of product p from source s during period t	\$/Qty
Λ^{min}_{ps}, Λ^{max}_{ps}	Minimum [maximum] supply of product p from source s during the planning horizon	Qty
φ_{ps}	Percentage of product p in a lot supplied from a source s	%
Transport		
$\sigma_{nn'}$	Transportation delay from node n to node n'	Week
$u_{pnn',t-\sigma_{nn'}}$	Quantity of product p that started to be transported on road $(n, n^{'}) \in \mathbf{Ro}^p$ before the beginning of the current planning horizon ($t - \sigma_{nn'} < \tau$)	Qty
$\nu^{min}_{nn^{'}t}$, $\nu^{max}_{nn^{'}t}$	Minimum [maximum] quantity transported on road *(n,n')*during period t	Qty
Sales		

Table 2.: Parameters (continued)

Parameters	Description	
D_{pmt}^{min}	Minimum demand to fulfill of product p for market m during period t (contracts)	Qty
D_{pmt}^{max}	Maximum demand to fulfill of product p for market m during period t (market demand forecasts)	Qty
d_{pgt}^{max}	Maximum demand to fulfill of product p for segment g during period t (segment demand forecasts)	Qty
z_{pgt}^{sell}	Commitments to sell product p to segment g during period t, already made in previous order promising cycles	Qty
Inventory		
i_{pn0}	Initial inventory of product p in node n	Qty
i_{nt}^{max}	Maximum inventory allowed in node n during period t	Qty
Production		
δ_{ean}	Capacity of resource type e used by activity $a \in \mathbf{A}^n$	Hr
Δ_{ent}	Capacity of resource type e in node n during period t	Hr
Φ_{ap}^{con}	Quantity consumed by activity a to produce product p	Qty
Φ_{ap}^{pro}	Quantity of product p generated by activity a	Qty

Table 3.: Decision variables

Decision variables	Description	
I_{pnt}	Inventory of product p in node n at the end of period t	Qty
L_{ant}	Production level of activity $a \in \mathbf{A}^n$ over period t	Qty
R_{snt}	Quantity received from source s to node n during period t	Qty
R_{psnt}	Quantity of product p received from source s to node n during period t	Qty
$\mathrm{U}_{pnn't}$	Quantity of product p transported on road *(n,n')* $\in \mathbf{Ro}^p$during period t	Qty
V_{pnmt}	Quantity of product p sold from node n to market m at period t	Qty
X_{pngt}	Quantity of product p from node n allocated to segment g for period t	Qty

The objective function (equation 1) maximizes the total company profit margin over all T periods. The first two parts of equation 1 compute the total selling revenue, considering segment allocations for short-term and market sales targets for medium-term. Then, costs of the whole planning horizon are subtracted. We first consider total supply cost, including purchase and transportation of raw materials costs. Second, production cost is set depending on the activity level over the planning horizon. Next, inventory holding costs and transport costs are depicted. Since reassignment is allowed (decisions of how confirmed orders have to be fulfilled can be changed when the tactical model is re-executed), sales decisions to segment g at period t already taken in previous order promising cycles will be included in the allocations X_{pngt} of the new tactical model.

The objective function is subject to several sets of constraints described in text as follows:

(2)	Products are supplied in predefined proportions depending on the source.
(3)	Supply limits from each source s per period.
(4)	Supply limits from each source for the whole planning horizon.
(5)	Transportation limits on each road over a period.
(6)	Quantity of each product p sold from a node n to a specific market m at a period t is defined as quantities of this product transported from the node n to the market m.
(7)	Quantities sold to each market m must respect a minimum demand to fulfill. The maximum between market demand forecasts and sales commitments is set as an upper bound: when sales commitments exceed market demand forecasts, they should be considered as maximum limits for short-term sales.
(8)	A yearly inventory cycle.
(9)	Maximum inventory.
(10)	Maximum resources capacities.
(11)	Product flow balances: The inventory in a node n at the end of a period t can be generalized as the inventory of the previous period, plus the quantity received at the current period (considered only for raw materials), minus the quantity consumed by production activities over the current period, plus quantity generated by production activities over the current period, plus the difference between incoming and outgoing flows over the current period. Incoming quantities can include quantities that started to be transported before the beginning of the current planning horizon τ.
(12)	Product flow balances for the period τ.
(13),(14)	All variables are non-negative.

Allocation planning constraints need more explanation. Constraints 15 allocate sales targets for market m to segments G^m. Allocations should exceed sales commitments z^{sell}_{pgt} (left part of equation 16). Similarly to equation 7, segment demand forecasts d^{max}_{pgt} should be considered as maximum limits for short-term sales, except when quantities already committed exceed forecasts. So, the maximum between segment demand forecasts d^{max}_{pgt} and sales commitments z^{sell}_{pgt} is set as an upper bound for allocations (right part of equation 16).

Maximize

$$\sum_{p\in\mathbf{P}}\sum_{n\in\mathbf{N}}\sum_{g\in\mathbf{G}}\sum_{t=\tau}^{\tau+T^{'}-1}\beta_{pgt}\mathrm{X}_{pngt}+\sum_{p\in\mathbf{P}}\sum_{n\in\mathbf{N}}\sum_{m\in\mathbf{M}}\sum_{t=\tau+T'}^{\tau+T-1}\alpha_{pmt}\mathrm{V}_{pnmt}$$
$$-\sum_{n\in\mathbf{N}}\sum_{s\in\mathbf{S}^n}\sum_{t=\tau}^{\tau+T-1}c^{sup}_{snt}\mathrm{R}_{snt}-\sum_{n\in\mathbf{N}}\sum_{a\in\mathbf{A}^n}\sum_{t=\tau}^{\tau+T-1}c^{pro}_{ant}\mathrm{L}_{ant}$$
$$-\sum_{p\in\mathbf{P}}\sum_{n\in\mathbf{N}}\sum_{t=\tau}^{\tau+T-1}c^{hol}_{pnt}\mathrm{I}_{pnt}-\sum_{p\in\mathbf{P}}\sum_{(n,n')\in\mathbf{Ro}^p}\sum_{t=\tau}^{\tau+T-1}c^{tra}_{pnn't}\mathrm{U}_{pnn't} \quad (1)$$

Supply constraints

$$R_{psnt}=\varphi_{ps}\mathrm{R}_{snt} \qquad \forall p\in\mathbf{P},\forall n\in\mathbf{N},\forall s\in\mathbf{S}^n, t=\tau..\tau+T-1 \quad (2)$$

$$\lambda^{min}_{pst}\leq\sum_{n\in\mathbf{N}}\mathrm{R}_{psnt}\leq\lambda^{max}_{pst} \qquad \forall p\in\mathbf{P},\forall s\in\mathbf{S}, t=\tau..\tau+T-1 \quad (3)$$

$$\Lambda^{min}_{ps}\leq\sum_{n\in\mathbf{N}}\sum_{t=\tau}^{t=\tau+T-1}\mathrm{R}_{psnt}\leq\Lambda^{max}_{ps} \qquad \forall p\in\mathbf{P},\forall s\in\mathbf{S} \quad (4)$$

Transport constraints

$$\nu^{min}_{nn't}\leq\sum_{p\in\mathbf{P}}\mathrm{U}_{pnn't}\leq\nu^{max}_{nn't} \qquad \forall(n,n^{'})\in\mathbf{Ro}, t=\tau..\tau+T-1 \quad (5)$$

Sales constraints

$$\mathrm{V}_{pnmt}=\sum_{t-\sigma_{nm}<\tau}u_{pnmt-\sigma_{nm}}+\sum_{t-\sigma_{nm}\geq\tau}\mathrm{U}_{pnm(t-\sigma_{nm})}$$
$$\forall p\in\mathbf{P},\forall n\in\mathbf{N},\forall s\in\mathbf{M}, t=\tau..\tau+T-1 \quad (6)$$

$$D_{pmt}^{min} \leq \sum_{n \in \mathbf{N}} \mathrm{V}_{pnmt} \leq \max\left(D_{pmt}^{max}, \sum_{g \in \mathbf{G}^m} z_{pgt}^{sell} \right)$$
$$\forall p \in \mathbf{P}, \forall n \in \mathbf{N}, \forall s \in \mathbf{M}, t = \tau..\tau + T - 1 \quad (7)$$

Inventory holding constraints

$$\mathrm{I}_{pn(\tau+T-1)} = i_{pn0} \qquad \forall p \in \mathbf{P}, \forall n \in \mathbf{N} \quad (8)$$

$$\sum_{p \in \mathbf{P}} \mathrm{I}_{pnt} \leq i_{nt}^{max} \qquad \forall n \in \mathbf{N}, t = \tau..\tau + T - 1 \quad (9)$$

Production constraints

$$\sum_{a \in \mathbf{A}^n} \delta_{ean} \mathrm{L}_{nat} \leq \Delta_{ent} \qquad \forall (e, n) \in \mathbf{E} \times \mathbf{N}, t = \tau..\tau + T - 1 \quad (10)$$

Flow balances

$$\mathrm{I}_{pnt} = \mathrm{I}_{pn(t-1)} + \sum_{n \in \mathbf{N}} \mathrm{R}_{psnt} - \sum_{a \in \mathbf{AC}^p} \phi_{ap}^{cons} \mathrm{L}_{nat} + \sum_{a \in \mathbf{AP}^p} \phi_{ap}^{prod} \mathrm{L}_{nat} - \sum_{(n,n') \in \mathbf{Ro}^p} \mathrm{U}_{pnn't}$$
$$+ \sum_{(n',n) \in \mathbf{Ro}^p} \sum_{(t-\sigma_{n'n}) < \tau} u_{pn'n(t-\sigma_{n'n})} + \sum_{(n',n) \in \mathbf{Ro}^p} \sum_{(t-\sigma_{n'n}) \geq \tau} \mathrm{U}_{pn'n(t-\sigma_{n'n})}$$
$$\forall p \in \mathbf{P}, \forall n \in \mathbf{N}, t = \tau + 1..\tau + T - 1 \quad (11)$$

$$\mathrm{I}_{pn\tau} = i_{pn0} + \sum_{n \in \mathbf{N}} \mathrm{R}_{psn\tau} - \sum_{a \in \mathbf{AC}^p} \phi_{ap}^{cons} \mathrm{L}_{na\tau} + \sum_{a \in \mathbf{AP}^p} \phi_{ap}^{prod} \mathrm{L}_{na\tau} - \sum_{(n,n') \in \mathbf{Ro}^p} \mathrm{U}_{pnn'\tau}$$
$$+ \sum_{(n',n) \in \mathbf{Ro}^p} \sum_{\sigma_{n'n} > 0} u_{pn'n\tau} + \sum_{(n',n) \in \mathbf{Ro}^p} \sum_{\sigma_{n'n} = 0} \mathrm{U}_{pn'n\tau} \qquad \forall p \in \mathbf{P}, \forall n \in \mathbf{N} \quad (12)$$

Non-negativity constraints

$$\mathrm{L}_{ant},\ \mathrm{R}_{snt},\ \mathrm{R}_{psnt},\ \mathrm{I}_{pnt},\ \mathrm{U}_{pnn't},\ \mathrm{V}_{pnmt} \geq 0$$
$$\forall a \in \mathbf{A},\ \forall p \in \mathbf{P},\ \forall s \in \mathbf{S},\ \forall n, n^{'} \in \mathbf{N},\ \forall m \in \mathbf{M}, t = \tau..\tau + T - 1 \quad (13)$$

$$\mathrm{X}_{p,n,g,t} \geq 0 \qquad \forall p \in \mathbf{P},\ \forall n \in \mathbf{N},\ \forall g \in \mathbf{G}, t = \tau..\tau + T^{'} - 1 \quad (14)$$

Allocation constraints

$$\mathrm{V}_{pnmt} = \sum_{g \in \mathbf{G}^m} \mathrm{X}_{pngt} \qquad \forall p \in \mathbf{P},\ \forall n \in \mathbf{N},\ \forall m \in \mathbf{M}, t = \tau..\tau + T^{'} - 1 \quad (15)$$

$$z_{pgt}^{sell} \leq \sum_{n \in \mathbf{N}} \mathrm{X}_{pngt} \leq \max\left(d_{pgt}^{max},\ z_{pgt}^{sell}\right) \quad \forall p \in \mathbf{P},\ \forall g \in \mathbf{G}, t = \tau..\tau + T^{'} - 1 \quad (16)$$

4.2. *Order promising model based on RM concepts (Stages 3 and 4)*

Once the tactical model is executed, we start to receive demand from customer segments for different delivery periods. An order promising model is required to instantaneously make promises to orders, while respecting the medium-term decisions and previous previous sales commitments. Since the model is based on RM concepts, we use nested booking limits to decide from which allocations we should consume to fulfill segment demands for each due date. So, we have to assign demand required by segment $g^{'}$ for delivery period $t^{'}$ to allocations x_{pngt} initially set to a segment g for delivery period t. Since it is an assignment problem, we formulate it as a linear programming (LP) model. In contrast to Meyr (2009) and Azevedo et al. (2016) order promising models, our formulation allows order reassignment (i.e. changing decisions of how confirmed orders have to be fulfilled as late as possible).

Table 4 describes additional sets, parameters and decision variables involved in

Table 4.: Additional notation for the order promising model

Set	Description	Unit
$\tilde{\mathbf{G}}$	Spot segment $\tilde{g}$ ($\tilde{\mathbf{G}} = \tilde{g} \subseteq \mathbf{G}$)	
Parameters		
j	Current period	Index
$\sigma_{ng'}$	Transportation delay from node n to segment g'	Week
$\eta_{png'tt'}$	Profit margin for selling a product p, available in node n at period t, to segment g' at period t'	Qty
$q_{pg't'}$	Quantity of product p required by segment g' for period t', including previous commitments and the new order demand	\$/Qty
x_{pngt}	Quantity of product p from node n allocated by the tactical model to segment g for period t	Qty
$y_{pngg'tt'}$	Quantity from allocation x_{pngt} set for segment g' at period t' already transported ($t' - \sigma_{ng'} < j$)	Qty
Decision variables		
$\mathrm{Y}_{pngg'tt'}$	Quantity from allocation x_{pngt} consumed by segment g' for period t' not transported yet ($t' - \sigma_{ng'} \geq j$)	Qty

the order promising model. An order required by segment g' for delivery period t' and fulfilled from allocations x_{pngt} has to be transported at $t' - \sigma_{ng'}$. Thus, $y_{pngg'tt'}$ represent quantities already transported at current period j, while $\mathrm{Y}_{pngg'tt'}$ are not transported yet and can be modified.

Customers in the softwood lumber context can be categorized according to their willingness to pay (Azevedo et al. 2016). In addition, various studies of FORAC [2] research consortium (e.g.: Frayret et al. (2007); Lemieux et al. (2008)) affirm that softwood lumber companies also have to handle sporadic customer orders, corresponding to a spot demand from occasional customers offering low prices. These customers are referred to as the spot segment $\tilde{g}$ in the model.

Figure 4 represents an example where all transportation delays are set to zero. Assignments are illustrated as arcs between allocations and requested quantities. Since order reassignment is allowed, we can review these assignments as often as needed, i.e. after each tactical planning and whenever a new order is received.

2. FORAC research consortium works in collaboration with forest products industry stakeholders (companies and government) in the province of Quebec and contributes since its launch in 2002 to the advancement of research in the forest products industry, https://www.forac.ulaval.ca/en/home/

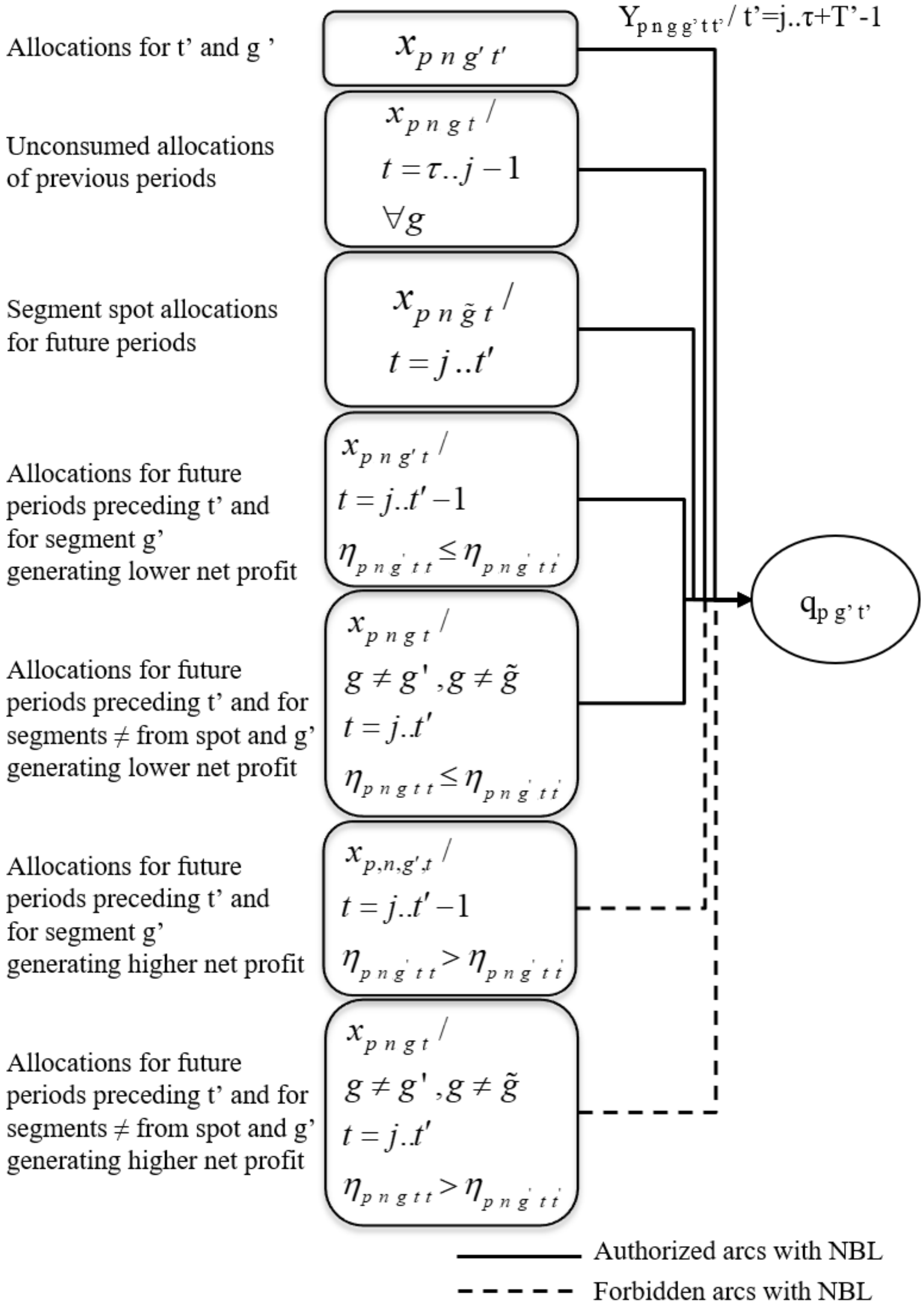

Figure 4.: Allocations assignments to quantity requested by segment $g^{'}$ for due date $t^{'}$ (example where all transportation delays are set to zero)

4.2.1. Nested booking limits (NBL)

The concept of booking limits (BLs) is used to take advantage of customer heterogeneity and profitability variation over time. According to Talluri and Van Ryzin

(2004), setting BLs is a way to control the availability of capacity. In our case, allocations x_{pngt} represent capacities in each node n designated to a segment g for a delivery period t. With NBL, capacities (allocations x_{pngt}) designated to a combination (segment g, period t) can be sold to other combinations generating better profits. It is as though capacities overlap in a hierarchical manner depending on the expected profit margin.

Figure 4 shows that, to fulfill demand requested by segment $g^{'}$ and delivery period $t^{'}$, NBL allow us to consume from:

— allocations set to segment $g^{'}$ for delivery period $t^{'}$;

— unconsumed allocations set for previous delivery periods $t(\tau < t < j)$;

— allocations set to spot segment $\tilde{g}$ for any delivery period (quantities allocated to spot segment can be consumed by any other segment);

— allocations set to segment $g^{'}$ for future delivery period t preceding period $t^{'}$ and generating lower profit than being consumed at period $t^{'}$ $(j \leq t < t^{'}, \eta_{png'tt} \leq \eta_{png'tt'})$

— allocations set to segment g different from $g^{'}$ and $\tilde{g}$ for any future delivery period t generating lower profit than being consumed by segment $g^{'}$ at period $t^{'}$ $(j \leq t < t^{'}, \eta_{pngtt} \leq \eta_{png'tt'})$

4.2.2. Mathematical model

The goal of the order promising model is to maximize the objective function expressed by equation (17), which is the short-term profit margin of fulfilling demand requested for periods between the current period j and the end of the short term horizon $(\tau + T^{'} - 1)$.

$$\sum_{p \in \mathbf{P}} \sum_{n \in \mathbf{N}} \sum_{g \in \mathbf{G}} \sum_{g' \in \mathbf{G}} \sum_{t'=j+\sigma_{ng'}}^{\tau+T^{'}-1} \sum_{t=\tau}^{t^{'}} \eta_{png'tt'} \; \mathrm{Y}_{pngg'tt'} \tag{17}$$

The model is subject to the following constraints: First, constraints 18 ensure that quantities consumed from allocation x_{pngt} set to a segment g for delivery period t will not exceed x_{pngt}. This includes quantities $y_{pngg'tt'}$ consumed by delivered orders that we can no longer change (be reassigned), which is expressed for allocations that have been designated for past periods of the allocation horizon by equation 19, defined only if $\tau < j$.

Allocation consumption

$$\sum_{g' \in \mathbf{G}} \sum_{\substack{t'=t \\ t' \geq j+\sigma_{ng'}}}^{\tau+T'-1} \mathrm{Y}_{pngg'tt'} \leq x_{pngt}$$

$$\forall p \in \mathbf{P},\ \forall n \in \mathbf{N},\ \forall g \in \mathbf{G}, t = j..\tau + T' - 1 \quad (18)$$

$$\sum_{g' \in \mathbf{G}} \left(\sum_{t'=j+\sigma_{ng'}}^{\tau+T'-1} \mathrm{Y}_{pngg'tt'} + \sum_{t'=t}^{j+\sigma_{ng'}-1} y_{pngg'tt'} \right) \leq x_{pngt}$$

$$\forall p \in \mathbf{P},\ \forall n \in \mathbf{N},\ \forall g \in \mathbf{G}, t = \tau..j - 1 \quad \mathit{defined\ if}\ \tau < j \quad (19)$$

Second, nested booking limits (NBL) constraints are expressed by constraints 20 and 21: we force forbidden consumptions to be zero in order to avoid consumptions from allocations set to more profitable segments and delivery periods (consumptions represented by forbidden arcs in Figure 4).

Forbidden consumptions for NBL

$$\mathrm{Y}_{pnggtt'} = 0 \qquad \forall p \in \mathbf{P},\ \forall n \in \mathbf{N},\ \forall g \in \mathbf{G}, t' = j + \sigma_{ng'}..\tau + T' - 1,$$

$$t = j..t' - 1, \eta_{pngtt} > \eta_{pngtt'} \quad (20)$$

$$\mathrm{Y}_{pngg'tt'} = 0 \qquad \forall p \in \mathbf{P},\ \forall n \in \mathbf{N},\ \forall g' \in \mathbf{G},\ \forall g \in \mathbf{G} \backslash \{g', \tilde{g}\},$$

$$t' = j + \sigma_{ng'}..\tau + T' - 1, t = j..t', \eta_{pngtt} > \eta_{png'tt'} \quad (21)$$

Third, to guarantee previous commitments, additional constraints are expressed by equation 22. Quantities consumed by segment $g^{'}$ for delivery period $t^{'}$ always have to be equal to demand of segment $g^{'}$ for period $t^{'}$, which includes previous commitments and the new order demand. Otherwise, the new order cannot be fulfilled. Finally, constraints 23 assure that all variables are non-negative.

Respect of previous commitments

$$\sum_{n \in \mathbf{N}} \sum_{g \in \mathbf{G}} \sum_{t=\tau}^{t^{'}} \mathrm{Y}_{pngg^{'}tt^{'}} = q_{pg^{'}t^{'}}$$

$$\forall p \in \mathbf{P},\ \forall g^{'} \in \mathbf{G},\ t^{'} = j + \sigma_{ng^{'}}..\tau + T^{'} - 1 \quad (22)$$

Non-negativity

$$\mathrm{Y}_{pngg^{'}tt^{'}} \geq 0$$

$$\forall p \in \mathbf{P},\ \forall n \in \mathbf{N},\ \forall g, g^{'} \in \mathbf{G},\ t^{'} = j + \sigma_{ng^{'}}..\tau + T^{'} - 1,\ t = \tau..t^{'} \quad (23)$$

5. Data generation and experiments

5.1. *Data generation and assumptions*

In order to validate the proposed demand management process, an experimental case (see Table 5) is considered based on softwood lumber manufacturers located in Eastern Canada. In this region, lumber manufacturers principally offer their products to Central Canadian market (CAC), Eastern Canadian market (CAE), Northeastern American market (US) and a spot market. There is little data available to model demand according to known probability distribution. Generally, softwood firms only keep the information on shipped quantities, not demand information (Lemieux et al. 2008). Moreover, if a substitute product is shipped, the original demand information disappears from the database. Therefore, we made simple assumptions to have market and segment demand and further ordering quantities, which seem to fit the real case of most softwood lumber firms from the Eastern Canadian region.

Table 5.: Scope of the simulated case

Sets	Size	Details
Nodes (sawmills)	3	
Products	10	2x4 8', 2x4 12', 2x4 14', 2x4 16' 2x6 8', 2x6 12', 2x6 14', 2x6 16' Premium grade products
Markets	4	US, CAE, CAC and spot market
Segments	10	Spot market is composed of one segment. Other markets are composed of 3 segments each.
Average number of orders incoming weekly	100	Average weekly arrival rate is one order per combination (segment, product), where one product is required per order.

For data generation, we assume that the yearly global demand is 150% of the maximum output that can be produced by pushing an infinity of supply into the supply chain. This assumption is acceptable for lumber softwood commodity products (Marier et al. 2014) since demand is too high and firms often produce at full capacity. Based on Frayret et al. (2007) and Lemieux et al. (2008), we assume that 80-95% of demand corresponds to a demand from US, CAE and CAC markets, while 5-20% of demand corresponds to a spot demand from occasional customers offering low prices (in our case, 0.8 of US market price). Such as in the study of Azevedo et al. (2016), we assume that markets US, CAE and CAC are composed of three segments each:

— High-priority customers (10% of the market demand), typically home improvement warehouse companies and housing component manufacturers (Gaston and Robichaud 2017), are ready to pay 10% more than the market price to have shorter transport lead-times,

— Medium-priority customers representing the majority of customers (70% of the market demand) pay exactly the market price,

— Low-priority customers (20% of the market demand), typically dealers and distributors (Gaston and Robichaud 2017), pay 10% less than the market price.

In what follows, we consider various demand scenarios as presented in Table 6. We assume that the demand can be seasonal or stable and that the demand of the spot market (considered as one customer segment paying low prices) represents 20% or 5% of the total demand. Scenario 1 is the most realistic scenario for the softwood lumber context in Eastern Canada. Appendix A gives more details about how data have been generated.

Table 6.: Demand scenarios considered for data generation

Scenarios	% of the demand of spot market	Seasonal demand
1	20%	✓
2	20%	
3	5%	✓
4	5%	

5.2. *Experiments*

Experiments will be conducted in order to evaluate the benefits of **integrating S&OP and RM concepts**. Four demand management processes (see Table 7) will be evaluated with the demand scenarios presented in Table 6. For the tactical level, we consider two different lengths T of medium-term horizon: 8 and 52 weeks. With $T = 8$, the tactical model is used just for allocation planning, while with $T = 52$, we have S&OP coupled with allocation planning. For the operational level, we compare two order promising models: the first model uses NBL, while the second model handles orders according to a First-Come First-Served basis (FCFS) and decides if we accept or refuse each order assuming that all allocations are available to all (we do not use booking limits).

SA-NBL is the demand management process proposed in Figure 2, integrating S&OP, allocation planning and an order promising model using NBL. For all processes presented in Table 7, order reassignment is allowed (it can be done after receiving each order and after each tactical planning), and the tactical level is re-planned each month. The simulation is conducted with weekly planning periods over a year.

For each process presented in Table 7, a simulation algorithm developed in Visual Basic.NET sequentially called the tactical and the order promising models. These models are developed within IBM ILOG CPLEX Optimization Studio version 12.4.

Table 7.: Simulated demand management processes

Tactical level	Operational/execution level	Process	Tactical constraints	Operational constraints
S&OP/**A**llocation planning ($T = 52$)	**N**ested **B**ooking **L**imits	(SA-NBL)	1, 2-16	17, 18-19, 20-21, 22-23
	First-**C**ome **F**irst-**S**erved	(SA-FCFS)	1, 2-16	17, 18-19, 22-23
Allocation planning ($T = 8$)	**N**ested **B**ooking **L**imits	(A-NBL)	1, 2-16	17, 18-19, 20-21, 22-23
	First-**C**ome **F**irst-**S**erved	(A-FCFS)	1, 2-16	17, 18-19, 22-23

More details about the simulation algorithm can be found in Appendix B. We needed 8.5 seconds for each order processing and so a total of almost 12 hours for all the orders of a year (8.5 sec/order x 100 orders on average/week x 52 weeks). Expanding 8.5 seconds for each order processing seems to be acceptable in practice since in the worst case for a medium softwood lumber firm, 600 orders will be received daily and so a total processing time less than 1.5 hours will be needed.

Five replications [3] are simulated, i.e. a different seed is used for each replication to generate different lists of orders as presented in Appendix A. We should note also that a warm-up period has been considered.

6. Results and discussion

6.1. *Results analysis*

In order to evaluate the global performance and the service level offered to high-priority customers, results are analyzed regarding three performance indicators:

— The yearly profit margin (YPM) is calculated as the total selling price minus production, transportation and inventory costs. This output is measured over a year to take into account the benefits of tactical planning considering cyclical rises of demand/price.

— The yearly sales (YS) represent the total volume sold and delivered over a year.

— The HP fill rate (HPFR) measures the proportion of demand received from high-priority customers that has been fulfilled.

We evaluate the benefits of integrating S&OP and NBL compared to process A-FCFS, which considers only a short-term allocation planning and makes real-time decisions according to FCFS basis. We use average values [4] of YPM, YS and HPFR to compute the benefits [5] of integrating S&OP and NBL in the different demand scenarios (see Table 8). Thus, we can investigate i) the benefits of the S&OP by comparing SA-

3. The number of replications was sufficient to observe a significant difference between the compared processes.

4. Average values through the five replications.

5. Example: YPM benefits for A-NBL=(Average value of YPM for A-NBL – Average value of YPM for A-FCFS)$\times$ 100 $\div$ (Average value of YPM for A-FCFS).

FCFS to A-FCFS, ii) the benefits of the NBL by comparing A-NBL to A-FCFS and iii) the benefits of integrating both S&OP and NBL by comparing SA-NBL to A-FCFS.

The value of integrating S&OP and NBL is obvious in Table 8: SA-NBL process achieves the highest high-priority fill rates (HPFR) and an improvement of the yearly profit margin (YPM) ranging from 69% to 119%. The impact of integrating S&OP and NBL is more significant with seasonal demand and with a low proportion of spot demand. In what follows, a more detailed analysis is depicted.

Table 8.: Benefits of integrating S&OP and NBL compared to process A-FCFS

Spot demand	Seasonality	Processes	YPM	YS	HPFR
20%	✓	SA-NBL	84%	21%	65%
		SA-FCFS	49%	23%	19%
		A-NBL	24%	0%	63%
20%	-	SA-NBL	69%	21%	65%
		SA-FCFS	46%	22%	17%
		A-NBL	22%	0%	62%
5%	✓	SA-NBL	119%	25%	67%
		SA-FCFS	70%	26%	23%
		A-NBL	18%	0%	64%
5%	-	SA-NBL	103%	25%	68%
		SA-FCFS	66%	25%	24%
		A-NBL	20%	0%	65%

Benefits on the yearly sales (YS) and the high-priority fill rate (HPFR)

Regarding the yearly sales (YS), we can see that we can sell 21-26% more by integrating S&OP with NBL/FCFS order promising models. Indeed, SA-NBL and SA-FCFS processes could deal better with the demand rise occurring at the mid term. Moreover, it is obvious that the use of NBL does not affect the yearly sales (YS), but allows us to fulfill more high-priority demand and drives a more efficient use of the resources. As shown in Table 8, SA-NBL and A-NBL achieve an improvement around 65% of the high-priority fill rate (HPFR) compared to A-FCFS.

Benefits on the yearly profit margin (YPM)

YS and HPFR average values seem to be relatively stable through the different demand scenarios that we have considered, in contrast to the yearly profit margin (YPM). Figure 5 gives more details about the average values and the 95% confidence intervals of the YPM.

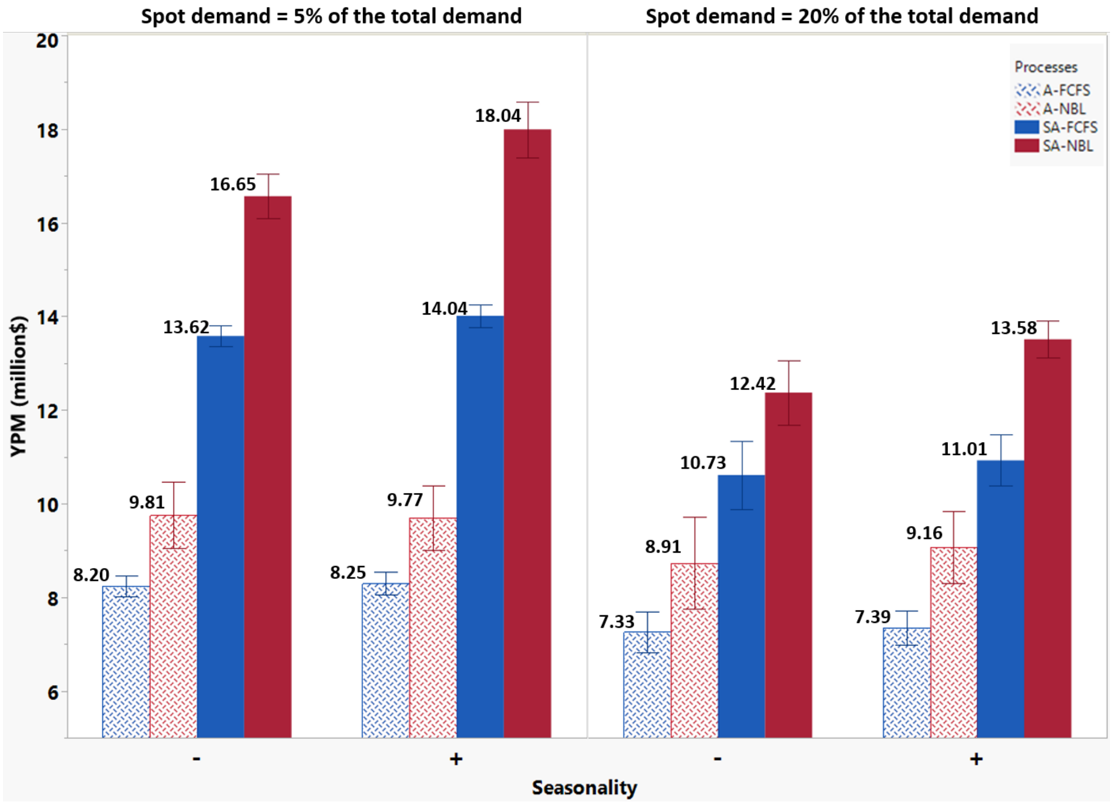

Figure 5.: Yearly profit margin

First, Figure 5 allows us to confirm findings of previous studies of Marier et al. (2014) and Azevedo et al. (2016) in the softwood lumber industry. In fact, we can confirm statistically, based on 95% confidence intervals, that:

— we can achieve a better yearly profit margin by integrating S&OP: a benefit ranging from 46% to 70% can be observed if we compare SA-FCFS to A-FCFS,

— we can achieve a better yearly profit margin by using NBL: a benefit ranging from 18% to 24% can be observed if we compare A-NBL to A-FCFS since A-NBL prioritizes orders from high-priority segments (an improvement of the HPFR up to 65% compared to A-FCFS), while the A-FCFS does not differentiate between orders and focuses on feasibility rather than profitability.

In addition, we can see that, as expected, the SA-NBL process is statistically [6] better than other processes regarding the yearly profit margin (YPM) for all demand scenarios. The value of integrating S&OP and NBL (SA-NBL compared to A-FCFS)

6. The 95% confidence intervals of SA-NBL process do not overlap with the confidence intervals of other processes

can be reflected by a benefit on the YPM ranging from 69% to 119%. The higher profit generated by integrating S&OP and NBL is a result of the increased revenue by fulfilling more orders from profitable customers and for more remunerative periods.

Moreover, the SA-NBL process significantly takes advantage of demand seasonality. This can be proved by comparing the YPM confidence intervals of the SA-NBL with stable demand vs. seasonal demand. This demonstrates that a potential profit can be obtained by efficiently allocating the limited capacity (i.e. accumulating inventories to be sold when demand rises in high-price periods and rejecting orders, not only if not enough resources are available, but in anticipation of more valuable ones for more remunerative periods).

The impact of integrating S&OP and NBL is more significant if low-profitable demand such as spot demand represents a low proportion of the total demand (Spot demand represents 5% of the total demand in the left part of Figure 5). This underlines the interest of the customer segmentation: offering specific services (shorter lead-times in our case) to customers less sensitive to price and preserving long-standing relations with them can potentially support softwood lumber companies to remain profitable.

6.2. *Managerial implications*

In this study, firstly, we aim to appreciate the value of integrating revenue management (RM) and S&OP. Considering current demand management practices and existing IT-systems, we developed a platform—integrating an S&OP model with an order promising model based on RM concepts—in order to help managers with the implementation challenges. Indeed, the integrated demand management process proposed in Section 3 illustrates the different stages of the integration and so supports managers having limited experience with RM\S&OP.

Second, we provide evidence to managers in regard of the benefits of implementing different strategies of integration. Our simulation results demonstrate, based on a case study in the softwood lumber industry, the improvement on the yearly profit margin and the service level offered to high-priority customers that can be achieved by integrated demand management processes. This can help managers to overcome their fear of changes and losses, which is a common barrier to the introduction of

RM and S&OP evoked in literature (Kolisch and Zatta 2011; Oliva and Watson 2011; Noroozi and Wikner 2017).

We should note that, in addition to the required models/softwares to implement the integrated demand management process proposed, we need the involvement of the different actors who participate in the process (Oliva and Watson 2011; Noroozi and Wikner 2017). Hence, the realization of the benefits of integrating S&OP and RM is bound to the cultural context of the organization and requires cross-functional efforts (production, sales, distribution, logistics, finance, marketing, etc). Efforts should also be made to ensure the acceptance of the RM on the client side since it implies the prioritization of high-priority orders.

The platform developed in this study can be also an efficient tool for softwood lumber managers to simulate new business models. It can be used to evaluate various what-if scenarios and to anticipate how a demand management process integrating RM and S&OP will be affected in typical situations like introducing a new high value-added product, changing the capacity of sawmills, entering a new market, concluding contracts with other suppliers/customers, etc.

7. Conclusion and future research

In this paper, we extend the research in demand management for MTS manufacturing systems. While existing studies dealt separately with revenue management (RM) and S&OP, we propose a process integrating these two common methods and capturing feedbacks between different sales planning levels.

The proposed simulation framework offers guidance for a business problem presently faced by managers in softwood lumber industry and provides a deeper understanding of the link between the S&OP and the order promising function, particularly when the organization strategy focuses on customer heterogeneity. Considering differentiated demand segments, divergent product structure and multiple sourcing locations in a multi-period context, we develop an order promising model using nested booking limits (NBL) and allowing order reassignment, while respecting S&OP decisions and previous sales commitments. A rolling horizon simulation is used to evaluate the performance of the integrated process in various demand scenarios.

Simulation results provide evidence of the value of integrating RM and S&OP and show that we can offer better service level to high-priority customers and higher profit margin by integrating S&OP and NBL compared to common demand management practices.

In this study, supply, production and transport decisions are limited to the aggregated tactical level assuming that these optimal decisions can be implemented at the operational level. In reality, operational plans need to be taken into account. Also, considering different supply chain setups and different market variations may be of theoretical and practical interest.

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8. Appendices

Appendix A. Data generation

Weekly demand and prices are generated by a Visual Basic for Applications (VBA) code as follows:

— The yearly global demand is 150% of the maximum output that can be produced by pushing an infinity of supply into the supply chain. Then, we compute average weekly demand by dividing yearly demand by 52 weeks. We multiply the average weekly demand by seasonality factors to obtain the weekly demand. Seasonality factors are equal to 1 with stable demand (for scenarios 2 and 4 presented in Table 8).

— Since US market represents the largest export market for Eastern Canadian softwood companies, we set weekly demand forecasts of US market, CAE market, CAC market and spot market as respectively 40%, 20%, 20% and 20% of weekly global demand for scenarios 1 and 2 and 40%, 27.5%, 27.5% and 5% of weekly global demand for scenarios 3 and 4 (see Table 8).

— We suppose that, for each market, segments 1, 2 and 3 require respectively 10%, 70% and 20 % of all market demand. We consider these quantities as segment demand forecasts.

— We suppose also that CAE market, CAC market and spot market offer respectively 0.9, 0.9 and 0.8 of US market price. These prices are used as market prices forecasts.

— For each market, segments 1, 2 and 3 offer respectively 1.1, 1 and 0.9 of the market price.

— Unit transport costs are proportional to distance between nodes and segments.

Afterward, we randomly generate orders using probability distribution as follows. Assuming that we receive 100 orders weekly, i.e. 1 order per combination (segment, product), we generate random variables for as many as we have orders per combination (segment, product) in a year. For each order of a combination (segment, product):

— We generate reception period based on inter-arrival times, which follow a Poisson distribution. Average weekly arrival rate of order depends on product required and on customer segment.

— We generate delivery delays following a triangular distribution. Maximum, average and maximum delays are respectively set to 1, 3 and 4 periods for segments 2 and 3 and to 1, 2 and 3 periods for segments 1. Then, we deduce delivery periods.

— We compute average quantity required by an order of a combination (segment, product) as weekly segment demand forecasts of the product demanded divided by the average weekly arrival rate. Quantity demanded by an order is then deduced as inverse of normal distribution using as mean the average value previously obtained and 0.1×mean as a standard deviation.

— We generate orders as a list ordered by reception date.

Appendix B. Simulation algorithm

The simulation algorithm presented by Figure B1 is as follows:

(1) Initialize the current period j to period 1. Since we are at the beginning of the month, we go to step 2.

(2) Execute the tactical model. New allocations decisions $x_{p,n,g,t}$ are generated taking into consideration previous sales commitments $y_{p,n,g,g',t,t'}$. Go to step 3.

(3) Execute the order promising model. New sales commitments $y_{p,n,g,g',t,t'}$ are taken. Go to step 4.

(4) If we have an order received at period j, update demand requested $q_{p,g',t'}$, then go to step 3. Otherwise, go to step 5.

(5) Compute end-of-period inventory $i_{p,n,j}$ and increment current period ($j \leftarrow j+1$). If the new period j is larger than to 52, stop. Otherwise, if the new period j is the first period of the month (j mod 4=1), go to step 2. Otherwise, go to step 4.

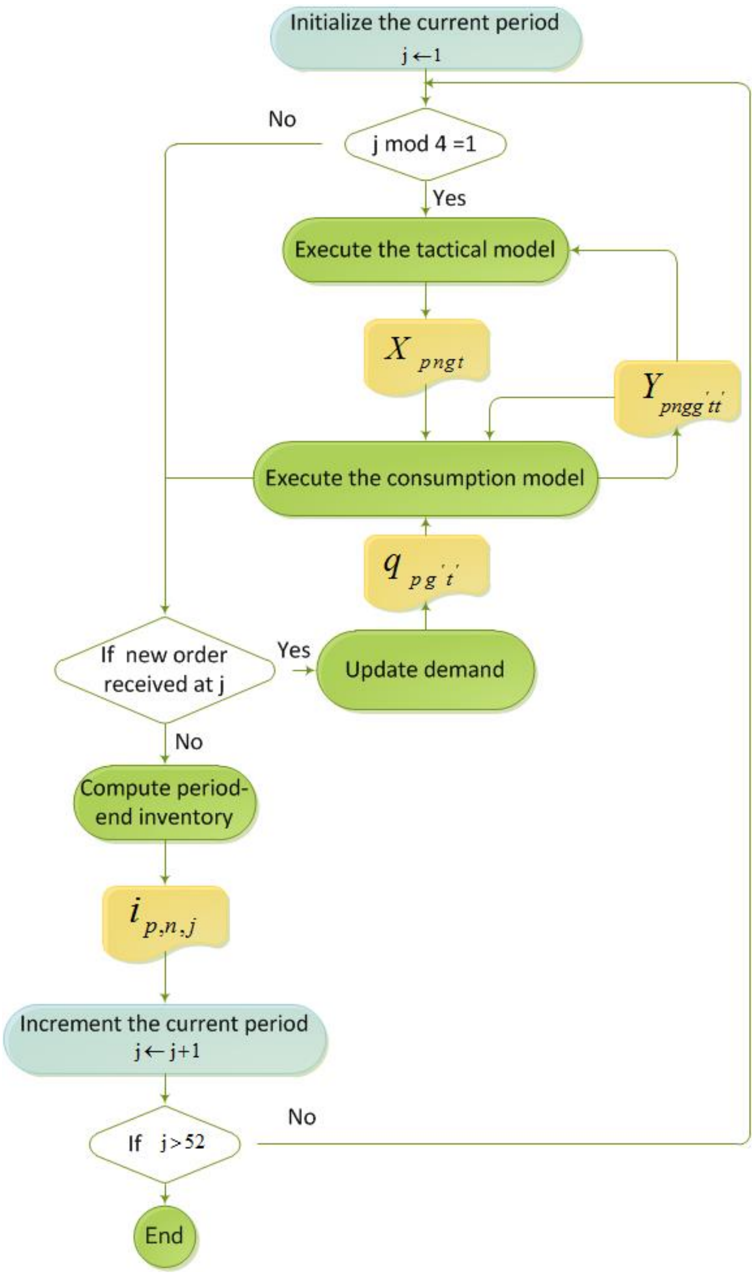

Figure B1.: Simulation algorithm