A MULTI-LEVEL FRAMEWORK FOR DEMAND FULFILLMENT IN A MAKE-TO-STOCK ENVIRONMENT- A CASE STUDY IN CANADIAN SOFTWOOD LUMBER INDUSTRY

Maha Ben Ali, Jonathan Gaudreault, Sophie D'amours, Marc-André Carle

A MULTI-LEVEL FRAMEWORK FOR DEMAND FULFILLMENT IN A MAKE-TO-STOCK ENVIRONMENT- A CASE STUDY IN CANADIAN SOFTWOOD LUMBER INDUSTRY

Maha BEN ALI, Jonathan GAUDREAULT, Sophie D'AMOURS, Marc-André CARLE

FORAC Research Consortium, Université Laval, G1V 0A6, QUÉBEC, CANADA
maha.ben-ali.1@ulaval.ca, jonathan.gaudreault@forac.ulaval.ca,
sophie.damours@gmc.ulaval.ca, marc-andre.carle@forac.ulaval.ca

ABSTRACT: *This paper proposes a demand fulfillment process for Make-To-Stock environments, integrating sales and operations planning (S&OP) and order promising, for a commodity market characterized by prices and demand seasonality. Considering differentiated customers, different products and multiple sourcing locations in a multi-period context, we define a multi-level decision framework in order to support short and medium term sales decisions in a way to maximize profits and to enhance the service level offered to high-priority customers. Our research exhibits three valuable elements: (1) we developed an order promising model based on nested booking limits and which allows order reassignment i.e. changing decisions of how firm orders have to be fulfilled; (2) we used a rolling horizon simulation to evaluate performance of the demand fulfillment process proposed; and (3) we compare it with common fulfillment processes such first-come first-served order processing. In order to evaluate the demand fulfillment process proposed, a numerical application based on softwood lumber manufacturers located in Eastern Canada is conducted and provides evidence that better performances (overall service level, high-priority service level and overall net profit) can be achieved by using nested booking limits and reviewing previous order promising decisions whilst respecting sales commitments.*

KEYWORDS: *Demand fulfillment process, Sales and operations planning, Order promising, Nested booking limits, Order reassignment, Rolling horizon simulation.*

1 INTRODUCTION

Demand fulfillment, a key operations within the supply chain management paradigm, requires cross-functional efforts (Oliva and Watson, 2011) to ensure customer satisfaction and to maximize medium and long term profitability. To meet these challenges, sales and operations planning (S&OP) is a periodic review procedure for providing leaders, managers and professionals with the right information to decide of future actions of supply, production, sales and transport. This process is notably interesting for cyclical industries to take advantage from demand and price fluctuations.

First, S&OP identifies sales targets based on forecasts. Further, more accurate information about demand and prices can be available when we start receiving customer orders. A real-time decision system is then needed to support order promising. To remain competitive and offer short delivery lead times , companies operating in a supply constrained mode and in a Make-to-Stock (MTS) environment, as softwood lumber companies, can achieve higher profitability by prioritizing orders from customers less sensitive to price (Stadtler and Kilger, 2005) and for more profitable periods and by selecting the most profitable sourcing location for each order. Average selling price can be increased by allocating scarce supply (inventory on hand and production planned or sales targets) to high priority orders, instead of giving it away to any order on a first-come-first-served (FCFS) basis as in traditional order promising policies. Furthermore, it is interesting that high priority orders can consume from allocations assigned to less priority orders, similarly to nested booking limits used in airline and other revenue management (RM) applications (Quante et al., 2009b).

Thus, sales decisions have to be taken at multiple planning levels and at different frequencies. In this paper, we propose a demand fulfillment 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 (section 3). A network perspective is considered and an order promising model is formulated as a linear program (LP) so that order assignment to a sourcing location may be changed until the last moment, although the decision of accepting or refusing an order is instantaneous and definitive (section 4). Order reassignment, i.e. changing decisions of how firm orders have to be fulfilled, can be made after receiving each order and after each tactical planning. A rolling horizon simulation is used to re-execute and update each level as often as needed. This is conducted for a case study with a commodity-type market, which is the softwood lumber market (section 5). Afterward, we attempt to reveal the potential benefits of using nested booking limits and order

reassignment as compared to common fulfillment processes (section 6).

This paper aims to improve demand fulfillment in MTS environments by synchronizing mid-term, short-term and real-time sales decisions. The fundamental contributions are: (1) to define a rolling horizon decision framework integrating S&OP and order promising, considering differentiated demand classes, different products and multiple sourcing locations in a multi-period context; (2) to develop a real-time order promising model with nested booking limits, which allows order reassignment; and (3) to evaluate the demand fulfillment process performance via a rolling horizon simulation in the Canadian softwood lumber industry and emphasize the potential benefits of using nested booking limits and order reassignment as compared to some common fulfillment processes such as FCFS order processing.

2 PRELIMINARY CONCEPTS

Few contributions dealt with demand fulfilment integrating different planning levels, notably S&OP and order promising based on RM concepts. In this section, we proceed with a literature revue to describe the basis of S&OP and analyze the current research on order promising and ATP allocation.

2.1 Sales and operations planning S&OP

S&OP can be defined as a periodic tactical planning process that links vertically business plans and strategic plans with operational plans, and horizontally demand with supply chain capacities (Feng et al., 2008). According to APICS (2010), the 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 the strategic and business plans covering a planning horizon between one and two years. Affonso et al. (2008) argue that the length of the planning horizon should be at least the length of the budget horizon.

S&OP mainly deals with organizational aspect and incertitude. 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 the integrated supply chain planning and the involvement of all functions in every stage through a constant criticism. Based on the right information and effective planning procedures, a good performance can be achieved. Oliva and Watson (2011) show that the quality of information, the quality of planning procedures and the quality of alignment between the different actors are the key success drivers supporting the S&OP process. S&OP can also support strategic decisions such as capacity decisions (Olhager et al., 2001). Moreover, S&OP supports integration between supply chain companies and ensures scheduling control to reduce delays. For instance, Affonso et al. (2008) have proposed a S&OP model linking, in one hand, marketing department of a company with procurement services of its customers and, on the other hand, the purchasing department with sales departments of its suppliers.

In an uncertain environment, S&OP aligns sales targets with resource availability. First, S&OP has an important role as a mediator to improve operational performance in production environments characterized by market incertitude (Olhager and Selldin (2007), Sodhi and Tang (2011), Feng et al. (2010b)). By simulating an S&OP model with a stochastic demand, Feng et al. (2010a) have proved that S&OP process reduces effects of forecast errors in a Make-To-Order environment. S&OP can also deal with order configuration uncertainty. In a Configure-To-Order environment, Chen-Ritzo et al. (2010) proposed a model supporting in a first stage supply planning, and in a second stage revision of demand and supply depending on suppliers' flexibilities. They showed that considering order configuration uncertainty through the S&OP process can achieve significant benefits in profit and revenue.

2.2 Order promising and ATP allocation

While S&OP makes decisions for a medium-term horizon, order promising is a real-time problem. It is a critical task (Fleischmann and Meyr, 2003) as it has not only impacts on the company's 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). Sales teams must decide which orders to fulfill, how much to sell, from which location and for which due dates. Such decisions are taken based on quantities Available To Promise (ATP), which concerns for MTS environments the availability of finished goods and for Assemble-To-Order (ATO) and Make-To-Order (MTO) environments the availability of all components used for assembling the finished product (Fleischmann and Meyr, 2003). ATP quantities can be assigned to new customer orders according to different allocation mechanisms, which were summarized by Pibernik (2006).

Several researches studied the application of the RM concepts for ATP allocation in a supply constrained situation. According to Phillips (2005), RM is a set of strategies and techniques managing capacity allocation to different customers classes and protecting capacity reserved for each class by defining booking limits. When all demand can't be fulfilled, RM can be considered as a powerful tool ensuring higher profitability and forging a stronger relationship with customers less sensitive to price (Stadtler and Kilger, 2005). RM has experienced great success with airlines and service industries, where capacity is perishable and fixed. However, the application of this concept in MTS manufacturing environments is still limited, although several studies in ATO and MTO environments (Tsai and Wang (2009), Chen and Ni (2010) and (Spengler et al., 2007)) exist.

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 known exogenous supply and developed a linear programming formulation composed of two stages: "ATP allocation" and "real-time ATP consumption" or "Single order processing after allocation planning". This research was expanded by Azevedo et al. (2014), who consider 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. (2009a) considered demand uncertainty and proposed a dynamic programming formulation using a Bellman recursion equation to take into account the impact of consumption decisions. Analyzing the interplay between demand variability, customers' heterogeneity and supply shortage, they showed that allocation model with nested booking limits always achieved better profits, as the deterministic model of Meyr (2009).

Pibernik and Yadav (2009) also dealt with stochastic demand, but with multiple receipts in the planning horizon. The framework proposed considers carry over between two levels: allocation planning, which the authors called "inventory reservation", and order promising. They developed a heuristic approach to identify relevant factors determining inventory reservation quantities. Service level target for high priority class and overall fill rate were considered instead of profit maximization. They showed that inventory reservation could detrimentally affect the overall system performance. This research was expanded (Samii et al., 2011) to provide a formulation of the trade-off between the benefits of reserving for high priority customers and the negative impact of inventory reservation based on the chosen reservation levels for the high priority customer class. This analysis was limited to a single period inventory reservation problem and two classes of customers.

3 DEMAND FULFILLMENT PROCESS PROPOSED

A company generally offers its products to different markets, which refers to customers from different geographical regions (Azevedo et al. 2014). Each market can be split into customer segments, according to different criteria such as willingness to pay (Feng and Xiao (2000), Zhang et al. (2006), Li and Chen (2010), Azevedo et al. (2014)), quality sensitivity (Xiaodong et al. 2007), lead times (Li and Chen 2010), etc.

Sales and price forecasting are critical inputs of the S&OP process (Mentzer et al., 2007). New information about demands and prices can be periodically obtained. While disaggregated forecasts can be made for short-term horizon, medium-term forecasts are generally more dubious (uncertain) 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... For instance, new forecasts of market demands and prices can be available each month as follows: weekly market forecasts for short-term and monthly market forecasts for the rest of the planning horizon. Moreover, new short term forecasts of segment demands and prices can be available each month. S&OP process can be re-executed as soon as new forecasts are available.

In this context, we define a demand fulfillment process (Figure 1) integrating S&OP and order promising based on RM concepts, which is composed of four principal activities:

1. S&OP: Considering market medium-term forecasts (e.g. twelve months), contracts, sales commitments made in previous periods and real inventories available (updated after each order delivered), the S&OP predetermines production, transport and supply plans and sales targets for each market. This activity is generally carried out each month.

2. Allocation planning: Quantities projected for each market, over short-term horizon, are allocated to different customer segments based on short term forecast (e.g. eight weeks). Sales commitments made in previous periods and weekly segment forecasts respectively represent lower and upper bounds for segment allocations. In industrial practices, S&OP and allocation planning are mostly planned by different teams. Nevertheless, it can be advantageous to simultaneously plan them as soon as we receive new forecasts (e.g. in the beginning of each month).

3. Booking limits identification: Before making promises, we identify, for each segment and for each period, from which allocations we can consume based on prices forecasts. This activity will be more detailed in section 4.2.

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 we should consume. We have also to reassign previously accepted orders, not yet delivered. Moreover, order reassignment has to be done after each tactical planning.

In our graphical representation of the demand fulfillment process (Figure 1), we suppose that S&OP is planned over a medium-term horizon (e.g. 52 weeks) and that we can make commitments just for short-term horizon (e.g. 8 weeks). Orders that should be delivered later will be postponed. Demand set by contracts is considered as a minimum demand to respect by the S&OP and is included in incoming orders. We also assume that an order can request multiple products and that partial fulfillment is allowed. As mentioned before, the decision of accepting or refusing an order is instantaneous and definitive. However, order assignment to sourcing location is temporary and may be changed.

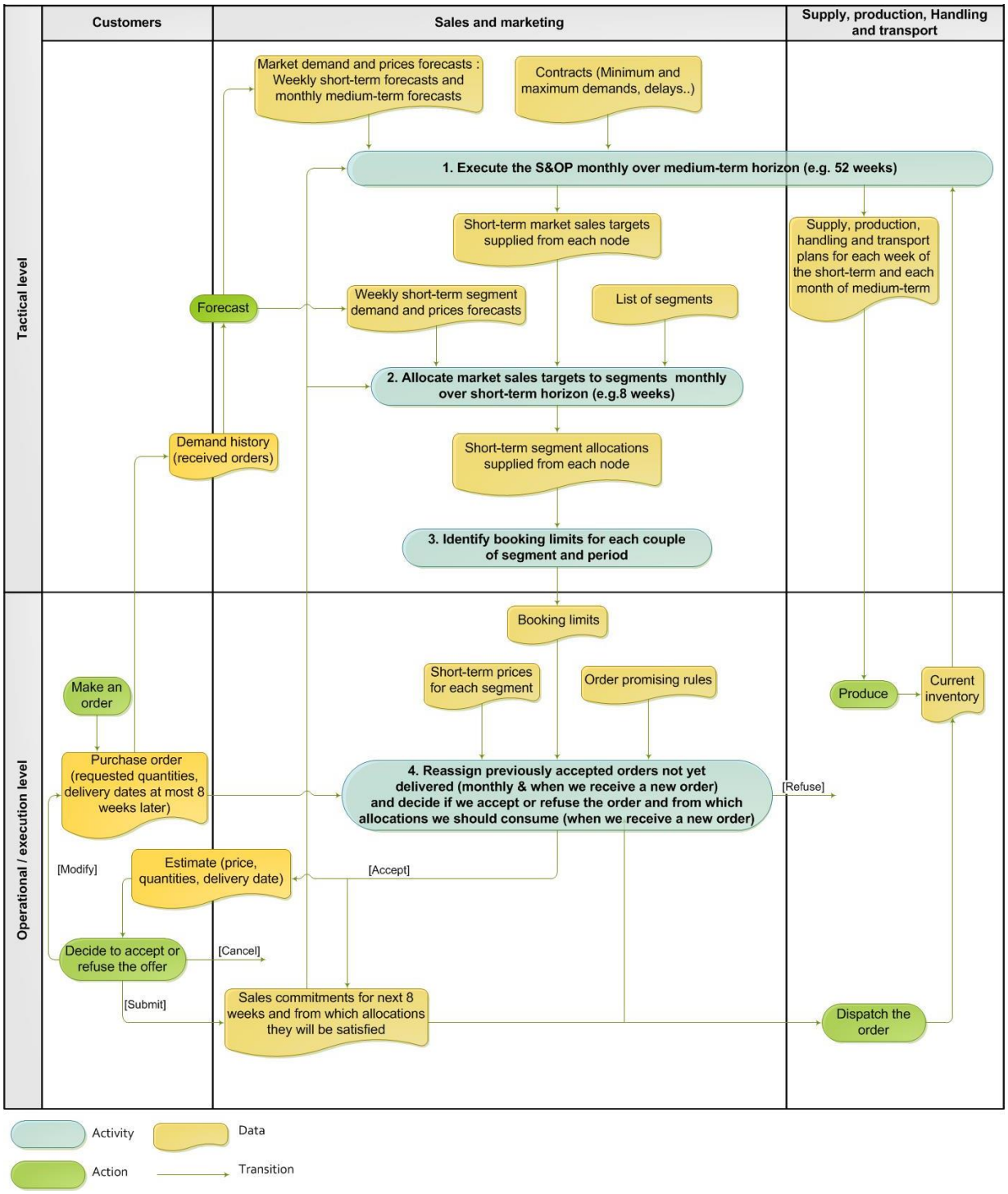

Figure 1 : Demand fulfillment process integrating S&OP and order promising based on RM concepts

4 MODEL FORMULATION

Figure 2 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 manufacturing plants and distribution centers. Nodes can be supplied by different suppliers and sold to various markets composed by differentiated segments g ($g \in \mathbf{G}$).

4.1 Tactical model (Activities 1 and 2)

At the beginning of each month, a tactical model simultaneously plans S&OP and allocation. We use the S&OP network model, proposed by Marier et al. (2014) for a softwood company, which takes decisions related to supply, production, handling, transportation and sales in order to optimize the total company's net revenue over T periods. Sales decisions are set by customer markets.

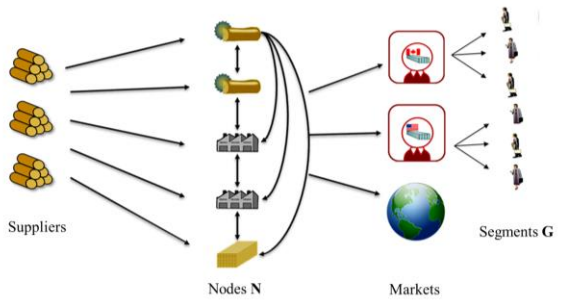

Figure 2 : Supply network of a multi-site softwood company

To incorporate the allocation planning, we expand this S&OP model (Marier et al. 2014) so that short-term sales decisions may be allocated to different customer segments. Sales commitments and demand forecasts are set as lower and upper bounds for both markets' sales targets and segments' allocations. Several adaptations were also made to have a rolling horizon planning.

4.2 Consumption model (Activities 3 and 4)

Once the tactical model is executed, we start to receive demand from customers segments for different delivery periods. Consumption model is required to instantaneously make promises to orders, while respecting the medium-term decisions and previous decisions.

Sets		
$\mathbf{G}$	Customer segments g	
$\tilde{\mathbf{G}}$	Spot segment $\tilde{g}$ $(\tilde{\mathbf{G}} = \{\tilde{g}\} \subseteq \mathbf{G})$	
$\mathbf{N}$	Nodes n (representing manufacturing plants and distribution centers)	
$\mathbf{P}$	Products p	
Parameters		
τ	1st period of the S&OP horizon	Index
i	Current period	Index
T'	Short-term length ($T' << T$)	Week
$\eta_{n,g',p,t,t'}$	Net profit for selling a product p, available in node n at period t, to segment g' at period t' ($t \leq t'$)	\$/Qty
$q_{g',p,t'}$	Quantity of product p required by segment g' for period t'	Qty
$x_{n,g,p,t}$	Quantity of product p from node n allocated to segment g for period t (tactical model decisions)	Qty
$y_{n,g,g',p,t,t'}$	Quantity from allocation $x_{n,g,p,t}$ fixed for segment g' at period t' ($t \leq t' < i$)	Qty
Decision variables		
$Y_{n,g,g',p,t,t'}$	Quantity from allocation $x_{n,g,p,t}$ consumed by segment g' for period t' ($t \leq t'$ and $i \leq t'$)	Qty

Table 1 : Sets, parameters and decision variables used by the consumption model

Consumption model decides from which allocations we should consume to fulfill segments demand for each due date. So, we have to assign demand required by segment *g'* for delivery period *t'* to allocations initially set to a segment *g* for delivery period *t*. Allocation delivery period *t* should always precede consumption period *t'* to guarantee that there are available quantities to promise.

Since it is an assignment problem, we formulate it as a linear programming (LP) model. Table 1 describes the sets, parameters and decision variables involved in the consumption model. Assignments are illustrated in Figure 3 as arcs between allocations and requested quantities. We can review these assignments as often as needed, i.e. after each tactical planning and whenever a new order is received.

The concept of nested booking limits (BL) is used to take advantage from customers' heterogeneity and profitability variation over time (Azevedo et al. 2014). BLs are set by segment, product and delivery period. At a current period *i*, BL of a product *p* for a segment *g'* and a delivery period *t'* ($BL^{i}_{g',p,t'}$) are defined as allocated quantities of product *p* that we can consume for *g'* and *t'* and are set by authorized arcs in Figure 3. They can be expressed by:

$$BL^{i}_{g',p,t'} = \sum_{n \in \mathbf{N}} \left(x_{n,g',p,t'} + \sum_{g \in \mathbf{G}} \sum_{t=\tau}^{i-1} x_{n,g,p,t} + \sum_{t=i}^{t'} x_{n,\tilde{g},p,t} + \sum_{\substack{t=i \\ \eta_{n,g',p,t,t} \leq \eta_{n,g',p,t,t'}}}^{t'-1} x_{n,g',p,t} + \sum_{g \in \mathbf{G} \setminus \{g',\tilde{g}\}} \sum_{\substack{t=i \\ \eta_{n,g,p,t,t} \leq \eta_{n,g',p,t,t'}}}^{t'} x_{n,g,p,t} \right) \quad (1)$$

Both equation (1) and Figure 3 show that, to fulfill demand requested by segment *g'* and delivery period *t'*, we can consume from:

- allocations set to segment g' for delivery period t';
- unconsumed allocations set for previous delivery periods t (t < i);
- allocations set to spot segment g̃ for any delivery period (Quantities allocated to spot segment can be consumed by any other segment since they are not dedicated to specific customers);
- allocations set to segment g' for future delivery period t preceding period t' and generating lower profit than being consumed at period t' ($i \leq t < t'$, $\eta_{n,g',p,t,t} \leq \eta_{n,g',p,t,t'}$)

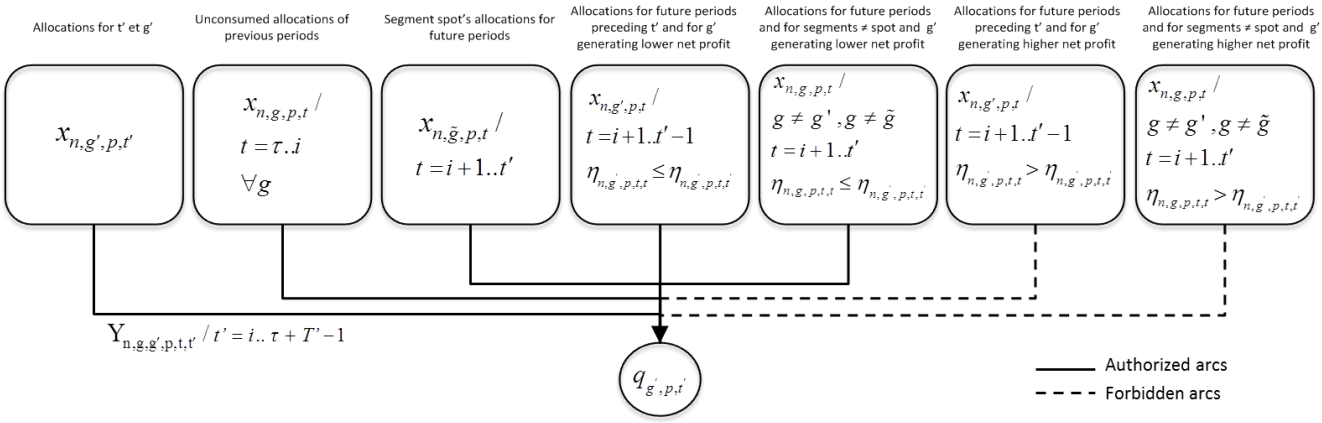

Figure 3 : Allocations assignments to quantity requested by segment g' for delivery date t'

- 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' ($i \leq t \leq t'$, $\eta_{n,g,p,t,t} \leq \eta_{n,g',p,t,t'}$)

The objective function (2) of the consumption model is to maximize short-term net profit of fulfilling demand requested for periods between the current period *i* and the end of the short term horizon *(τ+ T'-1).*

$$\sum_{n\in\mathbf{N}}\sum_{g\in\mathbf{G}}\sum_{g'\in\mathbf{G}}\sum_{p\in\mathbf{P}}\sum_{t'=i}^{\tau+T'-1}\sum_{t=\tau}^{t'}\eta_{n,g',p,t,t'}\,Y_{n,g,g',p,t,t'} \quad (2)$$

This objective function is subject to the following constraints:

Allocation consumption (3)

$$\sum_{g'\in\mathbf{G}}\left(\sum_{t'=t}^{\tau+T'-1} Y_{n,g,g',p,t,t'}\right) \leq x_{n,g,p,t} \qquad \forall n\in\mathbf{N}, \forall g\in\mathbf{G}, \forall p\in\mathbf{P}, t = i..\tau+T'-1 \quad (3.a)$$

$$\sum_{g'\in\mathbf{G}}\left(\sum_{t'=i}^{\tau+T'-1} Y_{n,g,g',p,t,t'} + \sum_{t'=t}^{i-1} y_{n,g,g',p,t,t'}\right) \leq x_{n,g,p,t} \qquad \forall n\in\mathbf{N}, \forall g\in\mathbf{G}, \forall p\in\mathbf{P}, t = \tau..i-1 \text{ Defined if } \tau < i \quad (3.b)$$

Forbidden consumptions (4)

$$Y_{n,g,g,p,t,t'} = 0 \qquad \forall n\in\mathbf{N}, \forall g\in\mathbf{G}, \forall p\in\mathbf{P}, t' = i..\tau+T'-1, t = i..t'-1, \eta_{n,g,p,t,t} > \eta_{n,g,p,t,t'} \quad (4.a)$$

$$Y_{n,g,g',p,t,t'} = 0 \qquad \forall n\in\mathbf{N}, \forall g'\in\mathbf{G}, \forall \boldsymbol{g}\in\mathbf{G}\backslash\{\tilde{g},g'\}, \forall p\in\mathbf{P}, t' = i..\tau+T'-1, t = i..t', \eta_{n,g,p,t,t} > \eta_{n,g',p,t,t'} \quad (4.b)$$

Non-negativity (5)

$$Y_{n,g,g',p,t,t'} \geq 0 \qquad \forall n\in\mathbf{N}, \forall g,g'\in\mathbf{G}, \forall p\in\mathbf{P}, t' = i..\tau+T'-1, t = \tau..t'$$

First, constraints (3) ensure that quantities consumed from allocation ($x_{n,g,p,t}$) set to a segment *g* for delivery period *t* will not exceed $x_{n,g,p,t}$. This includes quantities ($y_{n,g,g',p,t,t'}$) consumed by delivered orders that we can no longer change (reassign), which is expressed by equation (3.b) defined only if $\tau < i$. Second, constraints (4) translate nested booking limits concept. In fact, forbidden consumptions are forced to zero to avoid consumption from allocations set to more profitable segments and delivery periods. These consumptions are represented by forbidden arcs in Figure 3. Third, constraints (5) assure that all variables are non-negative. Finally, to guarantee previous commitments, additional constraints are expressed differently depending if reassignment is authorized or not.

If reassignment is authorized, equation (6) should be added. Quantities consumed by segment *g'* for delivery period *t'* have always to be equal to demand of segment *g'* for period *t'*. Otherwise, the problem cannot be resolved, i.e. when a new order cannot be fulfilled.

Respect of previous commitments (6)

$$\sum_{n\in\mathbf{N}}\sum_{g\in\mathbf{G}}\sum_{t=\tau}^{t'} Y_{n,g,g',p,t,t'} = q_{g',p,t'} \qquad \forall g'\in\mathbf{G}, \forall p\in\mathbf{P}, t' = i..\tau+T'-1$$

If reassignment is denied, constraints (6') should be added. Constraints (6'.a) ensure that quantities consumed by segment *g'* for delivery period *t'* is equal to demand of segment *g'* for period *t';* otherwise, the new order cannot be fulfilled. Since we cannot change previous assignments, consumed quantities may be increased, but not reduced (constraints (6'.b)).

Respect of previous assignments (6')

$$\sum_{n\in \mathbf{N}}\sum_{g\in \mathbf{G}}\left(\sum_{t=\tau}^{t'} Y_{n,g,g',p,t,t'} + \sum_{t=1}^{\tau-1} y_{n,g,g',p,t,t'}\right) = q_{g',p,t'} \qquad \forall\, g' \in \mathbf{G}, \forall\, p \in \mathbf{P},\ t' = i..\tau + T' - 1 \qquad (6'.a)$$

$$Y_{n,g,g',p,t,t'} \geq y_{n,g,g',p,t,t'} \qquad \forall\, n \in N, \forall g \in G,\ \forall\, g' \in G, \forall\, p \in P,\ t' = i..\tau + T' - 1,\ t = \tau..t' \qquad (6'.b)$$

5 APPLICATION TO SOFTWOOD LUMBER INDUSTRY CASE

5.1 Case description

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 Canada's forest product exports[1], destined for domestic and international markets where the U.S represents the largest export market for Canada.

During recent years, this industry have faced various trades and economic pressures (Dufour, 2007), including Canada-United States Softwood Lumber Agreements, the American anti-dumping, a rise in energy and raw material prices, a decline in lumber prices, a higher exchange rate for the Canadian dollar and the U.S. housing bubble burst. Within this context, softwood lumber companies try to remain profitable and to maintain positive profit margins.

A softwood lumber company can be considered as a MTS environment as its activities are driven by forecasts. It is composed generally of multiple facilities including mills and distribution centers. It offers a large portfolio of products to heterogeneous customers, having different attitudes and priorities. Home improvement warehouse companies and housing component manufacturers, for example, are willing to pay more for better products and better services. Other customers, such as dealers and distributors, are more sensitive to price than to quality.

A softwood lumber company generally operates in supply constrained mode as raw material availability and capacity are bottlenecks. Consequently, all demand cannot always be fulfilled and the supply chain may offer less finished products than customers' requests. 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 would experience 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 of seasonal fluctuations in softwood lumber prices can be explained by demand seasonality related to construction activities. Tactical planning is important to take advantage from the cyclical nature of the softwood lumber industry.

In order to validate the demand fulfillment process proposed, an experimental case 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. The scope of the case is outlined in Table *2*.

Sets	Size	Details
Nodes (mills)	3	
Products	10	2x4 8', 2x4 12', 2x4 14', 2x4 16' , 2x4 8', 2x4 12', 2x4 14', 2x4 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 from 3 segments each.
Average number of orders incoming weekly	150	Average weekly arrival rate is 1.5 order / couple (segment, product). One product is required per order.

Table 2 : Scope of the simulated case

5.2 Data generation

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

- Magnitude order of yearly global demand is based on the study of Marier et al. (2014). Then, we compute average weekly global demand by dividing on 52 weeks.
- Since US market represents the largest export market for Canadian Est softwood companies[1], 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. 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, for each week, CAE market, CAC market and spot market offer respectively 0.9, 0.9

[1]Natural Resources Canada, Forest products , accessed on May 15th 2014, http://www.nrcan.gc.ca/forests/industry/13317

and 0.8 of US market price. There are used as market prices forecasts.

- For each market, segments 1, 2 and 3 offer respectively 1.15, 1 and 0.85 comparably to 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. 1order per couple (segment, product)), we generate random variables as many as we have orders per couple (segment, product) in a year. For each order of a couple (segment, product):

- We generate reception period based on inter-arrival times, which follow a Poisson distribution. Average weekly arrival rates depend on product required and on customer segment, as presented in Table 3.

Product	2x4 8'	2x4 10'	2x4 12'	2x4 14'	2x4 16'	2x6 8'	2x6 10'	2x6 12'	2x6 14'	2x6 16'
Average weekly arrival rate	7.5	7.5	10	15	20	7.5	7.5	7.5	7.5	10
Segment	US 1	US 2	US 3	CAE 1	CAE 2	CAE3	CAC 1	CAC2	CAC3	SPOT
Proportion of orders incoming weekly	4%	28%	8%	2%	14%	4%	2%	14%	4%	20%

Table 3 : Average weekly arrival rate per product and segment proportion of orders incoming weekly

- 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 deduct delivery periods.
- We compute average quantity required by an order of a couple (segment, product) as weekly segment demand forecasts of the product required divided by the average weekly arrival rate. Quantity required by an order is then deducted as inverse of normal distribution using average value previously obtained.
- We generate orders as a list ordered by reception date.

6 SIMULATION AND RESULTS

The simulation is conducted with weekly planning periods over a year. S&OP supply, production and transport plans are supposed to be met and operational constraints of supply, production and transport are not taken in consideration in the order promising activity.

6.1 Experimental design

Table 4 presents an experimental design to evaluate the performance of the demand fulfillment process (SA-BL-R), presented in Figure 1 and integrating S&OP, allocation planning and order promising with nested booking limits and reassignment option. Constraints (6) are activated, as described in section 4.2.

In order to highlight the combined effect of using booking limits and reassignment, we evaluate three additional processes/approaches: (S-GO), (S-FCFS-R) and (S-FCFS).

Process	Tactical level	Operational/execution level
(S-GO)	S&OP	· Global Optimization executed once for all orders of the planning horizon
(SA-BL-R)	S&OP/Allocation	· Executed for each single order and after each tactical planning · Nested Booking Limits · Reassignment allowed
(S-FCFS-R)	S&OP	· Executed for each single order and after each tactical planning · Order promising in a First-Come First-Served manner · Reassignment allowed
(S-FCFS)	S&OP	· Executed for each single order · Order promising in a First-Come First-Served manner · Reassignment denied

Table 4 : Experimental design

The (S-GO) process is used to define an upper bound on the profit that we could get. We assume an "oracle ", which knows all orders arriving within the planning horizon before making promises. For the (S-FCFS-R) process, constraints (4) are deactivated, so we do not use booking limits. This process simply decides if we accept or refuse each order assuming that all allocations are available to all. Such as for (S-BL-R), order reassignment is done after each order is received. The (S-FCFS) process is similar to the (S-FCFS-R) process, but without the reassignment option. Constraints (6') are then activated instead of constraints (6), as described in section 4.2.

For each process, a simulation algorithm is developed in Visual Basic.NET to sequentially call tactical and consumption models, developed within IBM ILOG CPLEX Optimization Studio version 12.4. To obtain confidence intervals of 95%, four replicates were performed for each process.

6.2 Results and discussions

In this section, we examine how the use of booking limits and the order reassignment can affect the overall performance and the service level for high priority customers. While Figure 4 illustrates the yearly net profit for all processes presented in Table 4, Figure 5 presents overall demand fill rate and high priority demand fill rate achieved for each process.

Effect of using booking limits: Focusing on processes with reassignment, we can observe in Figure 4 that the (SA-BL-R) net profit is higher than (S-FCFS-R) net profit. In fact, using nested booking limits achieves not only a better high priority service level but also a higher overall system performance. Figure 5 clearly shows that (SA-BL-R) ensures a better high priority fill rate compared to (S-FCFS-R) since we prioritize orders from high-priority customers.

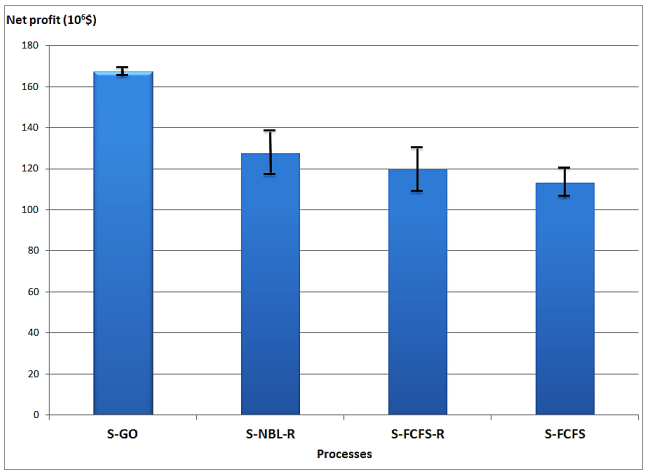

Figure 4 : Yearly net profit

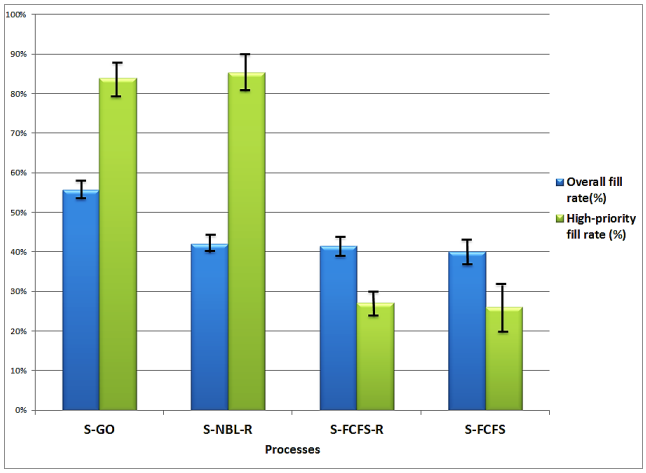

Figure 5 : Overall fill rate and high priority fill rate

Reassignment effect: Furthermore, the (SA-FCFS-R) process, where reassignment is allowed, outperforms (S-FCFS) process. Figure 4 and Figure 5 show that better performances (net profit, overall fill rate and high priority fill rate) can be achieved. In fact, whilst respecting orders already promised, reassignment generates each time the most profitable set of assignments between allocations and requested quantities and so offers more flexibility for consumption decisions.

Combined effect of using booking limits and reassignment: Average values show that the overall performance achieved by the (SA-BL-R) process is the closest to the overall performance of (S-GO) process (in term of net profit and overall fill rate). (SA-BL-R) process also offers the best service level for high priority customers. However, these preliminary results should be statistically validated by simulating more replications.

7 CONCLUSION AND PERSPECTIVES

In this paper, we extend the research in demand fulfillment for MTS manufacturing systems and present a framework integrating S&OP and order promising, considering differentiated demand segments, different products and multiple sourcing locations in a multi-period context. Our study is among the very few studies that use a rolling horizon planning to simulate a demand fulfillment process. Contrarily to most previous studies which have assumed a deterministic demand or a stochastic demand with simplistic assumptions, we propose a process that captures demand incertitude and feedbacks between different sales planning levels.

In addition, we develop a real-time order promising model based on RM concepts, in order to ensure a high service level for high priority customers. This model allows also order reassignment, which offers more flexibility for consumption decisions and improves the overall system performance.

Results obtained from our case study show that we can offer better service level to high priority customers and higher overall net profit by using nested booking limits and reviewing previous order promising decisions.

In our data generation, we assumed that the demand within the planning horizon is stationary. Future extensions will be eventually to consider seasonality demand in order to emphasize the S&OP potential gain. Also, we assumed that orders can be either accepted or rejected. Analyzing the performance of the demand fulfillment process presented with backorders will be interesting.

ACKNOWLEDGMENTS

The authors would like to thank Philippe Marier for his technical support as a FORAC research professional and FRQNT and NSERC for financial support.

REFERENCES

Affonso, R., Marcotte, F., Grabot, B., 2008. Sales and operations planning: The supply chain pillar. *Production Planning and Control*, 19, p. 132-141.

Blackstone, J.H., 2010. *APICS Dictionary*, 13.

Azevedo, R.C., D'Amours, S., Rönnqvist, M., 2014. Advances in Profit-driven Order Promising for Make-to-Stock Environments – a case study with a Canadian Softwood Lumber Manufacturer. Manuscript submitted for publication.

Chen-Ritzo, C.-H., Ervolina, T., Harrison, T.P., Gupta, B., 2010. Sales and operations planning in systems with order configuration uncertainty. *European Journal of Operational Research*, 205, p. 604-614.

Chen, H., Ni, Y., 2010. Performance analysis of order promising based on allocated ATP, *International Conference on Communication Systems, Networks and Applications (ICCSNA 2010)*, Hong Kong, China, p. 14-18.

Dufour, D., 2007. L'industrie canadienne du bois d'oeuvre : tendances récentes. *Statistique Canada*, p. 3-16.

Feng, Y., D'Amours, S., Beauregard, R., 2008. The value of sales and operations planning in oriented strand board industry with make-to-order manufacturing system: Cross functional integration under deterministic demand and spot market recourse. *International Journal of Production Economics*, 115, p. 189-209.

Feng, Y., D'Amours, S., Beauregard, R., 2010a. Simulation and performance evaluation of partially and fully integrated sales and operations planning. I*nternational Journal of Production Research*, 48, p. 5859-5883.

Feng, Y., Martel, A., D'Amours, S., Beauregard, R., 2010b. A stochastic programming approach for coordinated contract decisions in a make-to-order manufacturing supply chain, *CIRRELT*, Research paper CIRRELT-2010-11.

Feng, Y., Xiao, B., 2000. Revenue management with two market segments and reserved capacity for priority customers. *Advances in Applied Probability*, 32, p. 800-823.

Fleischmann, B., Meyr, H., 2003. Planning Hierarchy, Modeling and Advanced Planning Systems, *Handbooks in Operations Research and Management Science. Elsevier*, p. 455-523.

Li, L., Chen, Z.-X., 2010. A revenue management model in BTO manufacturing over an infinite horizon, *IEEE International Conference on Industrial Engineering and Engineering Management (IEEM2010)*, Macao, China, p. 1349-1352.

Marier P., Bolduc S., Ben Ali M., Gaudreault J., 2014. S&OP network model for commodity lumber products, *CIRRELT*, Research paper CIRRELT-2014-25.

Mentzer, J.T., Myers, M.B., Stank, T.P., 2007. Demand management. *Sage Publications*.

Meyr, H., 2009. Customer segmentation, allocation planning and order promising in make-to-stock production. *OR Spectrum*, 31, p. 229-256.

Olhager, J., Rudberg, M., Wikner, J., 2001. Long-term capacity management: Linking the perspectives from manufacturing strategy and sales and operations planning. *International Journal of Production Economics*, 69, p. 215-225.

Olhager, J., Selldin, E., 2007. Manufacturing planning and control approaches: market alignment and performance. *International Journal of Production Research*, 45, p. 1469-1484.

Oliva, R., Watson, N., 2011. Cross-functional alignment in supply chain planning: A case study of sales and operations planning. *Journal of Operations Management*, 29, p. 434-448.

Phillips, R.L., 2005. Pricing and revenue optimization. *Stanford Business Books*, Stanford, Californie.

Pibernik, R., 2006. Managing stock-outs effectively with order fulfilment systems. *Journal of Manufacturing Technology Management*, 17, p. 721-736.

Pibernik, R., Yadav, P., 2009. Inventory reservation and real-time order promising in a Make-to-Stock system. *OR Spectrum*, 31, 281-307.

Quante, R., Fleischmann, M., Meyr, H., 2009a. A Stochastic Dynamic Programming Approach to Revenue Management in a Make-to-Stock Production System. *SSRN eLibrary*.

Quante, R., Meyr, H., Fleischmann, M., 2009b. Revenue management and demand fulfillment: matching applications, models, and software. *OR Spectrum*, 31, p. 31-62.

Samii, A.-B., Pibernik, R., Yadav, P., 2011. An inventory reservation problem with nesting and fill rate-based performance measures. *International Journal of Production Economics*, 133, p. 393-402.

Sodhi, M.S., Tang, C.S., 2011. Determining supply requirement in the sales-and-operations-planning (SOP) process under demand uncertainty: A stochastic programming formulation and a spreadsheet implementation. *Journal of the Operational Research Society*, 62, p. 526-536.

Spengler, T., Rehkopf, S., Volling, T., 2007. Revenue management in make-to-order manufacturing - an application to the iron and steel industry. *OR Spectrum, 29*, p. 157-171.

Stadtler, H., Kilger, C., 2005. Supply chain management and advanced planning : concepts, models, software and case studies. *Springer*, Berlin , New York.

Tsai, K.-m., Wang, S.-c., 2009. Multi-site available-to-promise modeling for assemble-to-order manufacturing: An illustration on TFT-LCD manufacturing. *International Journal of Production Economics*, 117, p. 174-184.

Xiaodong, S., Peng, T., Yun, C., Yue, J., 2007. Revenue management for two quality level products, *3rd International Conference on Wireless Communications, Networking, and Mobile Computing (WiCOM 2007)*, New Jersey, United States, p. 5079-5082.

Zhang, Z., Wu, L.-w., Jin, C., 2006. The simulation research on inventory control of distribution system based on customer segmentation, *International Conference on Management Science and Engineering*, New Jersey, United States, p. 203-207.