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Rezvan Rafiei
Mustapha Nourelfath
Jonathan Gaudreault
Luis Antonio Santa-Eulalia
Mathieu Bouchard

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Bureaux de Montréal :
Université de Montréal
C.P. 6128, succ. Centre-ville
Montréal (Québec)
Canada H3C 3J7
Téléphone : 514 343-7575
Télécopie : 514 343-7121

Bureaux de Québec :
Université Laval
2325, de la Terrasse, bureau 2642
Québec (Québec)
Canada G1V 0A6
Téléphone : 418 656-2073
Télécopie : 418 656-2624

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A Reactive Planning Approach for Demand-Driven Wood Remanufacturing Industry: A Real-Scale Application

Rezvan Rafiei[1,2,*], Mustapha Nourelfath[1,2], Jonathan Gaudreault[1,3], Luis Antonio Santa-Eulalia[4], Mathieu Bouchard [1,2]

[1] Interuniversity Research Centre on Enterprise Networks, Logistics and Transportation (CIRRELT)

[2] Department of Mechanical Engineering, Université Laval, Pavillon Adrien-Pouliot, 1065, avenue de la médecine, Québec, Canada G1V 0A6

[3] Department of Computer Science and Software Engineering, Université Laval, Pavillon Adrien-Pouliot, 1065, avenue de la médecine, Québec, Canada G1V 0A6

[4] School of Applied Sciences, University of Campinas, rua Pedro Zaccaria, 1300, 13484-350, Limeira, São Paulo, Brazil

Abstract. Managing uncertainty is one of the main challenges within the forest supply chain. This paper studies a wood remanufacturing mill that experiences important disruptions due to uncertain demands. In order to handle these demands, a mathematical programming model is sketched as a baseline to provide a reactive planning strategy using a periodic policy. By changing the objective function of this baseline model, several approaches are selected. The effectiveness of the reactive planning strategy is then illustrated, and the impact of the selected approaches is evaluated, considering planning period length and planning time window. Various comparisons are made among approaches based on backorder levels and cost values. The experiments results based on this real-scale industrial case show that backorder quantity can be minimized but a huge cost. However the trade-off between backorder and cost can be established.

Keywords. Reactive planning, uncertain demand, wood remanufacturing industry, mixed integer programming, simulation.

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* Corresponding author: Rezvan.Rafiei@cirrelt.ca

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1. Introduction

One of the fundamental aspects that a manufacturing system faces is that uncertain demands increase the complexity of the manufacturing processes. Most industries are confronted with varying customer demands for different products. The performance of a plan in "pull" systems (wherein demands from customers are taken into account) is very sensitive to demand fluctuations, and it is not trivial to efficiently adjust the production plan to changes. As a result of demand fluctuations, the production process outputs and inputs become different from the planned quantities. In fact, over or underestimating uncertain demands and its side effects could lead to inefficient production plans as well as loss of market share (Gupta and Maranas 2003). Therefore, a particularly challenging problem for mills is to make decisions under uncertainty in demands.

Many existing papers use a stochastic programming (SP) approaches to manage uncertainties. The SP method expresses uncertainties as probability density functions. Unfortunately, uncertainties will not be predictable if no information exists about their behaviour. Under conditions that uncertainty level is important and the data follows no known probability distribution, reactive planning approaches have been recommended by many researches (e.g., Li and Ierapetritou 2008 and Lou et al. 2012). This approach generates an on-line plan which makes decisions locally in real-time. Reactive actions can take place at the edge of fixed intervals of time or when uncertainties unfold. In both situations, the plan is updated based on the new upcoming information.

This study is motivated by a real-scale case in a wood remanufacturing industry. Uncertainty of demands is a key problem in this mill and has a major influence on its processes. It is in fact very difficult for managers to adequately handle these unpredictable demands. Any pre-computed or predictive plan inevitably requires continuous updates to quickly react to disturbances from the business milieu, which can be costly. In a remanufacturing unit (*e.g.*, bed frame components manufacturing), managers are obliged to review the production plans daily due to the arrival of new and unexpected orders from clients. In practice, this is handled through manual approaches by supply chain planners, who usually rely mostly on their experience and intuition. It is quite hard for them to efficiently manage the large quantity of information from the complex business environment in order to be sure that their adapted plans are really cost-efficient. That is, when demand goes up, planners are not able to have a swift reaction to demand change and decide whether to lose sale or to encounter a stock-out. It is likely that either the customer will go to elsewhere or the mill will pay a backorder penalty. This issue is aggravated by a co-production system wherein multiple types of finished products are produced at the same time from a single raw material. In co-production systems with a finite production capacity a given demand may face with backorder, because other products mostly with smaller market demand and high inventory level are simultaneously produced. Therefore, production planning is a complex procedure in this mill by having a co-production system together with highly uncertain demands. Decreasing the backorder quantity to reach a high service level is a challenging problem for this wood remanufacturing mill. The present paper presents a reactive planning strategy to help managers for making decisions about how to deal swiftly with uncertain demands.

Following these introductory remarks, a literature review is given and the paper contribution is highlighted in Section 2. A case in wood remanufacturing industry will be described in Section 3. In Section 4, a mathematical programming model is developed. Then, considering different kinds of disturbances of this initial plan, an efficient re-planning strategy is proposed and validated by simulation in Section 5. Finally, conclusions are drawn in Section 6.

2. Literature review

Various types of uncertainty may be encountered in a manufacturing environment. Such uncertainties according to the characteristics and resources can be distinguished as one of three types (Lou *et al.* 2012): 1) *Complete unknown uncertainties* which are unpredictable events, such as a sudden accident, strike, or similar. 2) *Suspicious uncertainties about the future*, which are not easy to quantify, for example, rush order arrivals, order cancellations, machine breakdowns and demand fluctuations. 3) *Known uncertainties* are those about which some information is available, for example, processing times and demand with known probability distributions.

No advance information is available about *complete unknown uncertainties* so developing a plan is hard in this condition. They are beyond the scope of the current work. Preventive scheduling generates scheduling policy before the uncertainty occurs. It is also often applied when the uncertainty can be quantified in some way (Li and Ierapetritou 2008). Therefore it can deal with *known uncertainties.* Planning approaches such as stochastic programming, robust optimization methods, fuzzy programming methods, and sensitivity analysis were identified in *known uncertainties* category (Li and Ierapetritou 2008). This kind of planning generates an off-line plan which is executed regardless of events occurring after its formation. A new schedule would not be constructed before the complete execution of the current plan (Wan 1995).

There is not enough information in advance for realization of *suspicious uncertainties about the future* parameters. Therefore, the reactive planning approach is followed in which a plan is generated or modified when decisions are made locally in real-time. In fact it generates an on-line plan that will allow a protective action. The on-line planning practice makes decisions using either a complete reactive planning or a predictive–reactive (repair) planning approach. Complete reactive planning regenerates a new plan from scratch and decisions are made locally in real-time whereas predictive–reactive planning is a process to repair or modify the preventive plan. In this case, the reactive planning is in fact complementary to the preventive planning to respond to *suspicious uncertainties about the future*. An interesting debate among researchers is to select between predictive–reactive, or complete reactive rescheduling. This issue is stated by Sabuncuoglu and Bayiz (2000), Sun and Xue (2001), Cowling and Johansson (2002), Vieira *et al.* (2003), Aytug *et al.* (2005) and Ouelhadj and Petrovic (2009). Sun and Xue (2001) recommended to revise only part of the original plan whereas Aytug *et al.* (2005) believed if there is little uncertainty in manufacturing environment, predictive–reactive methods are highly likely to provide better plans, than complete reactive approaches.

Another controversial issue is about when to use rescheduling strategy in the presence of *suspicious uncertainties about the future. Periodic policy*, *event-driven policy*, and *hybrid policy* are distinguished as rescheduling policies (Vieira *et al.* 2003, Aytug *et al.* 2005, Ouelhadj and Petrovic 2009). From the perspective of the authors, *periodic policy* defines a regular interval between rescheduling actions while rescheduling actions are not allowed during each interval. In *event-driven policy*, rescheduling action is triggered when events with higher potential of disruption to the system happen. A *hybrid policy* reschedules the system periodically as well as when an exception event takes place. In the following some of recent studies will be presented.

Duenas and Petrovic (2008) developed a predictive schedule with uncertain material shortage in parallel machines scheduling problem. Also, Gholami and Zandieh (2009) presented a hybrid scheduling for a flow shop with sequence dependent setup times and machines with random breakdowns. In recent years, Frantzen *et al.* (2011) used a predictive-reactive approach, where rescheduling was executed periodically. They also applied a complete reactive approach to support the work of the production planner by regenerating feasible schedules when required. The approach presented by Lou *et al.* (2012) applied a proactive–reactive scheduling for job shops to handle uncertainties in dynamic manufacturing environments. In the proactive scheduling stage, their objective was to generate a robust predictive schedule against *known uncertainties*. In the reactive scheduling stage, the objective was to modify the predictive schedule to adapt to *suspicious uncertainties about the future*.

As mentioned in the literature, one of the fundamental issues in the re-planning strategy is the approach selection. If there is little uncertainty in demand, a predictive–reactive approach is recommended otherwise a complete re-planning approach has a better performance. In our case, a complete re-planning approach is applied to take into account the high uncertainty in demand. The other issue is when the selected approach has to be used. Selection of re-planning policy depends on the previous plan, for example an event–driven policy often has a good performance when a predictive plan exists in advance. We focus on the periodic policy, because there is no predictive plan in this case and we decided not to build one. Moreover the periodic policy yields more plan stability (Ouelhadj and Petrovic 2009)

The purpose of this paper is to prescribe for the forest industry on how to improve the current practices, and on how to plan and re-plan efficiently the supply chain under uncertain demands using a periodic complete re-planning approach. Many researches have been applied a reactive scheduling using one of the approaches and policies defined in the literature at the operational level. In general, the majority of this works generates a new schedule or modifies the exiting schedule and compares that with the initial one by specific performance measures. We did not find any research explaining how a complete re-planning approach by periodic policy works at the operational planning level, especially for the wood manufacturing industry. This paper fills this gap by proposing a planning/re-planning strategy. This process involves the interplay between generating a plan by an optimization approach, and the impact of different values of re-planning period length and planning time window on this plan. A simulation model then is needed to evaluate the impact of different values of systemic parameters in the production planning. This study considers four optimization approaches, eight levels of re-planning frequency, and seven levels of planning time window in a real-scale industrial case. A simulation model is developed to compare the performance of different approaches in various re-planning configurations by calibrating that against the real-world data from a wood remanufacturing mill which is described in the next section.

3. Industrial case: a remanufacturing mill

Our industrial case is a wood remanufacturing mill in Eastern Canada. In this mill, the production planning system involves processes of lumber sorting, lumber drying, and remanufacturing. Lumber remanufacturing is a secondary business that generates value added products to be used in specialized applications. This mill uses the defective lumbers which are transported from different sawmills. They can be green or dried lumbers and have already been categorized based on the Canadian lumber grading rules and standards. These graded lumbers are classified again consistent with home-made grade rules in the mill. Green lumbers will be dried to reach appropriate moisture content. The remanufacturing process, thus, adds value to dried lumbers through new cuts, grades and packaging. These final products are transported to the domestic or international markets. Figure 1 illustrates the typical processes.

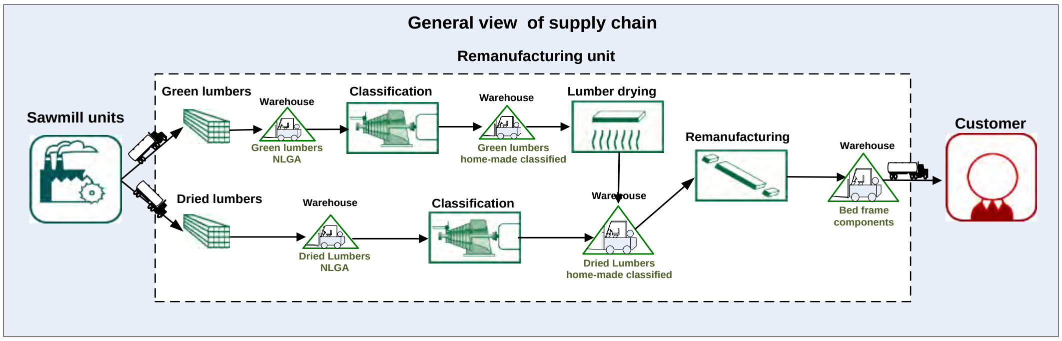


Figure 1 - Illustration of unit processes

Planning process has a complex nature in this mill because it consists in determining which batch of lumbers has to be used, in which remanufacturing line, according to which alternative processes, all the while taking into account demands, available quantities of raw materials, finished products, and resource availability. This production system is characterized as a co-production system. The production capacity is applied for producing a family of several different products simultaneously. Although in this mill there is a software tool that allows planners to observe the results of using different alternative processes, planner's intuition and experience play an important role to make a decision with this software. Due to that, professional planners take a lot of time daily to generate production plans which do not handle demand uncertainty properly as inventories and backorders rarely attaint their business expectations. This way is not practically efficient to make decisions in such a dynamic environment. The most important lesson from this case study is that a demand-driven planning process requires flexibility on the production planning to respond to unexpected demands.

4. Problem formulation

After presenting a mathematical model, we develop a re-planning algorithm to deal with uncertain demands.

4.1 The mathematical model

Consider a production unit with a set of $P^{consumed}$, $P^{produced}$, and R. A planning horizon consisting of T periods with the index t that refers to periods $t = 1,...,T$.

4.1.1 Notations

Sets

$P^{consumed}$	Products p that can be consumed
$P^{produced}$	Products p that can be produced
R	Set of recipes r (A recipe is called an alternative process)

Parameters

mc_r	Marginal contribution of recipe r that is the marginal profit of all products $p \in P^{produced}$ to be produced simultaneously using recipe r (Note that it includes the production costs)
i_{pt}	Inventory holding cost per unit of products $p \in P^{produced}$ in period t
bo_{pt}	Backorder cost per unit of product $p \in P^{produced}$ in period t
sc	Cost for changing a setup
c_{rt}	Production costs associated with using recipe r in period t (This parameter is used when the marginal contribution is not considered)
δ_r	Capacity required for each recipe r per unit time
sc_t	Setup time needed to changeover between recipes
c_t	Available capacity of machine for period t (number of time units)
ic_{p0}	The inventory of raw material $p \in P^{consumed}$ at the beginning of planning horizon
s_{pt}	Supply of raw material $p \in P^{consumed}$ provided at the beginning of period t
φ_{pr}	The units of raw material $p \in P^{consumed}$ consumed by recipe r
ip_{p0}	The inventory of product $p \in P^{produced}$ at the beginning of planning horizon
ρ_{pr}	The quantity of product $p \in P^{produced}$ produced by recipe r
d_{pt}	Demand of product $p \in P^{produced}$ to be delivered by the end of period t

Decision variables

X_{rt} Number of times each recipe r should be run in period t

Z_{rt} Binary setup variable, 1 if there is a machine changeover for recipe r at period t. 0 otherwise

IC_{pt} Inventory size of raw material $p \in P^{consumed}$ by the end of period t

IP_{pt} Inventory size of product $p \in P^{produced}$ by the end of period t

BO_{pt} Backorder size of product $p \in P^{produced}$ by the end of period t

4.1.2 The mixed integer programming (MIP) model

The objective function has an essential role in production planning optimization problems which may have a remarkable influence on the model efficiency. As previously mentioned, the goal is to reduce the amount of backorder. Hence many possible alternative objective functions are considered in the following four different approaches.

The first approach consists in minimizing the sum of backorder quantities. Hence, the objective function of Approach 1 is:

$$Minimize \sum_{t}^{T} \sum_{p \in P^{produced}} BO_{pt} \tag{1}$$

The second approach consists in maximizing the "marginal contribution", which is calculated as the prices of finished products minus their total variable costs of production and consumed raw materials. Marginal contribution can determine the profitability of individual products or a family of products. In addition, an essential part of obtaining an appropriate cost function is taking into account the products holding costs, backorder costs and setup costs. Therefore, the objective function of Approach 2 is:

$$Maximize\ \sum_{t}^{T}\sum_{r\in R} mc_r X_{rt} - \sum_{t}^{T}\sum_{p\in P^{produced}} (i_{pt} IP_{pt} + bo_{pt} BO_{pt})\ - \sum_{t}^{T}\sum_{r\in R} scZ_{rt} \tag{2}$$

In the previous case, we may drop the greater market demand products in order to produce alternative products with higher marginal contributions. Therefore we consider another typical optimization approach that consists in minimizing the costs. Considered costs include in backorder costs, inventory holding costs, setup costs and production costs (variable costs of production plus cost of raw material):

$$Minimize\ \sum_{t}^{T}\sum_{r\in R} c_{rt} X_{rt} + \sum_{t}^{T}\sum_{p\in P^{produced}} (i_{pt} IP_{pt} + bo_{pt} BO_{pt}) + \sum_{t}^{T}\sum_{r\in R} scZ_{rt} \tag{3}$$

Operational constraints

One way of dealing with backorder is to use extra production capacity. This capacity can be applied for producing products either to meet customer demands in current period or to be stocked for future periods. In backorder minimization (Approach 1), the model emphasizes on having the least backorder level over time without consideration of future demands. It is not mandatory for the model to use all available capacity in a period. Approach 2 inherently uses all the available capacity in a period to produce products with high value of marginal contribution. In fact the model produces and stocks products with high marginal contribution for the future periods. For the costs objective function, we consider two different situations as Approaches 3 and 4. The only difference between these two approaches is on how to use the extra production capacity. Approach 3 decides freely about production capacity in a period and it is not mandatory to use all production capacity. However, in Approach 4 all of the production capacity must be used in a period. Regarding the objective function of this approach, the model decides to produce the products with fewer costs for future periods in extra production capacity. In the following these capacity constraints will be shown.

Constraint requires that the total production time and setup time do not exceed the available time and production capacity. In other words, the sum of capacity consumption by corresponding recipe in each period and setup time needed to changeover between recipes should not be greater than the capacity of that machine in that period in constraint (4). Constraint (5) ensures the use of full machine capacity as well. Constraint (6) ensures that a recipe can be used more than one time in each period.

$$\sum_{\forall r\in R} \delta_r X_{rt} + \sum_{\forall r\in R} sc_t Z_{rt} \le c_t \qquad \forall t = 1,...,T \qquad (4)$$

$$\sum_{\forall r\in R} \delta_r X_{rt} + \sum_{\forall r\in R} sc_t Z_{rt} = c_t \qquad \forall t = 1,...,T \qquad (5)$$

$$X_{rt} \le (M \times Z_{rt}) \qquad \forall r \in R,\ t = 1,...,T \qquad (6)$$

where M a significantly large number

Flow equilibrium constraints

Constraints (7) and (8) ensure that the total inventory of raw materials at the end of the period t is equal to its inventory in the previous period plus the quantity of raw materials $p \in P^{consumed}$ supplied at the beginning of that period (s_{pt}) minus its total consumption in that period. It should be noted that the total consumption of each raw material in each period is calculated by multiplying the material consumption factor of each process (ϕ_{pr}) by the number of times that process is executed in that period.

$$IC_{P1} = ic_{p0} + s_{p1} - \sum_{\forall r\in R} \phi_{pr} X_{r1} \qquad \forall p \in p^{consumed},\ t = 1 \qquad (7)$$

$$IC_{pt} = IC_{pt-1} + s_{pt} - \sum_{\forall r\in R} \phi_{pr} X_{rt} \qquad \forall p \in p^{consumed},\ t = 2,...,T \qquad (8)$$

Constraints (9) and (10) ensure that the sum of inventory (or backorder) of product $p \in P^{produced}$ at the end of the period t is equal to its inventory (or backorder) in the previous period plus the total production of that product in that period, minus the product demand for that period. Total quantity of production for each product in each period is calculated by multiplying the production factor of each recipe (ρ_{pr}) by the number of times that recipe is executed in that period. Note that in this paper demand is considered as a hard constraint.

$$IP_{p1} - BO_{P1} = ip_{p0} + \sum_{\forall r \in R} \rho_{pr} X_{r1} - d_{p1} \qquad \forall p \in P^{produced}, \quad t = 1 \tag{9}$$

$$IP_{pt} - BO_{pt} = IP_{pt-1} - BO_{pt-1} + \sum_{\forall r \in R} \rho_{pr} X_{rt} - d_{pt} \qquad \forall p \in p^{produced}, \quad t = 2,...,T \tag{10}$$

Finally, constraints (11)-(13) enforce the non-negativity and binary restriction on the decision variables.

Non-negative and binary variables:

$$X_{rt} \geq 0, Z_{rt} \in \{0,1\} \qquad \forall r \in R, \ t = 1,...,T \tag{11}$$

$$IC_{pt} \geq 0 \qquad \forall p \in P^{consumed}, \ t = 1,...,T \tag{12}$$

$$IP_{pt} \geq 0, BO_{pt} \geq 0 \qquad \forall p \in P^{produced}, \ t = 1,...,T \tag{13}$$

4.1.3 Approaches of the MIP model

The proposed MIP model is a baseline to provide different approaches which will be used independently to evaluate the suggested re-planning strategy. Table 1 shows these approaches.

Table 1: Approaches of the MIP model

Approaches	Objective function	Constraints
Approach 1: Min Backorder quantity	Equation 1	Equations 4,6-13
Approach 2: Max Marginal contribution	Equation 2	Equations 4,6-13
Approach 3: Min Costs	Equation 3	Equations 4,6-13
Approach 4: Min Costs + Full capacity	Equation 3	Equations 5,6-13

Some assumptions make the foundation of this MIP model. The drying activities of the mill are not considered in the model. Note that machine reconfiguration (setup) for switching from one recipe to another recipe is constant. Also no limitation is considered on supply of raw materials.

4.2 The re-planning approach

To include the real-time nature of demand variations in the production planning, we applied the MIP model for a complete re-planning approach with periodic policy.

We define some expressions that are used in this paper. In the planning horizon the beginning period is considered as the *Initial period* and the ending period is considered as the *final period*. *Time Step* (TS) is the re-planning period length. *Time Window* (TW) is the planning time window. In a TW, the beginning period is the *first period* and its ending period is the *end period.* The time between the first and the end period in a TW is considered as an interval. The first and end period of the next interval are obtained by adding TS to the first and the end period of the current interval.

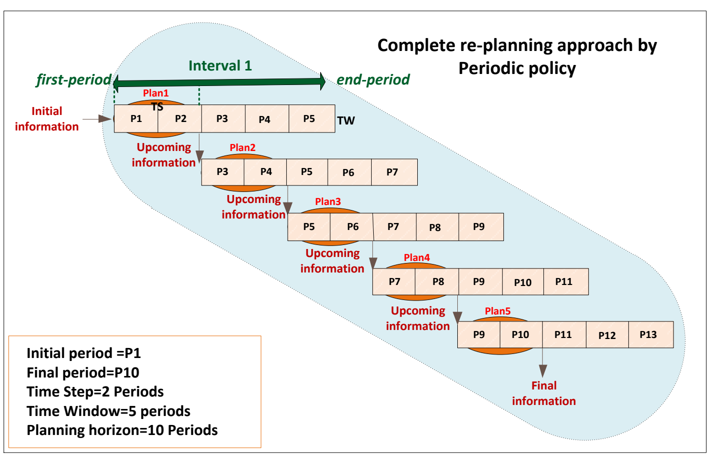


Figure 2: Illustration of complete re-planning approach by periodic policy

In Figure 2 an example is illustrated about how the complete re-planning approach by the periodic policy works. This figure shows representative problem instances during 10 periods. Here the initial period is the period 1^{st} and the final period is the period 10^{th}. TS of example is equal to 2 periods that results in revising the plan every two periods and for the total of 5 times. Here, TW is equal to 5 periods. The initial information, such as initial inventory of raw materials, and finished products, will be the input data of the first interval. Plan1 makes a decision in the first interval based on the relevant information for 5 periods. The output of plan1, such as inventory of raw materials, backorders, and finished products quantities at the end of period 2 will be the input of the second interval. This procedure continues until the final period.

From the perspective of the periodic complete re-planning strategy, re-planning is carried out as an algorithm in Figure 3. Before starting the algorithm TS and TW have to be defined. In lines (1) the primary setting for the initial and final periods are determined. The first and end periods are defined in lines (2:3). Lines (4:11) are a loop to solve the model in the current interval until the final period is reached. Line (5) sets the current interval. The model is executed for the current interval on line 6. In lines (7:8) the result of the current interval is transferred to the next interval as the initial data. Lines (9:10) add TS to the first and end periods to obtain the next interval. Line 4 is the stopping criterion. When all periods are covered, the algorithm is terminated with success, otherwise continues for new interval.

Periodic re-planning approach algorithm

1: define the *initial_period* and *final_period*
2: set *first_period* = *initial_period*
3: set *end_period* =*TW*+ *initial_period-1*
4: **While** *first_period* $\leq$ *final_period*
5: set *current_interval* = [*first_period*, *end_period*]
6: solve the MIP model for the *current-interval*
7: put the result of the model decision variable in the data base for the end of period (*first_period* + *TS-1)*
8: consider the value of decision variables in 6 as the initial value in the next interval
9: set *first_period* = *first_period* + *TS* *//the beginning period of the next interval*
10: set *end_period*= *end_period* + *TS* *//the ending period of the next interval*
11: **end while**

Figure 3: Algorithm of periodic re-planning strategy

5. Simulation experiments

Data from our industrial partner were used to evaluate the proposed approaches according to different values of TS and TW. The model was implemented in ILOG OPL STUDIO version 6.3 and is solved by CPLEX 12.1.

The case involves a total of 107 products. Orders were the real data for a 27-day planning horizon while this unit worked 5 business days every week. Each day included 3 shifts. One shift was considered as a period. Therefore for total of 18 business days in 3 shifts resulted in 54 periods. The number of orders was 565 orders. In this mill the demand were often responded to within two business days after the order arrival, so the lead time in this case is between 1 to 8 periods. For this reason we considered only value of TS up to 8. These were 1, 2, 3, 4, 5, 6, 7 and 8. Here, 1 corresponds to revise the plan every period for the total of 54 times. Another level, for instance, level 6 results in the plan to be revised 9 times. We also considered 7 levels of TW in our experiments. These were 2, 3, 6, 9, 12, 15 and 27. For understanding the impact of re-planning configuration, 8 levels of re-planning period length and 7 levels of planning time window for four approaches were considered. This yielded 43 different combinations for an approach that included the total of 172 simulation runs for four approaches in each replication. To determine the number of replications, we applied two alternative methods presented by

Itami *et al.* (2005) to obtain 90% confidence intervals. The results showed that more than 35 replications were needed. Thus, for each approach, 40 replications were performed to get average estimations on performance measures with 90% confidence intervals.

5.1 Data analysis

The results are presented in Figures 4-7 and Tables 2-5. In Figures 4, 5, 6, and 7, backorder levels in simulation experiments are shown for different approaches. The minimum level of backorder belongs to Approach 1 that is shown in Figure 4 because the only purpose of this approach is to decrease backorder quantity without considering the costs values. In an interval the model avoids to postpone orders to the future intervals as long as production capacity allows. After Approach 1, Approach 4 has the minimum level of backorder in most of the cases (see Figure 7). In this approach, although the model uses all the production capacity to satisfy current demands and to predict future demands, the backorder level is almost three times that of Approach 1 in small TSs. The reason of this difference is that this approach focuses on the costs reduction, therefore in addition to decreasing the backorder level the costs values also have to be controlled by the model. Figure 5 shows that Approach 2 competes with Approach 4 in the amount of backorders, and it has even better results in a few experiments. Approach 2 has acceptable results and has a significant difference with highest level of backorder in Approach 3. In the second approach the model applies all the available production capacity to meet demands. Demands should be prepared by alternative processes that have the maximum value of production among others whereas one alternative process needs a specific production time to produce a group of products. In this approach, variation in the required time and profit margins of the alternative processes will result in the higher level of backorder compare to other mentioned approaches. Approach 3 has much higher level of backorder that is shown in Figure 6. This figure shows the backorder quantity of different experiments in this approach up to 2000 MBF, but there are a lot more experiments with the values more than 2000 that have not been shown in this figure. The behaviour of the backorder level in Approach 3 is more informative. This approach is very sensitive to costs values so when the production costs are more than backorder penalty costs, the model accepts the high levels of backorder for reducing the costs. In small TWs, the production cost is higher than the backorder penalty cost because of small planning time windows, therefore the model prefers to have backorder. As a result, backorder level is increased and this large difference is caused. When TWs are increased (e.g. in TW=9), if the orders are not responded, the number of backorders are accumulated in any given period. So the significant value of the backorder penalty cost forces the model to produce, in order to decrease these backorder levels. It is concluded that the backorder penalty has intuitively a specific effect on the model performance.

Now considering these figures an important question is: which one is more important in decreasing the backorder quantity; TS or TW. The results demonstrate that the impact of TS is significantly more effective than TW. Consequently these results confirm that an appropriate re-planning period length seriously affects the system performance.

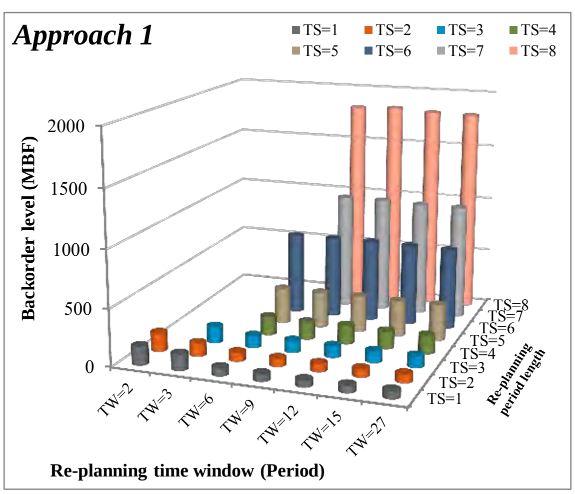


Figure 4: Backorder levels in approach 1

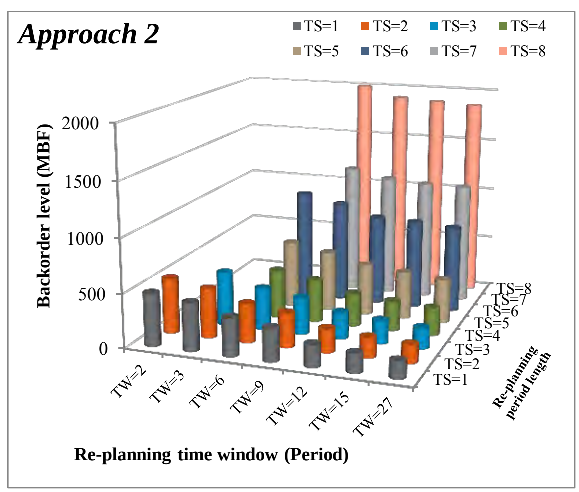


Figure 5: Backorder levels in approach 2

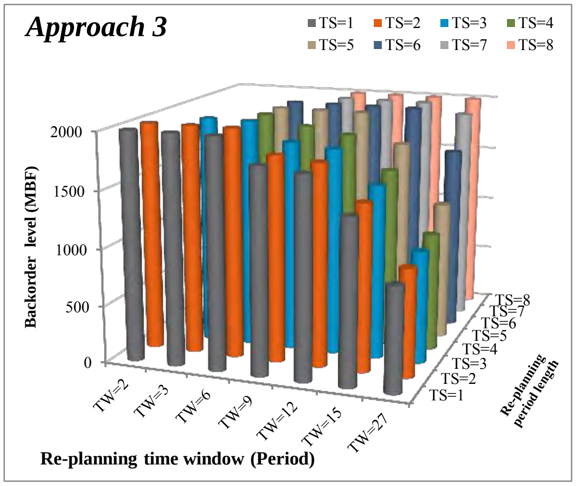


Figure 6: Backorder levels in approach 3

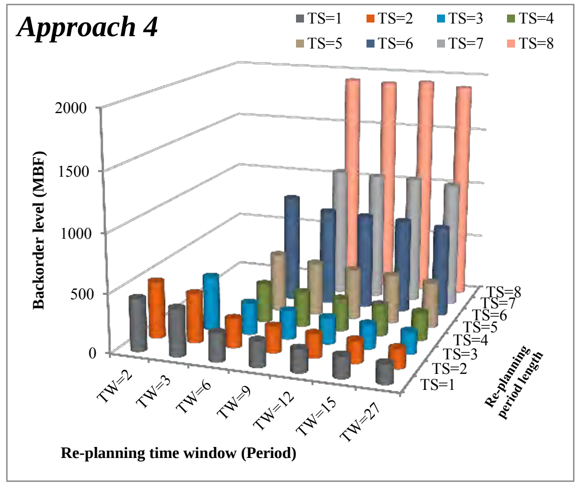


Figure 7: Backorder levels in approach 4

Moreover, the maximum delay that was considered here is 8 periods, so there is no demand for TWs larger than 8, but the results demonstrate increasing the value of backorder in this case. This is due to hidden backorders. In high TWs, when order period is larger than the first period of an interval, and also its due-date period is less than the first one plus TS, the order is hidden. We considered these orders as backorders for the next interval. Therefore despite not existence of demand for TWs larger than 8, the model responds to hidden backorders and decreases backorder levels.

In Table 2, 3, 4, and 5 the costs values of the approaches are shown. These costs include production costs, inventory holding costs and setup costs. The lowest level of costs belongs to Approach 3 in Table 4. Regarding to high level of backorders in this approach the backorder penalty has the maximum value and consequently the production costs have smaller values. Hence, the considered costs have significantly smaller value in these experiments. Following Approach 3, Approach 4 has minimum results in terms of costs value as it is shown in Table 5. In Table 2 Approach 1 despite having the lowest level of the backorder has a dramatic difference in the costs value, in comparison with the approaches that have been proposed so far, because the model in this approach emphasizes only on reducing the amount of the backorders, and does not take into the account the costs value. Approach 2 has the maximum value of costs. Its model insists on increasing the estimated value of production, so production rate of this approach is more than others. As a consequence the stock level and costs components have the maximum level in this approach (see Table 3).

Table 2: Costs values ($ CAD/MBF) in Approach 1

Costs	TS=1	TS=2	TS=3	TS=4	TS=5	TS=6	TS=7	TS=8
TW=2	535,477	566,113						
TW=3	523,592	610,896	634,402					
TW=6	619,680	643,560	650,307	645,156	652,328	650,463		
TW=9	629,917	646,882	650,567	645,174	655,275	650,704	656,364	655,526
TW=12	632,118	651,436	655,212	649,392	660,043	654,537	659,035	658,947
TW=15	629,216	646,411	651,641	647,663	654,506	653,186	654,506	656,214
TW=27	626,899	646,440	651,001	645,868	651,412	650,965	653,729	654,165

Table 3: Costs values ($ CAD/MBF) in Approach 2

Costs	TS=1	TS=2	TS=3	TS=4	TS=5	TS=6	TS=7	TS=8
TW=2	662,885	663,019						
TW=3	662,026	662,227	662,872					
TW=6	655,884	656,257	657,773	658,864	660,195	661,248		
TW=9	649,994	651,395	651,530	652,611	653,233	654,787	654,181	657,583
TW=12	642,222	643,411	644,375	644,738	645,594	645,735	647,436	647,241
TW=15	640,836	641,961	642,691	643,346	644,467	645,357	646,357	645,827
TW=27	640,907	641,410	642,092	642,777	643,411	645,902	645,902	644,418

Table 4: Costs values ($ CAD/MBF) in Approach 3

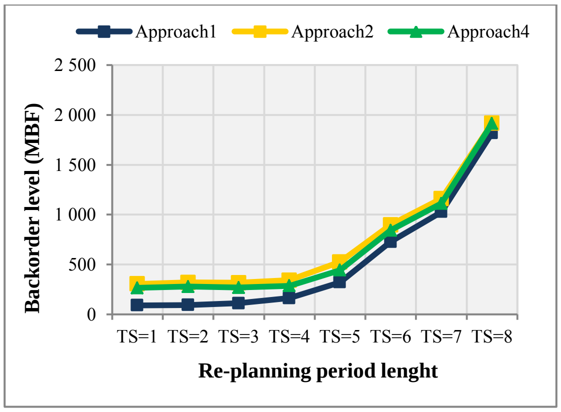
Costs	TS=1	TS=2	TS=3	TS=4	TS=5	TS=6	TS=7	TS=8
TW=2	28,057	28,057						
TW=3	77,339	77,055	75,441					
TW=6	198,921	198,904	198,888	198,870	198,574	198,428		
TW=9	219,894	219,870	219,844	219,181	219,829	215,094	215,142	208,963
TW=12	222,268	221,380	220,200	219,978	219,985	219,936	219,980	215,660
TW=15	240,652	239,721	238,094	237,963	236,776	233,737	232,072	225,247
TW=27	271,005	268,420	267,330	267,343	265,763	264,821	264,820	260,565

Table 5: Costs values ($ CAD/MBF) in Approach 4

Costs	TS=1	TS=2	TS=3	TS=4	TS=5	TS=6	TS=7	TS=8
TW=2	566,844	566,847						
TW=3	566,886	566,849	566,849					
TW=6	570,134	570,096	570,061	569,919	5669,632	568,736		
TW=9	570,252	570,223	570,195	570,195	570,195	570,242	570,260	569,148
TW=12	570,489	570,318	570,294	570,183	570,191	570,197	570,204	569,052
TW=15	570,854	570,854	570,984	570,406	570,392	570,320	570,208	569,105
TW=27	572,302	572,329	572,329	572,336	570,336	572,668	572,377	571,357

5.2 Discussion

The simulation results confirm that the TS parameter has a greater impact than TW to reduce backorder quantity. Hence, we calculated average values of backorder and costs for all TWs in each TS. Approach 3 is even more significantly different from others in terms of backorder level and costs, so we remove this approach. Figurers 8 and 9 show the others compete with each other. In Figure 8, the average value of backorder is shown for three remained approaches. The best results of backorder clearly belong to Approach 1. In Figure 9, also the average value of costs is shown. The lowest level of costs belongs to Approach 4. Approach 2 has the highest level of costs with less difference with Approach 1.



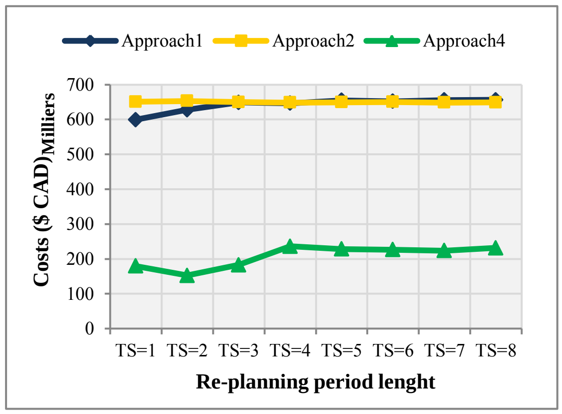


Figure 8: Backorder levels in three approaches   Figure 9: Costs values in three approaches

Approach 3 with considered backorder penalty cost does not satisfy the customers' demands as much, because it prefers to increase the backorder levels for minimizing the costs rather than producing products with high production costs. Here an important question is how much penalty should be considered so that the model tends to meet demands. We carried out new tests in which backorder penalty cost in equation (3) is increased by multipliers 5, 10, 20, 50 and 100. Also these tests do not necessarily use all available production capacity using constraint (5). The simulation results of these tests are compared with results of Approach 3 (which has backorder cost with Multiplier 1) for a specific re-planning configuration (TS=3 with TW=9). In Figure 10, the variations of backorder quantity and cost values in these new tests are shown and compared with Approach 3. Whatever the backorder quantity decreases conversely the costs value increases. The least value of the backorder belongs to Multiplier 100. Note that this value is less than 200 and it is even better than the value of Approach 4 in terms of backorder. The most value of the cost among the approaches belongs to Multiplier 100 as well. Note that this value is less than 500,000 and it has even better result than Approach 4 in terms of costs.

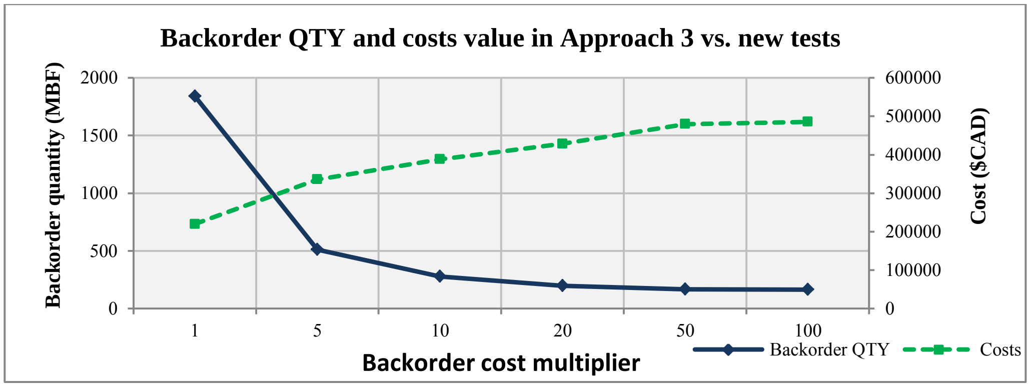


Figure 10: Comparison of backorder levels in new tests vs. Approach 3

The simulation results of these new tests and Approach 3 are also compared with results of Approach 1 as a benchmark because it has the minimum value of backorder. In Figure 11, the variations of backorder quantity and cost values are shown to compare these new tests with Approach 1.

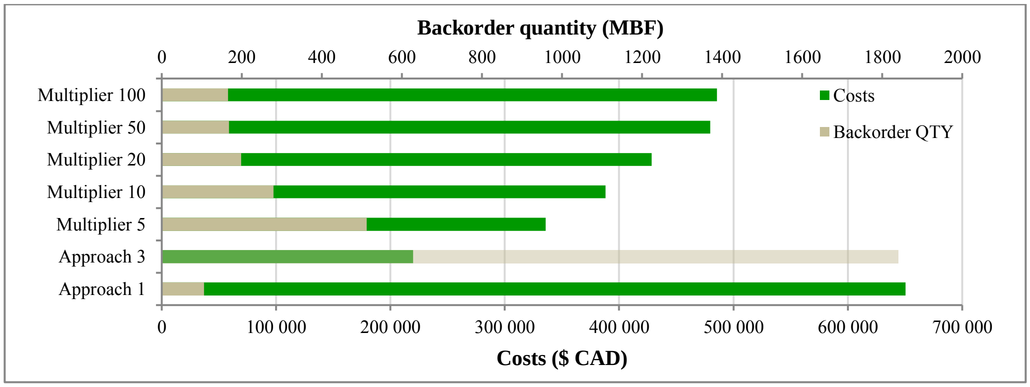


Figure 11: Comparison of backorder levels in new tests vs. Approaches 1 and 3– for all costs components

Although Approach 1 has the lowest level of backorder and it is even better than Multipliers 100 and 50, its cost is more than the others. As a consequence, if the model is not forced to use all the available time, it has to have a high level of backorder penalty in this case, otherwise it tends to have backorder.

Now an interesting question regarding Figure 11 is why the backorder level in Multiplier 100 is more than that of Approach 1 while its backorder penalty costs raises as much as possible. This is because the objective function of this test is a combination of cost components. Although the backorder penalty costs has a significant value in this approach, it cannot disregard the impact of other costs (inventory holding, setup and production costs) and it is expected that it acts like Approach 1 in terms of backorder quantity. In Figure 12, it is supposed that the inventory holding costs have been considered zero. The backorder quantities in this figure have smaller value than those of Figure 11 however the costs in this figure have larger value than those in Figure 11. Because when the model does not pay penalty for keeping inventory, it tends to produce more for future periods and consequently the backorder level is decreased and production costs are increased.

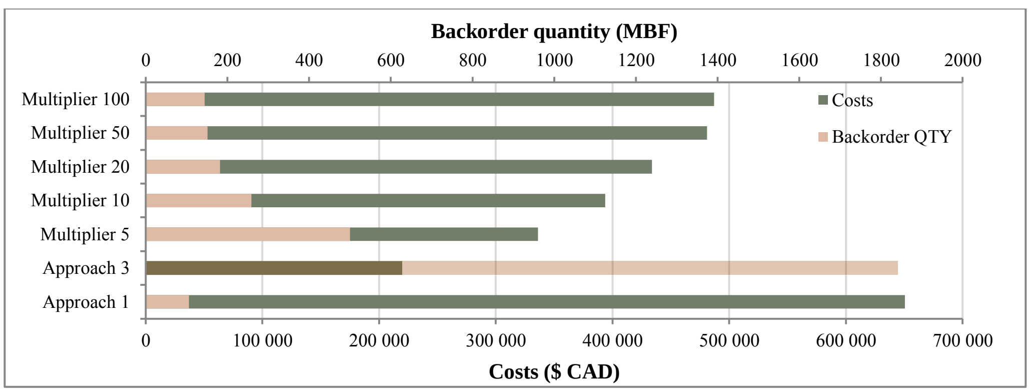


Figure 12: Comparison of backorder levels in new tests vs. Approaches 1 and 3– without considering inventory holding costs

Note that in Multiplier 100 if the model emphasizes only on the backorder penalty costs and disregards the negligible setup costs and significant production costs, it will act quite similar to Approach 1 in terms of backorder level.

6. Conclusion and future directions

This paper described the production planning problems and models for a real-scale wood remanufacturing unit in the North American forest industry. This unit, like many other production units, faced with demand fluctuations and absence of an effective plan for handling these fluctuations.

We applied an approach for revising a plan at regular intervals in order to respond to demand fluctuations. The simulation experiments demonstrated the advantage, in term of responding to uncertainties by the complete re-planning strategy through the periodic policy. First, the effectiveness of different approaches was examined in the reactive planning strategy. We observed that the performance of suggested strategy was sensitive to model objective functions. According to performance of backorder level and costs value and also predictions for the future, among different proposed planning approaches, Approach 4 had good results. On the other side, Approach 1 with minimum level of backorder had the best results in terms of backorder level, although it had high level of costs. Second, we noted that re-planning frequency had significant impact on the performance of planning methods. The configurations with the low re-planning period length upon high planning time window performed better than the other ones. This observation also was held in all approaches.

The approach proposed in the present paper can be extended in many ways. We intend that some of the assumptions will be consistent with reality, for instance variable setup time. These new constraints will certainly increase the backorder level. Then an inventory policy will be developed to improve the efficiency of the reactive planning strategy in a co-production system.

Acknowledgement

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