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# IMPLEMENTING A MIP MODEL TO PLAN AND SCHEDULE WOOD FINISHING OPERATIONS IN A SAWMILL: LESSONS LEARNED

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**ABSTRACT:** *This paper present the path we took adapting and implementing a MIP model for operational planning of the wood finishing operations in a sawmill. Following a company request to develop a planning tool for their finishing operations, we adapted a model developed by Gaudreault et al (2010). Preliminary testing and results showed great potential. Using the Gusek open source solver for the problem, we had to further adapt the methodology to get solutions satisfying both solution time and operational constraints. The MIP model was integrated into the ERP system of the company, allowing the production of an initial solution that minimizes order lateness.*

**KEYWORDS:** *Production planning, scheduling, MIP, optimization, sawmill, implementation.*

## 1 INTRODUCTION

Wood finishing is the third stage of the lumber transformation process. Historically, operational planning of these operations involved maximizing the throughput and lumber value produced. This is still how numerous mills produce for commodity lumber products. But for the company involved in this project, many of their lumber products meet specific customer requirement.

Due to the nature of the material used in the finishing process, there is no certainty about what will be produced. This adds complexity to the planning of that production stage as, it seems difficult for the planning personnel to plan while taking into consideration commitments to customers. However, machine settings do play a role in what is produced. Companies do have standard recipe, but most of the time, it's a variation of these recipes that gets used on the production floor in trying to match customer demand. Using historical production data in the planning of the finishing operations allows the system to learn new ways of making different lumber grades.

Moreover, to sell the right products and promise sensible delivery dates, the sales department needs to know two to three weeks in advance which product will be available according to current planning. At some point in time, it is desired that a sales representative be able to enter a tentative customer order and get feedback as to when the production should be able to make it available. In order to have such an order promising system, the company first needs to put in place automated planning of production.

The company we work with is currently in the process of implementing a user-interface that helps in the manual planning of the wood finishing operations. Having a first plan generated automatically will allow the planner to concentrate on special issues rather than plan to push the wood out as soon as possible without too much consideration for order lateness.

In this paper, we first recall what the lumber finishing operation planning problem is. Section 3 shows the MIP model used to solve it. It is followed by the description of the cases and the difficulties and methodology we used to solve these cases.

## 2 PROBLEM DESCRIPTION

Wood finishing operations planning has been described in detail by Gaudreault *et al* (2010). As shown in Figure 1, lumber production involves three main steps. First, logs of different dimensions and species are sawed. This is a divergent process as any given log will yield a set of different lumber products varying in length, dimensions and quality.

The second step is a drying operation, which is done to reduce the moisture content of the lumber and which will give the lumber more stability over time. Lumber drying is done by batches in large kilns. The lumber is stacked in bundles, and bundles requiring the same drying time and temperature are allowed to enter a given kiln together for the same duration. Kiln drying time typically varies between 16 and 150 hours. As kiln drying is a batch operation with long processing time, inventory of green lumber occurs before the kiln operation and inventory of dry lumber accumulates after the kiln operation.

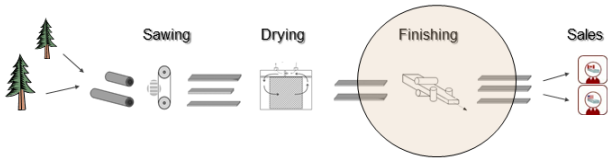


Figure 1 : Lumber transformation process

Once the lumber is dried, it can go through a planer machine for the finishing operation that gives it the desired thickness and surface finish. The width and length can also be adjusted at this stage and final grading decisions are made. The cycle time of this operation may be determined by the speed of the planer, which also has an impact on the quality of the planed lumber.

Wood finishing can be performed on green as well as dry lumber, but the latter is more common. The operation generally takes place at the sawmill site, but it may have to be performed elsewhere if mill planer capacity is insufficient.

As illustrated in Figure 2, this operation produces several final products at the same time. Each rough piece of lumber is optimized based on its defects. It may be trimmed into two pieces, or crosscut if trimming can remove a defect to increase its market value. In North America, where lumber is a commodity product (dimensions and quality are standardized) this process is fully automated. Decisions regarding trimming are based on expected value of the lumber, not on actual demand.

Because a large quantity of lumber is produced every day, it is possible to model the output of the process as a percentage expressing expected output distribution in terms of lumber final characteristics.

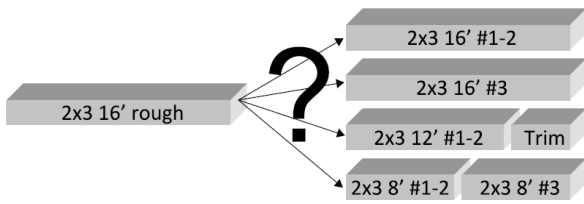


Figure 2 : Example of possible outputs from a rough piece of lumber

The output distribution thus depends on the lumber product input and the products' priority settings for that lumber input. Each different combination of {lumber input, priority setting} can be referred to as a recipe and each recipe has a distribution of lumbers with final characteristics. This process, generating a multitude of different outputs, cannot be avoided from a planning point of view: it is embedded within the transformation process. It is common to obtain more than 20 different types of product from a single type of product.

There is a setup cost each time the facility processes a different dimension (e.g. from 2"x3" to 2"x6"). Consequently, most sawmills allow such a

setup only between production shifts as they prefer a production mode (a batch of products of the same dimension but variable length / different recipe) with a duration of at least one shift. This is the case of the mill involved in our project.

To sum up, the decisions that must be taken in order to plan the finishing operations are the following: (1) which campaign to realize (i.e. which lumber dimensions), (2) when and for how long and (3) for each campaign, what quantities and what recipes to process. Figure 5 shows a simple example of a production plan, including the campaigns (2"x3", 2"x6" and 2"x4") and the time spent on each length (different recipes).

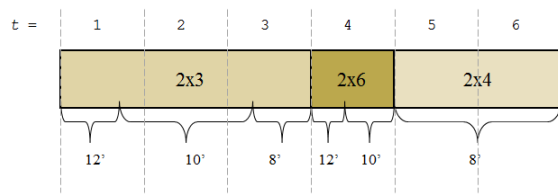


Figure 3 : Production plan for a finishing line for six consecutive production shifts

Also to be considered by the planning algorithm, the finishing production line may sometimes be down for maintenance or busy with special operations not to be considered by the current planning.

Because wood finishing is the third and last stage in the transformation process, it consumes products from the previous stage. It is thus a requirement to have the plans of the kilns, or at least the scheduled end of drying operations, so that we know the earliest time the different input products will be available to be processed by the planer.

### 3 MIP MODEL

Gaudreault *et al* (2010) have developed a MIP model for this problem, as part of a broader operations planning system. Their objective function has four main components: back order cost, inventory holding cost, setup cost and processing cost.

In their model, they introduce a binary variable  $Y_{f,t}$  to identify if the mill has been planned to be using mode  $f$  at period  $t$ . At any given period, only one production mode can be selected. Three other binary variables were introduced to implement campaigns and setup costs in the model. Two of them are of dimension  $T$  and specify if a campaign starts or ends at a period  $t$ . The last one is of dimension  $F \times T$  and states whether or not a campaign using mode  $f$  begins at period  $t$ .

Their MIP has proven to be too slow to obtain good feasible solutions in reasonable time for real industrial problems without using a heuristic or massively parallel computing (Moisan *et al*, 2013). But in our specific industrial application, we can include some

simplifications which we describe in this section. We have also added some constraints related to the minimum processing time and changed the objective function.

The main simplification we carried out relates to the fact that for the company that we studied, there is no setup cost to consider as all production changes are made between production shifts or during break periods. Another simplification is that, in our context, campaigns almost always have a duration equal to one period. This simplifies the problem as there is no need to follow up on campaign starts and ends, and as such, the only binary variable required in our model is  $Y_{f,t}$ .

In Section 2, we have presented the concept of recipe which links a product input with a production mode and a machine configuration to products output. For the studied company, when a recipe is scheduled to be used, it must be so for at least  $\lambda$  units of time (15 minutes in our case). This constraint was modeled in the MIP by adding a binary variable  $W_{r,t}$  which takes a value of 1 if the recipe  $r$  is scheduled at period  $t$ , 0 otherwise. With  $UC_{r,t}$  being the volume of product input in recipe  $r$  to process at period  $t$ , we have to add the following two constraints:

$$UC_{r,t} \leq (\infty W_{r,t}) \quad \forall r \in \mathbf{R}, t=1..T \quad (1)$$

Where  $\infty$  is a significantly large number

$$\delta_{r,t} UC_{r,t} \geq \lambda W_{r,t} \quad \forall r \in \mathbf{R}, t=1..T \quad (2)$$

Equation (1) states that recipe  $r$  has to be scheduled at  $t$  if there is a volume of product input to recipe  $r$  at the same period. With  $\delta_{r,t}$  being the time needed to consume one unit in recipe  $r$ , equation (2) ensures the minimum process time  $\lambda$  when a recipe is used.

The new objective function has three main components. The most important one is the back order value which must be minimized. The back order value is computed as the lateness multiplied by the product value. The second criteria after minimizing the back order value is the maximization of the value produced. This is computed using the selling price of the lumber produced times the volume produced. Finally, the company wanted to maximize the planer capacity used.

This new objective function creates several flaws which we will discuss in Section 5.

#### 4 THE CASE STUDY

When the company first approached us with the project in the summer of 2011, they were having many late orders and wanted to see if the use of optimization to plan the finishing operations of lumber production could help them reduce their order lateness. At that time they were planning manually using MS Excel spreadsheets.

The company specializes in producing custom and specialty lumber products. It has more than 250 finished lumber products and 80 wood finishing recipes to play with. They have implemented many modules of a manufacturing system, making easily available most of the information required to plan finishing operations. We started our study with data from three different weeks, each time planning for three weeks ahead and comparing with actual manual planning done by the company. The results are presented in Figure 4 below.

Dataset 1	266 orders
	<b>Tool</b>
Late orders	↓ 32%
Volume late	↓ 22%
Value being late	↓ 20%
<hr/>	
Dataset 2	205 orders
	<b>Tool</b>
Late orders	↓ 28%
Volume late	↓ 13%
Value being late	↓ 11%
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Dataset 3	158 orders
	<b>Tool</b>
Late orders	↓ 19%
Volume late	↓ 18%
Value being late	↓ 16%

Figure 4 : Preliminary results in 2011

The number of orders ranged from 158 to 266 (251 and 305 order lines). We used three performance indicators to compare the results of their manual planning with the results of the optimization model, each being measured at the end of the first planning week. With the use of the model, the number of *late orders* decreased between 19% and 32%. The company was motivated by the results and asked to start a transfer project of the technology so that their company could start planning wood finishing activities on a weekly basis using the optimization model.

As depicted in Figure 5, manual planning is done based on a set of recipes (and inventories, supply to come, current orders, special requests from sales – all of which are not represented on the figure). That set exists formally, but the scheduler also has some tacit knowledge of what will be generated from executing each recipe and he uses that knowledge to create a schedule which will be executed.

Automating the making of the schedule required much more than just running the mathematical model. As such, good results depend greatly on the set of recipes that is used by the MIP model. There are many challenges in the process of getting the right recipes for the planning by the model.

The first challenge comes from the fact that no two runs of the same recipe yield the exact same result. We thus have to use and average the last few executions of the recipe to infer what the output generated might be. It could be based on a number of past executions or the executions done during a fixed period of time (e.g.: past six months).

The second challenge comes from the fact that company standard recipes are seldom used. It is rather the variations on these recipes that get executed. For example, based on one of their standard recipes, they might avoid the production of some output products and change the priority of others. This in fact would represent a new recipe as the execution parameters have changed.

In the obtained list of recipes, many of the co-products are not products that we plan for, as they are low-value lumber with no customer orders. Their output percentage is also highly variable and they are pushed to the market once their production is completed.

The process of extracting recipes thus requires a lot of data cleaning to ensure only the relevant data is extracted. And because the finishing process yields may evolve over time (due to different factors such as raw material quality change over the year) and because new recipes may be created with the creation of new products, the processes need to be extracted every time the MIP model is to be executed. In that sense, the MIP solutions evolve in time with the company as it acquires a longer history of finishing process execution.

To remove or reduce the variability that we see from one execution to the next, we have chosen to include within the recipe only the higher grade output products or products for which there are customer orders. And for the volume of products output, we take a moving average over the last X executions of the recipe, where X is a parameter to be set at implementation time.

The right-hand side of Figure 5 presents the feedback loop from *execution to recipes*, showing a learning effect from the real executions. It also shows that the schedule generated through the MIP model is always reviewed by someone.

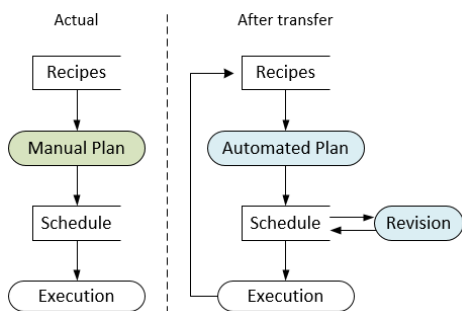


Figure 5 : Planning process - before and after the transfer project

The transfer project involved automating the data extraction from the ERP system of the company, calling our MIP model and reading back the results to the ERP system. For this transfer project, we used GUSEK, an open source LP/MIP IDE for Win32 constructed over the GLPK solver. It is in the summer of 2013 that the

integration of our MIP model (to be used with GUSEK) into the ERP of the enterprise was completed.

Throughout that summer, we gathered seven real cases to be solved, each covering a three-week planning horizon. In those cases, there is an average of 155 different products ordered, 325 order lines and 119 recipes, each having an average of 12 output products.

## 5 METHODOLOGY AND RESULTS

For operational planning, the company expects to obtain solutions from the model within a five-minute time frame. It quickly became apparent that solving to optimality was not an option. We opted for a 5% gap tolerance which seemed reasonable for the type of solution we were looking for. Figure 6 shows that capacity utilization of the planer in the solutions given by our original model varies from 83% to 97%. This result was unacceptable for the company which requires the planer to be used at 100% of its capacity. With our objective function, we were expecting higher values of capacity utilization as it seems logical that to maximize the lumber value produced (which was the second criteria of importance in our objective function) the available capacity would have to be fully utilized. Moreover, the third optimization criterion was the maximization of the capacity utilization. One key explanation is that allowing a 5% gap automatically blinds the portion that maximizes the value produced and the capacity utilization in the objective function: their importance is far less than the one of minimizing the back order value.

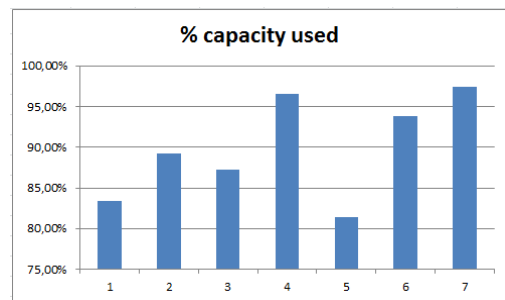


Figure 6 : Percent capacity used in each case

We thus reviewed the objective function. Looking at the “value produced” term of the objective function, we concluded that this measure was not to be present in the objective as the potential value of a piece of dry rough lumber is always waiting to be exploited. If a given piece of rough lumber is not finished in the current planning horizon, chances are it will be finished in the following one and its potential value will then be realized. Over a longer time period, all of the available rough lumber will be finished and as such it is not a real criterion to have its value realized as quickly as possible.

Looking at the last objective function term (capacity usage maximization) we decided to replace it by a constraint that would ensure at least a minimum percentage

of machine usage. Figure 7 shows the computation time according to the minimum capacity use required (from 86% to 100%) (the company asked for 100%).

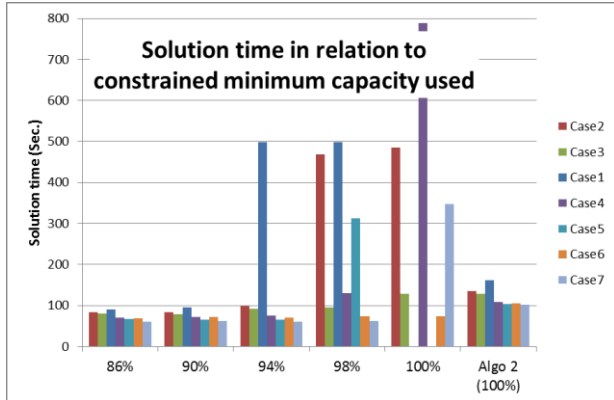


Figure 7 : Solution time with constraint on minimum capacity usage

When it is mandatory to use 90% or less of available capacity, the computation time stays under 100 seconds. But when we require a higher capacity usage, we see more and more cases take over 300 seconds to be solved. At the level of 100% capacity usage, two out of the seven cases were not solved after 12 hours of computer time, only two instances were below 300 seconds and one took up to 788 seconds.

With the planer capacity utilization being an important factor for any solution to be adopted by the company, we had to review the model formulation of Gaudreault *et al* (2010) so as to ensure 100% planer capacity utilization with a solution time below 300 seconds. Instead of using a variable determining how many times each recipe has to be executed in any given period (and then another variable to compute the percentage of capacity used), we use a variable indicating the fraction  $0 \leq G_{r,t} \leq 1$  of the period  $t$  planer available time allocated to each recipe  $r$  done. Ensuring 100% planer capacity utilization is easily modeled in constraint (3) below:

$$\sum_{r \in \mathbf{R}} G_{r,t} = 1 \quad t = 1..T \quad (3)$$

With that new notation and introducing the parameter  $c_t$ , the planer available time for production at period  $t$ , the constraint guaranteeing the minimum process time  $\lambda$  when a recipe is used becomes:

$$c_t G_{r,t} \geq \lambda W_{r,t} \quad \forall r \in \mathbf{R}, t=1..T \quad (4)$$

Constraint (5) ensures process  $r$  is set to be used if the fraction of available time used by that same process is greater than zero.

$$G_{r,t} \leq W_{r,t} \quad \forall r \in \mathbf{R}, t=1..T \quad (5)$$

With that new formulation, all of the seven instances were solved in less than three minutes. This is shown with the bars on the right in Figure 7 (algo 2; 100%).

The results shown so far are for a one-week planning horizon (14 periods). However, we were told that for the sales department to be able to plan in advance, a three-week planning horizon is desired which represents, at two periods per day, a 42 period horizon.

Figure 8 shows the impact of the planning horizon size on solution time. To see if we were able to solve instances of that size, we ran the seven cases with the new formulation (algo 2) for 14 (one-week), 28 (two-week) and 42 (three-week) periods planning horizon.

As seen previously, the one-week scenarios are solved within less than three minutes. For the two-week scenarios, three instances took more than 300 seconds to solve, the first case not being solved after 12 hours of running time. For the three-week scenarios, four instances took more than 2000 seconds and again, the first case was not solved after 12 hours of running time, case seven taking a bit more than 6 hours and case two 1,5 hours.

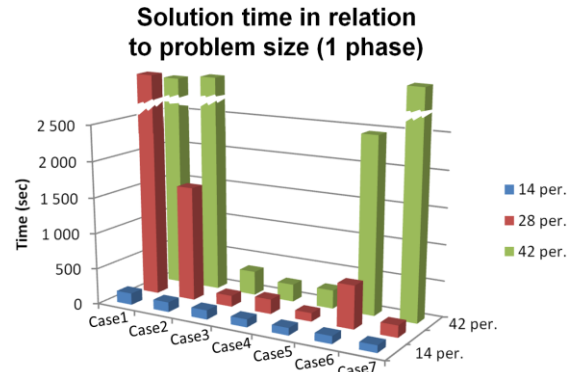


Figure 8 : Solution time in relation to problem size

Of course, we were expecting the solution time to increase according to the number of periods. For each period added to the planning horizon, we must add  $|\mathbf{R}| + |\mathbf{F}|$  integer variables where  $|\mathbf{R}|$  is the number of recipes and  $|\mathbf{F}|$  is the number of production modes.

With these results (unacceptable from our industrial partner's point of view), we decided to implement a multi-phase algorithm that would reduce the number of integer variables to be considered at once for longer planning horizon. In each phase, we select a consecutive subset of the periods to be planned. Let  $\alpha$  be the number of such selected periods. We call  $\alpha$  the phase size. At each phase, only  $\alpha$  periods are planned using integer variables and remaining periods are a relaxation of the problem, using only non-integers variables. So in each phase, only  $\alpha$  periods are fully constrained with the integer variables. These variables allow enforcing the minimum time spent running a recipe ( $\lambda$ ) and only one production mode  $f$  to be used at period  $t$ . With the

proposed algorithm, the number of integer variables to be determined at each phase is never greater than  $\alpha (|\mathbf{R}| + |\mathbf{F}|)$ .

In the multi-phase algorithm, the problem is still solved using the MIP model at each phase, but only a portion of the full horizon is fully constrained. Using this algorithm, the planning horizon is divided into three sections. Figure 9 presents these sections after one phase of the algorithm using  $\alpha = 14$  periods.

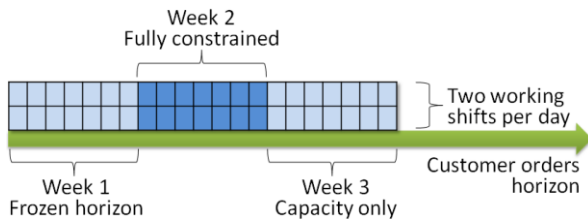


Figure 9 : Horizon split in multi-phase algorithm

Except for the section that is fully constrained, the other sections vary in number of periods as the algorithm progresses. The first section is the frozen horizon. Within that horizon in the model, the integer variables are replaced with constant parameters taking the value of the integer variables from the previous phase. When we start the algorithm, the frozen horizon is of size 0. In the second section (darker blue in the figure), all integer constraints are satisfied. In the third section, integer constraints are removed so that any recipe can run for any length of time and regardless of the production mode, provided that mill capacity is not exceeded and raw material is available.

The algorithm consists in solving a number of our MIP model in turns, each time moving the second section by  $\alpha$  periods and solving again for the whole horizon  $1..T$ . The frozen horizon increases by  $\alpha$  each iteration and the third section decreases by the same amount. Starting with an empty first section (frozen horizon), the algorithm completes when the third section is empty. The solution time required to perform each phase depends on the size of  $\alpha$ .

Aside from optimizing the model, each iteration takes some time to load data from CSV files and to write back results to CSV files. So although decreasing the size of  $\alpha$  decreases the solving time for the MIP model, it increases the number of iterations required to solve the problem and thus the total time spent to set up the model over all the iterations.

Figure 10 shows the computation time (including the time to load and save the data, and to construct the model) in relation to the size of  $\alpha$  (or the number of phases as all of these cases are 42 periods). For only three instances out of the seven, the one-phase scenario gave a shorter solution time. Compared to the three-phase scenario, the two-phase scenario gave a longer solution time in only one instance. As the solution time

difference for cases 1-6 is not very large compared to the solution time difference of case 7, we consider the three-phase scenario to be a better choice, ensuring an acceptable computation time in all instances.

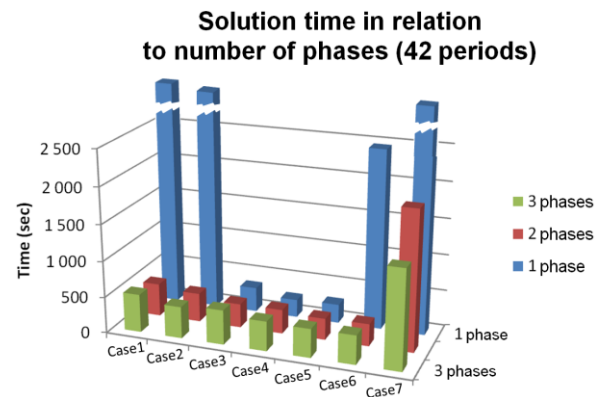


Figure 10 : Solution time in relation to number of phases

Solution time is of some importance in our problem because we want to be able to propose solutions in less than 5 minutes. For case 7, even the proposed solution procedure did not reach that goal.

The solution time is not the only factor of importance: the problem objective was to minimize order lateness. In any iteration, we ran the optimization allowing for a 5% optimality gap. Using three phases for the 42-period planning horizon, it is possible to get solutions further from the optimal. Comparing the one-phase solutions with the three-phase solutions, we were surprised to see an average improvement (decrease) in the volume delivered late by 2,5% and also an average improvement of the value delivered late by 3%. Also, in terms of objective function, the two-phase solutions outperformed the three-phase solutions by about 1%.

These results show that the planning algorithm in multiple phases does not decrease the quality of the solution obtained.

## 6 CONCLUSION

In this paper we have presented an adaptation of a MIP model and a solution methodology to plan the lumber wood finishing operations in a sawmill. Model adaptation and reformulation was required for some constraints specific to the mill and to get solutions within an acceptable time frame.

With this new formulation, the model implicitly requires the wood finishing equipment to be used 100% of its available time. The planning horizon has been divided into three segments such that only part of it ( $\alpha$  periods) has to be planned using integer variables. In our context, we used an  $\alpha$  of 14 periods (one week) and three iterations were required to solve the three-week planning horizon.

The mill managers are very enthusiastic about this new planning aid, but its integration is not that easy. In order to automate the planning, it is required that the finishing recipes stored within the mill ERP system have to be representative of the real production processes. With the stochastic nature of that process, it has been a challenge to extract recipes which are representative of the production. We are now working with the company to define standard recipes that will help predict the production output with more accuracy.

As presented in Section 2, wood finishing is the third step of the production process. Drying is the step that immediately precedes it and kiln planning, currently done manually at the mill, is an input to the planning of the finishing operation, and as such, bad planning of the kilns in regard to order lateness will result in poor performance in the planning of the finishing operations. We have thus undertaken the development of a model for the scheduling of the kilns and we are planning to implement that tool at the company in the coming year.

With that same company, we are also working on integrating tactical planning with operational planning. One of the challenges in integrating the tactical level with the operational one is in ensuring the feasibility of the operational plan. To do so, end of period inventory levels per product family are set within the objective function and not as hard constraints.

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