Original Research

Optimization model for remanufacturing in a real-world sawmill

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Abstract
Sawmills are an important part of the forest supply chain, and as at any company, their production planning is highly complex. Planning in the remanufacturing area, in terms of its economic contribution to the sawmill and the supply chain, has not been studied in the scientific literature. The goal of this study was to develop and solve a mixed-integer linear programming model by employing an efficient allocation of cutting patterns on in-stock logs to maximize profits. To quantify the impact of an appropriate use of raw materials in the remanufacturing area in a sawmill, real and generated data were used. The model considers fixed and variable production costs, the availability of raw material, the capacity of the processes, the sale price of the products and the demand, for a process period of one month. The proposed compact mixed-integer linear programming model was solved using the commercial solver IBM ILGO CPLEX12.8. It was determined that the additional margin in USD earned in the remanufacturing area for the considered scenarios amounted to an average of 21.6%. The proposed method facilitates evaluating the economic contribution of remanufacturing while identifying bottlenecks and assessing proposed scenarios.

Keywords - Forest industry; Planning in sawmills; Tactical planning; Mixed-integer programming; Forest optimization.

1.INTRODUCTION

Currently, one of the most important decisions in sawmills is to determine a production strategy that maximizes the yield in the remanufacturing area in terms of processes, demands, and log stock. Three levels are identified in the decisions associated with industrial forest production planning. The first is strategic planning to establish administrative and developmental policies that support the satisfaction of external demand according to a company's global long-term goals. The second is middle-term tactical planning involving decisions related to resource use, such as production capacity, labor and inventory. The third is operational control, which considers short-term decisions relative to daily operations and sequencing (D'Amours, Ouhimmou, Audy, & Feng, 2016; Troncoso, D'Amours, Flisberg, Rönnqvist, & Weintraub, 2015; Weintraub, Romero, Bjørndal, & Epstein, 2007; Rönnqvist, 2003). The forestry industry can also consider applying the optimization models and proposals of Rabbani, Ramezankhani, Giahi, and Farshbaf-Geranmayeh (2016).

When reviewing several industrial practices regarding production planning in local firms in southern Chile, it was observed that current sawmill and remanufacturing processes are typically independently planned such that each business unit seeks to maximize its yield of raw materials according to the demand for different types of wood product. This decision-making is inherently combinatorial and usually depends on corporate policies that to the best of our knowledge rarely formulate appropriate decision problems or employ mathematical programming models.

Thus, sawmill production planning is a difficult problem, and a mathematical programming model would be of great assistance in the decision-making process such planning involves. The literature is inconclusive regarding the applicability of unique and holistic mathematical models: real-world sawmill production planning typically occurs in private companies and firms, each with its own set of circumstances characterized by different product demand, cost structure, and internal culture. Therefore, it would appear that case-specific and tailored models must be formulated if such models are to be valuable to the firms. Consequently, the solution approach will also depend on the firm's requirements with respect to whether a solution will be valid for a particular set of circumstances within a much larger sawmill industry. Additionally, given the local conditions of forestry companies, with vertical integration in the forest supply chain, it is necessary to model and optimize the entirety of the business units to avoid individually optimizing each one, thus establishing the local optimum but sacrificing the benefits of integration.

In this paper, we introduce a new mathematical programming formulation in the form of a mixed-integer programming model for a forestry company with sawmill operations in the city of Los Angeles (southern Chile). As this company is a specific local firm, the model has not been considered in the literature. Our objective is to maximize profit margin in the remanufacturing stage of the sawmill subject to various constraints with which the firm must comply. In addition, our model optimizes aggregate production by including all business units, i.e., including processes that occur after the sawmilling line: drying, sorting, planning, ripping, cutting, and finger jointing processes up to the completion of the molding.

Finally, we produce and solve a set of instances unique to the firm using a commercial mixed-integer linear programming solver (i.e., IBM ILOG CPLEX). These instances represent typical demand, price, and resource constraint scenarios that the firm faces within the industry. We include a baseline case that reflects the current situation. Computational results are consequently tabulated and analyzed. The remainder of the paper is organized as follows. The “Literature review” section describes the most relevant and recent scientific articles on forest planning. “Mathematical programming model for remanufacturing in sawmills” introduces a mixed-integer programming formulation for the problem.

In the “Results” section, the primary results are described, and their corresponding analysis is presented in the “Discussion” section. "Conclusions and further research" summarizes the main conclusions of the study and proposes future research to improve understanding of this topic.

2. Literature Review

When reviewing the literature on production planning, it was observed that many studies have developed models and solved them with exact and heuristic methods. Dao et al. (2017) proposed a mixed-integer programming model and a genetic algorithm to address a problem that included production planning and scheduling. Such decision-making concerns what to produce, in what quantity, the production location, and the order of production. The algorithm was tested in a generic example. Kumar et al. (2012) addressed production planning in a flexible manufacturing system in which a set of jobs must be assigned or loaded into a set of machines. The jobs are divided into tasks, several of which can be performed by different machines. The paper formulated a mathematical model that was solved using LINDO software and proposed a hybrid algorithm based on a genetic algorithm and particle swarm optimization that achieved better results. The problem addressed by Hamidi et al. (2017) consisted of determining the production level of different products in a production line under environmental and system uncertainty. They used fuzzy simulation to address the uncertainty. Mehrjoo and Bashiri (2013) also addressed a problem that included uncertainty. However, this case was related to detailed planning and scheduling in the automotive industry. They proposed robust decision support based on the multivariate statistical method.

The previously mentioned studies represent only a small selection from the vast literature on production planning (Maravelias & Sung, 2009). Hafezalkotob et al. (2019) introduced cooperative aggregate production planning as a way to decrease costs. Additionally, a study on the remanufacturing of products with preventive maintenance has been performed (Agahtani & Gupta, 2018). However, neither of these studies is applicable to the sawmill industry, which has particularities that must be considered in the applicable correct solution. Noori-Darvish and Tavakkoli-Moghaddam (2012) minimized the total delay in production scheduling. Another study established that the parameters used in the processes affect the quality of the solution. Therefore, the use of genetic algorithms for the optimization of parameters as employed in the Taguchi method was proposed (Mariajayaprakash et al., 2013).

Vanzetti et al. (2018) considered mixed-integer linear programming (MILP) for optimal multiperiod planning in sawmills. Fuentealba et al. (2019) investigated an integrated tactical planning model for forest harvest and sawmills. Pradenas et al. (2009) addressed tactical programming for multiple periods and products in sawmills and their operations management. Generally, the production schedule in sawmill has been theoretically studied. Most of these studies focus on harvesting and distributing logs to the sawmills for processing (Linfati-Medina et al. 2016). The possibility of sending a better-quality product than that required by the customer is proposed as opposed to using a cutting ruler or cutting scheme. In addition to optimization and problem-solving for assigning cutting schemes, Pradenas et al. (2013) proposed a model for optimization problems that involved cutting planks in the cross-sectional area of a log using a genetic algorithm. Zanjani et al. (2013).

An unexplored research avenue in the literature is the one of incorporating uncertainty in sawmill operations. For example, Alvarez and Vera (2014) proposed the use of stochastic optimization for sawmill planning but only recently, Rahimi et al. (2020) build a two stage mathematical program with recourse for the problem of selecting supplying contracts. This latter is a highly combinatorial problem involving the decision of what contracts to establish between sawmills and pulp, paper companies such that a feasible and non-interrupted flow of raw materials is secured. Given the uncertainty inherent in northern climates, for example, where logistics are complicated in winter and spring times (i.e. snowy roads and ice melting in the spring), then decision makers must evaluate multiple scenarios when deciding on production quotas. The authors build on a previous formulation of Rahimi et al. (2019) who formulate a compact mixed-integer program (polynomial in the number of variables and constraints) for a fully deterministic version of the supply-contract-selection problem.

In spite of the previously detailed endeavors, the trend in the search for robust optimizations models for integrated sawmill operations continues to grow in recent literature. This is partially explained because since every sawmill has its own particular set of production lines, operational conditions, environmental regulations, among many other unique features, it is not likely that a holistic “one-size-fits-all” approach is to be found (neither desired). Hence recent literature is abundant in tailored, case specific approaches to deal with a unique set of features under which sawmills operate. Even more so, Ouhimmou et al. (2021) claim that the forestry industry is becoming more complex as more problem features are included in the analysis. However, it is no discouragement what so ever because as even more players are entering the market, the increased competition has left the sector with augmented supplies and reduced prices. Therefore, the authors claim that there is an even larger need for better optimization models and thus present their own compact mathematical programming model to assess the impact of integrating new production lines into a large network with many players. Specifically they address how to effectively integrate production into an already existing value chain network. Similarly, Pereira et al. (2020) address the issue of integrating sales and operational plans in middle run decision making for the forest sector. They claim that individually addressing the functions of supply chain (which they identify to be procurement, production, distribution and sales) can have obvious “tempting” gains in reducing managing complexities. Nonetheless, like thirst seamen should never turn to salted seawater, decision makers should not make for this line of thinking as it can most likely lead to a set of infeasible individual plans (when assembled together). Hence, the authors contribute with a review of best practices involving optimization models to assist decision making in sales and operational plans.

Lastly, the recent literature no only dwells on robust optimization models but also on the physical and chemical properties of the raw material: the timber. Da Silva et al. (2020) bring forth the notion that optimization models might not even be sufficient if one is to achieve sustainable production, because of lack of knowledge on the raw material. They claim that without proper insights of key performance metrics such as volumetric lumber yield per log, or the quality of the logs themselves, it is hard to estimate production outputs, efficiency of sawmills, financial returns, and climatological impacts. In particular, there is a lack of data this type for tropical log species in regions of Latin America like the Amazon forest.

As concluding remarks for this literature review, it is safe to say that there is vast body of groups and studies for sawmill and forestry operations, and the combinatorial set of features that make each problem “one of a kind”. We seek to contribute by introducing new tools and models that we validate with instances adapted from real world situations.

3. Problem Description

The process of obtaining lumber involves cutting patterns or schemes to transform logs into lumber. We characterize each scheme by the consumption per time unit (m3/hour) of a certain log type (identified by its diametric class) and the productivity per time unit (m3/hour) for each product. Each product is characterized by a price and a family of qualities and measurements. In each planning period, important factors include production capacity, demand for a specific product or family of products (m3) and the available log supply [m3Jas]. Costs include raw materials (i.e., log consumption) and operational costs (i.e., operation hours, sawmill performance, and all subsequent processes).

One key to increasing lumber production efficiency consists of programming for every log to be processed according to the log’s diameter, length, and quality. The log supply typically includes units with different diameters, lengths, and qualities. These variables determine the cutting pattern or how the log will be processed and are considered in estimating or determining both products and yield. That is, the process includes how most of the volume of the log is transformed into finished products. The remainder of the log corresponds to sub products, such as sawdust, chips, edging, and bark. Product quality is determined by the quality of the log. The sawmill examined in this study belongs to a company located in a developing country with more than 20 years in the market. Its consumption volume is approximately 25,000 [m3Jas] with a monthly output of approximately 15,000 [m3/month] of greenwood, primarily depending on the average diameter and length of the logs consumed during the month. The mill performs all the transformation processes applied to solid wood, including green sawmilling, drying, planning/sorting, and the subsequent consumption of side woods in the remanufacturing area. The latter includes ripping, cutting and finger jointing, and molding, and the use of a precision end trimmed (PET) machine, a radiofrequency glue dryer, and a vacuum and GESSO painting line. Each production process involves different flow balances and operational costs.

All the remanufacturing processes produce wood sub products, such as shavings, sawdust or edgings, which are used as fuel (i.e., biomass). In addition, there are other remanufacturing processes (such as painting, plywood production and squaring) that are not investigated in this study because only certain products use these processes, and their economic contributions are lower.

The studied company uses two production lines in process sawmilling to transform a log (i.e., a cylinder) into rectangular sections of different dimensions and qualities depending on market needs and current product prices. The first product line is referred to as green (e.g., wooden planks that have just been cut from the log and that have not undergone any drying process) and corresponds to the thin line, i.e., the line for smaller logs between 16 and 34 cm. In the sawmill, the log is scanned at the entrance to determine how it will be processed and transferred to one of the cutting schemes for fixed central woods, whereby preprogrammed software is used. The second production line corresponds to a tape cart that consumes thick logs and is optimized according to the cutting pattern provided to the operator (or, for pruned logs, according to lumber quality). The thin line produces approximately 65-70% of the total sawmill volume. In connection with these sawmill characteristics, periodic meetings are held to analyze production strategies for the coming weeks by considering a large number of variables and parameters related to supply, process costs, demand, prices, and other variables. This analysis is performed in a structured way but without specific tools to obtain an appropriate solution that maximizes profitability and maintains balanced stocks in the different production areas of the factory. On certain occasions and particularly in periods of crisis, the contribution of the remanufacturing area to the aggregate profits of the entire factory has been questioned. Therefore, this study assesses whether a mathematical model can be formulated and solved that optimizes the contributions of the remanufacturing area to the entire factory.

4. Mathematical Programming Model for Remanufacturing in a Sawmill

Figure 1 presents a detailed diagram of the involved processes and flows.

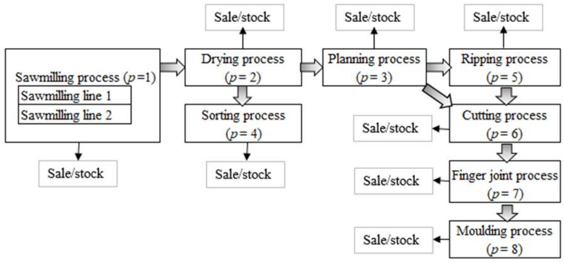

FIGURE 1
FLOW DIAGRAM OF THE SAWMILL PROCESSES UNDER STUDY.

The following elements must be considered relevant.

a. Capacity: We must consider the capacity of the factory and each process in terms of available hours and productivity with respect to each product. We consider the eight processes of sawmilling, drying, planning, sorting, ripping, cutting, finger jointing and molding, which result in 96 products.

b. Logs and cutting schemes: The study considers 100 cutting schemes (50 per production line) in the sawmill. There are 15 diametric classes (diameters between 16 and 44 cm) and their associated buying prices. The logs used in the model are no pruned and 4.0 m in length. These logs constitute 70% of the sawmill's consumption.

c. Yields: The yields for each product in the different cutting schemes were considered in addition to the yields of the eight subsequent processes for the 96 products.

d. Process costs: Variable and fixed costs per process are considered.

e. Selling process of products and demands: Generally, prices for each product in all processes were considered. The same was undertaken for demand.

f. Sales: The study considered that 100% of the products were sold at the prices defined by the price matrix.

The following definitions of sets, parameters, and variables were established.

Sets and subscript

R: Number of diametric classes considered, $r = 1, 2, \dots, R$

K: Number of cutting schemes considered, $k = 1, 2, \dots, K$

I: Number of product types considered, $i = 1, 2, \dots, I$

P: Number of processes considered, $p = 1, 2, \dots, P$

Parameters

ST_r: Stock of logs available with diameter r [m3]

TCA_k: Consumption rate of logs with cutting scheme k in the sawmill [m3 / hour]

CR_k: Costs associated with cutting scheme k [USD/m3]

CF_p: Fixed costs associated with process p [USD]

CV_p: Variable costs associated with process p [USD/hour]

HR_p: Hours available for process p [hour]

PRA_{ik}: Productivity of product i in cutting scheme k [m3 / hour]

P_{ip}: Selling price of product i in process p [USD / m3]

PR_{ip}: Productivity of product i in process p, where $p > 2$ [m3 / hour]

D_{ip}: Demand for product i in process p [m3]

R_{ip}: Performance of product i consumed in process p [%]

THL1: Total hours available on line 1 in sawmill [hour]

THL2: Total hours available on line 2 in sawmill [hour]

CVAL1: Variable costs associated with line 1 in sawmill [USD/hour]

CVAL2: Variable costs associated with line 2 in sawmill [USD/hour]

CFAL1: Fixed costs associated with line 1 in sawmill [USD]

CFAL2: Fixed costs associated with line 2 in sawmill [USD]

M: very large number

Decision variables

HA_k: Hours of consumption of logs with cutting scheme k in the sawmill [hour]

B_p: Binary variable equal to 1 if process p is used and equal to 0 if process p is not used

X_{ip}: Volume of product i manufactured in process p [m3]

The model facilitates the maximization of the total economic benefit due to the use of the remanufacturing area. In this model, a 100% utilization of the raw material is considered so that the unit of measurement [m3Jas] is equivalent to [m3]. The proposed mathematical programming model, including relationships (1)–(21), is summarized as follows.

Equation (1) is the objective function of the mathematical model and corresponds to the maximization of the total economic benefits due to the use of the remanufacturing area. Its first 8 components reflect the income from the sale of products from processes 1, 3, 4, 5, 6, 7 and 8 (Figure 1). Everything that was not processed in a subsequent stage is sold. The ninth component corresponds to income from the sale of product 96 (dry chip), which is generated from the planning process onwards from processing the raw material. The tenth component of the objective function corresponds to the costs associated with the consumption of raw materials in the sawmill. The remaining components correspond to fixed and variable costs for each line and the remaining processes in the sawmill.

$$
\begin{aligned}
\max z = & \sum_{i=1}^{I} P_{i1} * (x_{i1} - x_{i2}/R_{i2}) + \sum_{i=2}^{85} P_{i3} * (x_{i3} - x_{i6}/R_{i6}) \\
& + \sum_{i=86}^{94} P_{i3} * (x_{i3} - x_{i5}/R_{i5}) \\
& + \sum_{i=1}^{I} P_{i4} x_{i4} + \sum_{i=1}^{I} P_{i5} * (x_{i5} - x_{i6}/R_{i6}) \\
& + \sum_{i=1}^{I} P_{i6} * (x_{i6} - x_{i7}/R_{i7}) \\
& + \sum_{i=1}^{I} P_{i7} * (x_{i7} - x_{i8}/R_{i8}) + \sum_{i=1}^{I} P_{i8} x_{i8} \\
& + \sum_{i=1}^{I} \sum_{p=3}^{P} P_{96\,p} * (x_{ip}/R_{ip} - x_{ip}) \\
& - \sum_{k=1}^{K} CR_k * HA_k * TCA_k \\
& - (CFAL1 + CFAL2) * B_1 \\
& - \sum_{k=1}^{50} CVAL1 * HA_k \\
& - \sum_{k=51}^{K} CVAL2 * HA_k - \sum_{p=1}^{P} CF_p * B_p \\
& - \sum_{p=1}^{P} \sum_{i=1}^{I} CV_p * (x_{ip}/PR_{ip})
\end{aligned} \quad (1)
$$

$$\sum_{k=1+5*(r-1)}^{5*r} HA_k * TCA_k \leq ST_r \qquad r = 1,2,3,4,5 \quad (2)$$

$$\sum_{k=1+5*(r-1)}^{5*r} HA_k * TCA_k + \sum_{k=21+5*r}^{25+5*r} HA_k * TCA_k \leq ST_r \qquad r = 6,7,8,9,10 \quad (3)$$

$$\sum_{k=21+5*r}^{25+5*r} HA_k * TCA_k \leq ST_r \qquad r = 11,12,13,14,15 \quad (4)$$

$$x_{i2} = x_{i3}/R_{i3} + x_{i4}/R_{i4} \qquad \forall\, i \in I \quad (5)$$

$$x_{i3} + x_{i5} - x_{i6}/R_{i6} \geq D_{i3} + D_{i5} \qquad 2 \leq i \leq 85 \quad (6)$$

$$x_{i3} - x_{i5}/R_{i5} = x_{i3} \qquad 2 \leq i \leq 85 \quad (7)$$

$$x_{i3} - x_{i5}/R_{i5} \geq D_{i3} \qquad 86 \leq i \leq 94 \quad (8)$$

$$x_{i3} + x_{i5} - x_{i5}/R_{i5} - x_{i6}/R_{i6} \geq D_{i3} + D_{i5} \qquad 86 \leq i \leq 94 \quad (9)$$

$$x_{i5} - x_{i6}/R_{i6} \geq D_{i5} \qquad 86 \leq i \leq 94 \quad (10)$$

$$x_{ip} - x_{i\,p+1}/R_{i\,p+1} \geq D_{ip} \qquad p = 1,6,7;\ \forall\, i \in I \quad (11)$$

$$x_{ip} \geq D_{ip} \qquad p = 4,8;\ \forall\, i \in I \quad (12)$$

$$\sum_{k=1}^{K} PRA_{ik} * HA_k = x_{i1} \qquad \forall\, i \in I \quad (13)$$

$$\sum_{k=1}^{50} HA_k = THL1 \quad (14)$$

$$\sum_{k=51}^{100} HA_k = THL2 \quad (15)$$

$$\sum_{i=1}^{I} x_{ip}/PR_{ip} \leq HR_p \qquad p \geq 2 \qquad (16)$$

$$\sum_{k=1}^{K} HA_k \leq B_1 * M \qquad (17)$$

$$\sum_{i=1}^{I} x_{ip}/PR_{ip} \leq B_p * M \qquad p \geq 2 \qquad (18)$$

$$B_p \in \{0, 1\} \qquad \forall p \in P \qquad (19)$$

$$x_{ip} \geq 0 \qquad \forall i \in I, \forall p \in P \qquad (20)$$

$$HA_k \geq 0 \qquad \forall k \in K \qquad (21)$$

Regarding the constraints, (2) - (4) limit the use of logs of different diameters in the sawmill according to the cutting schemes allowed for each particular diameter. Constraints (5) - (12) correspond to flow balances that guarantee the correct flow of products through the network and ensure compliance with external demand in those processes that directly sell their products. Constraint (13) transforms the hours assigned to the sawmill to the different cutting schemes (HA_k) into the quantity of each product i generated (x_{i1}) because of this assignment (since the sawmill is the process p = 1). Constraints (14) - (16) correspond to production capacity constraints, specifically the hours available for each of the processes that are part of the area under study. Constraints (17) and (18) allow only those processes that are determined to operate (B_p=1) to process products. Finally, constraints (19) - (21) define the domain of the decision variables of the mathematical model.

5. RESULTS

A set of instances was generated to test the model. Every instance shown presents the same number of constraints, data and decision variables. Only a limited number of data are changed to find solutions for different realistic scenarios. These instances are described as follows.

AS. (Current situation) This instance considers the current conditions of prices, supply, process costs, and other variables and is the basis for the instances that follow that cause only a few modifications to the results.

VT1000. This instance does not consider log constraints and has 1,000 hours available from the drying process onwards. This instance is intended to determine the best conditions in terms of supply and equipment capacity to find the most profitable cutting schemes. It verifies whether the manufacturing hours must be increased to enlarge the profit margin of the factory.

LPR10. This instance indicates a 10% decrease in the price of remanufactured products. This decrease only affects those products that would be sold and that are produced by the manufacturing area processes (i.e., ripping, cutting, finger jointing and molding).

LPR20. This instance indicates a 20% decrease in the price of remanufactured products. It is similar to the previous instance but a less favorable scenario.

LOG1. In this instance, only 18 cm (line 1) and 34 cm (line 2) diameter logs are available in the yard, which strongly decreases the opportunities to combine cutting schemes.

PR30. This instance reveals a decrease of 30% in all prices, which would be the most unfavorable condition. The model would most likely indicate a value equal to zero, which would indicate that it is better to shut down and not process the lumber to avoid a negative profit margin.

The described instances are quantified with and without remanufacturing. Once the mathematical model is complete and validated in IBM ILOG CPLEX, the decision variables HA_k, B_p and X_{ip} and all yields, productivities and costs data are analyzed to determine the exact cost of each product consumed by remanufacturing in both the ripping (p = 5) and cutting (p = 6) processes. The actual costs of each product (raw material) consumed in remanufacturing is identified and then subtracted from the final sales price for the particular instance. Thus, the margin or utility that remanufacturing contributes to the global margin of the factory is obtained. With the weighted costs of the products manufactured at the sawmill, the weighted cost of the raw material and both fixed and variable costs are added and weighted according to the productivity of each cutting scheme. The costs for each product are divided by the yield of each process, and both fixed and variable costs are added to this outcome. (These will be larger or smaller depending on the productivity of the item.) Once the costs of the products (before entering into the ripping or the cutting process) have been obtained, the values are multiplied by the consumption of each process (always one and never both) to obtain the real value (USD) of the raw material consumed in the remanufacturing. This value is subtracted from the volume and price of the sales made that involve products generated by remanufacturing to obtain the actual remanufacturing costs. For each test, the proposed mathematical model was executed using IBM ILGO CPLEX 12.8 in a computer with a 2.5 GHz Intel Core i5-2400 processor, 8 GB installed RAM memory and the Red Hat Linux Enterprise 8 operating system. The following results were obtained. In Table 1, the solved instances are located in the rows, and in column 1, there is a code associated with each instance. Each instance is performed twice (with and without remanufacturing) to visualize the impact of this area. Column 1 lists the names of the instances explained in the previous chapter.

TABLE 1
COMPANY MARGIN (USD)

Instances	With or without remanufacturing	Total margin (USD)	Margin sawmill, drying, planning and sorting (USD)	Margin remanufacturing (USD)	Cost of raw material, consumption remanufacturing (USD)
AS	C/R[a]	1,076,882	653,661	423,221	444,463
	S/R[b]	914,667			
WT1000	C/R	1,309,114	521,967	787,147	1,083,932
	S/R	1,070,547			
LPR10	C/R	1,070,547	653,944	337,756	444,006
	S/R	991,701			
LPR20	C/R	914,667	914,667	0	0
	S/R	914,667			
LOG1	C/R	922,114	739,723	182,391	609,779
	S/R	797,471			
PR30	C/R	100,435	- 43,156	143,591	463,787
	S/R	60,655			

Column 2 indicates if the instances were solved, considering or not considering available hours in the processing of the remanufacturing area (ripping, cutting, finger jointing and molding). Column 3 shows the values in USD of the profits or the total margin from the mathematical model. Column 4 present the margin of only the sawmilling, planning and sorting processes. The isolated margin of the remanufacturing is provided, which is calculated according to the explanation in section 3. The last column is the actual cost of the lumber consumed in remanufacturing. Finally, the last column, "Additional margin for the cost of raw material", is obtained by dividing the previous column into the last columns of Table 1. Table 2 provides the economic percentage contribution from remanufacturing. The central column presents the "increase in the margin by using the manufacturing process (in percentages)." This increase is obtained by dividing the total margin obtained by each instance with the manufacturing process by the margin obtained by each instance without the manufacturing area.

TABLE 2
ECONOMIC GROWTH IN % FOR EACH INSTAN

Instance	Increase in percentage margin by using the manufacturing process [%]	Remanufacture contribution to global margin [%]	Additional margin respect to the cost of raw material [%]
AS	17.7	39.3	95.2
WT1000	22.3	60.1	72.6
LPR10	8.4	34.1	76.1
LPR20	0	0	0
LOG1	15.6	19.8	29.9
PR30	65.6	143.0	31.0

The column "Remanufacturing contribution to the overall margin" is obtained by dividing Column 5 (Remanufacturing margin USD) into the total margin in USD presented in Table 1.

In Table 3, dual prices of the logs in the different diameters can be observed. The table also includes the dual prices of the hours occupied in line 1 and line 2 of the sawmill obtained from the output of the solver.

TABLE 3
DUAL PRICE OF CONSTRAINTS OF DIFFERENT RESORCE TYPES

Constraints	Dual price
Constraint (2) with $r = 1$	0.0
Constraint (2) with $r = 2$	9.7
Constraint (2) with $r = 3$	16.6
Constraint (2) with $r = 4$	18.9
Constraint (2) with $r = 5$	21.3
Constraint (3) with $r = 6$	31.5
Constraint (3) with $r = 7$	30.8
Constraint (3) with $r = 8$	28.2
Constraint (3) with $r = 9$	26.1
Constraint (3) with $r = 10$	25.0
Constraint (4) with $r = 11$	32.6
Constraint (4) with $r = 12$	35.5
Constraint (4) with $r = 13$	39.9
Constraint (4) with $r = 14$	40.8
Constraint (4) with $r = 15$	38.6
Constraint (16) with $p = 2$	55.0
Constraint (16) with $p = 3$	55.0
Constraint (16) with $p = 4$	38.0
Constraint (16) with $p = 5$	45.0
Constraint (16) with $p = 6$	768.1
Constraint (16) with $p = 7$	35.0
Constraint (16) with $p = 8$	80

6. DISCUSSION

According to the results, the average remanufacturing margin was 21.6%. The only instance in which remanufacturing produced no additional profits was LOG1, where prices were lowered by 20%. Regarding the AS instance, the marginal increase from using the painting line versus the same instances without considering the painting line generated an additional profit of 17.7%, which was less than 22.3% in the next instance (without log constraints and with 1,000 hours available for production from the drying process onwards). The reason is that this area began to consume other products previously sold with more hours available in remanufacturing, but every one of the consumed products had a marginal profit lower than that of those initially selected. The proof of this outcome is that the additional remanufacturing input with respect to the cost of the raw materials consumed was 95.2% versus 72.6% in instance 2. For instance PR20 (a decrease in the prices of items produced by remanufacturing of 20%), the decrease is significant, and the remanufacturing process provided no margin. Thus, the products were sold before being consumed in this area.

Instance PR30 generated more remanufacturing profits (65.6%) when margins with and without remanufacturing were compared. The margin was 143.0% when manufacturing and sawmill margins were separated in the AS instance when considering the remanufacturing process (C/R). Manufacturing must grow to increase the margin to the extent that the market situation remains stable. This necessity can be clearly observed by considering the dual prices of the capacity constraints in the manufacturing processes.

The completion times for each instance were 2 to 3 seconds, with an average of 410 iterations per instance. Conversely, it is observed that the yields of the sawmill are highly similar with and without remanufacturing since the products that have more dead edgings (i.e., rounded edges instead of straight edges in the margin of the planks) may be sold locally albeit at a lower price than if they were consumed by manufacturing. Thus, on many occasions, the same cutting patterns were used during similar times.

The dual prices enable us to obtain important information regarding how the objective function is affected if the right side of the constraints is modified. To obtain the dual prices, the binary variables must be set at their optimum values, and then, the linear relaxation of the proposed model is solved. This approach implies that we maintain the same processes and that we only analyze the quantity to be produced. Table 3 shows the dual prices corresponding to constraints 2, 3, 4, and 16. The dual prices of constraints 2, 3 and 4 indicate that the objective function would be modified due to an increase in the availability of different diameter logs. In contrast, the dual prices of constraint 16 reveal how the objective function would change due to an increase in the availability of hours for the production processes without considering the sawmill. Based on this result, it is observed that the cutting process ($p = 6$) would act as a bottleneck. Therefore, increasing the availability of hours to perform this process would facilitate an increase in the objective function in a more significant way than increasing the availability of hours in other processes. Given its structure and size, this model always returns the optimal solution in a few seconds. The optimization problem has a linear objective function, linear constraints, and continuous variables except for the variable B_p, which depends on the number of processes.

The model can grow with respect to the sets R (diametric classes), K (cutting schemes), I (product types), and this growth is not problematic since it corresponds to the linear part of the model.

Regarding the set P (processes) associated with the binary variable B_p, there are currently seven processes. Their number will always be small because this variable is limited to the number of processes.

7. CONCLUSIONS AND FUTURE RESEARCH

In this paper, we presented a new mathematical programming model for a real-world sawmill production planning problem faced by a firm in southern Chile. The theoretical aspects of the problem as addressed in the literature indicate the difficulty of solving it manually, and the fact that real-world applications require case-specific modeling means that there is not a holistic one-size-fits-all solution.

We input into our model instances that represent real scenarios faced by the firm and found that on solving them the economic contribution of remanufacturing depends on the proposed scenario. Remanufacturing can increase the margin by more than 65%, demonstrating the importance of including these decisions in the model.

It may be concluded that in the current circumstances it would be desirable to increase the production hours in the cutting process in the remanufacturing area. Thus, the mathematical programming model can be of substantial assistance in the decision-making process.

Future research could involve extending the model to include multiple periods for production planning. Such a model would be useful in coordinating production with the forest supply chain, which supplies the logs to the sawmill. Finally, it would be interesting to develop a model in which the system requires no data on the cutting schemes of the sawmill. Instead, this approach would employ a mathematical model that generates optimal cutting schemes for each log according to price, cost, productivity, and other variables.

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