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A COMPARATIVE STUDY OF PRICE-DRIVEN PRODUCTION CONTROL METHODS USING A SAWMILL SIMULATOR

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ABSTRACT

In today's dynamic markets, decision-making relies heavily on simulation models to evaluate different production control methods. Although price-driven production control methods have proven their effectiveness in exploiting price volatility, certain industries are still reluctant to adopt these methods in their operational decision-making. This research demonstrates the relevance of price-driven methods for the wood products industry. A sawmill simulator is used to illustrate this. Since the simulation of the sawmill production process is time-consuming, we propose a probabilistic sampling-based method to rationalize the dataset size. A comparative study shows that exploiting historical and recent price data increases sawmill revenues.

1 INTRODUCTION

Various production control methods have evolved to meet the demands of modern industries, with two prominent approaches being push and pull methods. A push method makes stocks, whereas a pull one responds directly to incoming orders (Pillet et al. 2011). While these methods remain relevant, recent research has explored data-driven approaches, which leverage pertinent data such as demand (Ptak and Smith 2016) or prices (Wang et al. 2021; Zouadi et al. 2019), to optimize decision-making processes.

Production in the sawmilling industry has the peculiarity of being a divergent process. Wooden logs undergo processing in sawmill machines to yield a diverse range of products. Producers can select from various feasible sawing recipes, resulting in products of different dimensions (2×4, 1×3, etc.) and co-products like bark, chips, and sawdust. While hardwoods like oak and teak are prized for their aesthetic qualities in applications like staircases and wardrobes, softwoods such as spruce and pine are valued for their strength, predominantly in the construction sector.

Naturally, softwood producers aim to maximize the value of each processed log by generating the most lucrative basket of products. The real-world sawmilling machines use "product weights" as input (which can correspond to the market price or the physical volume of wood for each product) to decide how each log will be cut. In practice, products weights used by producers to control production are not changed dynamically as they prefer a steady and predictable product flow. Moreover, the producer employs sawmilling simulators to evaluate different machine configurations and forecast sawmill outputs (Wery et al. 2018).

This paper aims to demonstrate the value of considering dynamic prices and to demonstrate the relevance of price-driven production control methods for sawmills, which can be very relevant and crucial for softwood producers. The rest of the paper is structured as follows: Section 2 delves into a comprehensive literature review and delineates the research contributions. Section 3 presents the case study, the methodology and the experimentation. While Section 4 is dedicated to a comparison of results, Section 5 culminates in insights and actionable managerial implications, supplemented by suggestions for future research trajectories.

2 RELATED LITERATURE REVIEW

2.1 Sawing Pattern Problem

Lumber industry represents 1.71% of the Gross Domestic Product of the Province of Québec (PWC 2020). The lumber supply chain involves interdependent actors, whose common objective is to get the maximum value out of a heterogeneous raw material (Simard et al. 2023). To maintain consistency and to limit the costs, sawing operations are generally managed in a "push" mode (Wery et al. 2018). A log generates a basket of products and coproducts. While byproducts have no particular standards, softwood products are characterized by standard grading rules, such as the standard grading rules of the National Lumber Grades Authority (NLGA) which differentiate products. The choice of the sawing pattern (see Figure 1) is an operational decision which is done in real-time by machines in order to minimize the waste or by considering the production weights. In any case, the sawing pattern aims to create a basket of products in the range of the NLGA grading rules, and therefore has a direct impact on the revenues.

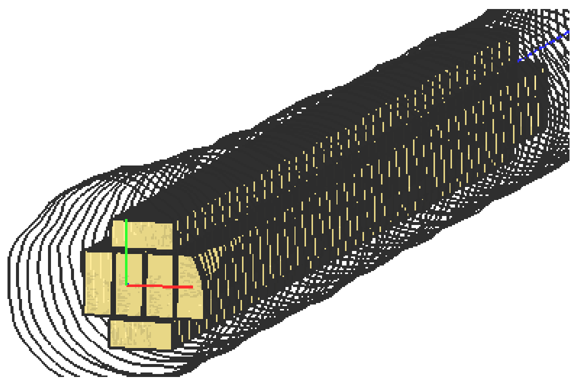

Figure 1: A sawing recipe applied to a log results in a basket of products

Softwood producers recognized the importance of optimizing their raw materials to maximize log value and minimize material loss. To address modeling complexities, three-dimensional (3D) scanners have been developed to accurately represent log shapes (Åstrand 1996). Then, online optimizers find the best sawing recipe considering log geometry, machine parameters, and other relevant factors (Todoroki 1990). To incorporate market value considerations, product prices can be used as production weights therefore prioritizing profitability, but they usually prefer not to make any dynamic change because the production manager does not know the potential impact on the production (Cid Yañez et al. 2009).

A variety of solution approaches have been proposed to tackle the sawing pattern problem, ranging from exact algorithms to metaheuristics and hybrid approaches (Galvez et al. 2018). First research has been focused on standard methods, such as dynamic programming (Faaland and Briggs 1984) and three-dimensional knapsack problem resolution (Reinders and Hendriks 1989). Exact algorithms and methods, such as branch-and-bound and dynamic programming, offer guarantees of optimality but may struggle with scalability for large-scale instances (Haberl et al. 1991). Metaheuristics, including genetic algorithms, simulated annealing, and particle swarm optimization, provide efficient and effective solutions for larger problem sizes, but lack optimality guarantees (Padrenas et al. 2013). Hybrid approaches that combine the strengths of both exact methods and metaheuristics have emerged as promising strategies to achieve high-quality solutions within reasonable computing time.

Recent research in the sawing pattern problem within the sawmilling industry has focused on developing advanced optimization models, solution algorithms, and decision support systems tailored to specific applications and operational constraints. Advanced mathematical formulations, such as mixed-integer linear programming (MILP) (Maness and Adams 1991; Gaudreault et al. 2010; Gaudreault et al. 2011; Galvez et al. 2018) and constraint programming (CP) (Gaudreault et al. 2011), have been proposed to improve solution quality and address practical complexities, such as log variability and sawmill constraints. Todoroki and Rönnqvist (2002) developed a profit maximization model considering dynamic values to ensure the changing levels of demand, proposing an optimization framework implemented in a log sawing simulator. Furthermore, advancements in computing techniques, such as parallel computing (Moisan et al. 2014), have enabled faster and more scalable solutions for decision-making in wood processing operations. Ide et al. (2015) used robust optimization to solve a multi-objective sawing problem considering logs with variable qualities.

2.2 Simulation in the Sawmilling Industry

Sawmill simulators are widely used to depict the course of a log in production line. While the algorithms in the equipment (heuristics or optimization techniques) are employed to make the real cutting decisions, simulation can be used offline, simulation is extensively utilized for assessing machine parametrization and testing production control methods (Wery et al. 2018; Dumetz et al. 2017). Simulation can be employed for tactical planning in order to identify or to evaluate equipment changes (for example change a machine, add a new line, etc.). Notable commercial sawing simulators include SAWSIM (HALCO 2016), SIMSAW (Singmin and National Timber Research Institute (South Africa) 1978), Autosaw (Todoroki 1990), Saw2003 (Nordmark 2005), WoodCIM (Usenius and Heikkila 2007) or Optitek (Grondin and Drouin 1996).

In the literature addressing sawmill problems, simulation-optimization has been applied in various ways (Ladier et al. 2014). The integration of those methods is particularly relevant for sawing operations where optimization resolves planning issues and simulation serves as a tool for testing tactical decisions (Wery et al. 2018). Firstly, an optimization model can be incorporated in a simulation model, as in Ben Ali et al. (2019). Secondly, simulation-generated data can be injected in an optimization model. For example, Sinclair and Erasmus (1992) proceed with SIMSAW and a sawing recipe generator. Additionally, Wessels et al. (2006) used SIMSAW results to develop a mixed-integer linear program to improve operational, tactical and strategic planning. Thirdly, it is possible to use simulation to evaluate the output of an optimization model (Ladier et al. 2014). Jerbi et al. (2012) for example use a similar method by evaluating with a simulation the performance of a tactical plan obtained with optimization. Dumetz et al. (2017) used it to compare order approval policies in different market conditions. Finally, a simulation model can be integrated into an optimization model to explore various scenarios, as illustrated by Wery et al. (2018) which evaluates the capacity of different sawmill configurations to optimize tactical decisions regarding machine parameters and order quantities.

2.3 Article Contribution

To the best of our knowledge, literature addressing sawing pattern problems does not use dynamic market prices to control production. Besides, no proper sampling method has been proposed to streamline the computing time of a sawmill simulator. In this paper, we first propose a probabilistic sampling method to reduce the size of a real log dataset. Then, we use a sawmill simulator to compare different methods to set the production weights for sawmills and to demonstrate the relevance of price-driven methods.

3 METHODOLOGY

3.1 Context

Our case study is based on a typical sawmill located in the Province of Québec in Canada, encompassing standard processes that are sawing, drying and finishing (see Figure 2). Yet, our focus lies specifically on the sawing process, which holds paramount importance in the production line. The sawmill is able to produce 121 different products defined by a tuple comprising thickness (inches), width (inches), length (feet), grade and market (i.e. the place the products are sold). The grade denotes the quality of the product, directly impacting its selling price. While we possess data for four different markets (Boston, Great Lakes, Toronto, and Montréal), we concentrate our analysis on the Great Lakes market, deemed the most pertinent for local sawmills. As raw materials, we consider a real set of over 2,000 logs. We utilize price data from 2018, a notably profitable year for softwood producers, characterized by higher sales volumes compared to preceding years.

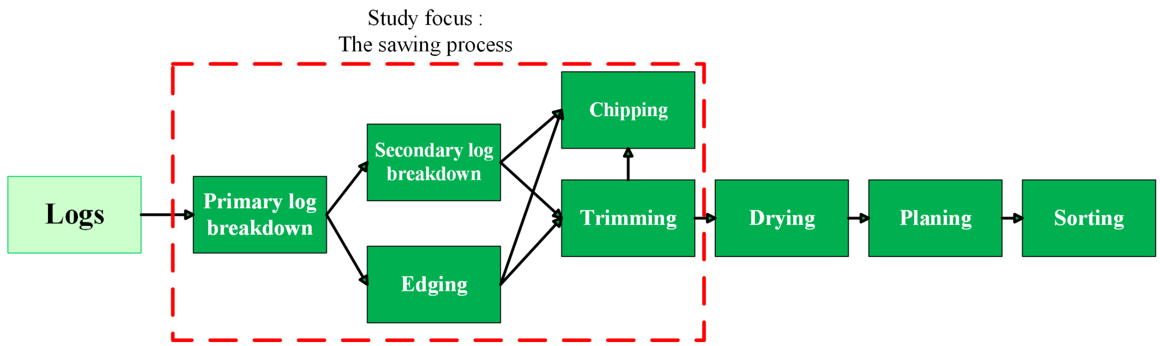

Figure 2: Production processes in a sawmill

As a hypothesis, we assume an infinite demand scenario. We suppose that each product is sold at its respective market price, thereby positioning producers as "price-takers" with no influence over selling prices. We acknowledge the temporal constraints of the drying and planing processes, although we disregard their specific time delays, as they typically span several weeks.

We employ Optitek, a sawmill simulator developed by FPInnovations. This simulator offers flexibility in adjusting numerous parameters, including machine settings and product weights in the machine optimizer. The simulation model used in this study is illustrated by Figure 3 and can be described as follows. Upon processing a specific sample of logs (see Section 3.2), logs undergo optimization by a sawing optimizer, which determines the optimal sawing pattern aligned with specific objectives such as maximizing revenues or material yield. Subsequently, the prescribed sawing recipes are executed to produce finished products, which will be sold at their respective market prices.

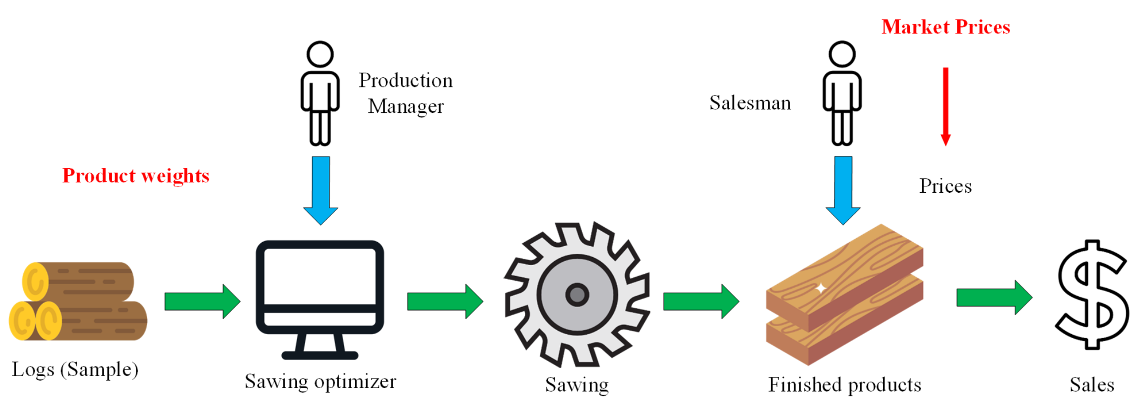

Figure 3: A simplified representation of the simulation model used in this study

3.2 Data Sampling

Processing 2,000 logs can be time consuming, the Optitek simulator might require up to 20 hours to simulate a one-week horizon. To streamline our computing efforts, we reduce this raw material set to a more manageable sample of 200 logs, now taking approximately 2 hours for a one-week simulation horizon. To accomplish this, we employ a four-step probabilistic sampling technique based on stratified sampling.

Stratified data sampling is a method used in simulation to ensure that the sample drawn is representative of different subgroups within the population. Instead of randomly sampling from the entire population, the population is divided into strata (groups) based on certain characteristics, and then samples are drawn from each stratum (Anupama and Lakshmi 2022). Stratified sampling has been shown to outperform a simple random sampling method (Anupama and Lakshmi 2022).

In simulation, this approach can be particularly useful for ensuring that a sample captures the variability within different segments of a population, as Cervan et al. (2023) show by improving the reliability evaluation of Monte Carlo simulations. More generally, Baik et al. (2023) demonstrate the interest of stratified sampling for simulation with multiple uncertain input models. In our specific case, we need to simulate logs with different characteristics, such as length, curving, diameter or volume. Thus, it is essential to consider a sample that has a representative proportion of each of these segments. By using stratified sampling, we can reduce the variability within each stratum and improve the accuracy of our simulation results (Jain et al. 2022). It also improves performance and reduces the amount of computational resources needed, since the same accuracy can be obtained from a smaller sample (Baik et al. 2023). It is important to note that implementing stratified sampling in simulation requires careful consideration of how to define the strata and how to allocate samples within each stratum to ensure that the resulting sample is truly representative of the population (Jain et al. 2022).

The initial step of the stratified sampling involves selecting pertinent features from our dataset. Our data includes Thin End Diameter (TED), Big End Diameter (BED), Curvature, Taper, Length and Volume. Upon analyzing scatter plots and correlation matrices (see Figure 4), we observe overlapping clusters or a single cluster for most features, with the exception of Length, which exhibits four separate clusters. Certain features, such as Volume versus TED and Curvature versus TED, display non-linear clustering patterns. Notably, TED demonstrates a strong correlation with both BED (0.93) and Volume (0.87). Consequently, we opt to exclude BED and Volume from the sampling process. Although Curvature and Taper show weaker correlations with other features and lack distinct clusters, their inclusion does not appear advantageous for cluster sampling. Regarding all this information, we chose to keep only the TED and the Length features in order to achieve the clustering. Among statistical consideration, those two features are often used to proceed to the log classification.

The second step involves defining a distance metric to determine whether two points can be considered neighbors. This distance metric must accurately reflect the shape of the data and undergo calibration and validation. Initially, we employ the Euclidean distance in a two-dimensional space. Subsequently, we introduce coefficients into the distance formula to weigh the importance of each feature while considering the arrangement of the data. These coefficients are determined through a trial-and-error approach, iteratively adjusted until consistent and logical strata are obtained (further details on the formation of strata will be provided later in this section). The final distance formula is presented in equation (1) for two logs x and y.

$$\sqrt{\frac{1}{4}(TED_x - TED_y)^2 + 2(Length_x - Length_y)^2} \tag{1}$$

In the third step, we generate the strata. We use the Density-Based Spatial Clustering of Applications with Noise (DBSCAN) (Ester et al. 1996). This method is based on the formation of clusters with points considered as neighbors, treated as strata. As the algorithm traverses the data, strata emerge to group together points with similar characteristics based on the defined distance metric (see equation (1)). DBSCAN exhibits robustness against noise, as it can effectively detect outliers. Moreover, it does not require prior knowledge of the number of strata (Ester et al. 1996). We apply this method with $\varepsilon = 0.08$ and $m = 25$, ε being the distance threshold to consider two points as neighbors, and m the minimal points to form a cluster. We then obtain the stratification depicted in Figure 5. Outliers are depicted by purple points and are disregarded during strata formation.

With the strata completed, we now proceed to the fourth step involving subsampling. This step aims to obtain a representative sample from the real set of 2,000+ logs. To achieve this, we randomly select

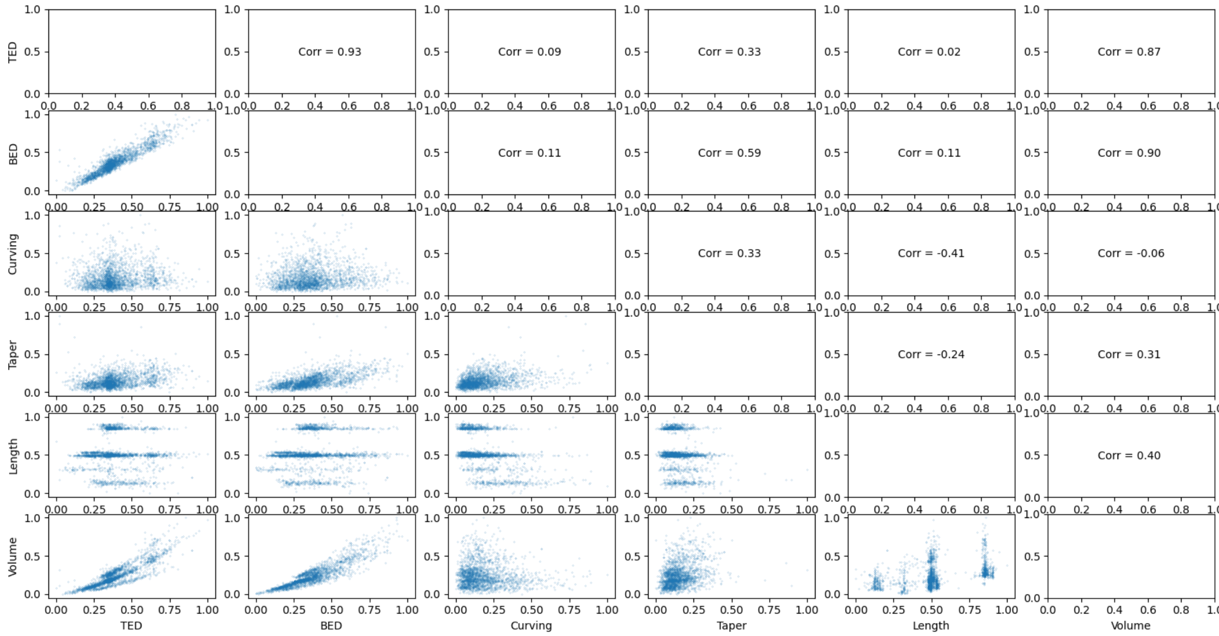

Figure 4: Scatter plot and correlation matrix

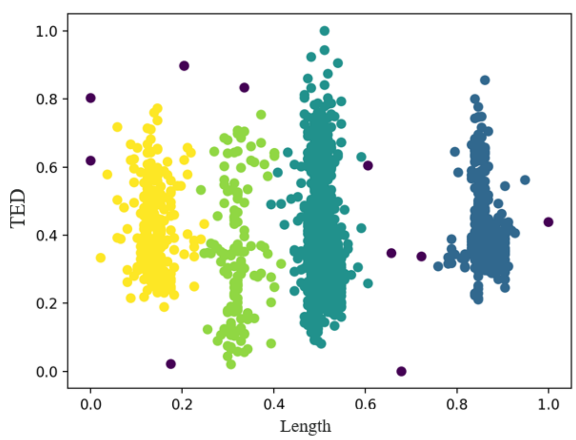

Figure 5: Visualization of the strata of the real dataset

a subsample from each stratum, with the size of each subsample being proportional to the size of its respective stratum according to Anupama and Lakshmi (2022). By aggregating these subsamples, we obtain a representative sample of the real dataset. We can see in Figure 6 that the data distribution of the sample closely mirrors the distribution of the real dataset shown in Figure¸ 5. This visual similarity underscores the representativeness of the sample and reaffirms its suitability for subsequent analyses.

3.3 Experimentation

The goal of the experiments is to compare, by simulation, different methods to set the production weights. Each method represents a different way of setting product weights used in sawmill optimizers. The product

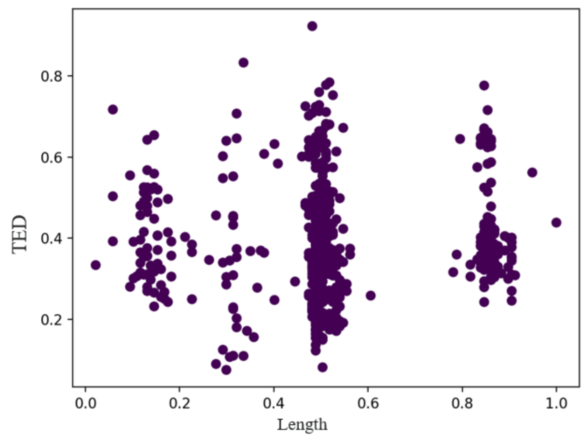

Figure 6: Visualization of the representative sample

weights are then considered as simulator parameters. We simulate these methods using the same sample of 200 logs and the weekly market prices. Finally, we estimate the weekly sawmill revenues.

Initially, we establish an upper bound which represents the best possible revenues achievable and is determined by utilizing the selling prices as product weights. Essentially we assume the ability to produce with prior knowledge of the upcoming prices. While this is not feasible in reality—given that softwood producers lack knowledge of exact selling prices when selecting sawing recipes—it serves as an idealized benchmark in simulation, allowing us to estimate the shortfall of different production control methods. These methods are described in the following.

The first method maximizes the material yield which is common in sawmills. It prioritizes raw material usage by minimizing material loss, disregarding product weights.

Next, we introduce four price-driven methods that use historical prices to set product weights. Except for one method (Fixed Weights), the idea is to take advantage of the volatility of prices by adjusting product weights weekly. The four parametrization methods to set the production weights of a given week t are defined as follows (see also Figure 7):

- **Fixed Weights**: using the average prices of 2017, with product weights remaining fixed throughout 2018;
- **Trimester**: using the average prices of the trimester preceding week t (12 weeks);
- **Month**: using the average prices of the month preceding week t (4 weeks);
- **Week**: using the prices of the week preceding week t.

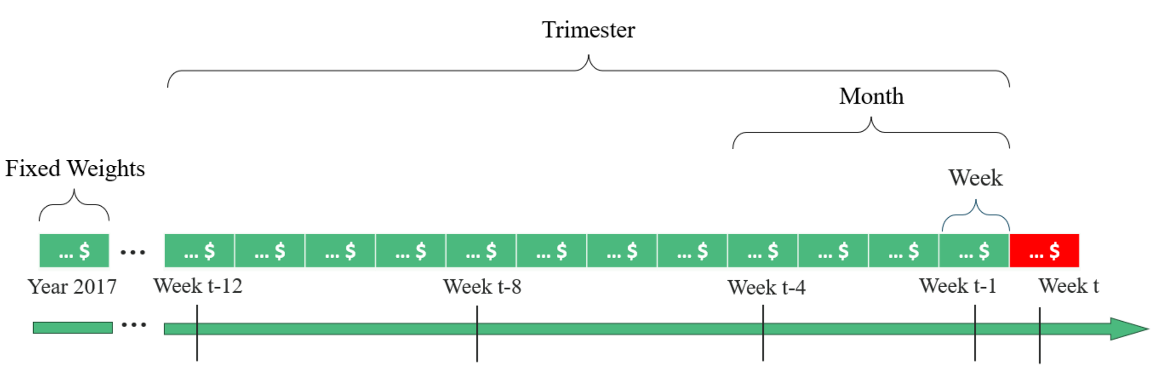

Figure 7: Parametrization methods

Finally, we consider a last method which implies that product weights are slightly deviated from the prices at which we sell. This may be the case if a planner is using price forecasts and forecast errors are observed. In our case, we suppose a random error following a Gaussian distribution between \$-15 and \$15 per unit of volume (i.e. a distribution of mean \$0 and standard deviation \$7.5).

The production control methods are compared in terms of three performance indicators:

- Shortfall (\$) $=$ Revenues(Upper Bound) $-$ Revenues(Method): represents the gap to the highest possible revenue.
- Revenues by Raw Material $(\$/ft^3) = \frac{\text{Revenues}}{\text{Volume of raw material}}$: commonly used in the sawmilling industry, and provides insight into revenue generation efficiency concerning the utilized raw material.
- Weekly Shortfall $(\%) = 100 \times \frac{\text{Weekly Revenues(Upper Bound)} - \text{Weekly Revenues(Method)}}{\text{Weekly Revenues(Upper Bound)}}$: expressed as a percentage, this metric represents, for each week, the gap to the highest possible revenue.

4 RESULTS AND DISCUSSION

Initially, we assess the shortfall obtained with each method. We recall that the shortfall is the difference between the revenues of the upper bound and the revenues of the parametrization method, which allows us to consider the upper bound as a reference. Figure 8 illustrates that the method maximizing the material yield (red) exhibits the largest shortfall, which represents a loss of 7.86% compared to the highest possible revenue. In addition, we can clearly see that price-driven methods achieve a narrow gap compared to the method that maximizes material yield. Notably, the Week method (gold) achieves a shortfall of 0.04% compared to the highest possible revenue. These results demonstrate the relevance of price-driven methods compared to the common method (maximizing material yield). When prices are not considered in production decisions, a large shortfall can be observed. Our case study shows that by dynamically adjusting the product weights using the most recent prices (ideally from the previous week), better revenues can be achieved. Given the larger shortfalls observed with the Trimester and Month methods, the use of older data seems less appropriate. Lastly, our case study results underscore the potential of the forecast-based method, which assumes a random error of less than \$15.

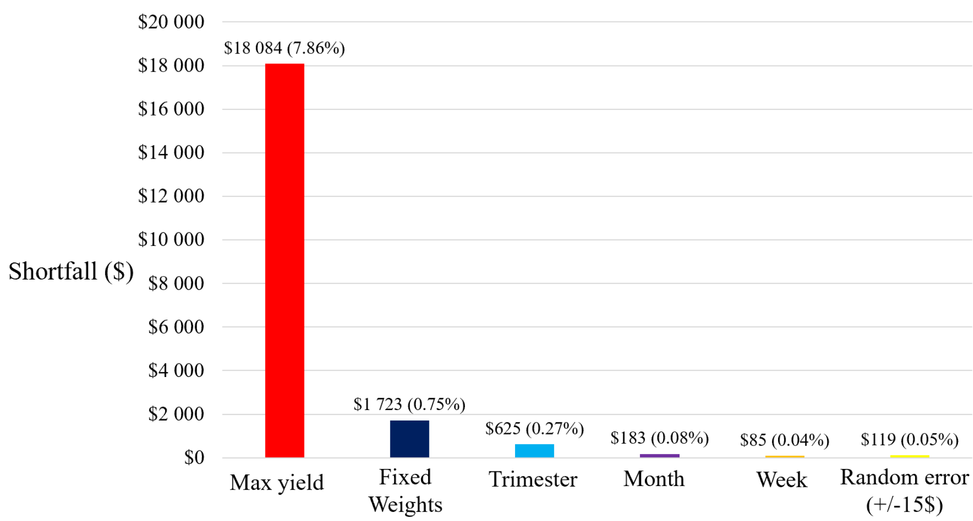

Figure 8: Shortfall by parametrization method

The metric “Revenues by Raw Material”, as depicted in Figure 9, provides insights based on common indicators in the sawmilling industry, offering valuable managerial perspectives. While the common method (maximizing material yield) proves to be suboptimal, resulting in a loss of $17.78\$/\text{ft}^3$ per cubic foot compared to the upper bound, the price-driven methods show remarkable efficiency, with a value of revenues by raw material very close to the highest.

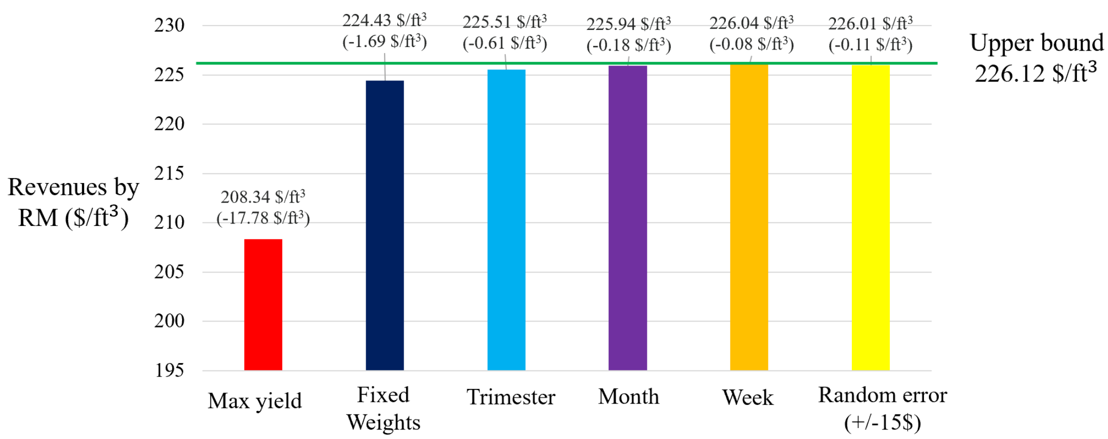

Figure 9: Revenues by raw material for each parametrization method

Figure 10 depicts the weekly shortfall. We can see a significant trend. Initially, at the start of the year, the Fixed Weights method is very close to the upper bound. But over the course of the year, they progressively diverge. Throughout the year, the prices change depending on various market factors, including demand, supply and competition. Since the market situation changes from 2017 to 2018 and during 2018, the use of fixed weights does not allow to capture the market opportunities in 2018, unlike the dynamic parameterization methods (Week, Month, Trimester). This observation confirms the importance of dynamically adjusting product weights in response to price changes.

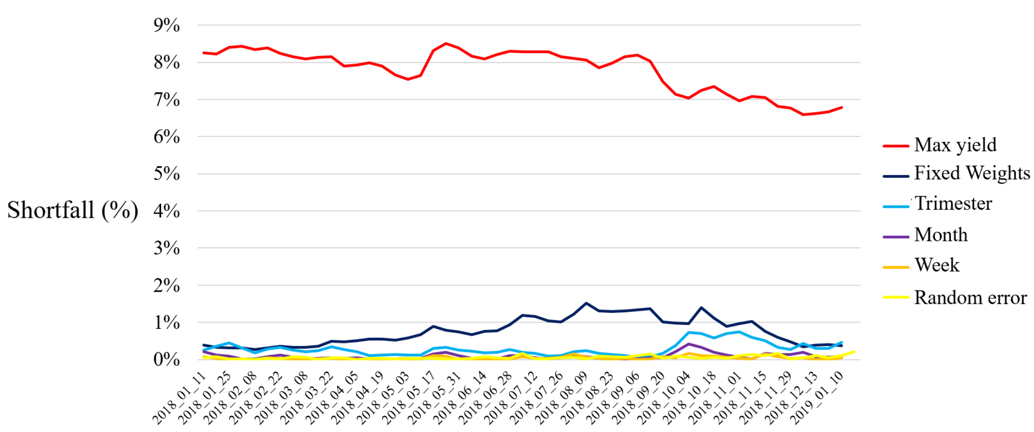

Figure 10: Weekly shortfall by parametrization method

5 CONCLUSION

In this paper, we explored the potential of price-driven methods for maximizing revenues in a sawmill. A sawmill simulator is used to compare different production control methods. The case study results demonstrate the importance of dynamically adjusting product weights in response to price changes. Compared to the common method of maximizing material yield, the price-driven methods achieve higher revenues. In addition, the results of this case study highlight the potential of anticipating selling prices.

In terms of future research directions, several hypotheses warrant exploration. Firstly, it may be pertinent to account for drying and planing delays, as these processes can span several weeks. Additionally, using machine learning to improve decision-making seems promising.

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