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Abstract. Industries with variable inputs, such as the forest product industry (FPI), the mining industry or the recycling industry, must cope with material variability, which affects both their efficiency and their ability to accurately predict output yields. In order to deal with this, the industry can use transformation processes and technologies that adapt to variability, or plan operations taking material variability into account. In the FPI, the first approach is generally used. For instance, the Canadian softwood lumber industry has adopted sophisticated transformation technologies that adapt sawing patterns to logs' and work-in-process characteristic using scanners technology that acquire accurate information about their shape. Another approach to deal with material variability is input material classification. Specific characteristics can be measured to classify input material and reduce variability within each class. However, whether the process involves logs, mining ores or recycled papers, material classification has both a value and a cost. This paper first proposes a method based on classification tree analysis to classify hardwood logs. Next, using agent-based simulation, it analyses the value of different classification strategies, from detailed, to no classification at all. Results show in the context of the Québec hardwood lumber industry that the benefit of detailed classification is offset by its cost, while a relatively simple classification strategy dramatically improves output yield at relatively low cost.

Keywords: Hardwood timber industry, material classification, classification tree analysis, agent-based simulation.

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1 Introduction

A common issue faced by many industries, such as the forest product industry (FPI), the mining industry or the recycling industry, concerns the need to make decision with unreliable or incomplete information about input material. This variability concerns many aspects of decision-making, including demand, input material attributes, cost, prices, quality, and transformation yield. On the one hand, studies have shown that more detailed and accurate information can lead to better supply chain performance (D'Amours, Montreuil, Lefrançois, & Soumis, 1999). On the other hand, flexibility and agility in manufacturing are instrumental to dealing with both input and demand variability (Kouiss, Pierreval, and Mebarki (1997), J. M. Frayret, D'Amours, Rousseau, Harvey, and Gaudreault (2007)). However, in order to become agile, it is necessary to develop advanced processes and technologies that detect and adapt to changes and variability.

This paper proposes and analyzes an approach to deal with input material variability in the context of the Quebec hardwood timber industry. In this industry, logs have unique and variable attributes. For sawmill managers, unless logs are systematically scanned and somehow tagged when there are delivered, this variability leads to information incompleteness about their status, which, in turn, leads to uncertainty with respect to their transformation. In other words, it is difficult to predict both the transformation output yield (i.e., sawn timber volume) and mix (i.e., sawn timber attributes and quality).

Traditionally, sawmills managers organize operations and procurement in order to increase total yield, based on sawn timber dimensions and quality parameters specified by the NHLA standards (i.e., National Hardwood Lumber Association). Sawmills can also produce specific timber dimension and quality according to the specific needs of their customers. Next, timber is transformed into specific secondary product components such as floors, cabinets, and palettes. This general transformation strategy assumes that most NHLA standard timber products provide adequate secondary transformation (i.e., component manufacturing) yields, instead of adapting operations to meet actual demand requirements. This results in inadequate inventory levels of products that do not meet demand expectations, and consequently, a loss of opportunity and profits due to inventory cost and discount sale.

These inefficiencies are mainly the consequence of three causes. First, the use of NHLA standards makes hardwood timber a commodity product. Therefore, the industry focuses its continuous improvement efforts on yield maximization, in order to increase production volumes. Second, the use of NHLA standards also leads the industry to ignore the specific needs of secondary transformations. In other words, first transformation is not managed in order to maximize the yields of secondary transformations, which leads to inefficient use of material and resources. Finally, logs have very different attributes with respect to their physical dimension and quality, which makes it even more difficult to accurately predict the secondary transformation yields of every single log and every single potential secondary application.

Therefore, this paper proposes a hybrid methodological approach in order to solve this issue by combining a statistical classification method of logs, and an agent-based simulation to analyse the value of different classification strategies.

2 Literature review

The forest product industry (i.e., FPI) has been extensively studied in the scientific community. The operation research and industrial engineering community has proposed many approaches to maximize output yields and lower cost in many different contexts. Rönnqvist (2003) proposes a complete review of optimization problems in forestry, as well as the most common techniques for solving them. Along the same line, Gunn (2009) proposes a review of mathematical optimization methods for forest management. These two contributions illustrate both the extent of OR applications in forestry, the efficiency of these methods and, indirectly, the potential value of quality information in decision-making.

With a focus on sawmill operations optimization, Maturana, Pizani, and Vera (2010) and Alvarez and Vera (2011) highlight the need for reliable information in the context of robust optimization and heuristic techniques applications. The need to deal with information uncertainty has also been addressed in other contexts of forestry. For instance Beaudoin, LeBel, and Frayret (2007) propose a mixed integer programming approach to support the annual harvest planning process, which uses a Monte Carlo analysis (see below) and a simple rule-based simulation in order to address information uncertainty. Similarly, Zanjani, Nourelfath, and Ait-Kadi (2009) proposed a multi-stage stochastic programming model for sawmill production planning with input materials and demand information uncertainty. The same authors developed a similar approach, which uses robust optimization for sawmill production planning with random yield (Zanjani, Ait-Kadi, and Nourelfath (2010)). These technics were proven to be efficient approaches to deal with information variability issues. However, they do not consider the impact of input material information uncertainty on secondary transformation yields, which is addressed in this paper.

Another effective tool to deal with uncertainty is simulation. Computer simulations can be used to better understand the impacts of specific decisions, policies, or systems configurations through the use of computer simulation of real systems. Computer simulations can also be used in educational settings in order to develop specific skills, in which students control part of the computer simulation variables through user interfaces. Beside spreadsheet simulation, there are four main simulation technics, including Monte Carlo simulation, Discrete-Event Simulation, System Dynamics and Agent-Based Simulation.

Monte Carlo Simulation uses, repeatedly, random sets of numbers from known probability distribution of different sources of uncertainty in order to compute the results of a mathematical model or algorithm (i.e., the system's model). From these results, the general behavior or performance of that system can be inferred. It is used in practice when the behavior of the system cannot be easily calculated analytically. Discrete-Event Simulation aims to create simulation models of queuing-type systems, in which time moves forward either by equal time increments or from one event to the next. Events and flows between the system’s components occur according to known probability distributions, which specify processing and transit times, and priority rules. Similarly, System Dynamics aims to model complex systems in order to analyze their general behavior. However, System Dynamics uses a top-down modeling approach based on stocks, flows, feedback loops and time delays, in order to simulate the complex interactions between the components of a system. In other words, System Dynamics aims to capture the ripple effect of changes to these components throughout the entire system, in order to model and study the resulting non-linear behavior of the system. System Dynamics only models the mutual dependencies between these components. It does not model the elementary interactions between the individual elements of the system, which is what Agent-Based Simulation aims to model and simulate. Agent-Based Simulation is an emerging simulation tool (Macal & North, 2006), which takes a bottom-up approach to model the individual behaviors and interactions of a system's elements, referred to as agents. Therefore, instead of modeling the relationships between the components a system, Agent-Based Simulation captures how the individual elements of a system behave with respect to their own local environment and state, and how they interact, communicate, make collective decisions, or influence each other. The Agent-Based Simulation modeling paradigm generally uses theoretical models to capture individual behaviors.

In the timber production context, Reeb (2003) and Grigolato, Bietresato, Asson, and Cavalli (2011) use Discrete-Event Simulation in order to develop production scenarios and forecast production outcomes based on attributes such as length and logs diameter. More recently, in the context of a log yard management, Beaudoin *et al*. (2012) achieve to reduce the average truck cycle time and the total distance per loader, by changing the allocation strategy, using Discrete-Event Simulation to test several configurations.

Concerning Agent-Based Simulation, Frayret (2011) presents an introduction of agent-based technology applications in the forestry sector. In the specific domain of forest product supply chain, several contributions have been proposed (Farnia et al. (2013), J. M. Frayret et al. (2007), Forget *et al*, (2008), Cid Yanez *et al* (2009), Elghoneimy and Gruver (2011)). In these applications, software agents are usually developed to simulate procurement and production planning and scheduling decisions and how they are coordinated across the supply chain in response to changing exogenous parameters. These applications are generally used to evaluate production planning methodologies or supply chain coordination technics. Again, these simulation applications are mainly concerned, so far, by forest operations and the first transformation (i.e., sawing, drying, planing). Secondary transformation operations are only modeled as randomly generated purchase orders.

Another important issue dealing with material variability is automated inspection technology. By providing detailed information about input material (i.e., trees, logs, work-in-process timber), these technologies enable the adaption of transformation operations to individual log and WIP attributes. For instance, in the softwood timber industry, scanners are used at different points in the transformation process in order to maximize productions yield according to specific price lists, which give a prioritizing value to each single type of WIP and timber piece. However, for various reasons, this technology is not used in the hardwood first transformation, although advanced applications exist in the furniture industry, which are capable of identifying knots and decay on both faces of a piece of timber in order to optimize component production.

Finally, a practical alternative approach to deal with material variability is material classification. Material classification aims to create classes of material, which attributes are similar, so the transformation of material (e.g., logs) within a class has similar output. More specifically, the characteristics of timber products made with logs of the same class are similar. Statistical analysis techniques are used to create such classes. For instance, Petutschnigg and Katz (2005) developed a non-linear model that can predict both timber performance according to log diameter and length, and the type of timber, based on historical observations. A similar procedure was used in Zhang & Liu (2006) by applying parametric and non-parametric regression methods to predict lumber volume recovery for black spruce. This technic leads to good results in small and medium sized trees. Finally, Tong and Zhang (2006) used detailed information from scanned logs in order to compute the production yields of a plant using a software simulation tool called Optitek. Optitek is a simulation tool that aims to predict yields based on log attributes and machine characteristics. This method, similar in part to the approach used in this paper, requires the scanning of a representative sample of logs.

3 Objectives and methodology

When logs are delivered to a sawmill, they are laid down in the log yard and measured in order to assess their volume and quality, for the sole purpose of paying the supplier. Then, they are sorted into different piles according to their species. This simple classification rule only allows production managers to select the logs to transform according to the most general attribute of customer demand (i.e., the species). Specific details about customers' applications are disregarded. Consequently, building on the reviewed literature, this paper aims, on the one hand, to propose a novel log classification approach based on secondary transformation yield similarities. More specifically, these similarities are based on the unit procurement cost of secondary transformation. More specifically, the first transformation of a single log is a diverging production process that leads to the manufacturing of several pieces of timber with different dimensions and quality. If used for a specific type of secondary application, these pieces of timber can be transformed into different volumes of components. Therefore, in order to produce a given quantity of a specific type of component, it takes different volume of each type of log according to their “appropriateness”. Consequently, it is theoretically relevant for the production manager of the first transformation to know what type of logs should be transformed in order to minimize the procurement volume of timber for each specific type of secondary application. However, because such detailed classification of logs can lead to high handling and sorting cost in the yard, its customer value can be offset by high first transformation cost.

Consequently, this study aims, on the other hand, to assess the performance of different levels of log class aggregation, and therefore, to measure the value of log attribute information.

3.1 General sawmill processes

Once logs are measured and valued, they are transported into different piles according to their species. This simple classification rule only allows production managers to select the logs to transform according to the most general attribute of customer demand (i.e., the species). Then, a loader takes several logs from a selected pile and puts them on the feeder of the sawing line, which contains about 20 minutes of workload. Next, they are transformed into several pieces of timber. Such a production campaign aims to transform a specific species, and not to produce specific timber for a second transformation application. The output timber is then planed, sorted according to NHLA standard, and dried before been sent to a second transformation process, which is usually carried out by other companies. Only specific classes of timber are sent. The remaining classes are sold later.

In this process, demand information is only used in order to select the appropriate standard timber products from inventory. This implies that such production campaigns (also referred to as production plans in the remaining of this work) are only planned based on the required species and not on customers' applications (e.g., furniture, panel, molding).

This approach has two consequences. The first is the general disconnection between demand and production, which is pushed to customers. The second consequence is the inability of hardwood sawmills to control production output, which leads to missed opportunities and the use of logs that are inappropriate for the required applications.

3.2 Available information

In order to develop log classes, we used actual data from a typical sample of logs. Data collection was carried out by FPInnovations. To do so, they analyzed the input logs and output products of a sawmill. Sawing is considered as a non-parametric process, which, for a given log, always produces the same output. The sample includes 240 yellow birch logs, for a population of 1900 logs transformed in a full workday of an average hardwood sawmill with two production lines in Quebec (Canada). For each log, the following attributes were known:

- The position of the log in the tree (i.e., U –up-, or B -bottom-);
- The log diameter measured under the bark at the small end;
- The number of clear faces;
- The percentage of heart wood;
- The deduction percentage of different defects in the log, such as curvature and decay;
- The log quality based on the Québec Minister of Natural Resources standard;
- The sawing time;
- The cost.

The statistical distributions of the main attributes of these logs are presented in Figure 1. These logs were cut into 2150 pieces of timbers, which were then analyzed with BorealScan (Caron, 2005). BorealScan is an industrial scanner developed by the *Centre de recherche industrielle du Québec*, which aims to optimize the use of hardwood timber for appearance wood applications. BorealScan is designed to scan the dimension and appearance of timber and anticipate its expected yield per volume for each type of secondary transformation application (i.e., foot-board produced per cubic meter of log, in fbm/m^3, McDonald and Drouin (2010); Drouin, Beauregard, and Duchesne (2010)). These secondary transformation applications are hardwood floor, wardrobe, staircase, paneling, cabinet, moulding and palette.

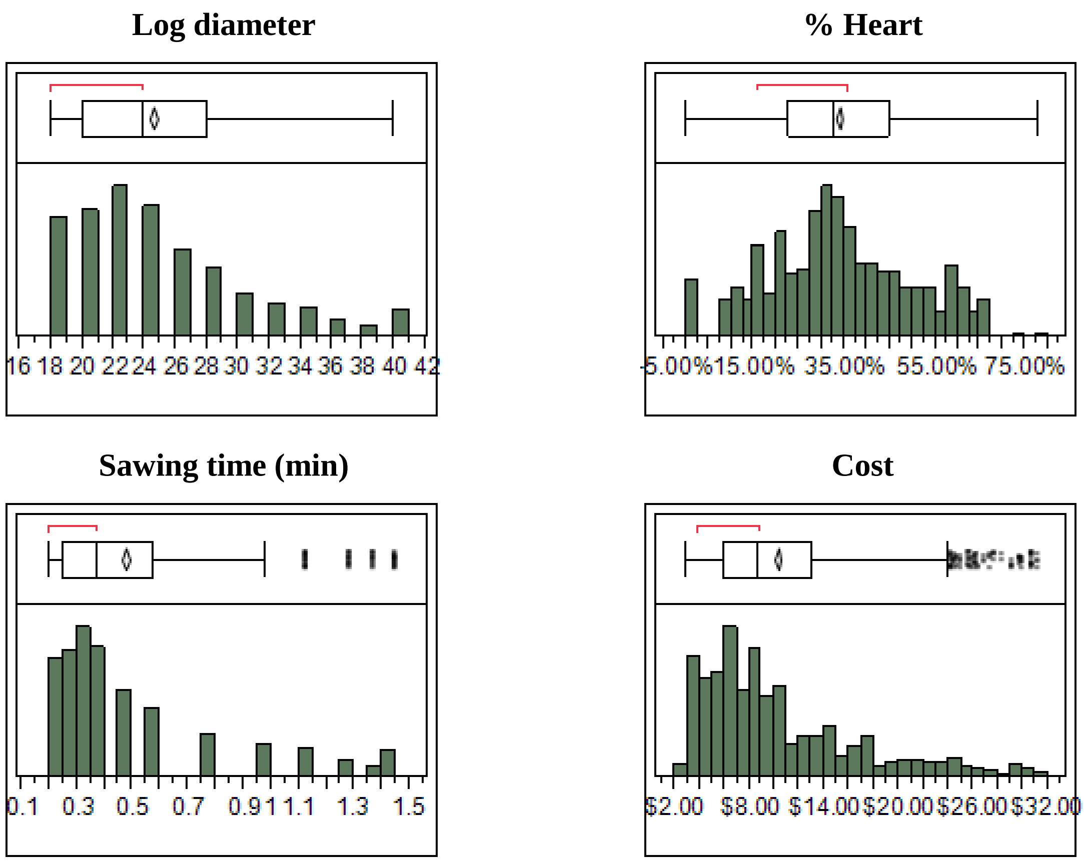

Figure 1: Logs statistical distributions of diameter, % of heartwood, sawing time and cost

Using this yield for each log and each application, and the cost of each log, we computed the unit cost of timber per 1.000 fbm (i.e., foot-board measure, 1 Mfbm) of secondary transformation component for log *l* and application *a*, expressed in $/Mfbm as follows, referred to as UC_l^a:

$$UC_l^a = \frac{C_l}{Y_{la}} \quad \text{unit cost of timber for log } l \in L \text{ and application } a \in A; \qquad (1)$$

with

L	set of all logs;
A	set of secondary transformation applications;
C_l	cost of log *l*;
Y_{la}	expected yield of log *l* for application *a*;

For each specific log, this unit cost represents the procurement cost to produce 1.000 fbm of components of a given application, if all logs had identical attributes. Because not all logs can produce pieces of timber useful for all applications, the terms useful log refers here to logs from which we obtained pieces of timber that can be used (i.e., subset L_u) for a given application (i.e., with a yield greater than zero). Next, we computed, the average procurement cost for logs $l \in L_u$ and for all application $a \in A$, $APC^a_{L_u}$ as follows:

$$APC^a_{L_u} = \frac{\sum_{l \in L_u} c_l}{n_u} \quad (2)$$

with

L_u set of useful logs;

n_u number of useful logs

The number of logs with available information and the average procurement cost per application are presented in table Table 1. Next, we identified the set of attributes to classify the logs according to the target application. To do this, we use classification trees.

Table 1: General procurement information per transformation application

	Floor	Wardrobe	Staircase	Paneling	Cabinet	Molding	Palette
# of useful logs (n_u)	240	170	179	170	240	94	226
APC ($/Mpmp)	$2,326	$3,498	$2,699	$3,664	$1,271	$6,964	$1,964

3.3 Classification trees

A classification tree is a nonlinear methodology, which uses decision rules to predict the membership of a case, to one of multiples categories based on a set of attributes called the predictor variables. In this data mining technique, the tree is constructed by partitioning the data into a tree-like structure with branches and nodes. At every node, a simple decision rule is defined by creating a linear relation between one of the independent predictor variables and the binary membership variable, which becomes the dependent variable. Here, the selection of a predictor variable at a given node was done using information theory, by measuring the Shannon entropy of every possibilities and selecting the one with the highest information gain. The number of branches depends on the type of variable (i.e., quantitative or categorical) and the algorithm used. One of the most effective and popular algorithms is the Classification And Regression Tree, CART (Breiman, Friedman, Stone, & Olshen, 1984). The partition is repeated until a pre-defined level (i.e. a fixed number of branches) or until a node is reached for which no split improves the information gain. The final nodes are known as terminals, and the resulting equations are used as classification rules.

In the dataset, the predictor variables are the logs' attributes and the dependent variables are the binary membership variables of each application (i.e., whether or not the log can be used for the application). Consequently, in order to apply this method, a classification tree must be built for each application. Since there is insufficient information for all the logs (i.e, not all logs have non-zero yield for all applications), the first step is to choose how many of the observations (i.e., logs) are relevant for each category (i.e., application). In order to do this, we divided the range of unit cost of timber per application of all logs (i.e., UC_l^a) into percentiles. This resulted in a matrix of binary values indicating whether or not the log belongs to the percentile. Since the cost C_l and yield Y_{la} for each application of all logs is known, as well as the number of logs in each percentile (Table 2), we calculated the average procurement cost $APC_{L_{pa}}^a$ of each percentile (Table 3).

Table 2: Observations (# of logs) per percentile and second transformation application

Percentile	Floor	Wardrobe	Staircase	Paneling	Cabinet	Molding	Palette
10%	24	17	18	17	24	10	23
20%	48	34	36	34	48	19	45
30%	72	51	54	51	72	28	68
40%	96	68	72	68	96	38	90
50%	120	85	89	85	120	47	113
60%	144	102	107	102	144	56	135
70%	168	119	125	119	168	66	158
80%	192	136	143	136	192	75	180
90%	216	153	178	170	239	94	226
100%	240	170	179	170	240	94	226

Table 3: Average procurement cost per percentile and second transformation application

Percentile	Floor	Wardrobe	Staircase	Paneling	Cabinet	Molding	Palette
10%	$ 788	$ 860	$ 746	$ 837	$ 599	$ 1,500	$ 535
20%	$ 876	$ 1,000	$ 822	$ 1,006	$ 652	$ 1,711	$ 666
30%	$ 941	$ 1,161	$ 914	$ 1,188	$ 698	$ 1,882	$ 782
40%	$ 1,010	$ 1,339	$ 1,019	$ 1,373	$ 735	$ 2,251	$ 899
50%	$ 1,085	$ 1,526	$ 1,146	$ 1,565	$ 769	$ 2,688	$ 1,025
60%	$ 1,167	$ 1,701	$ 1,297	$ 1,752	$ 806	$ 3,150	$ 1,154
70%	$ 1,261	$ 1,906	$ 1,475	$ 1,979	$ 847	$ 3,710	$ 1,292
80%	$ 1,378	$ 2,191	$ 1,709	$ 2,309	$ 896	$ 4,439	$ 1,418
90%	$ 1,547	$ 2,624	$ 2,674	$ 3,664	$ 1,265	$ 6,964	$ 1,964
100%	$ 2,326	$ 3,498	$ 2,699	$ 3,664	$ 1,271	$ 6,964	$ 1,964

Next, for all percentiles p and applications a, a decision tree DT_{pa} was built considering only the attributes of the logs in the selected percentile (i.e., $l \in L_{pa}$, with L_{pa} being the subset of logs of percentile p for application a). The resulting equations at the terminal nodes were used to predict the membership of all logs in the database to each application. The actual membership of log l to application a and percentile p is noted m_{lpa} (i.e., m_{lpa}=1 if $l \in L_{pa}$, 0 otherwise), while the prediction of m_{lpa} is noted $\widehat{m_{lpa}}$. In order to measure the quality of this learning process, we introduced the binary variable i_{lpa} and the prediction accuracy Π_{pa} of the decision tree DT_{pa} for percentile p and application a, as follows:

$$i_{lpa} = \begin{cases} 1 & if\ m_{lpa} = \widehat{m_{lpa}} \\ 0 & otherwise \end{cases} \tag{3}$$

$$\Pi_{pa} = \frac{\sum_l i_{lpa}}{|L_{pa}|} \tag{4}$$

This indicator allows us to evaluate the learning accuracy for each decision tree DT_{pa}, and its associated threshold (i.e., the value of p), and each application. The Π_{pa} of all the computed trees (i.e., for all applications and thresholds) is presented in Table 4, showing the high prediction efficiency of the methodology at every level. However, because the log sample used to build the trees did not include enough logs, we were not able to measure the overall prediction accuracy using an independent log sample. This aspect remains for future work.

The objective of this step is to find accurate classification rules (i.e., decision trees) that simultaneously optimize secondary transformation yield and procurement cost. However, as presented in Table 4, high learning accuracy is linked to high threshold p (i.e., with larger log sample), which has also a higher procurement cost (see Table 3). Therefore, the challenge is to find the right percentile per application, with low procurement cost and high accuracy. Appendix 1 presents the learning accuracy versus the average procurement cost.

Table 4: Learning accuracy per percentile and transformation application

Percentile	Floor	Wardrobe	Staircase	Paneling	Cabinet	Molding	Palette
10%	85%	95%	90%	93%	90%	95%	90%
20%	80%	88%	86%	88%	81%	92%	89%
30%	71%	86%	85%	85%	77%	90%	82%
40%	73%	79%	81%	82%	69%	89%	82%
50%	71%	75%	82%	80%	68%	88%	78%
60%	71%	78%	77%	79%	72%	83%	76%
70%	74%	78%	76%	77%	83%	80%	75%
80%	80%	80%	82%	80%	89%	76%	79%
90%	100%	85%	90%	85%	100%	75%	94%

In order to avoid small log samples, which can lead the procedure to exclude several relevant logs, we consider only percentile higher than 20%. In order to select the most appropriate classification tree for each application, we choose the highest learning accuracy beyond 20% with the lowest average procurement cost. Table 5 presents the chosen thresholds and the main indicators. Since the number of independent variables is relatively big, the number of branches found by the classification tree algorithm can also be large, however we tried to keep a relatively low number of branches in order to reduce the complexity of the methodology, granted this represents a loss in terms of both learning and prediction accuracy. An example of the classification trees is presented in the Figure 2.

Once a classification tree has been found for each application, we calculated the procurement cost per application based on the logs resulting for the use of these classification trees. In other words, since the learning accuracy of these trees is lower than 100%, the logs predicted to be useful for an application is different from the log sample used to build the trees. Therefore, a different average procurement cost is to be expected. Table 6 presents the final sample size and average cost per application once the classification trees are applied.

Table 5: Learning accuracy and average cost of chosen percentile per application

	Floor	**Wardrobe**	**Staircase**	**Paneling**	**Cabinet**	**Molding**	**Palette**
APC ($/Mpmp) before classification	$2,326	$3,498	$2,699	$3,664	$1,271	$6,964	$1,964
Chosen threshold	40%	30%	30%	40%	50%	50%	30%
# of logs in sample	96	51	54	68	120	47	68
Classification accuracy	73.3%	85.8%	84.6%	82.1%	67.5%	87.9%	81.7%
APC ($/Mpmp) of sampled logs	$1,010	$1,161	$914	$1,373	$769	$2,688	$782

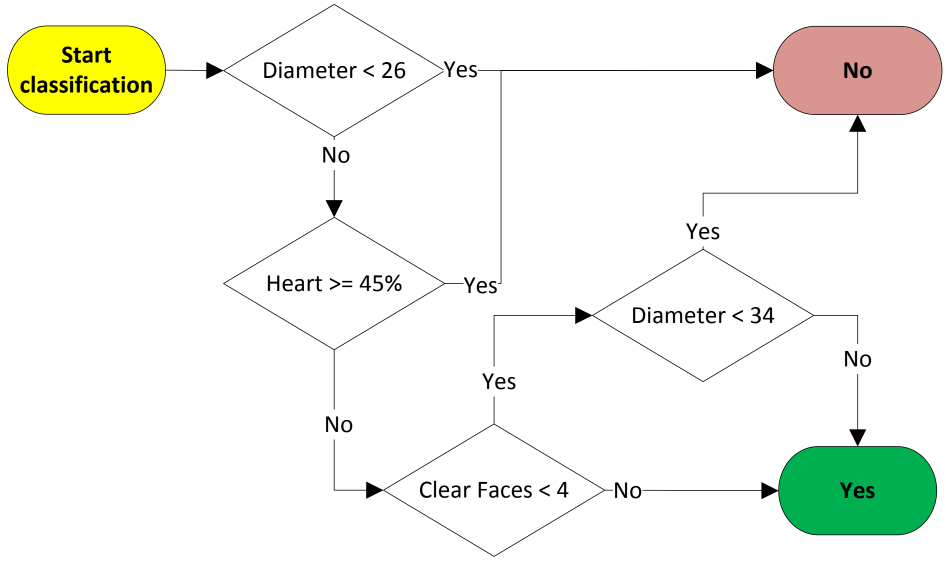

Figure 2: Example of a classification tree for the application wardrobe

The average cost reduction after classification shows that in all cases at least a 30% savings can be achieved. Based on these classification rules, we build a joint classification grid that can be used during the log reception process (see Annexe 2) to help operators classify logs according to the production campaign. In other words, this grid allows them to select the most cost effective logs to transform for specific secondary applications.

Table 6: General class characteristics for each application

	Floor	Wardrobe	Staircase	Paneling	Cabinet	Molding	Palette
APC ($/Mpmp) before classification	$2,326	$3,498	$2,699	$3,664	$1,271	$6,964	$1,964
Selected percentile	40%	30%	30%	40%	50%	50%	30%
# of branches	6	4	6	4	5	5	5
# of logs	109	53	44	53	72	26	78
Classification accuracy	75.4%	85.8%	87.5%	82.1%	67.5%	87.9%	81.7%
APC ($/Mpmp)	$1,594	$1,762	$1,216	$1,744	$866	$1,987	$1,235
Cost reduction	31.4%	49.6%	55.0%	52.4%	31.9%	71.5%	37.1%

4 Simulation and experimentation phase

This section presents an agent-based simulation study of various strategies to implement the classification rules identified in the previous chapter. Because these rules have been developed for each application, they may be lead in practice to complex sorting and yard management processes. Therefore, based on their similarity, these classes can be aggregated from 7 classes (i.e., one rule per application) to 1 class (i.e. no classification rule). Consequently, we developed seven aggregation strategies that needed to be evaluated. This chapter first presents the yard management and sawing processes as it is generally implemented in hardwood sawmills. Next, the agent-based simulation model is presented, as well as the seven aggregation strategies.

4.1 Yard management and sawing processes

The processes studied in this project include four main steps: log delivery; log handling in the yard; log feeding; and timber storage after sawing. First, trucks arrive at the reception area, carrying a load of 80 to 120 logs. During this step, logs are placed on the ground and measured for payment purpose. Next, a loader takes a small batch and transports them to specific piles in the log yard. As mentioned before, this basic yard management approach only segregates log species. Third, when the sawmill inventory buffer is below a specific threshold, the loader takes a batch of logs to the sawing feeding area. Finally, once logs are sawn, timber is temporarily stored until they are delivered to their customer.

The proposed simulation model considers the sawing process as an aggregated and divergent transformation process, which always transforms logs in a similar manner (i.e., a specific log will always produce the same mix of timber). As mentioned earlier, because different classification rules can be generated through different class aggregations, their practical implementation in this basic yard management process requires several adjustments to both yard management operations and layout configurations. Similarly, because these configurations involve different handling processes and transportation distances, their costs are not equivalent. Therefore, in order to identify an efficient log yard layout configuration and log class aggregation strategy, as well as to evaluate the impact of log handling on production, we developed an agent-based simulation of a log yard and sawmill. This simulation model is described in the next section.

4.2 Simulation model

The general architecture of this model is presented in Figure 3, which represents the basic process. However, information flows are slightly more complex to simulate the class aggregation strategies, which require log sorting to be coordinated with the production campaign. This section first presents in a general manner the model architecture, as well as the physical layout implemented. Next, the different agents and their function are described. Finally, the experimental design and the different log class aggregation strategies are presented.

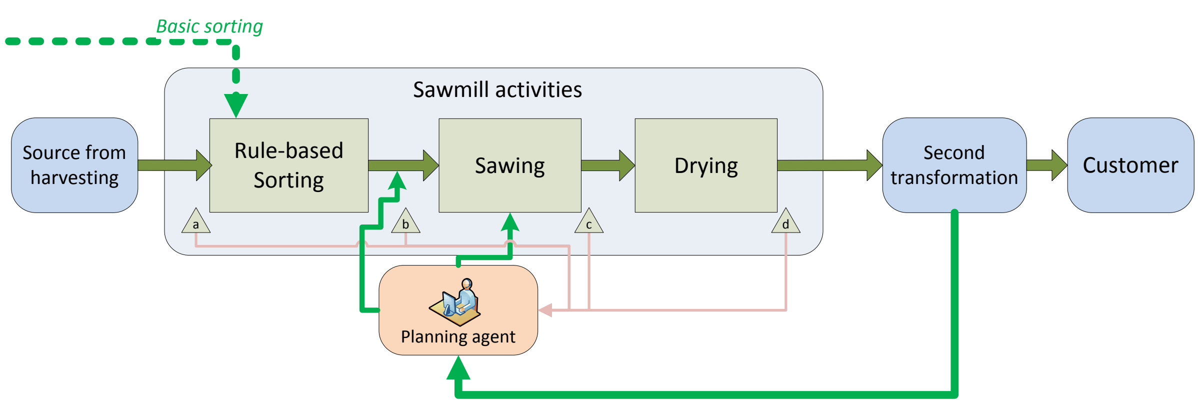

Figure 3: Basic sawmill process model

This simulation model was built using AnyLogic, a hybrid discrete-event and agent-based simulation platform. The development of the model was inspired by a real hardwood sawmill in the province of Québec, with a reception area, a log yard and a sawmill, as described previously. Handling distances are therefore roughly equivalent to that of the real sawmill.

4.2.1 Agents definition

Truck agents

Truck agents are responsible for delivering logs to the sawmill. They are simple reactive agents. Every truck agent has a similar transportation capacity. However, the mix of logs they deliver is different. In order to simulate a realistic procurement of various logs, logs are randomly chosen from the initial database containing 240 log, resulting in a dynamic mix of logs for each truck.

Loader agent

Loader agent carries out two tasks. The first task is to unload trucks, while the second is to sort logs at the receiving area. Concerning sorting, the loader use the classification grid developed in Section 3. Since all the attributes are measured at the reception of the logs in order to know their price, we assume that once a log is valued, the grid can be simultaneously used to identify the applications the log can be used for. According to the active aggregation strategy, these applications can also be merged together to create families of application (see further). The aggregated classes are then compared with the active production campaign. If there is a positive match between the log and the campaign, the log is temporarily placed in a pile with similar logs dedicated to the production campaign. Otherwise, it is temporarily placed in a different pile according to its potential application and the classification strategy.

After this pre-sorting process, the loader brings every pile of logs in batch of 5 to 10 to their final pile in the log-yard (storage area), using the same classification strategy. In the mean time, if the sawing process feeding inventory (i.e., the feeder) is below certain level (i.e. 20 minutes of workload), logs are transported directly to the feeder instead the storage zone.

Finally, loader agents are also responsible for transporting logs to the sawmill agent. Since all logs have been previously classified according to a specific application (or group of applications), one pile becomes the main source of logs for the sawmill according to the production campaign. Every time a feeding order is triggered (i.e., the sawmill inventory is below a certain level), the loader is responsible to feed the buffer with logs from this pile. If the pile is empty, the loader brings logs from the nearest alternative pile.

Sawmill agent

Like the truck agent, the sawmill agent is a simple reactive agent, which aims to emulate, in an aggregated manner, the sawing process. Because sawmills are currently managed to process logs in only one manner, each log leads systematically to the same mix of timber pieces. However, because logs are different, the resulting mix of timber is different for each log. Therefore, we used the data from the transformation of the initial log sample in order to create a large transformation matrix that describe the input-output relationship of the entire sample, as well as the processing time for each log according to the diameter. Thus, the role of the sawmill agent consists in simply transforming the logs brought by the loader into various pieces of timber.

Next, we simulate a week of production that follows a sequence of production campaigns (i.e., a series of 1 to 3 secondary applications), which we refer to as a production plan. Production plans do not affect the function of the sawing agent. They only affect the loader agents, which classify the logs according to the active production campaign. These production plans are exogenous parameters developed mainly to evaluate the different log yard configurations in all possible production settings. Finally, the sawn timber is classified according to NHLA standard, and performance indicators are computed for comparison purpose.

4.2.2 Log yard layout design

This study is inspired by an actual sawmill in Quebec. Since the log yard is where most activities take place, the proposed layout models are based on the log yard configuration of that sawmill. This log yard is a terrain with an irregular geometry surrounding the sawmill. In order to evaluate various classification strategies, we developed several log yard configurations and handling networks that represent each of the tested configurations. Each of these configurations was defined for a specific classification strategy. The next section describes the experiments carried out to evaluate the classification strategies.

4.3 Experimental design

In order to measure the value of log attributes information, we designed a set of experiments, which aims at emulating an extended range of production settings and evaluate all classification strategies within these settings. In order to create a first reference to which every configuration can be compared to, we also develop a reference simulation model using the basic layout configuration and classification strategy. For simplification purpose, and because we only had data for yellow birch, this experimental design also only considers one single species, which represents a limit of the study. However, it is not unusual for a sawmill to process only a single species during a week of production, which is the length of the simulation horizon.

The model simulates a 5-day period, with working shift from 8AM to 5PM, two breaks of 15 minutes, and one lunch hour at noon. The modeled sawmill uses one standard loader agent at the reception area, with a maximum capacity of 15 logs per charge. The sawmill has one production line, for a production capacity of 1000 logs. For comparison purpose, we computed the total yield, the yield of each target application, the total procurement cost of the transformed logs, the ratio between yield and cost, and finally the utilization rate of the loader.

4.3.1 Initial log inventory

Using the distribution of the initial log sample, we developed a random function to create three initial stock levels: 0, 12,000 and 24,000 logs. According to the sawmill average output, these inventory levels represents: no inventory, two weeks and four weeks of work, which is common. We also classified these logs and located them in the log yard according to the considered classification strategy. This process was carried out outside the simulation horizon in order to measure only the real loader utilization during the receiving and classification process.

4.3.2 Production plan generation

Sawmills' operations are generally organized by campaigns in a weekly manner, in order to meet the specific order for secondary transformation customers. In other words, a week is divided into at most 3 sequential campaigns of production, which represent the production plan of the week. The minimum length of a campaign is half a day, and the maximum is 5 days. Because each campaign can be set to produce timber for 1 of 7 possible types of application, there is a limited number of possible production plans. If a typical week can transform up to 3 products, the total number of scenarios is 259 (${}_7P_1$ + ${}_7P_2$ + ${}_7P_3$). However, since the palette application has a very low demand and only use low quality logs, no production campaign is normally allocated for this application. It is rather a by-product of log transformation. Nevertheless, because all logs must be transformed, including low quality logs that can only produce palette timber, in our simulation model, we allocated the last time slot of the week to producing palette timber using low quality logs (i.e. Friday afternoon). This also guaranties that classification does not improve performance based on the skimming of low quality logs. Consequently, the total number of scenarios is 156 (${}_6P_1 + {}_6P_2 + {}_6P_3$), as presented in Figure 4.

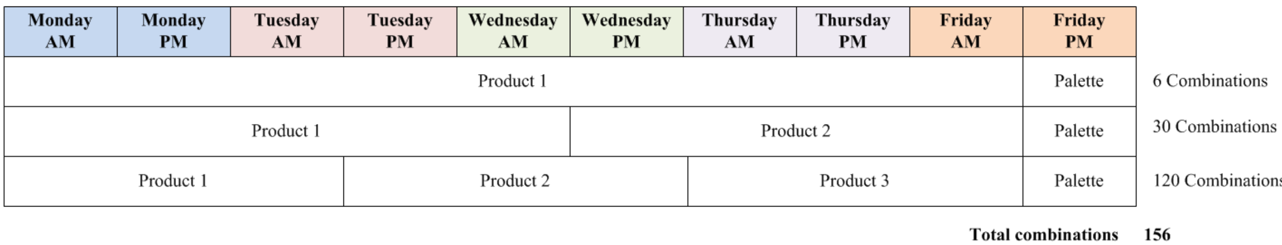

Figure 4: Production plan possible configurations

4.3.3 Classification strategies

In order to design classification strategies, we develop a process to aggregate several of the 7 initial classes (one per application) to obtain fewer classes. To do so, we analyzed the initial database and calculated the yield correlation between these classes (see Table 7).

Table 7: Correlation matrix of logs yield in each secondary application

	Floor	Wardrobe	Staircase	Paneling	Cabinet	Molding	Palette
Floor	1.000	0.320	0.380	0.320	0.879	0.307	-0.041
Wardrobe		1.000	0.873	1.000	0.631	0.941	-0.063
Staircase			1.000	0.873	0.720	0.812	-0.040
Paneling				1.000	0.631	0.941	-0.063
Cabinet					1.000	0.594	-0.024
Molding						1.000	-0.039
Palette							1.000

Many similarities can be observed. For example, the Wardrobe, Paneling and Staircase applications have a perfect, or near perfect match, meaning that the same logs can be used for any of these applications. Along the same line, the logs that are appropriate for these high value applications are not appropriate for lower value applications such as Palette. Next, to identify which class should be aggregated with another, we analyzed the correlation matrix and identified either the class with the least correlation, and created a new class, or the class with highest correlation and aggregated these classes. This process is illustrated in the next paragraph. Note that this aggregation strategy does not guaranty optimality, and other strategies exist.

4.3.4 Application of the classification strategies

The first classification strategy is to have a class per application with a total of 7 classes. Next, because Palette has the least correlation with any of the other applications, a second classification strategy can be to separate Palette from the other applications, and create a 2-class strategy. For a third strategy, we aggregated Floor and Cabinet into a single class. Keeping a separate class for the Palette, this strategy has 3 classes. For a fourth strategy, we use the third strategy and created a separate class for Molding. At this stage, we realized that the class for Floor and Cabinet contained too many logs. Therefore, for a fifth strategy, we separated Cabinet from this group, while keeping the same four other classes. For a sixth strategy we separated Staircase from the larger class group. These strategies are presented in Appendix 3. The next Section describes the different log yard layouts that were developed according these strategies.

4.3.5 Layout Strategy

Once the classification strategies classes were developed, we defined for each of them a specific layout configuration. In order to do that, using the distribution of the log sample, and therefore the volume of logs in each category, we first divided the yard layouts in seven zones to be allocated to specific log classes. Next, we developed a unified grid with specific applications per zone for each classification strategy, as presented in Table 8. Each of these 7 strategies was simulated with all 156 production plans, for a total of 1,092 combinations, with 10 replications and 3 initial stock scenarios for a total of 32,760 experiments. The results are presented and analyzed in the next section.

Table 8: Aggregation strategies applied to the layout zones in the log-yard

Strategy	Zone 1	Zone 2	Zone 3	Zone 4	Zone 5	Zone 6	Zone 7
1			Floor, Wardrobe, Staircase, Paneling, Cabinet, Molding, Palette				
2			Floor, Wardrobe, Staircase, Paneling, Cabinet, Molding				Palette
3	Floor, Cabinet		Wardrobe, Staircase, Paneling, Molding				Palette
4	Floor, Cabinet		Wardrobe, Staircase, Paneling		Molding		Palette
5	Floor		Wardrobe, Staircase, Paneling		Molding	Cabinet	Palette
6	Floor		Wardrobe, Paneling	Staircase	Molding	Cabinet	Palette
7	Floor	Wardrobe	Paneling	Staircase	Molding	Cabinet	Palette

5 Results and analysis

For each simulation run, we computed four key performance indicators in order to compare the general results. These performance indicators are:

1. The total first transformation yield;

2. The anticipated production yield;
3. The ratio between the anticipated yield and the total procurement cost;
4. The utilization rate of the loader.

5.1 Performance analysis

Once the results dataset were generated, data from the ten repetitions were averaged. The 156 production plans were also analysed by considering the number of production campaign (i.e. 1 to 3). Every indicator was also analyzed for each aggregation strategy (i.e. 1 to 7), and for different level of initial inventory (i.e. 0, 12,000 and 24,000 logs). The results are presented below.

5.1.1 Total first transformation yield

The first indicator is the total first transformation yield generated for each scenario. In this case we found that when the initial inventory is zero, the total production yield is reduced when a sorting strategy is introduced. This happens because the new log sorting and handling process increases loader utilization, which becomes a bottleneck (Figure 5).

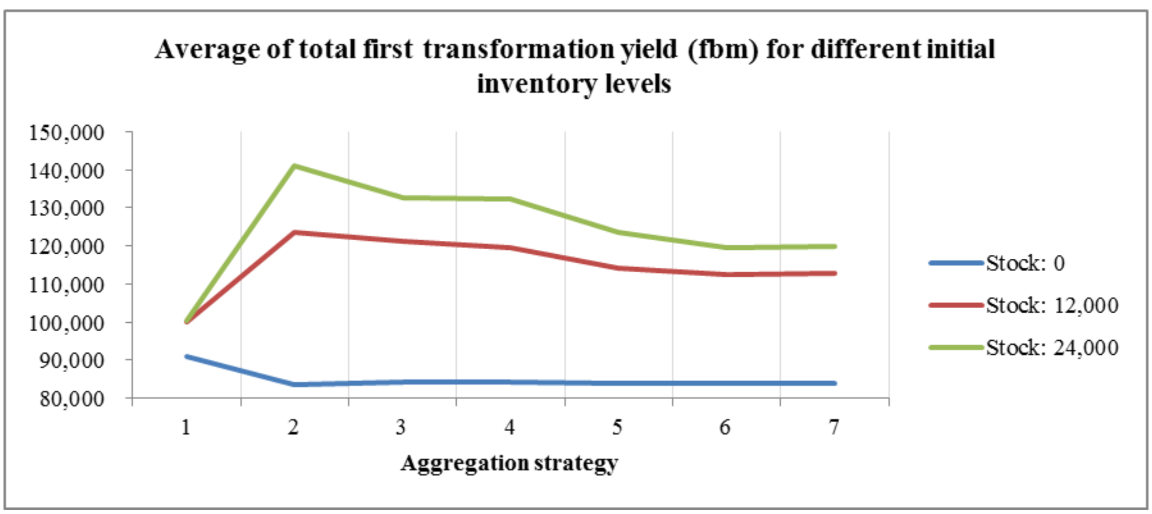

Figure 5: Total first transformation yield (fbm) per initial stock and strategy

When the initial inventory is positive, sorting increases yield by 8 to 20%. The peak yield level is reached with two piles (i.e., 2-class strategy). This suggests that only by separating the logs belonging to the Palette application, it is possible to achieve higher first transformation yields. Other strategies also exclude Palette application logs; however, they require more handling.

The analysis of this yield, for different number of products in the production plan, leads to similar conclusion when sorting is introduced (Figure 6). Similarly, we can also observe that the yield increases when more product types are produced (from 1 to 3). This improvement is linked to the increased effectiveness of classification strategies for a mix of products. Indeed, since classification requires predefined zones to store the logs per applications, only one pile is dedicated to feed the sawing process. Consequently, less handling is expected.

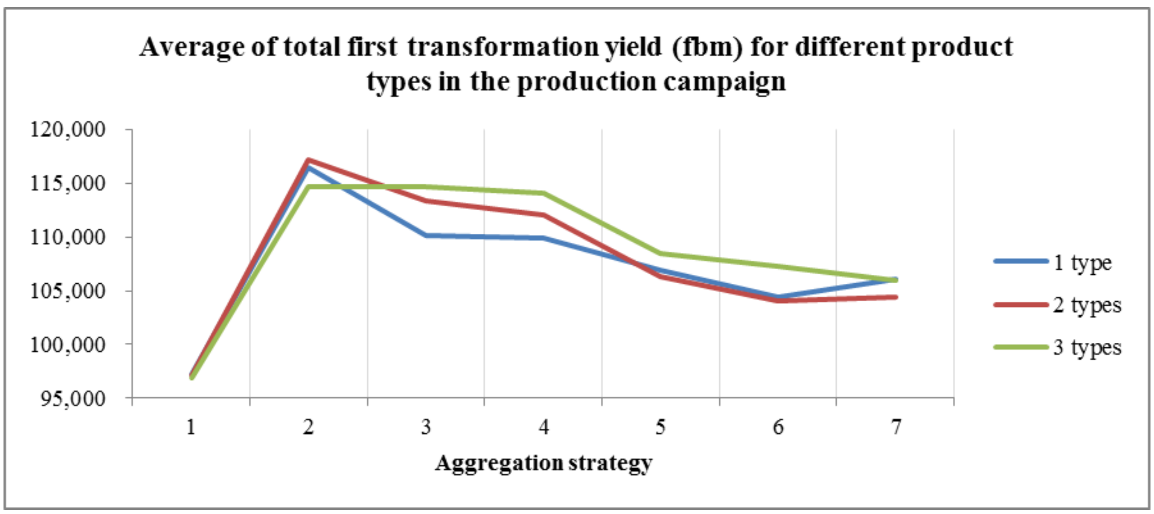

Figure 6: Total first transformation yield (fbm) for different product types in the production campaign

5.1.2 Anticipated production yield

The anticipated production yield is the volume of timber produced in each campaign for the corresponding secondary application. For this indicator, we observe that if there is no initial inventory, sorting has no impact on yield since the same logs are transformed in all scenarios. However, with initial inventory, the anticipated production yield increases by 28% on average, because of the ability of the system to use previously delivered logs (Figure 7). The anticipated production yield is also affected in similar proportion with respect to the number of product types in the production plan (Figure 8). Again, the indicator shows that the use of sorting strategies has a better performance in presence of a mix of products in the production plan, with an average increase of 2.9% when three product types are transformed instead of one.

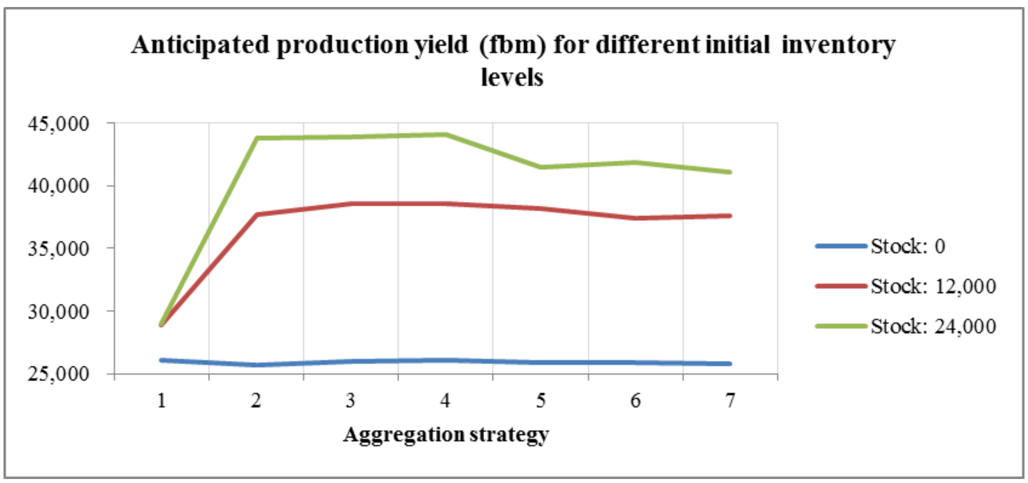

Figure 7: Average anticipated production yield (fbm) for every strategy and inventory level

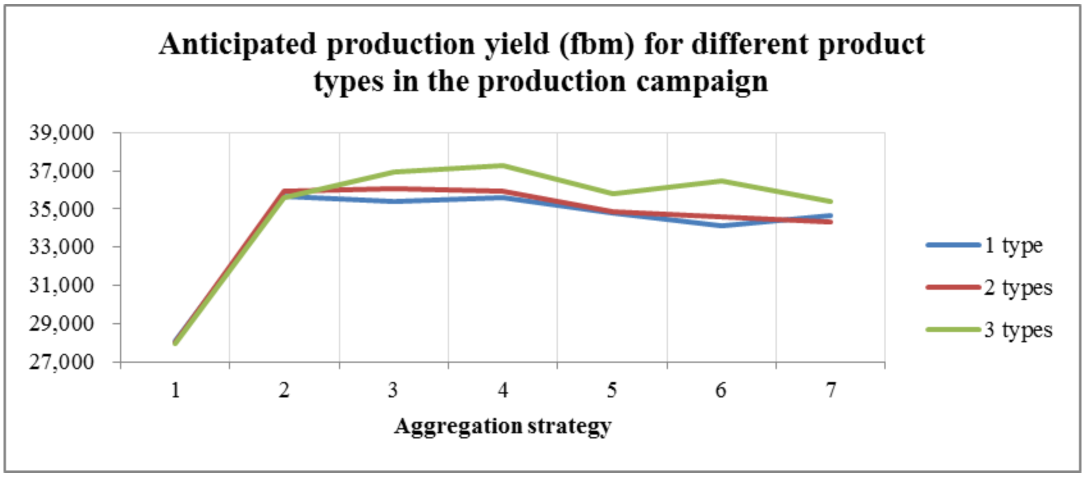

Figure 8: Average anticipated production yield (fbm) for different product types in the production campaign

5.1.3 Ratio between the anticipated yield and the total procurement cost

With the selection of more appropriate logs to transform for any secondary application, one expects to reduce procurement cost for a given volume of component produced. In order to validate this important benefit, we propose to study the ratio between the total procurement cost and anticipated secondary transformation yield ($/fbm). This indicator provides a measure of the total expenses for producing secondary transformation products.

The results show an average reduction of 12% of the ratio with sorting (Figure 9). Moreover, results show that sorting strategies with more classes have lower ratios. In other words, increased classification can lead to lower procurement cost with respect to the second transformation sector. Similarly, as expected, the indicator also shows that lower ratios are achieved when sorting is applied to production plans with several types of products, with an average reduction of 15.7% when three types of products are present in the production campaign (Figure 10).

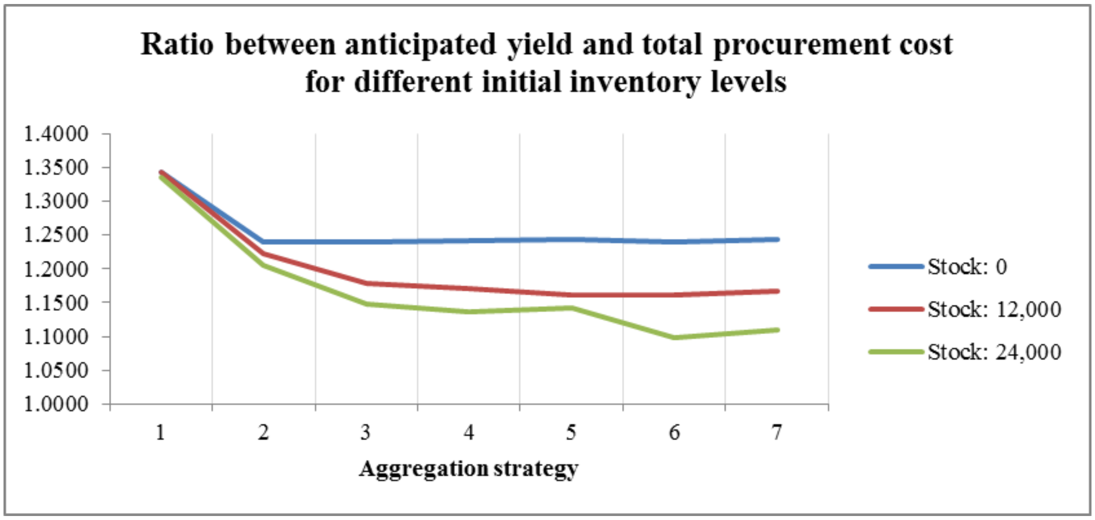

Figure 9: Ratio between anticipated yield and procurement cost for different initial inventory

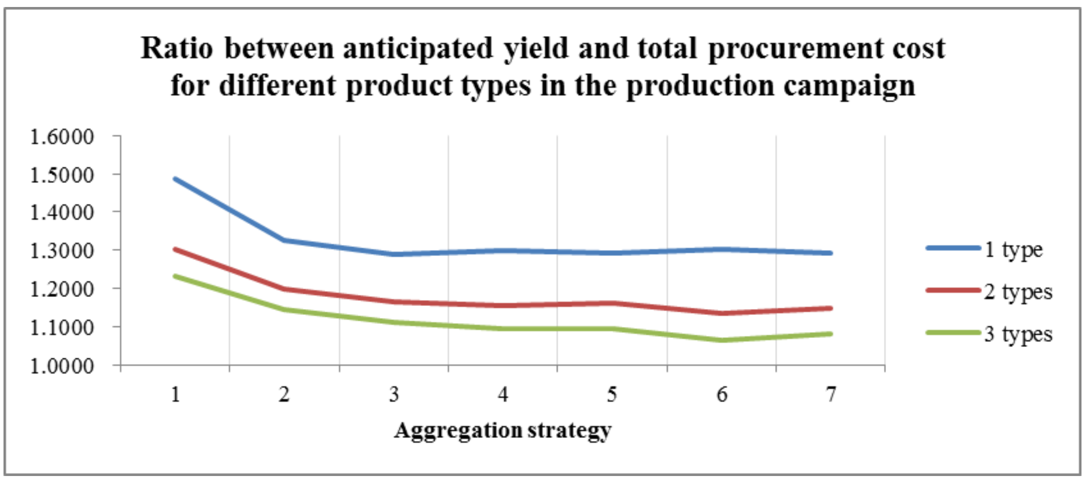

Figure 10: Ratio between anticipated yield and procurement cost for different product types in the production campaign

5.1.4 Loader utilization

Concerning loader utilization, the introduction of a sorting strategy represents an average increase of 37% of the loader utilization. This result is a logical consequence of the log-yard management and log handling (Figure 11). When the initial inventory is high and sorting involves many classes, loader utilization can increase by almost 100%, which means the loader is traveling all the time, incurring in higher utilization and maintenance costs.

Finally, Figure 12 compares loader utilization against the number of product types in the production campaign. In this case, we found that the product mix in the production campaign does not affect loader utilization.

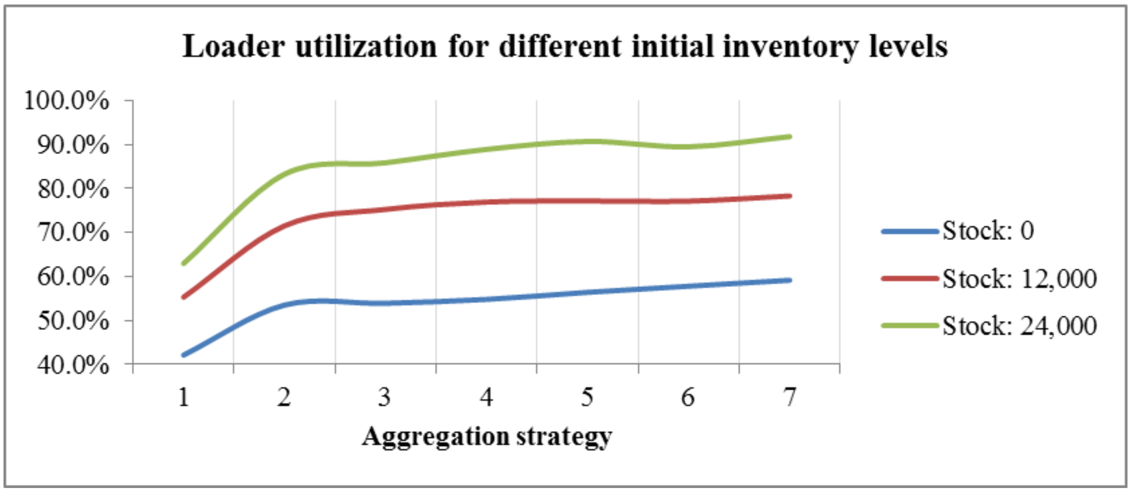

Figure 11: Loader utilization for different initial inventory levels

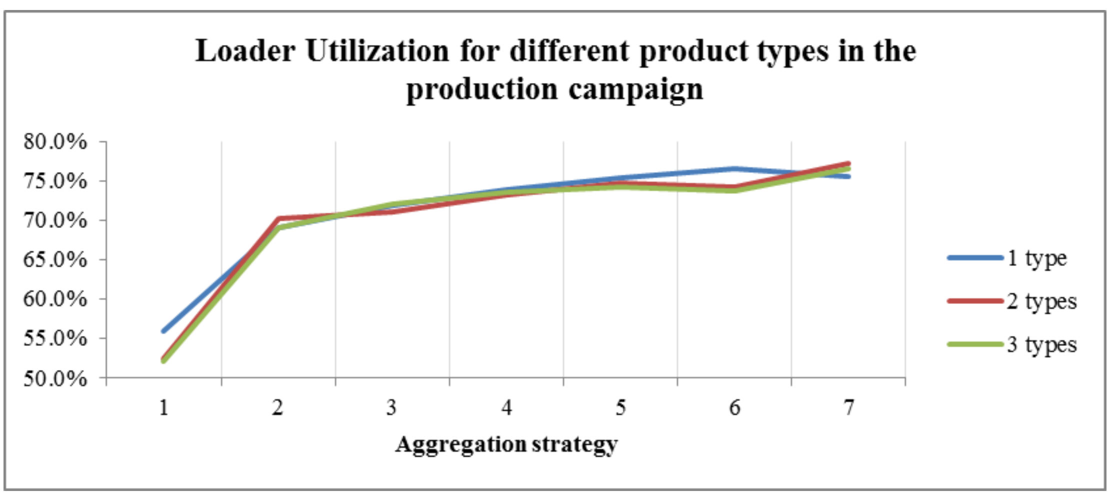

Figure 12: Loader Utilization for different product types in the production campaign

5.2 Results analysis

With the results of the simulation experiments, we found that the presence of a classification strategy can increase the total first transformation yield by 8 to 20%, as well as the anticipated volume of secondary transformation products by 28%. We also found that the use of classification strategies is more effective when the production campaign has more product types, which tends to lead to the conclusion that log classification might be necessary for a sawmill to become more customer-driven and agile. Along the same line, in all the measured indicators, the presence of initial inventory improves the results.

Although an average procurement cost increase of 11% has been observed with sorting, a higher production yield is also expected. The ratio between the total procurement cost and the anticipated yield ($/fbm) shows an average reduction of 12% when log sorting is used. This indicator also shows that sorting strategies of higher complexity (more sorting classes) has better results, meaning that a better initial classification can lead to lower procurement cost for the second transformation sector. However, loader utilization is also considerably affected. When sorting is implemented, an average of 37% increase is observed. In general, sorting strategies with 4 classes and more, lead only to the marginal contribution of the yield, while loader utilization increases more rapidly.

In conclusion, this study shows that the used of a classification strategy improves sawmill operations and performance. However, the benefits of complex classification strategies involving the use of many different classes can become quickly offset by increased loader utilization.

Furthermore, it is impossible to generalize these results to other industrial applications. Many industries must deal with variable raw material/input. For instance, recycling industries, such as the recycled pulp and paper industry, deal regularly with variable inputs. However, this study presents a basic methodological approach to evaluate to benefits of input material classification to any sectors.

6 Conclusion

This research proposed a new application and combination of known methodologies to deal with input uncertainty in terms of quality and performance. This study was specifically applied to a hardwood sawmill in Quebec (Canada), which transform yellow birch logs into pieces of timber for various secondary transformation applications. These logs were initially measured and their output transformation was analyzed with an industrial scanner in order to anticipate their yield for various secondary transformation applications. This methodology implies the development of a classification grid that can be used during the receiving process to classify raw material. It was demonstrated that this classification grid can lead to significant secondary yield performance improvement (i.e., 28%). However, this high quality production increase is offset by the increase in the resource utilization (i.e. loader), which increases its average utilization by 37%.

The procurement cost also increases by an average of 11% as a consequence of higher production. However, the ratio between the procurement cost and the secondary yield shows an average reduction of 12%, meaning that the total useful yield increased more than the procurement cost. In this research, we did not analyse this financial trade-off and further analysis is required. Finally, this study shows that a large portion of this improvement can be achieved by a classification strategy that involves much less classes. Indeed, after a large number of experiments, we found that using only 3 classes, instead of 7, can achieve more than 90% of this improvement, meaning an increase of 34% of loader utilization and 14% in procurement cost but also, an increase of 29% in the anticipated production yield (fbm).

6.1 Further work

Although this result is encouraging for sawmill managers, the tested log yard layouts were not optimal. Log yard layout design is a complex optimization process. Research must be done to improve how log yards are designed and operated. We also suggest a more detailed study of the financial benefits of the project, to compare whether the new approach results are sustainable. Also, the introduction of a new loader might also contribute to the result. Future work also includes the analysis of other species in order to develop new specific classification grids.

Future work also includes the adaptation of the proposed methodology to other sectors, such as the recycling of industrial and domestic wastes.

Acknowledgements

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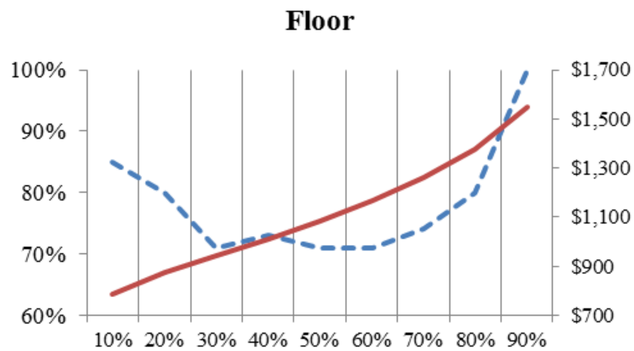
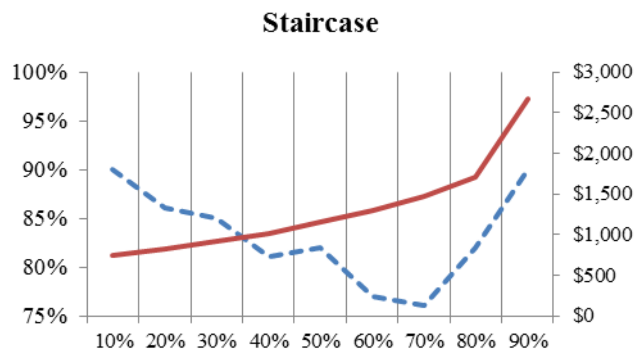
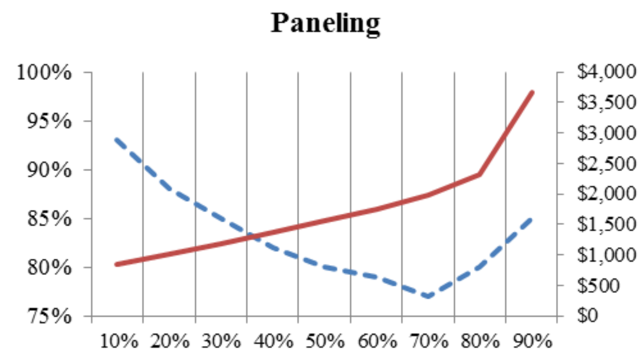
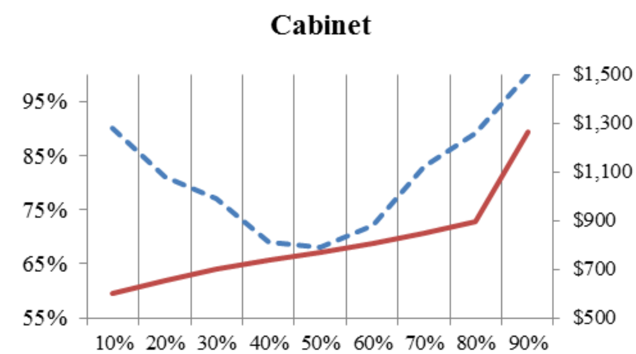
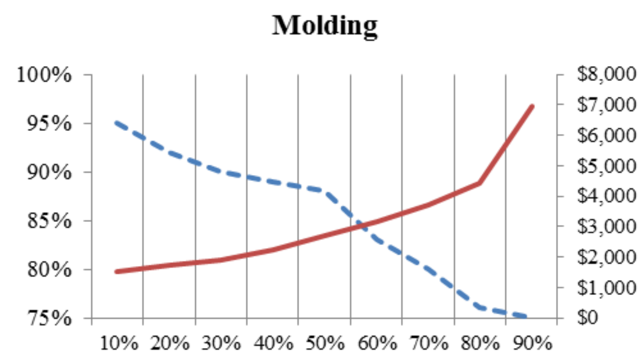
Annexe 1 – Classification tree accuracy vs. average cost per application

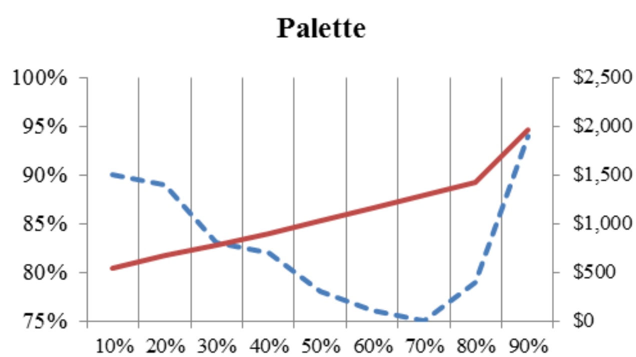


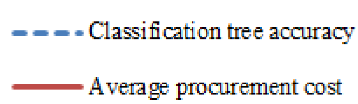












Note: The right axe belongs to the accuracy and the left to the procurement cost

Annexe 2 – Joint classification grid per transformation application

	Floor			Wardrobe		Staircase		Paneling		Cabinet		Molding	Palette	
Position	U		B				B			U	B			
Minimal diameter	>= 32cm		< 32cm	26 to 32 cm	>= 34 cm	26 to 30 cm	>= 32 cm	26 to 32 cm	>= 34 cm	>= 26 cm	>= 38 cm	>= 22 cm	<= 22 cm	24 to 26 cm
Number of clear faces	0 or 1	>= 2	>= 3	4	0 to 3	4	3 or 4	4	0 to 3			4		
Heart's size at point's end				< 45%		< 28%		< 45%				< 46%		>= 32%
% of deduction MRN			> 12%							17%		< 7%		

Annexe 3 – Aggregation strategies

# of classes	Applications in each group
1	All applications in the same group
2	G1: Floor, Wardrobe, Staircase, Paneling, Cabinet and Molding G2: Palette
3	G1: Floor and Cabinet G2: Wardrobe, Staircase, Paneling and Molding G3: Palette
4	G1: Floor and Cabinet G2: Wardrobe, Staircase and Paneling G3: Molding G4: Palette
5	G1: Floor G2: Wardrobe, Staircase and Paneling G3: Cabinet G4: Molding G5: Palette
6	G1: Floor G2: Wardrobe and Paneling G3: Staircase G4: Cabinet G5: Molding G6: Palette
7	A pile for each application