PERFORMANCE EVALUATION OF THE LEAST-COST LUMBER GRADE-MIX SOLVER

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Abstract. The least-cost lumber grade-mix problem is of high economic interest to industry. Finding the minimum grade or grade-mix for a given cutting bill can save a company large sums without incurring additional costs. To academia, the least-cost lumber grade-mix problem is of significance due to its complexity and the difficulty to obtain near optimal or optimal results.

An earlier study used a new statistical approach to solving the least-cost lumber grade-mix problem. A five-factor mixture design was used to create a lumber grade-mix response surface, on which the minimum cost point is determined. However, this model's merit has never been assessed so far. This study compares the performance of the new statistical model with solutions derived from the widely used OPTIGRAMI 2.0 least-cost lumber grade-mix program.

Results revealed that the statistical optimization approach provides better overall solutions for both raw material and total production cost scenarios. For 9 of 10 cutting bills tested, the statistical model found lower-cost solutions compared with those provided by OPTIGRAMI 2.0. The maximum savings found was \$70/m^3 of raw material (cost savings of 9%) and \$105/m^3 when processing costs were included (cost savings of 10%). Thus, the new model has the potential to help wood products manufacturers decrease their material and processing costs. This model has been incorporated into ROMI, the USDA Forest Service's rough-mill simulation tool.

Keywords: Rough mill, least-cost lumber grade-mix, performance evaluation, response surface.

INTRODUCTION

Lumber is a major cost component of the secondary hardwood industries (Wengert and Lamb 1994; Carino and Foronda 1990). The industry therefore is expending large efforts to use it as efficiently as possible. Computer-based optimization algorithms (eg simulation) are widely used, since the mathematical models cannot be set up and solved otherwise in a timely manner. In the 1960s, the wood products industry started using combinations of mathematical models and computers. Early applications included the use of linear programming methodology to solve,

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among other problems, the least-cost lumber grade-mix problem (Englerth and Schumann 1969; Hanover et al 1973). The implementation of mathematical models on computers also permitted the investigation of different scenarios with varying input parameters as is done in simulation (Banks 1998). Such changing scenarios can be used to find optimal or near-optimal solutions to a problem when a sequential search algorithm is involved. Such an algorithm changes the input parameters in a predefined way until there is no or only a marginal, predefined incremental improvement of the best result over a set quantity of iterations. Examples of such iterative search simulation software for the secondary wood industry are the lumber cut-up simulators offered by the USDA Forest Service (Thomas 1999), Mississippi State (Steele et al 2001), and the Center de Recherche Industrielle Québec (Caron 2003).

Zuo et al (2004) and Buehlmann et al (2004) have shown that the use of linear programming for solving the least-cost lumber grade-mix selection problem is not always appropriate. In fact, over 90% of test scenarios showed that a nonlinear relationship exists between lumber grade or grade-mix and yield. A statistical model to solve the least-cost lumber grade-mix selection problem was therefore developed (Buehlmann et al 2004). This model uses the USDA Forest Service's ROMI-RIP 2.0 (RR2) simulation software (Thomas 1999) and a five-factor mixture design (Myer and Montgomery 2002) to collect lumber cut-up yield information. The yield information then is used to construct a lumber grade–cost response surface using SAS 8.2 (SAS 2002) on which the minimum cost point can be found. However, this novel model has never been validated.

This study compares the performance of the new statistical approach to solving the least-cost lumber grade-mix problem (Buehlmann et al 2004) and the traditional, linear programming based approach used by OPTIGRAMI (Lawson et al 1996). OPTIGRAMI 2.0 evolved from OPTIGRAMI for PC's (Timson and Martens 1990) by adding the updated yield charts of yellow poplar and black walnut (Martens 1986; 1986a).

MATERIALS AND METHODS

This research relies on work described in Buehlmann et al (2004) and Zuo et al (2004); thus, the same methods and materials were used. This section provides a summary of the materials and methods used; more detailed information can be found in those papers.

Lumber Cut-up Simulator

The necessary lumber cut-up simulation runs to obtain yield information were performed on the USDA Forest Service's ROMI-RIP 2.0 (RR2) rip first simulator (Thomas 1999). The set-up included all-blades movable arbor, no excess salvage or random width or length parts allowed and 6-mm end- and side-trim (Buehlmann et al 2004).

Least-cost Lumber Grade-mix Optimizer

The USDA Forest Service's OPTIGRAMI 2.0 (Lawson et al 1996), which is based on Martens et al's (1985) and Timson et al's (1990) original OPTIGRAMI least-cost lumber grade-mix optimizer, and a new statistical model developed by Buehlmann et al (2004) was used in this research. Both models were used with the same input data.

Cutting Bill

Ten industrial cutting bills (Table 1) originally published by Thomas (1996) and by Wengert and Lamb (1994) were used. The "Buehlmann" (Buehlmann et al 2008) cutting bill used for the creation of new statistical approach to solve the least-cost lumber grade-mix problem (Buehlmann et al 2004) could not be employed in this performance review due to limitations of the OPTIGRAMI 2.0 software (Lawson et al 1996).

TABLE 1. *Summary of the requirements of the 10 industrial cutting bills used.*

Cutting bill	Rank*	# of parts	# of widths	# of lengths
A	1	5	3	4
B	2	10	4	9
C	3	25	7	16
D	4	5	3	5
E	5	4	4	4
F	6	12	4	6
G	8	20	7	12
H	9	8	2	8
I	10	16	4	11
J	11	9	5	4

*The cutting bills were ranked from easiest to hardest as defined in Thomas's study (1996), the ranking for Wengert and Lamb's (1994) cutting bill was done using the same criteria as employed in Thomas' study.

Lumber Data

Five grades of red oak, FAS, SEL, 1 Common, 2A Common, and 3A Common (NHLA 1998) were used in this study. Since three replicates were made for every simulation, three randomly generated lumber samples with approximately 2.4 m^3 of lumber were generated from the 1998 kiln-dried red oak data bank (Gatchell et al 1998) using RR2's MAKEFILE utility (Thomas 1999).

For minimum grade-mix cost calculations, the following prices for 4/4 kiln-dried red oak lumber were taken from the January 2002 issue of the Weekly Hardwood Review (2002): FAS–\$666/m^3; SEL–\$572/m^3; 1 Common–\$424/m^3; 2A Common–\$317/m^3; and 3A Common–\$212/m^3. For minimum production cost (eg the sum of lumber and processing costs) calculations, a uniform \$85/m^3 charge (Buehlmann and Zaech 2001) was applied to the above lumber prices. Thus, the following aggregate cost data were used for minimum production cost calculations: FAS–\$750/m^3; SEL–\$657/m^3; 1 Common–\$509/m^3; 2A Common–\$402/m^3; and 3A Common–\$297/m^3.

Performance Comparison

To evaluate the performance of the new statistical least-cost lumber grade-mix optimization model (Buehlmann et al 2004), cost comparisons were conducted between solutions produced by the USDA Forest Service OPTIGRAMI 2.0 (Lawson et al 1996) and the new statistical model (Buehlmann et al 2004). At present, OPTIGRAMI 2.0 is the most widely used tool to generate least-cost grade-mix solutions in the industry.

The ten industry cutting bills (Table 1) were executed in OPTIGRAMI 2.0 and the new least-cost lumber grade-mix model. For each cutting bill, OPTIGRAMI 2.0 reports the amount (m^3) of lumber by grade needed to satisfy the cutting bill requirements. The grade-mix suggested by OPTIGRAMI 2.0 was then calculated according to the quantities required for each lumber grade. The new least-cost lumber grade-mix model provides the actual grade distribution without conversion.

The grade-mix suggested by the models was then created from lumber contained in the 1998 kiln-dried red oak data bank (Gatchell et al 1998) using the RR2 MAKEFILE utility (Thomas 1999). Three randomly configured lumber data sets were created to allow for three replicates. The lumber cut-up was simulated using RR2 for each of the ten industrial cutting bills to obtain reasonable yield estimates (average of three replicates). Based on these results, costs were calculated using Eq (1):

$$COST_j = \frac{\sum_i^5 G_i * M_i}{YIELD_j} \qquad (1)$$

where:

G_i = the proportion of each lumber grade;
M_i = the market price/m^3 of each lumber grade;
i = 1 for FAS, 2 for SEL, 3 for 1 Common, 4 for 2A Common and 5 for 3A Common;
j = observation of a grade combination run.

Using the results from Eq (1), comparisons between the statistical least-cost lumber grade-mix model and OPTIGRAMI 2.0 could then be made and the model generating the lower cost solution be identified.

RESULTS AND DISCUSSION

To evaluate the performance of the new statistical least-cost-grade-mix solver (Buehlmann et al 2004), comparisons between the minimum cost lumber grade-mix solutions generated by OPTIGRAMI 2.0 (Lawson et al 1996) and the new model were performed.

Table 2 shows the lumber grade or grade-mix results for minimum lumber and for minimum production cost as calculated by the new statistical least-cost lumber grade-mix model for the ten cutting bills employed. Table 3 displays the minimum grade combinations that minimize raw material and production cost for the ten industrial cutting bills according to OPTIGRAMI 2.0 (Lawson et al 1996). According to Table 3, OPTIGRAMI 2.0 tends to avoid using 3A Common lumber, but favors 2A Common lumber. This impression is also supported by the lumber grade distribution that was observed when processing costs ($85/m^3) were included for the optimization using OPTIGRAMI 2.0 (Table 3, without processing costs vs with $85/m^3 processing cost). For all the optimization runs using OPTIMGRAMI 2.0 and the statistical model, the same lumber and processing cost information was used to make the solutions directly comparable.

Both OPTIGRAMI 2.0 and the statistical model produced the same solution for cutting bill A. A previous study (Zuo et al 2004) investigating the relationship between yield and lumber grade-mix found that cutting bill A only marginally violates the simple linearity assumption. Thus, it is assumed that employing a linear programming model, such as employed in OPTIGRAMI 2.0, generates optimum or near optimum solutions for cutting bills whose relationship between yield and lumber grade-mix is linear or near-linear. Zuo et al (2004) also found cutting bill D to have an almost linear relationship between lumber grade-mix and yield. With only minor changes, both models suggested the same optimum grade-mix for cutting bill D, confirming the hypothesis stated above.

Using the grade combinations suggested by the statistical model and OPTIGRAMI 2.0 (Tables 2 and 3), the ten industrial cutting bills were executed in RR2 to obtain yield information (3 replicates). Based on the resulting yield data, total costs were calculated. The results for all ten cutting bills used are presented in Table 4. Cutting bill F* in Table 4 is used to illustrate the sensitivity of the model to the response surface input data and is discussed later. Table 4 shows that, except for cutting bill G, the statistical approach provides better solutions minimizing raw material cost (eg when no processing costs are considered). For this scenario, the maximum absolute savings using the statistical approach is $70/m^3 (a savings of 9.2%) for cutting bill I. The maximum relative savings are 10.4% for cutting bill C (a savings of $61/m^3). On average, the statistical model found lumber grade or grade-mix combinations that resulted in savings of 3.2%/m^3. Only for cutting bill G did the statis-

TABLE 2. *Optimal lumber grade-mix to minimize raw material cost using the statistical model (without and with consideration of processing costs).*

	Without processing costs					With $85/m^3 processing cost				
Cutting Bill	FAS	SEL	1C	2ACom	3ACom	FAS	SEL	1Com	2Acom	3ACom
A				100%					100%	
D				20%	80%				100%	
C				20%	80%				20%	80%
B				100%					100%	
H			70%		30%			70%		30%
G			80%		20%			90%		10%
E	10%		70%		20%	50%		30%		20%
I			80%	20%				80%	20%	
F		50%	20%		30%		60%	10%		30%
J	40%		40%	20%		60%		10%	30%	

TABLE 3. *Optimal lumber grade-mix to minimize raw material cost using OPTIGRAMI 2.0 (without and with consideration of processing costs).*

	Without processing costs					With $85/m^3 processing cost				
Cutting Bill	FAS	SEL	1C	2ACom	3ACom	FAS	SEL	1Com	2Acom	3ACom
A				100%					100%	
D				100%					100%	
C			8%	92%				16%	84%	
B				72%	28%				100%	
H			41%	59%				56%		44%
G			61%	39%				74%	26%	
E			66%	34%				79%	21%	
I			90%	10%				100%		
F			71%	29%				100%		
J	48%		52%			48%		52%		

TABLE 4. *Total costs for least-cost solutions suggested by OPTIGRAMI 2.0 and the statistical (NEW) model without and with processing costs.*

	Cost ($) / m^3 without processing cost			Cost ($) / m^3 with $85/m^3 processing cost		
Cutting bill	NEW-model	OPTIGRAMI	diff.	NEW-model	OPTIGRAMI	diff.
A	733	733	0	891	929	−39
D	627	658	−31	834	834	0
C	527	589	−61	719	749	−30
B	571	571	−1	738	738	0
H	677	715	−38	836	830	7
G	752	714	38	814	857	−43
E	794	817	−23	955	980	−25
I	687	757	−70	835	893	−58
F	833	835	−2	1047	919	128
*F**	*747*	*835*	*−87*	*901*	*919*	*−18*
J	868	907	−39	989	1092	−103

*F** is the new result for cutting bill F when eliminating outliers from the input data to create the response surface

tical model produce an inferior solution compared with OPTIGRAMI 2.0. The solution suggested by the statistical model would cause lumber costs of $752/m^3, whereas OPTIGRAMI 2.0's solution would cost $714/m^3, or $38/m^3 less. Reasons for this problem will be elaborated after a discussion of the results for total production costs (eg lumber costs plus $85/m^3 processing costs).

When minimizing total production costs, the statistical model created a cheaper solution in 8 of 10 cases. The maximum savings created by the statistical model in this case were for cutting bill J in the amount of $105/m^3, or 9.4%. For cutting bill H, the statistical model generated a slightly higher cost solution ($7/m^3) than did OPTIGRAMI 2.0. For cutting bill F, a difficult-to-cut cutting bill (Thomas 1996), the statistical model suggested an inferior solution to OPTIGRAMI 2.0. The statistical model solution would cost $1047/m^3 as compared with $919/m^3 for the solution offered by OPTIGRAMI 2.0. Thus, OPTIGRAMI 2.0 suggested a solution that is $128/m^3 cheaper (12.2%) than the one suggested by the statistical model. Nonetheless, on average, the statistical model found lumber or lumber grade-mix solutions that were 1.9% cheaper than the solutions produced by OPTIGRAMI 2.0. Because of the two cases where the statistical model did perform inferior to OPTIGRAMI 2.0, the true potential of the new statistical least-cost lumber grade-mix model is convoluted.

As stated above, the solution generated by the statistical model for production costs for cutting bill F is $128/m^3 more expensive than that suggested by OPTIGRAMI 2.0. For this case, the grade combination suggested by OPTIGRAMI

TABLE 5. *Costs result for cutting bill F for the 25 sample runs performed to build the statistical model.*

Runs	FAS	SEL	1Com	2ACom	3ACom	Raw material cost	Production cost
			—(%)—			($/m^3)	($/m^3)
1	0	0	0	20	80	2,625	3,580
2	0	0	0	60	40	1,508	1,973
3	0	0	0	100	0	1,192	1,510
4	0	0	20	0	80	1,546	2,062
5	0	0	50	50	0	850	1,044
6	0	0	50	50	0	891	1,096
7	0	0	60	0	40	832	1,040
8	0	0	100	0	0	785	942
9	0	20	0	0	80	1,195	1,552
10	0	50	0	50	0	840	1,000
11	0	50	0	50	0	844	1,006
12	0	50	50	0	0	833	975
13	0	50	50	0	0	840	983
14	0	60	0	0	40	888	1,064
15	0	100	0	0	0	936	1,075
16	50	0	0	50	0	836	980
17	50	0	0	50	0	823	965
18	50	0	50	0	0	806	931
19	50	0	50	0	0	810	936
20	50	50	0	0	0	901	1,024
21	50	50	0	0	0	908	1,032
22	60	0	0	0	40	872	1,025
23	60	0	0	0	40	870	1,022
24	100	0	0	0	0	881	994
25	100	0	0	0	0	880	992

2.0 is 100% 1 Common whereas the statistical model suggested 60% SEL, 10% 1 Common and 30% 3A Common. It was hypothesized that this unfavorable outcome from the statistical model was due to extreme yield results from the simulation runs used to build the cost response surface.

Experiments performed to investigate the problem showed that the use of 20% 2A Common and 80% 3A Common (the lowest lumber quality combination in the experiment allowed within the boundaries set) results in extremely low yield due to the difficulties in obtaining the larger parts. Since costs are derived from yields (Eq (1); results in Table 5), the low yields obtained for the low grade-mix compositions resulted in extreme costs. For cutting bill F, the maximum cost differential found among the 25 test runs performed to establish the cost-response surface (five-factor mixture design, Myer and Montgomery 2002) is \$2649/m^3 between highest production cost (\$3580/m^3) and lowest production cost (\$931/m^3). The cost difference between the highest production cost (\$3580/m^3) and the second highest production cost (\$2054/m^3) is \$1514/m^3. Thus, the \$3580/m^3 point can be considered an outlier (Ott 1993; Rawling et al 1998). The further the outlier from the bulk of the data points, the greater the impacts on the regression results. An outlier may be the result of machine malfunction, recording mistake, or data entry errors. It may also be a valid data point that does not represent the process well. For the outliers from mistakes, a repeated measurement needs to be conducted and data need to be corrected. When it is impossible to repeat the experiment, this outlier should be excluded from the analysis. However, if the outlier is a valid point, it has to be included in the data analysis. In this study, it is found that the outlier is a valid data point because the lower yield came from the poor lumber quality used. Therefore, it has to be included in the analysis.

However, this outlier is so powerful that it skews the response surface, thus leading to an inferior least-cost lumber grade-mix solution.

This theory is supported by observations relating to the raw material cost response surface for cutting bill F. When using raw material costs only, the maximum cost range between maximum and minimum costs for cutting bill F was $1840/m^3 ($2625/m^3 vs $785/m^3, Table 5). The difference between highest raw material costs ($2625/m^3) and second highest raw material costs ($1546/m^3) was $1078/m^3. Thus, compared with the case when production costs are included, the differences in costs for different scenarios are smaller and the lumber grade - raw material cost response surface is not skewed as extremely as in the production costs scenario discussed previously. Thus, in this case, the solution produced by the statistical model for raw material cost minimization is superior to that produced by OPTIGRAMI 2.0.

To verify the implications based on the observations just discussed, the effects of outliers have to be reduced or avoided when creating the response surface for the statistical model. To achieve this, an appropriate upper bound constraint on the maximum yield (cost) difference between runs has to be determined. To verify this postulation, the minimum acceptable overall yield for cutting bill F* was set at 15% for the 25 sample runs generating the input data for the response surface. The new upper bound for 3A Common lumber based on the 15% minimum yield constraint was a maximum of 40% 3A Common lumber in the grade-mix, as extensive testing showed. Based on this new set of data, a new lumber grade–production cost response surface was generated. According to this new solution, the optimal grade-mix combination minimizing total production costs for cutting bill F* is 90% 1 Common and 10% 2A Common lumber. Total production costs are $901/m^3. This solution is $18/m^3 cheaper (2.0%) than the one suggested by OPTIGRAMI 2.0 ($919/m^3). Given the improved performance of the statistical model in finding a minimum cost solution for cutting bill F*, the average cost savings for the ten cutting bills tested achieved by the statistical model is 3.6% (vs an average of 1.9% prior to eliminating the unfavorable result) for the case when total production costs are used.

The change in the allowable amount of 3A Common lumber for the response surface tests to 40% also had a positive impact on the solution for raw material costs. Given these new input parameters, the new solution from the statistical model resulted in costs of $747/m^3 using a grade combination of 90% 1 Common and 10% 2A Common lumber. Clearly, this new raw material cost solution derived by the statistical model is superior to the original solution from the statistical model ($833/m^3), or a reduction of $86. This new solution also achieved $87/m^3 raw material cost savings compared with OPTIGRAMI 2.0 ($835/m^3), or 10.5%. Given that a small increase in material utilization can save an average rough mill in excess of $100,000 a year (Kline et al 1998), the cost savings potential of the new statistical least-cost lumber grade-mix model becomes evident.

As shown, outliers caused by too high a fraction of low-grade lumber in the lumber grade-mix can distort the response surface to such an extent that the resulting cost response surface is severely skewed. Thus, the minimum cost point found on such a surface is no longer close to optimal. However, although there is circumstantial evidence that for cutting bill F the minimum 15% yield requirement for setting the upper bound of 3A Common lumber in the grade-mix is reasonable, insufficient knowledge exists as to how this limit would perform for other cutting bills and other circumstances. Thus, further research is needed to dynamically adjust the minimum yield levels according to individual situations to avoid skewing the response surface and thus creating inferior solutions.

At present settings, the new statistical model does search the cost response surface only in 10% grade increments. This is done to save computing time. For example, the search will check the point 100% 1 Common and all other four grades 0% vs 90% 1 Common, 10% 2A

Common and the three remaining grades 0%. In such a way, every possible 10% grade combination among the five grades used are tested to find the lowest cost point. However, the model does not investigate the case of, say, 92% 1 Common, 5% 2A Common, 3% 3A Common and the two remaining grades at 0%. Although circumstantial evidence exists that the solutions generated by this resolution are close to minimal (optimal), the two cases where OPTIGRAMMI 2.0 produced a cheaper grade-mix solution than the statistical model are very likely caused by this rather large resolution used. Further research will need to show the trade-off between faster computing time and the potential loss of money due to obtaining an inferior solution.

The inferior solutions generated by OPTIGRAMI 2.0, which relies on linear programming algorithms, compared with the statistical approach, confirmed that the violation of the simple linearity assumption reduced the applicability of linear programming methods to solve the least-cost lumber grade-mix problem as pointed out in Zuo et al (2004). However, other factors, such as the yield estimation methodology or the fact that OPTIGRAMI 2.0's input data are rather dated may also influence the results. Thus, although the new statistical least-cost lumber grade-mix model performs better than OPTIGRAMI 2.0, further research will have to show how close the model comes to the true global optimum (minimum) cost point.

The new statistical least-cost lumber grade-mix has been incorporated into the USDA Forest Service's new ROMI rough mill lumber cut-up software (Weiss and Thomas 2005). Thanks to the way the least-cost lumber grade-mix model is designed, it can be used independently of rough-mill type (rip-first vs crosscut-first) or rough mill set-up. Also, lumber grade-mixes for any cutting bill part requirement, including random sized parts and panel requirements can be optimized using the new model.

SUMMARY AND CONCLUSIONS

Recent tests have shown that there is rarely a linear relationship between lumber grade or lumber grade combinations and yield. Yet, most, if not all, existing least-cost lumber grade-mix optimizers, such as the USDA Forest Service's OPTIGRAMI 2.0 software, rely on linear programming algorithms to find the least cost solution for a given cutting bill. This research compared the USDA Forest Service's OPTIGRAMI 2.0 and a newly developed, statistically-based least-cost lumber grade-mix model. Ten industry cutting bills ranging from easy to difficult to be cut and five grades of 4/4 kiln-dried red oak, namely, FAS, SEL, 1 Common, 2A Common, and 3A Common with prices from the Weekly Hardwood Review (2002) were used for this comparative study.

The tests showed that the new statistical least-cost lumber grade-mix model generates lower cost lumber grade-mix solutions than does OPTIGRAMMI 2.0. When the new statistical model is set up in a way that outliers do not skew the response surface, large cost savings can be achieved. When minimizing lumber costs only, the new statistical model saved on average 4.5%, or $\$31/m^3$ on lumber cost compared with the solutions produced by OPTIGRAMMI 2.0. However, maximum savings of $\$87/m^3$, or 10.5%, were observed. When minimizing total production costs for dimension parts, eg minimizing lumber and processing costs, the solutions generated by the statistical model were, on average of the ten tests made, $\$31/m^3$, or 3.6%, cheaper than the solutions provided by OPTIGRAMI 2.0. Maximum savings of up to $\$103/m^3$, or 9.4%, were observed when minimizing total production costs. In two instances, OPTIGRAMI 2.0 produced cheaper solutions to the least-cost lumber grade-mix problem. One for cutting bill G resulted in cost savings of $\$38/m^3$ (5.3%) in material costs and the second, for cutting bill H resulted in cost savings of $\$7/m^3$ (0.8%) in material and processing costs. It is hypothesized that these inferior results from the statistical model are due to the rather wide search grid resolution of 10% grade increments.

Overall, the statistical least-cost lumber grade-mix model achieves large cost savings. Future research is needed into how to dynamically avoid outliers that skew the cost-response surface and what level of resolution offers the best trade-off between finding the true minimum solution and computing time. Given the versatility of the model and the readily available software, ROMI, into which it is incorporated, rough mills can expect to lower their lumber and processing costs by utilizing the lowest cost lumber grade or grade-mix.

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