IMPACT OF OVER-RUN ON PROFITABILITY OF HARDWOOD SAWMILLS

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ABSTRACT

The objective of this paper is to ascertain if the common sawmill efficiency measure, over-run, bears a significant relationship to the ultimate measure of efficiency-profitability. A data set of log grades and lumber yields from twelve batches of red oak logs, representing about four weeks of production, was collected from a mill in central Pennsylvania. The over-run and actual profitability of each batch were calculated from mill results. For comparison, each batch was optimized through a linear programming technique to determine potential mill profitability under prevailing log and lumber prices; the corresponding over-run of each optimized batch was calculated. Stepwise linear regression techniques were utilized to prove a hypothesis that no relationship exists between over-run and profitability, either actual profit as realized by the sawmill studied or theoretically optimal profit as determined by a linear programming solution. Simple linear regression was then used to validate the result. The study demonstrates clearly that, in this case, over-run is not a predictor of profitability, and as influenced by a company's choice of log scale, is merely a relative measure of operational efficiency that may lead to mistaken assumptions about mill profitability.

Keywords: Over-run, optimal profitability, sawmill efficiency, stepwise linear regression, log scales.

INTRODUCTION

The sawmill industry faces many challenges: the amorphous nature of global competition, increasing log prices, environmental concerns, etc. But the inherent qualities of wood make it an important material; there seemingly will always be demand for softwood and hardwood lumber. As sawmills compete for raw material and markets, only those that evolve and improve management techniques will survive. There are various factors that contribute to the profitability of the typical sawmilling operation, such as log prices, log allocation, sawmill utilization, labor cost, logistics, etc. However, one ubiquitous management metric is usually found to be common to modern sawmill operations: the metric ***over-run.***

In sawmill operation, there is always some disparity between log scale and lumber yield, which is known as either over-run or under-run. If the lumber output is greater than that predicted by the log scale, then the excess difference is called the over-run. Over-run has been defined as the difference between the scale of a log and the board foot measure in that scale of the lum-

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ber obtained from the log expressed as a percentage of log input (Bryan 1996). It is typically given by the following formula:

$$\text{Percent of overrun} = \frac{\text{Lumber output} - \text{log scale}}{\text{log scale}} \times 100 \qquad (1)$$

There are different log scales by which over-run is measured via Eq. (1). This research tests the hypothesis for one specific scale, the Scribner Log Rule, as used by the sawmill in the study. Scribner rule is a common method of predicting lumber volume from specific logs, and is used frequently in the Northeastern United States hardwood lumber industry to establish the market value of logs. The Scribner scale was developed in 1846 based on a series of sawing diagrams of 1-inch lumber in various log length and diameter classes, allowing for a ¼-inch saw kerf (sawdust lost from lumber volume due to the sawing process) between each board. However, the Scribner scale, like all other log scales, was developed to estimate the lumber *footage* potential of a log, not the lumber *value* potential. The Scribner, like many other log scales, tends to be conservative and to underestimate the lumber potential of certain log categories. Since over-run measures, in effect, the error of the log scale used, sawmill managers have considered the metric to be an accounting of the amount of "free wood" produced from their mill, because the log was purchased based on this conservative log-scale estimate of lumber potential. From that line of thought evolved the common belief that higher over-run, since it indicates more "free wood" produced by the mill, necessarily indicates higher profitability. Therefore, most sawmill managers believe that over-run is an excellent indirect indicator of operational profitability. In this study, we tested this belief through empirical analysis of the relationship between over-run and profits as generated at one central Pennsylvanian hardwood sawmill.

The methodology used to test this theory was statistical linear regression. The single most important reason for using linear regression is that a deterministic mathematical model between over-run and profit is not possible due to the heterogeneous nature of wood and the dynamic nature of lumber markets and mill operations.

Application of operations research to sawmill operational optimization

The most critical factor in operational optimization of sawmills is log mix, for the following reasons (Bryan 1996):

- The log type directly affects the product-mix value.
- Production rates are a direct function of log mix.
- Lumber yields are also a function of log mix.

When it comes to log purchasing, tradition often rules. Preconceived notions, mill managers' personal biases, and previous practices have more weight than optimization and statistical models. This has helped perpetuate belief in certain simplified management metrics, even in many modern sawmill operations.

In those sawmills that employ analytical techniques to determine log mix, log procurement and allocation decisions are most often based on break-even or return-to-log calculations (RTL) (Bryan 1996). RTL is an accounting-based technique that uses predetermined breakdown patterns, allocated milling costs, and current product prices to estimate break-even log numbers. Based on its assumptions, the RTL calculation can provide, at best, a rough estimation of profits at given log prices. However, it may also induce a sense of false security in the minds of mill managers, as the operational assumptions become dated and cost allocations impose accounting-biased outcomes on the decisions.

There are many other factors that are influential in determining the sawmill profit besides the ones included in RTL calculation. Some of these are:

1. Sawmill utilization: An underutilized sawmill yields lower profits compared to a fully utilized mill, under the same market conditions.

2. Production rates: Production rates directly affect profit; in general, the higher the rate, the higher the profit.
3. Variability of sawing decisions: Different logs, different sawyers, different work conditions throughout the day mean that yield assumptions per type of log are "assumptions" at best.

The fact that these factors are not fully considered in RTL calculations makes it an incomplete tool for deciding strategic or even operational issues. A more complete consideration of optimality of sawmill operation has been developed over the decades through the use of linear programming (LP) applications.

Jackson and Smith (1961) were perhaps the first to use linear programming to determine the optimal combination of lumber sizes to be produced from each log diameter class-sawing pattern to maximize profits. Pearse and Sydneysmith (1966) developed a linear programming model to calculate the pattern of logs and intermediate products from a complex producing lumber, veneer, chips, pulp, plywood, and hog fuel to obtain the highest net economic value for that complex. Sampson and Fasick (1970) used a linear programming model to formulate management recommendations for operational time, minimum log diameter to be sawn, best primary breakdown, and bucking solutions. Maness and Adams (1991), in reviewing these early sawmill optimization efforts, noted that each was artificially constrained in problem formulation by sawing pattern and marketing conditions, thus yielding a sub-optimal "optimal" solution.

Carino and Foronda (1987) also solved the problem of optimal log allocation using LP. In their approach, they determined the optimal log requirement to maximize profits by emphasizing the minimum and the maximum log diameter that can be profitably processed and the impact of changing log input distribution.

Bare et al. (1989) described how to efficiently allocate logs to a set of interdependent utilization facilities while simultaneously designing the optimal characteristic of a production system. They used a *de novo* algorithm where the resource constraints are considered to be soft and are determined through iterative analysis. They then attempted to combine the log allocation and crosscutting process into one production system.

Maness and Adams (1991) formulated and demonstrated a technique of combined log bucking and lumber sawing optimization models. Their integrated model produced an improvement of roughly 36% over independently modeled solutions and demonstrated the importance of dynamic market inputs to realistic optimization results. Beauregard et al. (1994) then proposed and demonstrated a "systems" approach which, by modeling individual mill sub-systems with different tools, was then combined into one over-riding management decision tool.

So, even though sawmill profitability has been the target of extensive and long-running operations research efforts, little or none of the work as represented here has ever considered whether common operational metrics as used by most sawmill managers have relevance to true optimality or are appropriate for making log allocation or purchasing decisions. This paper focuses on testing the conventional wisdom that over-run has a direct and positive correlation to the profitability of the sawmill operation.

PROBLEM STATEMENT

The simple research hypothesis put forth in this study is

H_o: Over-run affects profit.

H_a: Over-run does not affect profit.

The ultimate objective of this research is to establish whether, under at least one set of log price/log grade/mill recovery/lumber market conditions, the assumed significance of a relationship between mill over-run and mill profitability, either actual or optimal, can be proven incorrect. If so, the justification for additional work related to mill efficiency and mill profitability, using modern tools of operation research relative to real-time market conditions, will have been established.

RESOURCES AND METHODS

Mill background

The study mill, Pine Creek Lumber, a subsidiary of Bingaman & Son Lumber, is a hardwood sawmill located in Mill Hall, Pennsylvania, USA. In the spring of 1978, Bingaman & Son Lumber Company purchased Fox Lumber Company, and formed the company known as Pine Creek Lumber. Pine Creek produces 6 million board feet per year of mixed species hardwood lumber with 25 employees.

Data collection

To demonstrate proof of principle at the simplest level, the data analysis was carried out for just one species, northern red oak *(Quercus rubra)*. The data were collected over a period of four weeks in the fall of 2003, on those days when red oak was sawn. The data consisted of the number of red oak logs sawn by grade and total lumber obtained from those logs, and included the entire production of red oak sawn by the mill during that period. Profit for the resulting lumber was calculated at the margins netted at prevailing market prices. Over-run was calculated by Eq. (1) for the sample.

Model variables

The various predictors, on which data were collected in this study, are:

1. Input log grade—Input logs are composed of six different grades, which are custom grades defined by Pine Creek Lumber (Table 1).
2. Over-run—Over-run, as previously defined, is the difference between actual lumber output and predicted lumber output as scaled by Pine Creek employees from logs input using the Scribner Log Scale.
3. Profit—Profit is the ultimate measure of efficiency in any organization, and therefore, the desired response variable. In this study, mill over-run is modeled against both actual and theoretical optimal profitability of the mill under study for the given time frame. The actual profit was attained from company records on prevailing costs and market prices, and optimal profit was established through linear programming as formulated in Wadhwa (2005) and described below.

TABLE 1. *Custom log grade specifications at mill studied.*

Log grade	Minimum tip diameter	Minimum length	Clear faces
Prime	16″	8′	4
Select	14″	8′	4
#1	12″	8′	3
#1B	11″	8′	2
#2	11″	8′	30%
Tielog	12″	8′6″	40%

$$\text{Maximize } z = \sum_j S_j y_j - \sum_i C_i x_i - \sum_i Pc_i x_i - f^*t$$

Subject to

$$\sum_i x_i \le \text{max log} \qquad i = 1 \ldots n$$

$$\sum_i x_i \ge \text{min log} \qquad i = 1 \ldots n$$

$$y_j - \sum_i Con_{ij} x_i - \sum_i Ove_{ij} x_i \le 0 \qquad j = 1 \ldots m$$

$$\sum_j y_j - \sum_i \beta_1 * x_i < \beta_0$$

$$y_j \ge D_j \qquad j = 1 \ldots m$$

$$x_i \le Sup_i \qquad i = 1 \ldots n$$

$$y_j \ge 0$$

$$x_i \ge 0 \qquad (2)$$

where

$\mathbf{C_i}$	Cost of buying logs of grade **i**.
$\mathbf{S_j}$	Selling price of lumber of grade **j**.
$\mathbf{Pc_i}$	Procurement cost (as a percentage of the total logs purchased).
$\mathbf{Con_{ij}}$	Conversion factor of log grade **i** to lumber grade **j**.
$\mathbf{Ove_{ij}}$	Over-run of lumber grade **j** obtained from log grade **i**.
Minlog	Minimum number of logs that must be processed each day.
Maxlog	Maximum number of logs that can be processed each day.

D_j Demand for lumber grade **j**.
Sup_i Supply constraint on log **i**.
f Manufacturing cost per hour.
t Total time required to process the logs.

and

Y_j Amount of lumber of grade **j** produced.
X_i Number of logs of grade **i** used.

Methodology

Stepwise regression was used for testing the stated hypothesis. A stepwise regression model was developed with mill-generated data, verified through iterative interaction with mill personnel, and validated by using a simple linear model of profit to over-run based on the generated data. If, in the stepwise regression, over-run was selected to be one of the predictors of mill profitability in the model, then we could accept the null hypothesis that over-run affected profitability. If over-run was not selected, then we could reject the null and accept the alternative hypothesis that over-run does not affect profit.

First, the normality of the response variable was checked. If the data are not normally distributed, then a transformation may be desired to convert them to normal. From Fig. 1 it can be seen that at the 95% confidence interval, the response variables (actual and optimal profit) are normally distributed.

We then performed the stepwise regression to determine the important predictors in the model. For carrying out stepwise regression, the six log grades and over-run were used as predictors, whereas actual (realized) and optimal (theoretical) profits were used as responses. The output of the stepwise regression runs, along with the corresponding over-run values, is shown in Table 2.

Minitab® was utilized as the solver for stepwise regression. This example uses seven pre-

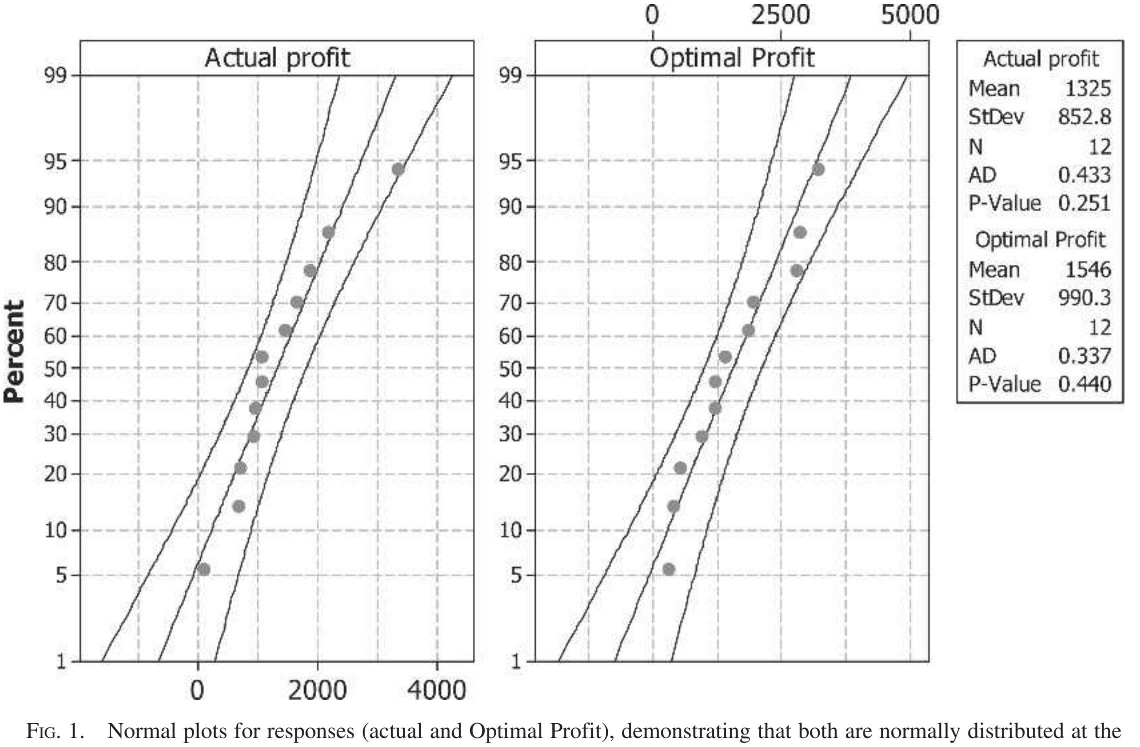

FIG. 1. Normal plots for responses (actual and Optimal Profit), demonstrating that both are normally distributed at the 95% confidence level.

TABLE 2. *Stepwise regression output for both actual and optimal profitability regressed against log grades and over-run. Note that the variable "over-run" is not selected for either model. Footage, profit, and over-run for each scenario are indicated.*

Model	Actual profit			Optimal profit
Step	1	2		1
Constant	581.50	602.30		690.40
Variables in Model	Select	Select	1B	Prime
Coefficient	0.69	1.26	−0.23	0.46
T-value	1.70	2.50	−1.68	2.50
P-value	0.12	0.03	0.13	0.03
S	788.00	724.00		814.00
R-Square	22.44	41.00		38.54
Adjusted R-square	14.69	27.89		32.39
C-p	2.90	2.30		−1.10
Log footage used (bf)		19114 (scaled)		19114 (constrained)
Lumber footage yield (bf)		24948 (actual)		23153 (estimated)
Profit		$1,443 (actual)		$1,852 (calculated)
Over-run		30.52% (calculated)		21.13% (calculated)

dictors, the six log grades and the calculated over-run. We specified that the software perform an automatic stepwise procedure, display the results, and allow the user to intervene. We also included the constant term in all the steps of the model. The P-value for any variable to enter or leave the model was specified at 0.15.

Various regression plots were then utilized to see if classical regression assumptions were satisfied. From Fig. 2 it can be seen that the residual vs. fitted values plot is the prototypical "good residual plot" in that the residuals bounce randomly in a horizontal band around the horizontal line of 0. The plot suggests that there are no problems with linearity and outliers, although non-constant error variance could be a problem; but since the models are not used for prediction in this case, a non-constant error variance can be tolerated. Figure 2 also illustrates that the assumption of normality is satisfied. Similar residual and normality results were verified for the optimal profitability model.

After fitting the models, they were checked for influential and outlier data. Standardized residuals, deleted t residuals, leverages, Cooks distance, and DFITS were used to conclude that there were no influential or outlier data affecting either model.

The next step was to check for the presence of multicollinearity. A formal method of detecting multicollinearity is "variation inflation factor" (VIF). If VIF for all the predictors is close to 1, there is no relation; any VIF greater than 10 is taken as an indication of presence of multicollinearity. The VIF for the actual profit model was 1.8 for both the predictors; hence multicollinearity was not a problem. Similar results were generated for the optimal profit model.

RESULTS AND DISCUSSION

With R^2 of 41.00 and adjusted R^2 of 27.89 (Table 2) after the second step, the actual profitability model was accepted as satisfactory. Likewise, with R^2 of 38.5 and adjusted R^2 of 32.4 (Table 2) after the initial step, the optimal profitability model was accepted as satisfactory.

In step 1 of the actual profitability model, the variable ***Select*** entered the model; variable ***#1B*** entered in step 2 (Table 2). Note that the P-value corresponding to both the variables is less than 0.15, which is α for a new variable to enter the model. No variables were removed on either of the first two steps. For the optimal profitability model, only one step was needed to arrive at the final model, with the variable ***Prime*** selected. The variable ***Over-run*** was not selected in either case as a significant variable.

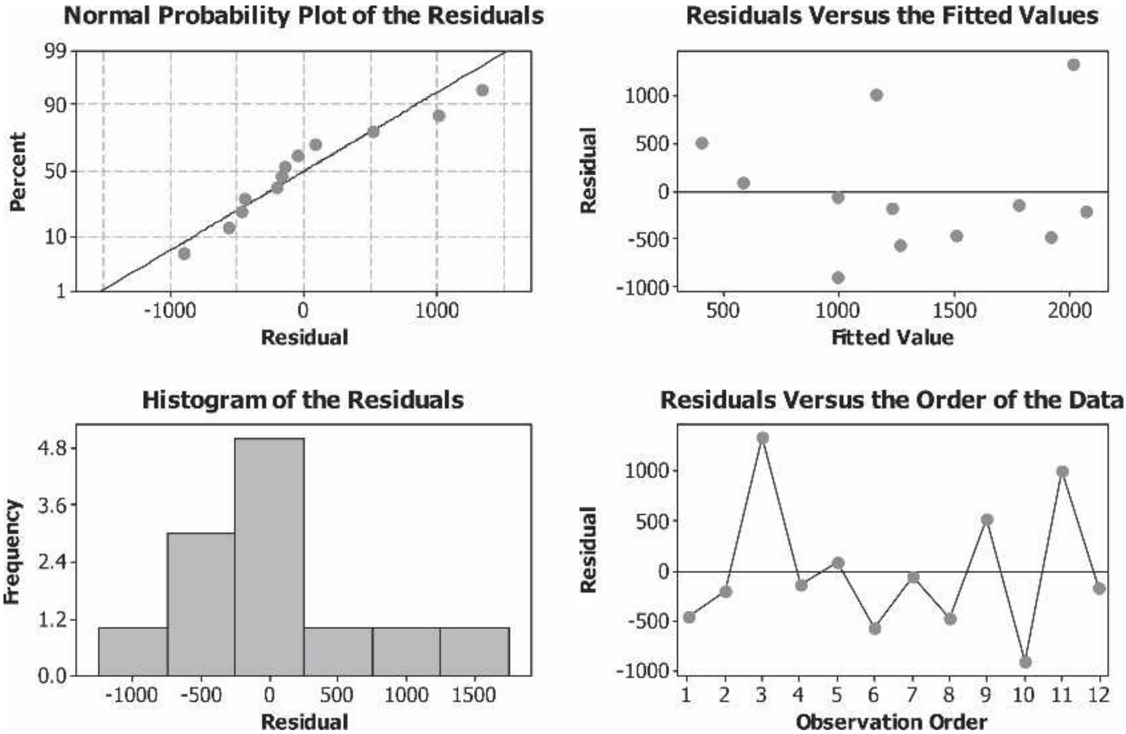

FIG. 2. Residual plots for actual profitability model.

Thus, Table 2 supports a hypothesis that the volume of Select and #1B logs were the only significant factors, of the variables tested, on mill profitability in the actual log mix run for the trial period. The volume of Select logs run had a favorable effect on profit, as denoted by their positive coefficient; the volume of #1B logs had a negative effect, due to the resulting value of the lumber yielded not offsetting the price of those logs. Over-run from the twelve batches of logs as sawn was calculated as 30.52% with a realized profit of $1,443.

The results in the last column of Table 2 support the hypothesis that under conditions of log mix optimality, as generated by Eq. (2) described above, the volume of Prime logs was the only significant determinant of mill profitability. This result would hold true until the price differentials of the logs were changed by the amount of the calculated shadow prices of each log grade, at which each would then enter (or leave) the optimal solution and have a significant impact on the profitability of the mill. Estimated profit for the resulting optimized log mix was $1,852, 28% higher than the actual realized profit despite having an over-run of nearly 10% less (21.13%).

Since the variable over-run was not added into either statistical model, it is concluded with 95% confidence that over-run, at least in this case, was not an important predictor of mill profitability and the alternative hypothesis is accepted.

Validation of stepwise regression conclusion

To further test the conclusion that over-run is not an important predictor of profitability, simple linear regressions between actual profit and over-run, and optimal profit and over-run, were performed. The results of these models showed extremely low adjusted R-squared values (0.0% in both cases) and the P-value corresponding to both constants and over-run coefficients is greater than 0.05 at a 95% confidence interval. These results gave further confirmation that, in this case, no linear statistical relationship exists between mill over-run and mill profitability.

LIMITATIONS

Only one log species and one log scale was tested; similar studies done for other species and log rules should shed additional light on the results found here. Furthermore, it might be that hardwood log and lumber margins are more complex and variable than softwood margins, so that over-run might be more correlated to profitability in softwood lumber production. Again, similar testing could bear this out or disprove it.

The size of the data set modeled was limited by the need to collect log grade and lumber profitability data on a distinct batch of logs. In this case, data on twelve batches of logs were collected. Further studies with similar or larger sets of data would better validate the concept. However, the strength of the conclusions from this study leads us to believe that the hypothesis as tested and proved here will hold with further study.

CONCLUSIONS

As hypothesized, the data as collected in this case study suggest that no real relationship exists between mill over-run and mill profitability, either actual or optimal. The calculated over-run and corresponding profit totals in this study demonstrate that higher profitability can be achieved with lower over-run. The supporting linear regression validation adds confidence to the conclusions reached through the stepwise regression procedure. Based on the results demonstrated, over-run should not be used as a measure of mill efficiency, or allowed to influence log purchasing strategy, because of the possible negative impact on profitability the resulting decisions could have. A better alternative for measuring mill efficiency is to measure actual yield of the processed logs against an established mill standard yield by log and lumber grade. The best solution, in terms of capturing potential mill performance, is to optimize the log mix for any particular sawmill through an appropriate log mix optimization model, similar to the one formulated in Eq. (2) of this paper, and reconciling actual mill performance against the theoretical optimum at regular intervals. While this conclusion has been proven for only this single case, the extreme significance of the results leads us to believe that the same conclusion could well hold true for other mills, other species, and alternative log rules.

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REFERENCES

Bare, B. B., D. Briggs, and G. Mendoza. 1989. Log allocation and soft optimization: A *de novo* programming approach. Forest Prod. J. 39(9):39–44.

Beauregard, R., M. Beaudoin, D. Ait-Kadi, and J. P. Mongeau. 1994. A systemic approach to consider complexity in sawmill modeling. Wood Fiber Sci. 26(3):421–437.

Bryan, E. L. 1996. The best possible sawmill. Miller Freeman Books, San Francisco, CA. 231 pp.

Carino, H. F., and S. U. Foronda. 1987. Determining optimum log requirements in lumber manufacturing. Forest Prod. J. 37(11/12):8–14.

Jackson, N. D., and G. W. Smith. 1961. Linear programming in lumber production. Forest Prod. J. 11(6):272–274.

Maness, T. C., and D. M. Adams. 1991. The combined optimization of log bucking and sawing strategies. Wood Fiber Sci. 23(2):296–314.

Pearse, P. H., and S. Sydneysmith. 1966. Method of allocating logs among several utilization processes. Forest Prod. J. 16(9):87–98.

Sampson, G. R., and C. A. Fasick. 1970. Operations research application in lumber production. Forest Prod. J. 20(5):12–16.

Wadhwa, V. 2005. Determination of the optimal performance of hardwood sawmills and its relationship to the metric "over-run". Unpublished Master's thesis, The Pennsylvania State University, University Park, PA. 74 pp.