

A THREE-DIMENSIONAL OPTIMAL SAWING SYSTEM FOR SMALL SAWMILLS IN CENTRAL APPALACHIA

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Abstract.—A three-dimensional (3D) log sawing optimization system was developed to perform 3D log generation, opening face determination, sawing simulation, and lumber grading. Superficial characteristics of logs such as length, large-end and small-end diameters, and external defects were collected from local sawmills. Internal log defect positions and shapes were predicted using a USDA Forest Service model. A 3D virtual reconstruction of a log and its internal defects was generated using 3D modeling techniques. Heuristic and dynamic programming algorithms were developed for opening face determination and sawing optimization while grading procedures were programmed based on the National Hardwood Lumber Association rules. The system was validated through comparisons of lumber results generated by the system and by sawmills. Our preliminary results indicated that a significant gain in lumber value can be achieved using this optimization system. This study will help small sawmill operators improve their processing performance and understand the impacts of defects on lumber grade, resulting in improved industry competitiveness.

INTRODUCTION

Currently, hardwood sawmills in the central Appalachian region face many challenges, including decreasing log size, low-quality logs, limited availability of logs, and pressure from foreign competition (Milauskas and others 2005). In addition, a weak global economy and the housing slow down have had impacts on the hardwood products industry in the region. All of these factors are pressuring hardwood sawmills to use more efficient processing methods that increase the value or volume of lumber produced.

Studies have shown that the value of hardwood lumber can be increased by 11 to 21 percent through optimal sawing strategies gained through the ability to detect internal hardwood log defects (Sarigul and others 2001). Existing nondestructive methods (x-ray or computed tomography) do not lend themselves to fast, efficient, and cost-effective analysis of logs and tree stems in the mill, especially for small sawmills. A three-dimensional (3D) laser-line scanner has been developed by the U.S. Forest Service in cooperation with Virginia Tech, and it uses relatively low-cost equipment (\$30,000 plus integration labor cost) (Thomas 2006). The Forest Service also has developed models to predict internal defect characteristics based on external defect measurements. A recent study has shown that the models can predict approximately 81 percent of internal red oak knot defects (Thomas 2010).

Log breakdown procedures must be combined with the scanned information to be successful at improving lumber value, otherwise it is not guaranteed (Occeña and others 1997). Software can generate hypothetical logs and defects, and simulate their breakdown. Over the past few decades, many log breakdown models

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and sawing simulation systems have been developed, but most lack practical sawing tools or 3D simulation training tools. The existing advanced sawing systems are not optimized for hardwood log breakdown or are not suitable for the small or portable sawmills typical of the central Appalachian region. To survive in a highly competitive marketplace in today's turbulent economic conditions, small sawmills need appropriate milling technology that will improve their profitability and competitiveness. One strategy is to use a cost-effective log sawing optimization system that combines the log breakdown models with the 3D scanned log data.

The overall objective of this study is to develop an optimal log sawing system for hardwood lumber manufacturing facilities. This paper mainly focuses on: 1) algorithms to determine the opening face and to improve lumber value recovery; 2) system development to implement the optimal computer algorithms; and 3) validation of the optimal sawing system by comparing computer-generated results and sawmill data.

MATERIALS AND METHODS

Twelve hardwood log samples were collected from the West Virginia University Research Forest in north-central West Virginia. Samples were taken from red oak (RO) (*Quercus rubra*) and yellow-poplar (YP) (*Liriodendron tulipifera*). The logs were all 8 feet in length and approximately 10-12 inches in diameter. To remove the influence of log sweep and crook on lumber value yields, the logs were chosen to be as straight as possible. Small- and large-end diameters were as close as possible to reduce the influence of log taper on lumber value yields. Six logs that met the above criteria were selected for each species.

Log profile data, including log length and small-end and large-end diameter, were taken. Other log characteristics such as log taper, sweep, and ovality were recorded (Table 1). Log external defect data was also collected, including: species; defect type, such as adventitious knot (AK), heavy distortion (HD), medium distortion (MD), light distortion (LD), overgrown knot (OK), sound knot (SK), and unsound knot (UK); linear position of defects from small end of log; defect's angle with respect to predetermined initial 0°; defect size; and defect surface rise. Log internal defect location was derived from Thomas' (2008) prediction model. Collected and predicted data were entered into a database.

Once all the logs were numbered and log data collected, the logs were transported to West Virginia University's band saw mill for processing into lumber. Boards sawn from the same log were numbered consecutively to track the source of the lumber, and measured after all sample logs had been sawn. Lumber length in feet, width and thickness in inches, and volume in board foot were then measured (Table 2). The grade and surface measurement of the lumber were determined by a National Hardwood Lumber Association (NHLA)-certified grader. The lumber values were based on the green rough lumber price across the state at the time of the assessment. The collected lumber data were used to compare with the simulation results generated from the optimal sawing system.

Table 1.—Characteristics of the sample logs.

Statistic categories	Small-end diameter (inch)	Large-end diameter (inch)	Taper (inch/foot)	Sweep (inch)	Ovality
Min	10.05	10.16	0.01	0.25	1.05
Max	11.96	12.34	0.07	1.13	1.12
Mean	10.84	11.1	0.03	0.53	1.08
Stdv ^a	0.62	0.7	0.02	0.03	0.03

^a standard deviation.

Table 2.—Characteristics of lumber from the sample logs.

Statistic categories	Width (inch)	Thickness (inch)	SM ^b	Volume (bf)	Value (\$)
Min	3.5	1	2	2.33	0.86
Max	8.44	2.25	6	10.69	5.34
Mean	6.1	1.42	4	5.58	2.27
Stdv ^a	1.12	0.16	0.9	1.44	0.88

^a standard deviation^b surface measure

OPTIMAL SAWING SYSTEM DESIGN

System Structure

The optimal sawing system consists of five major components: opening face, solid internal defect model, optimal log sawing, cant re-sawing, and lumber grading. This system was developed by utilizing object-oriented programming techniques with the Microsoft Foundation Class and Open Graphics Library (OpenGL). A relational database model with four entities (logs, defects, shapes, and lumber), was implemented using an entity-relationship model. The system accesses the database to retrieve data through an Active Data Object.

To provide users with a realistic log, 3D modeling techniques were used, together with OpenGL primitive drawing functions to generate three-dimensional log visualizations. A mathematical model was used to describe the geometry of the internal defects of a log (Thomas 2008). When a log was sawn, the locations and sizes of internal defects exposed on the surface of lumber could be determined using the developed procedures, and the lumber grade could be assigned accordingly. At this point, a cone model was used to represent internal defect, and its apex at the pith (central axis) of the log was assumed. When a sawing plane passed through an internal defect, a two-dimensional defect area was exposed on the surface. The defect area was mapped as rectangle on both sides of the lumber.

Sawing Algorithms

Opening face: Three steps were needed to determine the opening face. Log orientation needed to be determined first. When the defects were scattered over the entire surface of the log, they would be placed on the edge of the cutting plane. When defects were located on one portion of the log, they would be placed in one face. A procedure was developed to identify four log faces after orienting major defects at the edge of the cutting plane or in one face. The next step was to determine the best face. We assumed the opening face was cut from the best face that could be determined, based on log face grade. Each face was graded by a computer procedure based on the U.S. Forest Service hardwood log grading rules. The same grade will occur in more than one face of a log since there are only three grades (F1, F2, or F3). If the log has only one highest grade face, it is chosen as the best face. However, if there is more than one highest grade face, the face with the maximum clear area (curved-surface clear area) will be selected. Finally, the opening face dimension was determined. Lumber length was assumed to be the same as the log. The width of the opening face was determined as follows: if the grade of the best face was F1, the log would be slabbed to a width of 6.25 inches for logs of ≥ 13 inches in small-end diameter. For logs of < 13 inches in small-end diameter, the log would be slabbed to a width of 4.25 inches. For all logs that had a best face with grades of F2 or F3, the slab width was 3.25 inches.

Heuristic algorithm for log grade sawing: A heuristic algorithm was developed based on the Malcolm simplified procedure for hardwood log grade sawing (Malcolm 1965). Cutting from the small end, we set out the opening face full taper by using the small end of the log as the pivot, and the unopened face becomes parallel to the saw line. The log is not rotated unless one of the other log faces could yield a higher grade of lumber than could the current sawing face, in which case the log is rotated to the face with the potential for the highest lumber grade. After a log face has been cut completely, the grade of that face will be recorded, triggering the algorithm to move to the next face. This sawing process repeated until a specified size cant is produced, indicating that sawing is complete.

Mathematically-based algorithm for log grade sawing: In grade sawing, a log is broken into four portions at the small end (Fig. 1). For a given sawing orientation θ , a series of parallel cuts is performed along sawing orientation θ on portion 1 and 3 of the log. For portions 2 and 4, a series of parallel cuts with orthogonal orientation is used. When the first opening face was determined, θ was fixed correspondingly. A mathematical model for maximizing value through grade sawing can be expressed by the following function:

$$F = (L_1^*, L_2^*(L_1^*), L_3^*(L_1^*, L_2^*), L_4^*(L_1^*, L_2^*, L_3^*), V^*(L_1^*, L_2^*, L_3^*, L_4^*), S_1^*(L_1^*), S_2^*(L_1^*, L_2^*), S_3^*(L_1^*, L_2^*, L_3^*), S_4^*(L_1^*, L_2^*, L_3^*, L_4^*)) \quad (1)$$

where L_1 , L_2 , L_3 , and L_4 , and S_1 , S_2 , S_3 , and S_4 are the sawing planes and sawing patterns at each portion, respectively, V is the lumber value, and $*$ indicates an optimal value. This proposed model is based on an optimal log grade sawing procedure described by Bhandarkar and others (2008). The objective of function (1) is to find L_1 , L_2 , L_3 , and L_4 to maximize the total lumber value. For each portion, let $C = \{1, 2, \dots, n\}$ be a finite set of all the potential cutting planes, and $S = \{s_0, s_1, \dots, s_n\}$ is a subset of C that satisfies the following constraints:

$$(s_i - s_{i-1} - \left\lceil \frac{k}{c} \right\rceil) \cdot c \in T, \text{ for } 1 \leq i \leq n \quad (2)$$

$$s_0 = 1, s_n = n \quad (3)$$

where variables used in functions (2) and (3) are defined as following:

$T = (T_1, T_2, \dots, T_m)$ is a set of lumber thickness values (mm), it is an integer, and m is the total number of lumber thicknesses considered.

c is the sawing plane resolution (mm).

k is the kerf value (mm).

$n = \frac{CR}{c}$ is the total number of cutting planes within the cutting range, so the possible cutting planes are enumerated as $1, 2, \dots, n$, while CR is the cutting range between the opening face and central cant (mm).

A sawing pattern satisfying functions (2) and (3) will be seen as a feasible solution for log grade sawing as shown in Figure 2. Optimal sawing patterns can be determined by using a dynamic programming algorithm. Let $v^*(i)$ represent the optimal lumber value for each portion of the log between cutting planes 1 and i and $g(i, j)$ be the lumber value from the cutting planes i through j . Then a recursive mathematical equation for the dynamic programming can be formulated as follows (Bhandarkar and others 2008):

$$v^*(i+1) = \max_{j \in [0, m]} (v^*(i+1 - \frac{T_j}{c} - \left\lceil \frac{k}{c} \right\rceil) + g(i+1 - \frac{T_j}{c}, i+1)) \quad (4)$$

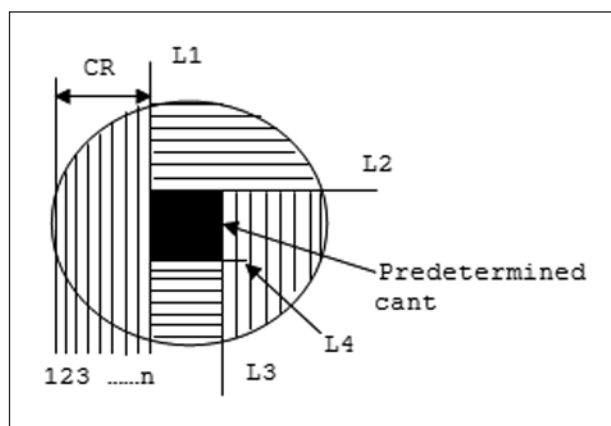


Figure 1.—All potential cutting lines for log grade sawing.

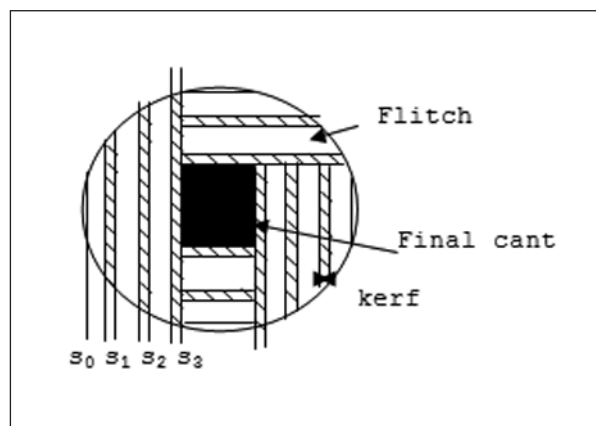


Figure 2.—A feasible solution for log grade sawing.

Cant Resawing

To compare the total lumber value from each log, the central cant must be sawn. Before sawing the central cant, we had to define a usable sawing region, and combine the given lumber thickness to obtain the best cutting solution. Because the taper sawing method was used, the initial cant is not square. So, the taper must first be removed from the cant. We assume the size of the cant at the small end of log to be the whole size of the final cant. Cant re-sawing can be done using live sawing or grade sawing; we used the former method in this study. The system saws the central cant from the best face of the log. Then, the system turns the central cant 90° clockwise and saws the cant again. The final sawing pattern was that which produced the largest total lumber value. During heuristic log sawing, no optimization algorithm is used as it simply makes a series of parallel cuts. While the dynamic programming algorithm was used to saw the log, the problem of central cant re-sawing can also be solved by the optimal algorithm used for live sawing. The cant re-sawing and log grade sawing parameters are the same with the exception of log sawing orientation and cutting range.

Lumber Grading

Before the lumber is graded, the sawn flitch must be re-sawn into lumber. All flitches were edged in this study to remove all wane. To generate this lumber pattern, the width of the lumber from the lowest width end is used as the width. The edged lumber is graded by computer algorithm based on the NHLA grading rules and a hardwood lumber grading program (Klinkhachorn and others 1988). Lumber grades used were First and Seconds (FAS), FAS-One-Face (F1F), Select, 1Common (1COM), 2Common (2COM), and 3Common (3COM).

RESULTS AND DISCUSSION

By specifying some parameters (i.e., kerf width, lumber thickness, cant size), users can interactively simulate the sawing process. In this study, sawing kerf width was chosen as 1/8 inch and lumber thickness was 1-3/8 inch, the same as the parameters used in the sawmill. The cant size was chosen as 4 x 6 inches since it is the most common in West Virginia sawmills (McDonald and others 1996).

OPENING FACE

To determine whether the optimal opening face derived by the procedure was better than other opening faces chosen randomly, we simulated log sawing based on the optimal opening face and other assumed opening faces from 0 to 85° in 5° increments. During the simulation, a series of parallel cuts was made on each of the four faces until a central cant remained, and then the central cant was also sawn by parallel cuts. Table 3 summarizes the results. When a log was cut from the optimal opening face, total lumber value was higher than the mean value by an average of 2.9 percent. At the best rotation angle, the maximum lumber value was 6.2 percent higher than the mean value. At the worst rotation angle, the minimum value was approximately 6.3 percent lower than the mean value.

The results suggested that lumber value can be improved based on opening face chosen (Table 3). However, the lumber value produced from the optimal opening face was not always the maximum. Only 25 percent of the lumber value produced from the optimal opening face cutting equaled the maximum value. It was also noted that the lumber value produced from the optimal opening face derived by algorithm was lower than the average lumber value produced from the 3rd and 10th logs. The reason for this shortfall may be that the log orientation determined by the opening face algorithm does not consider defect types and sizes. For example, the penetration depth and clear area between bark and defect area are different based on defect type. Severe defects may have more significant effects on lumber value than slight defects. Thus the major defects must be considered first and rotated to the edge of the log sawing planes. Therefore, the optimal opening face found was not the best opening face.

ACTUAL VS. OPTIMAL LOG SAWING

Comparisons between the actual lumber value obtained from the sawmill and the simulated solutions are presented in Table 4. In terms of average lumber value recovery, a sawmill could improve lumber value 22.02 percent and 33 percent if they used the heuristic and dynamic programming algorithms, respectively. If the average value of lumber produced were priced at 50 cents per board foot and 1 million board feet were sawn annually, the gain in lumber value could be as high as \$110,000 to \$165,000 per year. Additionally, recovery of high volume does not always lead to recovery of high lumber value. For example, when heuristic and

Table 3.—Lumber value vs. log rotation.

Log No.	Species	No. of defects	Opening ^a (\$)	Max ^b (\$)	Min ^c (\$)	Mean ^d (\$)
1	YP	5	19.79	19.79	18.72	19.55
2	YP	7	19.42	19.91	17.44	18.68
3	YP	11	14.73	17.48	13.73	15.75
4	YP	11	16.08	17.25	12.96	15.54
5	YP	10	23.8	25.38	21.01	22.8
6	YP	9	22	22	19.94	20.53
7	RO	4	28.66	29.28	26.1	27.86
8	RO	6	29.55	30.09	25.14	28.52
9	RO	7	27.36	27.36	23.53	24.89
10	RO	8	25.45	26.75	24.83	25.7
11	RO	6	32.42	32.74	32.04	32.25
12	RO	6	34.5	34.97	31.86	33.34

^a Determined by opening face algorithm.

^b, ^c, and ^d are the maximum, minimum, and average of lumber value at 18 log rotations, respectively.

Table 4.—Summary of log sawing simulation.

Log No	Actual			Heuristic			Dynamic		
	Volume (bf)	Value (\$)	\$/bf	Volume (bf)	Value (\$)	\$/bf	Volume (bf)	Value (\$)	\$/bf
1	43.77	17.06	0.39	45.27	20.12	0.44	38.04	20.26	0.53
2	35.56	14.27	0.4	40.08	19.42	0.48	37.65	19.53	0.52
3	36.34	21.67	0.6	38.54	28.66	0.74	38.84	29.26	0.75
4	45.22	26.44	0.58	46.54	32.35	0.7	43.65	32.93	0.75
5	35.69	10.4	0.29	42.69	14.73	0.35	39.94	14.89	0.37
6	37.07	11.29	0.3	41.75	16.08	0.39	39.08	16.53	0.42
7	40.71	20.97	0.52	40.08	27.36	0.68	40.05	28.57	0.71
8	36.92	21.44	0.58	38.75	25.45	0.66	34.06	25.58	0.75
9	56.74	18.9	0.33	57.16	23.8	0.42	53.06	23.8	0.45
10	52.23	18.38	0.35	53.32	22.18	0.42	48.56	22.67	0.47
11	51.91	30.46	0.59	50.01	35.3	0.71	46.53	35.88	0.77
12	52.23	27.68	0.53	52.89	35.06	0.66	48.51	35.79	0.74
Mean	43.67	19.91	0.46	45.59	25.04	0.55	42.33	25.47	0.61

dynamic programming algorithms were used to saw the logs, the average volume of lumber was 45.59 bf and 42.33 bf, respectively. However, the average value of lumber was \$25.04 and \$25.47, respectively.

The distribution of lumber grade produced by using algorithms and actual lumber grade production is shown in Figure 3. We found that the distribution of lumber grades differs among different sawing methods. In the actual log sawing production, 34 percent, 40 percent, and 17 percent of lumber were graded as 1COM, 2COM, and 3COM, respectively. When the heuristic algorithm is used to saw those logs, 48 percent, 32 percent, and 2 percent of lumber were graded as 1COM, 2COM, and 3COM, respectively. When the dynamic programming algorithm was used, 52 percent, 19 percent, and 1 percent of lumber were graded as 1COM, 2COM, and 3COM, respectively. About 8 percent, 18 percent, and 27 percent of lumber grade were Select or higher among the actual production, heuristic algorithm, and dynamic programming algorithm, respectively.

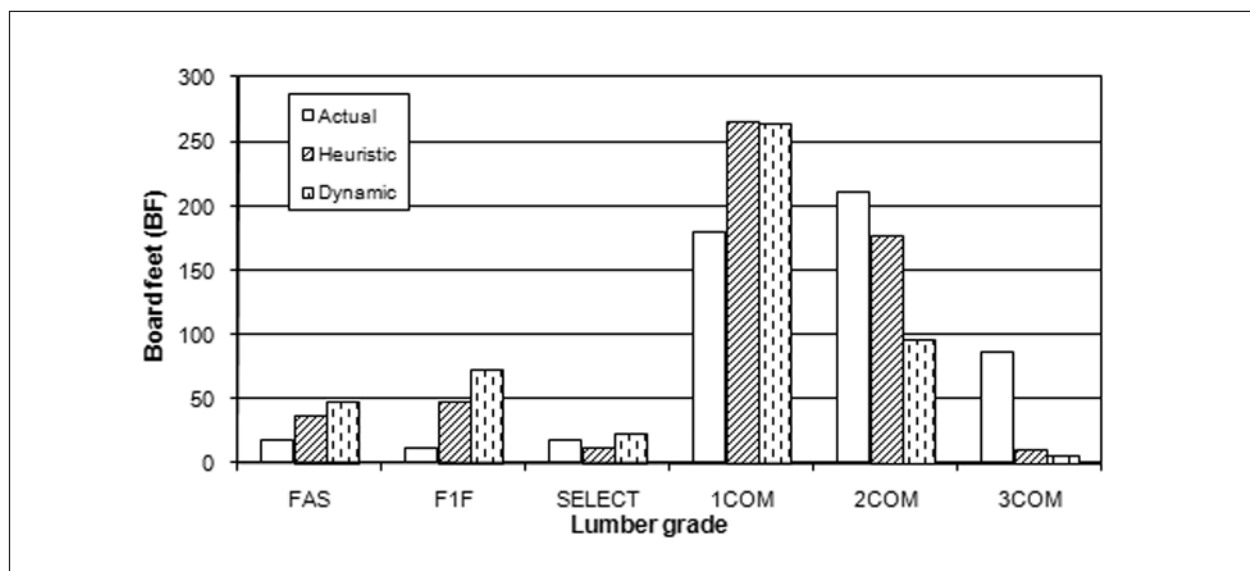


Figure 3.—Lumber grade distribution.

The results suggest that the difference in lumber value produced between actual sawmill and optimal sawing algorithm is rather large. One of the possible reasons is that real sawmill production depends on the sawyer's decisions. Such decisions are usually subjective and depend on the sawyer's skills and experience. Another reason is that external defects do not always indicate internal defects, especially for yellow-poplar. For example, only 7 external defects were found for log 2, but there were 10, 14, and 16 defects found in three pieces of lumber sawn from that log. In addition, some parts of the logs have no bark due to inappropriate operation or longtime storage, which affects the identification of external defects and predicted model accuracy. Finally, the precision of the predicted internal defect model also contributed to the difference between real production and simulations.

SPECIES COMPARISONS

In this study, yellow-poplar had more external defects than red oak (Fig. 4). Overgrown knots made up approximately one-third of observed defects for both species. In actual production, the average lumber value per board foot for yellow-poplar and red oak was \$0.35/bf and \$0.57/bf, respectively. However, if the heuristic algorithm is used to saw those logs, the average of lumber value per board foot could be \$0.42/bf and \$0.69/bf, respectively. If the dynamic programming algorithm is used, the average lumber value per board foot could be \$0.46/bf and \$0.75/bf, respectively. The improvement of lumber value per board foot using heuristic algorithm was 7 percent and 12 percent for yellow-poplar and red oak when compared to the actual production, respectively. The improvement of lumber value per board foot using the dynamic programming algorithm was 11 percent and 18 percent for yellow-poplar and red oak, respectively. Because the range of price change for yellow-poplar lumber at different grades is smaller than for red oak, and more defects were found in yellow-poplar logs, it makes sense that the improvement of lumber value recovery for yellow-poplar is smaller compared to red oak.

While lumber value has been improved by using the optimal sawing system, we must note some limitations. When the dynamic programming algorithm is used to optimize lumber value, the best cutting plane resolution is 0.04 in. In this study, the resolution was chosen as 0.16 in because run times for the program

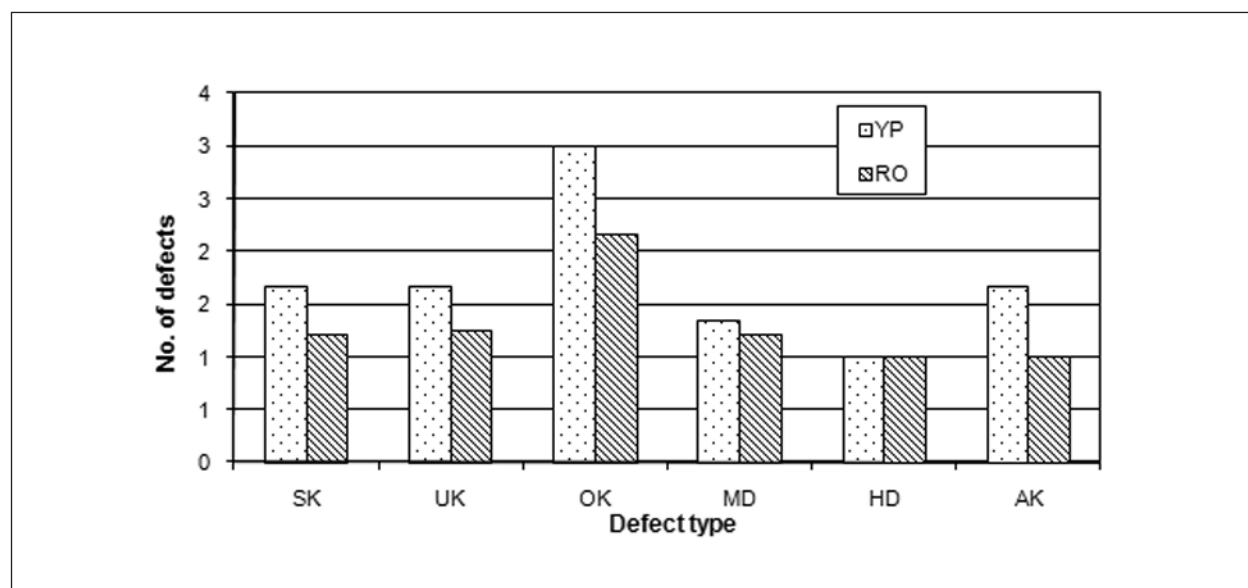


Figure 4.—Average log external defects by species. See page 68 for explanation of abbreviations.

are too great for this complicated algorithm. For example, if there were 75 cutting lines at each face of a log, there were approximately 7.6×10^{18} possible choices to consider. With an increase in the small-end diameter, the calculations are overwhelming. All flitches produced from log breakdown were edged to remove all waste. This processing method does not guarantee achievement of maximum value since flitch edging has significant effects on final lumber value. Using the optimum algorithm to deal with the flitch edging problem is essential to increase total lumber recovery. Additionally, the virtual shape of a log is not uniform. Thus, the precision of log sawing simulation is limited by using a truncated cone shape to represent the logs.

Future improvements that would extend the current findings include: 1) considering the real shape of the log in the sawing optimization system; 2) involving more variables, including external defects type and size as well as internal defects in the opening face cutting to improve the accuracy of the opening face cut; 3) combining the log sawing and flitch edging optimization; and 4) using multiple lumber thicknesses during the log sawing process.

CONCLUSIONS

A 3D log sawing optimization system was developed to perform 3D log generation, opening face determination, sawing simulation, and lumber grading. The system was then applied to 12 sample sawlogs at a sawmill in West Virginia. Comparisons between the actual lumber values and the simulated results from the same log were presented.

Preliminary results have shown that a typical hardwood sawmill potentially can increase lumber values by rotating logs and optimizing sawing patterns. In this study, we found that lumber value can increase 2.9 percent when opening face cutting is used, as compared to the average of lumber value produced from the 0 to 85° rotation. In terms of the average of lumber value recovery, sawmills have the potential to improve lumber value by 22 percent or 33 percent with use of the heuristic or dynamic programming algorithm, respectively. The lumber grade was improved from 2COM or 3COM to 1COM or higher grade by using the optimal algorithms. The results also indicated that high lumber value recovery does not necessarily mean high volume recovery.

LITERATURE CITED

- Bhandarkar, S.M.; Luo, X.; Daniels, R.; Tollner, E.W. 2008. **Automated planning and optimization of lumber production using machine vision and computer tomography**. IEEE Transactions on Automation Science and Engineering. 5(4): 677-695.
- Klinkhachorn, P.; Franklin, J.P.; McMillin, C.W.; Connors, R.W.; Huber, H. 1988. **Automated computer grading of hardwood lumber**. Forest Products Journal. 38(3): 67-69.
- Malcolm, F.B. 1965. **A simplified procedure for developing grade lumber from hardwood logs**. Res. Pap. FPL-098. Madison, WI: U.S. Department of Agriculture, Forest Service, Forest Products Laboratory. 13 p.
- Milauskas, S.J.; Anderson, R.B.; McNeel, J. 2005. **Hardwood industry research priorities in West Virginia**. Forest Products Journal. 55(1): 28-32.

- McDonald, K.A.; Hassler, C.C.; Hawkins, J.E.; Pahl, T.L. 1996. **Hardwood structural lumber from log heart cants**. Forest Products Journal. 46(6): 55-62.
- Occeña, L.G.; Schmoldt, D.L.; Thawornwong, S. 1997. **Examining the use of internal defect information for information-augmented hardwood log breakdown**. In: Proceedings, ScanPro - 7th International Conference on Scanning Technology and Process Optimization for the Wood Products Industry. 8 p.
- Sarigul, E.; Abbott, A.L.; Schmoldt, D.L. 2001. **Nondestructive rule-based defect detection and identification system in CT images of hardwood logs**. Review of Progress in Quantitative Nondestructive Evaluation. 20: 1936-1943.
- Thomas, E. 2008. **Predicting internal yellow-poplar log defect features using surface indicators**. Wood & Fiber Science. 40(1): 14-22.
- Thomas, R.E. 2011. **Validation of an internal hardwood log defect prediction model**. In: Fei, Songlin; Lhotka, John M.; Stringer, Jeffrey W.; Gottschalk, Kurt W.; Miller, Gary W., eds. 17th Central Hardwood Forest Conference proceedings; 2010 April 5-7; Lexington, KY; Gen. Tech. Rep. NRS-P-78. Newtown Square, PA: U.S. Department of Agriculture, Forest Service, Northern Research Station: 77-82.
- Thomas, L. 2006. **Automated detection of surface defects on barked hardwood logs and stems using 3-D laser scanner data**. Blacksburg, VA: Virginia Polytechnic Institute and State University. 131 p. Ph.D. dissertation.

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