DEVELOPMENT OF A 3D LOG SAWING OPTIMIZATION SYSTEM FOR SMALL SAWMILLS IN CENTRAL APPALACHIA, US

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Abstract. A 3D log sawing optimization system was developed to perform log generation, opening face determination, sawing simulation, and lumber grading using 3D modeling techniques. Heuristic and dynamic programming algorithms were used to determine opening face and grade sawing optimization. Positions and shapes of internal log defects were predicted using a model developed by the USDA Forest Service. Lumber grading procedures were based on National Hardwood Lumber Association rules. The system was validated through comparisons with sawmill lumber values. External characteristics of logs, including length, large-end and small-end diameters, diameters at each foot, and defects were collected from five local sawmills in central Appalachia. Results indicated that hardwood sawmills have the potential to increase lumber value through optimal opening face and sawing optimizations. With these optimizations, average lumber value recovery could be increased by 10.01% using the heuristic algorithm or 14.21% using the dynamic programming algorithm. Lumber grade was improved significantly by using the optimal algorithms. For example, recovery of select or higher grade lumber increased 16-30%. This optimization system would help small sawmill operators improve their processing performance and improve industry competitiveness.

Keywords: Heuristic, dynamic programming, grade sawing, modeling, optimization.

INTRODUCTION

Maximizing profits gained from the conversion of hardwood logs into lumber is a primary concern for both large and small forest product companies. Increased operating costs caused by higher fuel and electricity prices coupled with lower lumber prices are forcing wood processors to become more efficient in their operations. Conventional log sawing practices rely heavily on manual inspection of external log defects and are based on maximizing either volume or grade (Zhu et al 1996; Lee et al 2001). This process is limited by the decision-making ability of the operators. Because most log defects are at unknown internal locations within the log, it is difficult to give an optimal decision (Sarigul et al 2001). Problems that arise from manual log defect detection and conventional log sawing practices include low lumber yields, less than adequate lumber quality with respect to grade, and slow production, all of which result in inefficient use of forest resources (Thomas 2002).

Log scanning and optimization systems can be used in lumber production (Thomas et al

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2004). Preliminary studies have shown that implementing an automated log scanning inspection system has the potential to improve productivity and quality, or grade, of the hardwood lumber being produced (Zhu et al 1996). Hardwood lumber value can be increased 11-21% by using optimal sawing strategies gained through the ability to detect internal log defects (Sarigul et al 2001). Although internal defects are difficult to detect, any improvements in defect detection can contribute to recovery of higher quality lumber, increased profits, and better use of forest resources (Thomas 2002). Currently, most available scanning systems are based on external models that use a laser-line scanner to collect rough log profile information. These systems were typically developed for softwood (pine, spruce, fir) log processing and for gathering information about external log characteristics (Samson 1993) but are becoming more common in hardwood mills. The USDA Forest Service in cooperation with Concord University and Virginia Tech has developed a full shape 3D log scanner to detect severe log surface defects using relatively low-cost equipment ($30,000 plus integration labor cost) (Thomas 2002, 2006). In addition, internal log defect prediction models also were developed based on measurements of external defects (Thomas 2006, 2008). A recent study has shown that the models can accurately predict about 81% of internal knot defects for red oak (Thomas 2011). There are also several internal log scanning technologies being developed (X-ray, computed tomography, MRI, etc); however, none of them are efficient and cost-effective for small-scale hardwood sawmills.

Small hardwood producers are key contributors to the hardwood industry in the central Appalachian region. In West Virginia, 68.52% of the hardwood sawmills produce less than four million board feet (9440 m^3) of green hardwood lumber per year (West Virginia Division of Forestry 2004). In Pennsylvania, 50% of respondents in a hardwood sawmill profile survey produced less than 3.2 Mm^3 of lumber per year (Smith et al 2004). Most large softwood mills and many large hardwood mills have implemented the latest sawing and optimization technologies to increase lumber yield and value. However, small hardwood sawmills are less able to implement advanced technologies because of high initial cost, long payback period, and modifications to current operations (Occeña et al 2001). To survive in the highly competitive marketplace under current turbulent economic conditions, developing appropriate cost-effective milling technology for these smaller mills is essential for them to improve profitability and competitiveness. Therefore, the objectives of this study were to 1) design optimization algorithms to determine opening face and log sawing patterns to improve lumber value recovery; 2) develop a 3D visualization computer-aided log sawing simulation system for small hardwood sawmills to implement optimal computer algorithms; and 3) validate the optimal sawing system by comparing computer-generated results with actual output at existing sawmills.

LITERATURE REVIEW

Since the 1960s, there have been ongoing efforts to improve lumber value or volume recovery through either computer simulation or mathematical programming (Tsolakides 1969; Hallock and Galiger 1971; Richards 1973; Hallock et al 1976; Richards et al 1979, 1980; Lewis 1985; Occeña and Tanchoco 1988; Harless et al 1991; Steele et al 1993, 1994; Occeña et al 1997, 2001; Guddanti and Chang 1998; Chang et al 2005). For example, Tsolakides (1969) reconstructed a log as a cylinder and developed a digital computer analytical technique to study effects of alternative sawing methods. Hallock and Galiger (1971), Hallock et al (1976), and Lewis (1985) developed Best Opening Face (BOF) systems to maximize the volume of lumber produced from small-diameter softwood logs. The BOF program is a computer simulation model of the sawing process for recovering dimension lumber from small, straight logs. The sawing algorithm determines the initial opening face to produce the smallest acceptable piece from a given log. Once the opening face is found, consecutive cuts are made and the yield for the log is determined.

Then, the opening face is moved toward the center of the log by arbitrarily selected increments and the sawing process repeated. At last, all possible sawing results are compared and the BOF determined. The program was widely adopted during the 1980s, and many softwood sawmills still use it today to produce lumber. However, application of BOF in hardwood sawmills is very limited.

Richards et al (1979, 1980) designed a computer simulation program for hardwood log sawing. In this program, a log was represented by a truncated cone and each knot was simulated as a cone with its apex of 24° at the pith. Occeña and Tanchoco (1988) used a graphic log sawing simulator as an analytical tool for automated hardwood log breakdown. Log sawing optimization can be defined as a dynamic programming problem, and recursive equations were established to find optimum total lumber value or volume recovery (Faaland and Briggs 1984; Geerts 1984; Funk et al 1993; Todoroki and Rönnqvist 1997, 1999; Bhandarkar et al 2002, 2008), although Occeña et al (1997) and Thawornwong et al (2003) used heuristical algorithms to optimize log sawing patterns.

Although several optimal log sawing programs had been developed, they were either not suitable for hardwood log grade sawing practices or economically infeasible for small central Appalachian sawmills. For example, many existing programs did not provide a practical sawing tool or training tool with a 3D simulation environment. Some programs considered exterior defects only or internal defects obtained by X-ray/CT or MRI scanning methods. These methods were not fast, efficient, and cost-effective for small-scale and portable sawmills. Most optimal log sawing strategies use live sawing guided by heuristic algorithms or mathematical models. However, live sawing is not commonly used in hardwood sawmills. Although some researchers used heuristic log grade sawing methods in their studies, their solutions were not efficient because of effects of the log's rotational orientation and depth of the first opening face. In this study, we describe the design and implementation of a log sawing system for optimal lumber production. The system provides optimal opening face determination, mathematical models, and heuristic and dynamic programming algorithms for lumber production optimization. External log defect information is used to obtain internal log defect data, which are used to maximize lumber value recovery. The system can be used in decision-making for hardwood lumber production and as a training tool for novice sawyers.

MATERIALS AND METHODS

Data Collection

Log sawing practices for five small hardwood sawmills in North Central West Virginia were studied between October 2009 and August 2010 (Lin et al 2011). These mills were typical small-scale hardwood sawmills for this state in terms of equipment and sawing methods. All the sawmills used the grade sawing method to produce lumber. A total of 230 logs of two species, red oak (*Quercus rubra*) and yellow-poplar (*Liriodendron tulipifera*), were measured on site, of which 50 logs (25 of each species) were selected to test the program. Selected logs were 2.44-4.27 m long and 0.25-0.33 m in scaling diameter (Table 1). Log taper was calculated as the difference between large-end and small-end diameter divided by log length. Log profile data included log length, large- and small-end diameters, and diameters at every foot from the small end. External log defect data collected include 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]), distance of defects away from the small end of the log, defect angle with respect to the

Table 1. Characteristics of sample logs.

Statistic categories	Length (m)	Small-end diameter (m)	Large-end diameter (m)	Taper (mm/m)
Min	2.44	0.25	0.26	0.83
Max	4.27	0.33	0.38	25.83
Mean	2.74	0.29	0.31	6.67
SD[a]	1.62	1.14	1.43	5.83

[a] Standard deviation.

predetermined initial zero degree, defect size, and defect surface rise. Bark distortion usually indicates a knot that has been overgrown to the point of being completely encapsulated within the log. Bark distortions are classified as light, medium, or heavy (Carpenter et al 1989). External log defect data format is the same as that obtained with the 3D log laser scanner developed by the USDA Forest Service, which allows future integration of the laser scanning data process with the developed sawing system. Internal log defect locations were predicted using models by Thomas (2008). Recorded log and predicted data were stored in a MS Access (Microsoft, Redmond, WA) database.

All logs were marked with unique numbers, and corresponding boards sawn from each log were labeled to track the source of the lumber after completing the sawing process for the sample log. Logs were sawn according to the sawyer's choice, and the sawyer chose to use the grade sawing technique. All lumber sawn was 4/4 (25.4 mm) thickness with a saw kerf of 0.125 and 0.305 for band saw and circular saw, respectively. After edging and trimming, lumber length (m), width and thickness (mm), and volume (m^3) were measured (Table 2). Grade and surface measure of lumber were determined by a certified National Hardwood Lumber Association (NHLA) grader at each sawmill. Lumber prices were based on Hardwood Market Report for Appalachian Hardwoods (April 11, 2009). Collected lumber data were compared with optimal log sawing system simulation results.

System Structure and Design

The optimal sawing system consists of four major components: data input/storage, 3D modeling, sawing optimization, and lumber grading (Fig 1). The data input/storage component includes data acquisition, data standardization, and data storage, whereas the 3D modeling component handles 3D image display and 3D image transformation. The sawing optimization component determines opening face, log sawing, and cant resawing optimization, whereas the lumber grading component processes lumber grades during the optimization process. A component object model (COM) was used to integrate the system and was designed using the principles of object-oriented programming. The system was programmed using Microsoft Foundation Classes and Open Graphics Library (OpenGL) using MS Visual C++. ActiveX Data Object was used to retrieve data from and save sawing results to a Microsoft Access database.

Table 2. Characteristics of lumber from sample logs.

Statistic categories	Length (m)	Width (mm)	Thickness (mm)	SM[a]	Volume (m^3)	Value (US $)
Minimum	1.82	90	25	0.19	0.01	0.86
Maximum	4.27	214	54	0.65	0.03	6.93
Mean	2.75	155	36	0.37	0.01	2.27
SD[b]	1.52	1.12	0.16	0.08	1.44	0.88

[a] Surface measure (m^2).
[b] Standard deviation.

3D Log Modeling

3D modeling techniques together with OpenGL primitive drawing functions were used to generate 3D log visualization (Wang et al 2009). A log was reconstructed as a circular cross-section model (Zeng 1995). The cross-section model

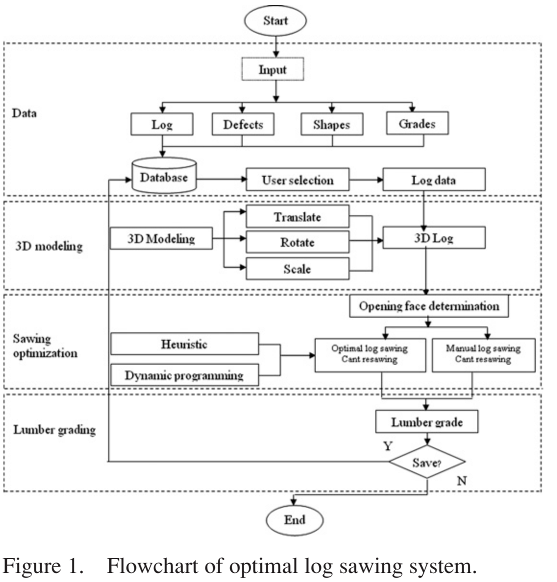

Figure 1. Flowchart of optimal log sawing system.

uses a series of cross-sections at a fixed interval along the log length. This model is closer to a real log shape because log sweep and crook were considered at each cross-section. A cone model was used to represent an internal defect (knot only), and its apex was assumed at the pith (central axis) of the log. Geometry of internal defects was described by a mathematical model developed by Thomas (2008). When a sawing plane passed through an internal defect, a 2D rectangle defect area was exposed on the lumber surface. Location and size of the defect area were determined using mathematical procedures. OpenGL functions such as translation, rotation, and scaling were used to facilitate visualization of the log. For example, rotation is performed by calling glRotatef (α, x, y, z), which generates the rotation matrix by defining the degrees to be rotated (α) and the axis to be rotated about (x-axis, y-axis, or z-axis). The generic matrix of rotation α angle around the three axes can be derived and expressed as (Woo et al 2000):

$$R_x(\alpha) = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & \cos\alpha & -\sin\alpha & 0 \\ 0 & \sin\alpha & \cos\alpha & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$
$$R_y(\alpha) = \begin{bmatrix} \cos\alpha & 0 & \sin\alpha & 0 \\ 0 & 1 & 0 & 0 \\ -\sin\alpha & 0 & \cos\alpha & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (1)$$
$$R_z(\alpha) = \begin{bmatrix} \cos\alpha & -\sin\alpha & 0 & 0 \\ \sin\alpha & \cos\alpha & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

To render a 3D log efficiently, simple triangle strips were used. Let the coordinates of the vertices of a triangle be (x_1, y_1, z_1), (x_2, y_2, z_2), (x_3, y_3, z_3), respectively. The coordinate matrix for this triangle after rotating by α degrees around the x-axis can be expressed as (Wang et al 2009):

$$\begin{bmatrix} x'_1 & x'_2 & x'_3 \\ y'_1 & y'_2 & y'_3 \\ z'_1 & z'_2 & z'_3 \end{bmatrix} = R_x(\alpha) \times \begin{bmatrix} x_1 & x_2 & x_3 \\ y_1 & y_2 & y_3 \\ z_1 & z_2 & z_3 \end{bmatrix}$$
$$TS' = R_x(\alpha) \times TS \quad (2)$$

where TS is the coordinate matrix for one triangle strip on the surface of a log before transformation and TS' is the coordinate matrix after transformation. Similarly, the coordinate matrices for the triangle strip can be rotated around the y- and z-axes. These transformation procedures can be applied to all triangle strips that form a 3D log.

Sawing Algorithms

Opening face. There are three steps to determine BOF: 1) identifying four sawing faces by log rotation (A mathematical procedure was developed to identify four log faces after placing the majority of the defects at the edge of the cutting planes or on one face.); 2) determining the best face (It is assumed that the opening face is cut from the best sawing face [Thawornwong et al 2003]. Procedures for determining the best face are based on the USDA Forest Service hardwood log grading rules [Fig 2a] [Rast et al 1973]); and 3) determining the dimension of the opening face. Width of the opening face is determined as follows (Malcolm 1965): if the grade of the best face is F1, the slab width should be 158 mm (152 mm is the minimum width for the highest lumber grade board, and 6 mm is the width of log sawing kerf) for logs greater than or equal to 0.33 m in small-end diameter; otherwise the log should be slabbed to 108 mm wide. For all logs that have a best face with grade of F2 or F3, slab width should be 83 mm.

Heuristic algorithm for log grade sawing. A computer-based heuristic algorithm was developed based on Malcolm's (1965) simplified procedures for hardwood log grade sawing. Cutting from the small end, the opening face is set out full taper by using the small end of the log as the pivot and unopened faces are parallel to sawing

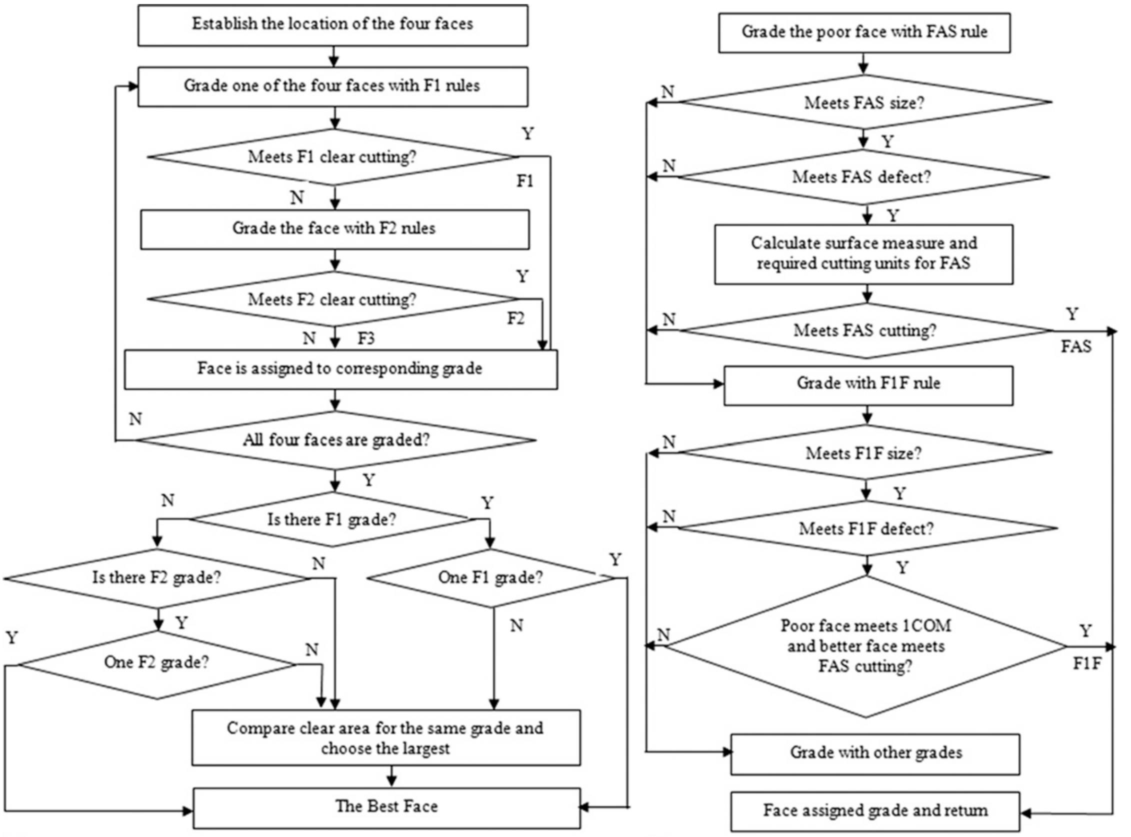

Figure 2. Procedures for determining best face and lumber grades. (a) Best face. (b) Lumber grades.

lines. As sawing progresses, the log is not rotated unless one of the other log faces will yield a higher-grade board than the current sawing face or the current cutting face reaches the central cant. Once a log face is sawn completely, the grade of the last board is recorded and this face will not be chosen again. The algorithm then considers the next face. This sawing process is repeated until a specified size cant is produced, indicating that the log sawing process is complete.

Mathematically based algorithm for log grade sawing. A log is broken into four portions at the small end in log grade sawing (Fig 3a). Once the first opening face is determined, the four log sawing faces are fixed. A sequence of parallel sawing planes is first performed on portions 1 and 3 of the log. Then the parallel sawing planes with orthogonal orientation are conducted on portions 2 and 4. A mathematical model for maximizing lumber recovery value through grade sawing can be expressed by the following function:

$$\begin{aligned} F = (&L_1^*, L_2^*(L_1^*), L_3^*(L_1^*, L_2^*), L_4^*(L_1^*, L_2^*, L_3^*),\\ &V^*(L_1^*, L_2^*, L_3^*, L_4^*), S_1^*(L_1^*), S_2^*(L_1^*, L_2^*),\\ &S_3^*(L_1^*, L_2^*, L_3^*), S_4^*(L_1^*, L_2^*, L_3^*, L_4^*)) \end{aligned} \quad (3)$$

where L_1, L_2, L_3, L_4 and S_1, S_2, S_3, 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 the optimal log grade sawing procedure described by Bhandarkar et al (2008). The objective of Eq 3 is to find the locations of

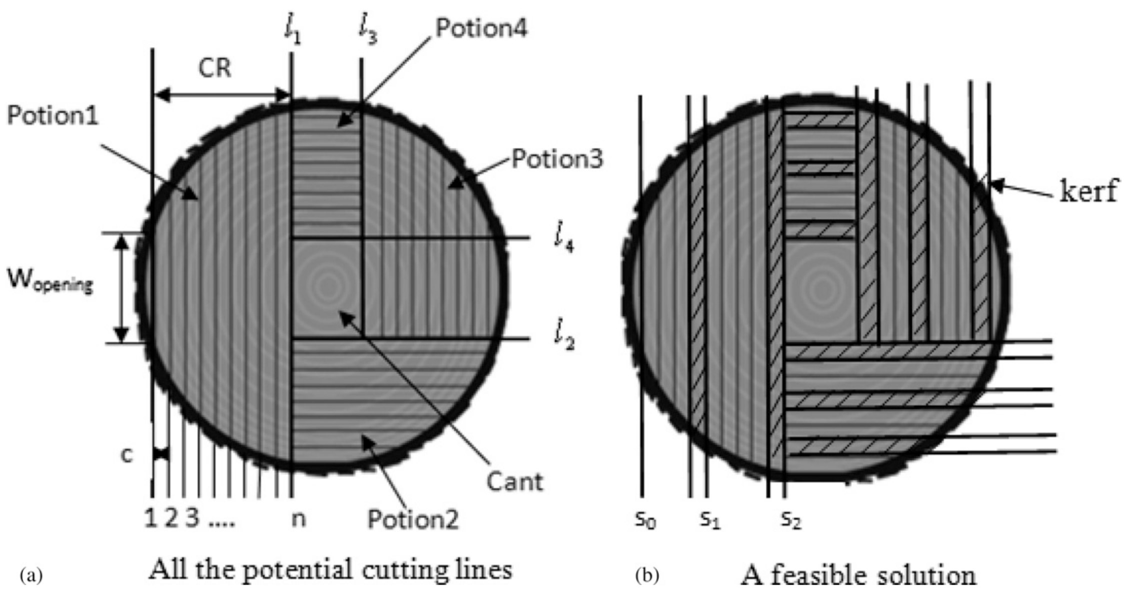

Figure 3. Dynamic programming for log grade sawing.

L_1, L_2, L_3, and L_4 to maximize total lumber value. To generate the candidate flitches, each portion of the log is divided into n equidistant sawing planes with resolution c, and a sawing plane is denoted by l_1 at the first portion (Fig 3a). Let $C = \{1, 2, \cdots, n\}$ be a finite set of all the potential sawing planes and $S = \{s_0, s_1, \cdots, s_n\}$ be a subset of C that satisfies the following constraints:

$$\left(s_i - s_{i-1} - \left\lceil \frac{k}{c} \right\rceil\right) \cdot c \in T, \textit{for}\ 1 \leq i \leq n \quad (4)$$

$$s_0 = 1, s_n = n \quad (5)$$

where $T = (T_1, T_2, \cdots, T_m)$ is a set of lumber thicknesses (mm); m is total number of lumber thicknesses considered; c is sawing plane resolution (mm); k is kerf thickness (mm); and $n = CR/c$ is total number of sawing planes within the cutting range. Therefore, the possible sawing planes are enumerated as $1, 2, \ldots, n$, whereas CR is cutting range between opening face and central cant (mm).

A sawing pattern that satisfies Eqs 4 and 5 was considered a feasible solution for log grade sawing (Fig 3b). The optimal sawing pattern can be determined using a dynamic programming algorithm. Let $v^*(i)$ represent the optimal lumber value for each log portion between cutting planes 1 and i, $g(i, j)$ be the lumber value from the cutting planes i through j, a recursive mathematical equation for the dynamic programming can be formulated as follows (Bhandarkar et al 2008):

$$v^*(i+1) = \max_{j \in [0,m]} \left(v^*\left(i + 1 - \frac{T_j}{c} - \left\lceil \frac{k}{c} \right\rceil\right) + g\left(i + 1 - \frac{T_j}{c}, i+1\right)\right) \quad (6)$$

Cant Resawing

The value of the central cant is essential when comparing the total lumber value derived from different sawing methods for each log. The 3D optimization system allows the user to make a decision whether to keep the cant or resaw it. If the central cant is sawn, a usable sawing region for the cant should be defined prior to sawing. Because the taper sawing method is used in the sawing process, the cant will not be square. Thus, the taper must be removed from the cant first. It is assumed that the size of the final cant is the same as the small end of the unfinished cant. Given lumber thickness and sawing kerf, the best cutting solution can be determined by comparing total lumber value obtained from two sawing directions (horizontal and vertical) using the live sawing method. The problem of central cant resawing can still be solved by the dynamic programming algorithm. Parameters used for cant resawing are the same as log grade sawing with the exception of log sawing orientation and cutting range.

Lumber Grading

Prior to lumber grading, the sawn flitch must be resawn into lumber. All the flitches were edged to remove wane. To generate this lumber pattern, lumber width was assumed to be the narrowest clear area width along the flitch. Edged lumber was graded by a computer algorithm based on NHLA grading rules and a hardwood lumber grading program (Klinkhachorn et al 1988) (Fig 2b). NHLA grading rules provide both the buyer and seller with a consistent language for conducting hardwood lumber transactions. NHLA grades are based on percentage of clear defect-free wood on a board (NHLA 2008). To determine the possible grade for a piece of lumber, width, length, and surface measure (SM) of the lumber must be computed and a potential grade assigned to the poor face. SM is the surface area of a board in square feet. After these steps, the potential number of clear cuttings and cutting units (CUs) can be calculated. By comparing the number of cuttings and CUs obtained from the lumber and the requirements in NHLA grading rules, a final grade can be assigned (NHLA 2008). Lumber grades considered in this study were: First and Seconds, FAS-One-Face, Select, 1Common (1COM), 2Common (2COM), and 3Common (3COM).

System Implementation

The optimization system can be implemented on either a desktop or a laptop and run on a Windows (Microsoft) platform. Details of the sawing system can be found in the user's manual (Lin 2011). For this study, all log sawing simulations were performed on a desktop PC equipped with 3.16 GHz CPU, 3.25 GB RAM, and a 300 GB hard drive.

Sawing begins by determining the BOF. Once this is accomplished, the user can choose either the heuristic or dynamic programming algorithm to saw the log. Prior to the interactive simulation process, the user needs to specify some sawing variables (ie kerf width, lumber thickness, cant size, and sawing interval) at the bottom left area and choose appropriate commands at each group box. When using the dynamic programming algorithm to optimize log grade sawing, a sawing interval must be selected.

The log grade sawing process using the heuristic or dynamic programming algorithm can be conducted after the sawing kerf, lumber thickness, cant size, and sawing interval are specified. Then the log can be sawn except for the central cant. The user can opt to saw the central cant or keep it. If the cant is left, its value will be computed based on its volume and price. All sawing solutions and results are displayed on the computer screen for the user. An easy-to-use interface allows users to quickly and easily change settings as desired and compare the results of different sawing strategies and methods.

RESULTS AND DISCUSSION

Opening Face

To determine if the optimal opening face is better than any faces chosen randomly, log sawing was simulated using the optimal opening face and other assumed opening faces with log rotation angle from 0-85° with a 5° increment and opening face width of 0.083, 0.108, and 0.159 m, respectively (Table 3). Thus, a total of 48 possible sawing patterns were tested by changing log rotation angle and initial opening face width in the assumed log sawing. A sequence of parallel cuts was performed for each log face until a central cant remained, which was sawn later by parallel cuts. Results showed that total lumber value

Table 3. Lumber value from optimal opening face cut vs average lumber value from other opening face cut.

Log no.	Lumber value[a]	Average lumber value[b]	Log no.	Lumber value[a]	Average lumber value[b]
1	12.91	10.59	26	34.72	30.79
2	16.06	15.25	27	40.04	38.6
3	17.01	15.95	28	43.02	45.05
4	14.57	12.97	29	55.23	54.34
5	20.52	19.83	30	43.06	40.7
6	12.48	12.66	31	32.02	28.91
7	27.12	25.39	32	21.05	20.96
8	20.4	19.71	33	32.02	32.51
9	18.93	17.39	34	17.22	15.05
10	20.13	19.8	35	23	22.46
11	30.02	28.58	36	23.35	21.68
12	25.17	24.92	37	35.64	33.83
13	17.5	15.66	38	21.15	18.73
14	16.84	14.7	39	27.69	27.36
15	28.26	26.28	40	26.18	24.04
16	32.76	31.63	41	47.25	45.85
17	35.04	34.29	42	22.15	20.49
18	28.29	26.08	43	24.14	23.47
19	40.38	39.78	44	34.28	33.8
20	18.92	17.91	45	29.67	28.08
21	23.27	22.5	46	29.5	28.62
22	30.56	28.39	47	21.15	20.97
23	37.24	37.24	48	19.82	18.75
24	31.17	30.74	49	33.18	31.83
25	39.09	38.29	50	22.76	21.32

[a] Lumber value from optimal opening face cut
[b] Average lumber value from other opening faces cut.

using the optimal opening face cut was higher than the average total value derived from any other opening face by an average of 4.31%. Log rotation angle and opening face width had impacts on total lumber value recovered.

Log Sawing Comparisons

Lumber value and volume improvement. If heuristic and dynamic programming optimizations are used, sawmills have the potential to improve their lumber recovery value by 10.01% and 14.21% (Figs 4 and 5), respectively. High volume recovery tends to result in high lumber value recovery. For example, when heuristic and dynamic programming algorithms were used to optimize log sawing, average lumber volume was 0.1311 and 0.1331 m^3, respectively, and average lumber value was US $28.18 and US $29.42, respectively. Average lumber volume improved 2.5 and 4.1%, respectively. However, high volume recovery does not always mean high lumber value recovery for some logs. Also, lumber value recovery could be improved significantly for logs with more defects. For instance, for logs with six or more defects, average lumber value recovery could be improved by 11.08 and 16.28% using heuristic and dynamic programming optimization methods, respectively. However, average lumber value recovery improved by 9.01 and 12.56% for logs with five or less defects. Average lumber value obtained by the dynamic programming algorithm was not always greater than the value generated by the heuristic algorithm, because the precision of the dynamic programming optimization depends on the selected stage interval. However, the more precise solution comes with the expense of longer computing time.

Lumber grade improvement. It was found that the distribution of lumber grades differed

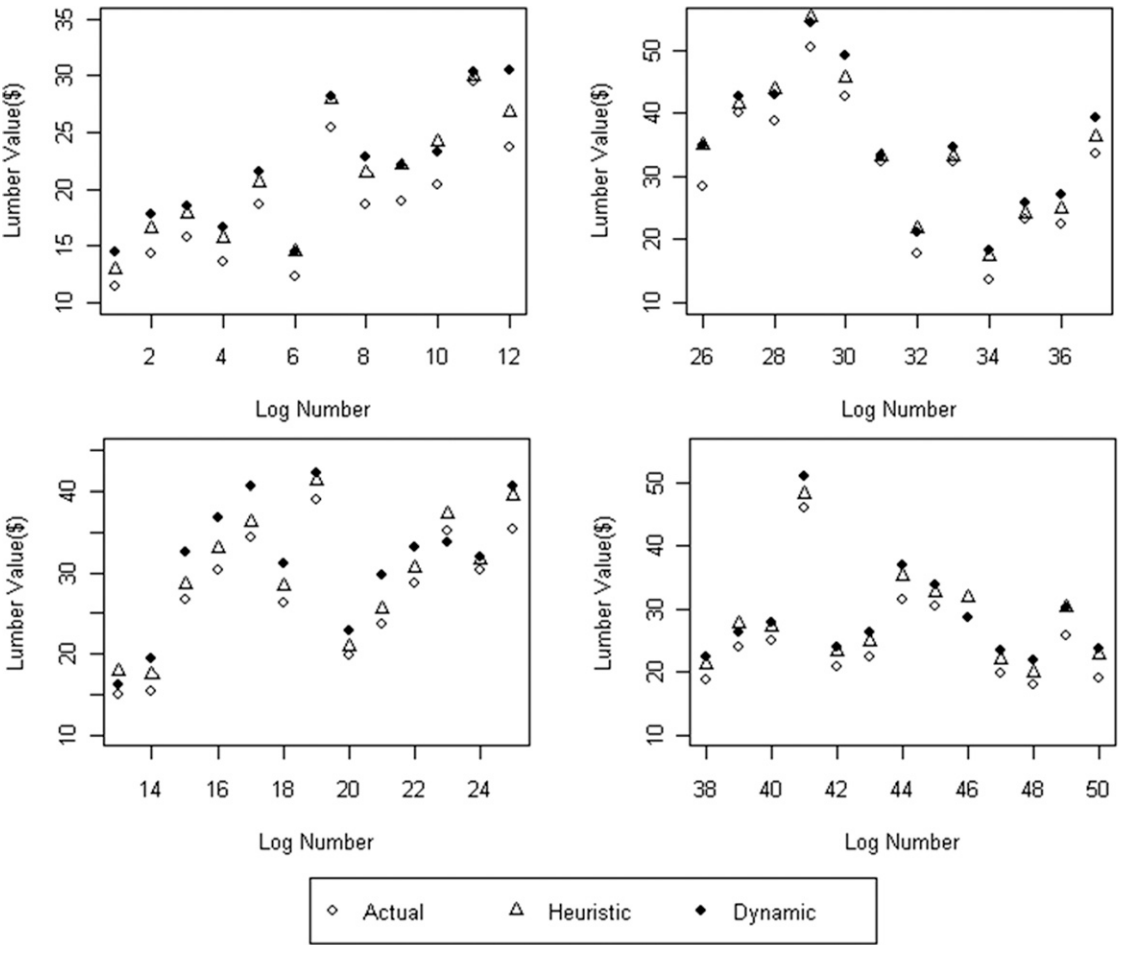

Figure 4. Average lumber value from actual sawmills and heuristic and dynamic programming algorithms.

among different sawing methods. About 16, 30, and 36% of lumber grades were Select or higher in actual sawmilling operation, heuristic optimization, and dynamic optimization (Fig 6), respectively. In the actual sawmilling operation, 44, 32, and 9% of lumber was graded as 1COM, 2COM, and 3COM, respectively. When the heuristic algorithm was used to optimize those logs, 48, 19, and 3% of lumber was graded as 1COM, 2COM, and 3COM, respectively. When the dynamic programming algorithm was used, 44, 18, and 2% of lumber yielded 1COM, 2COM, and 3COM, respectively. Therefore, lumber grades can be improved using optimization algorithms, resulting in a final lumber value recovery increase.

Lumber Value Recovery by Species

Average lumber value recovery was compared between two dominant species, red oak and yellow-poplar, in central Appalachia. Internal log defect prediction models embedded in the system were only available for the two species. Other species such as red maple and white oak may be considered in future analyses once prediction models are available. In the sawmill, yellow-poplar and red oak lumber values

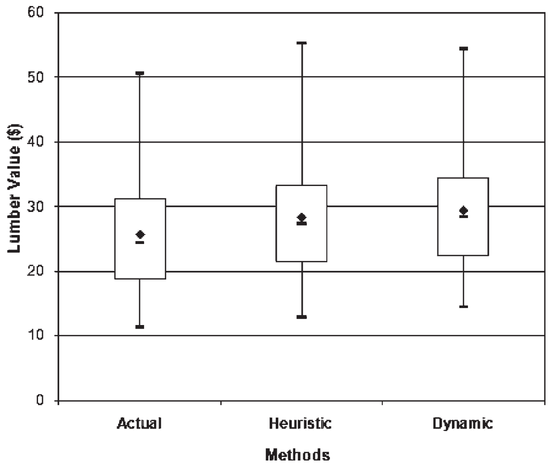

Figure 5. Distribution of lumber value by methods.

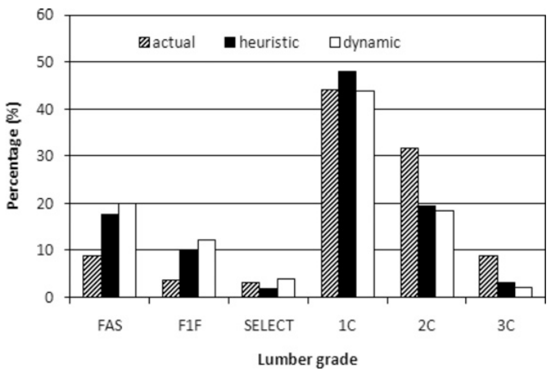

Figure 6. Lumber grade distribution.

averaged US $20.71 and US $29.28, respectively. If the heuristic algorithm was used to optimize log sawing, average lumber value could be US $23.01 and US $31.89, respectively, per log. If the dynamic programming was used, average lumber value could be up to US $23.81 and US $33.17, respectively, per log. Lumber value using the heuristic algorithm could improve 11.11% for yellow-poplar or 8.94% for red oak compared with the sawmill's results. Conversely, lumber value using the dynamic programming algorithm improved 14.95% for yellow-poplar and 13.29% for red oak. Lumber value recovery depended on log diameter, length, taper, quality, and other factors (Steele 1984). Among 50 selected sample logs, log dimension is not significantly different between yellow-poplar and red oak. However, number of external defects averaged 7.45 for yellow-poplar and 5.47 for red oak, which might explain why more improvement was achieved for yellow-poplar than for red oak logs using the sawing optimization system. Results also showed that lumber value recovery was different by species, which indicated that mill operators should pay more attention to valuable species when sawing.

Effects of Multiple Lumber Thicknesses

Approximately 70% of hardwood sawmills saw only 4/4 (25.4 mm) thickness lumber in the US (Chang et al 2005). In this study, we analyzed if high lumber value could be improved if multiple thicknesses were considered in the system using a dynamic programming algorithm and various lumber thicknesses (Fig 7). Results showed that using multiple lumber thicknesses can improve lumber value recovery. For example, when lumber thicknesses of 28 and 36 mm were used in log sawing optimization, average lumber value could increase 4.9% from US $29.42 to US $30.87. Therefore, if sawmills can efficiently handle different thicknesses of marketable lumber during lumber processing, they should gain more lumber value recovery. However, optimization time could be doubled compared with a single lumber thickness.

CONCLUSIONS

Currently, the hardwood industry in the central Appalachian region is facing a number of challenges including decreased log size and quality, limited resource availability, tightened environment restrictions on timber harvesting, decreased profit margins, and pressure from foreign competition (Milauskas et al 2005). Remaining viable and competitive, given the current market, has become a major concern for the hardwood industry (Wang et al 2010). In response to these issues, hardwood sawmills in the region need to take actions and aggressively search for new markets while adopting more efficient processing methods for using limited

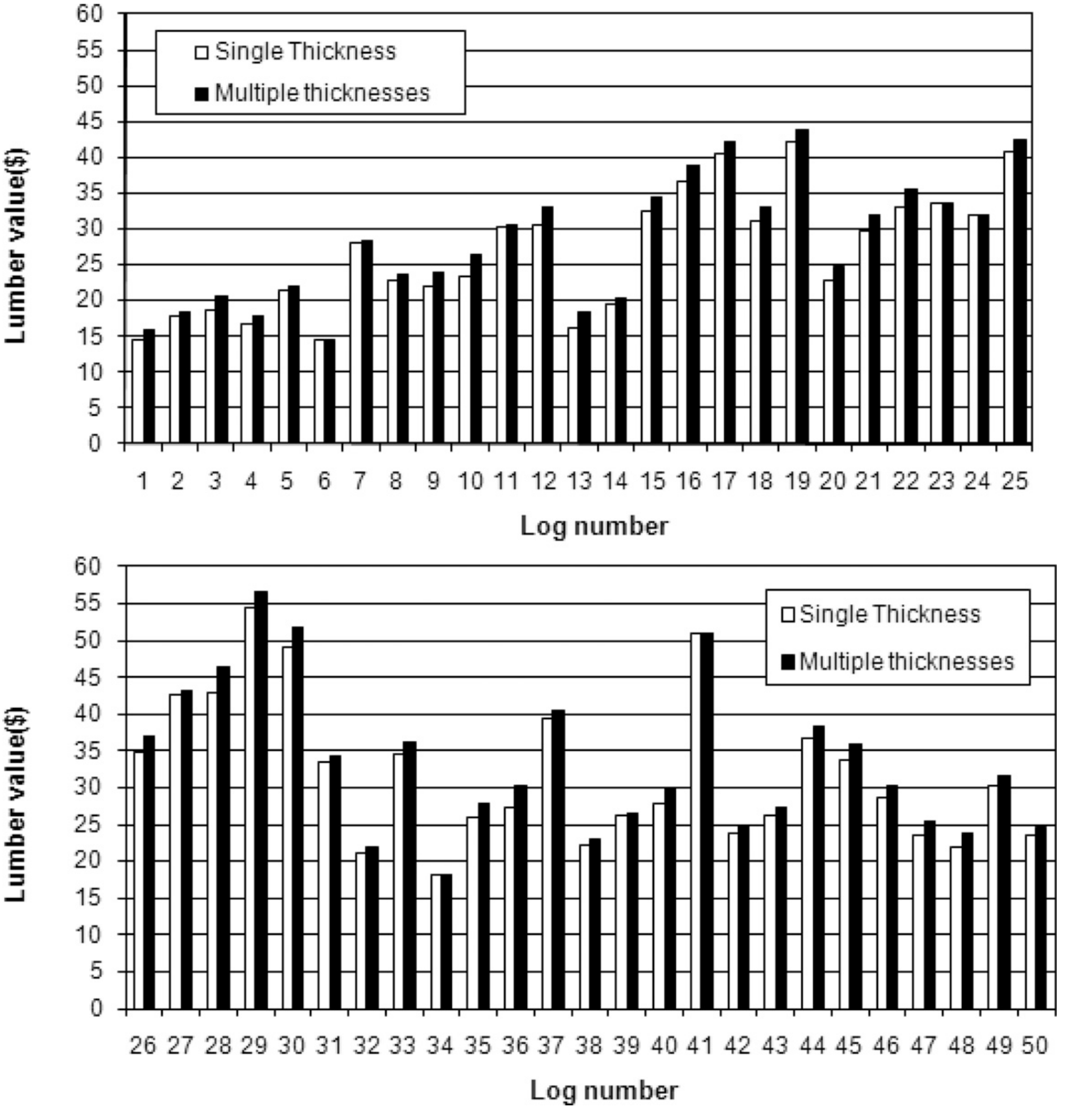

Figure 7. Average lumber value produced using single lumber and multiple lumber thicknesses.

forest resources. Application of appropriate computer-aided sawing and grading systems will be one of the strategies to improve processing performance and enhance competitiveness, specifically for small sawmills.

For this research, an inexpensive and user-friendly 3D log sawing optimization system was developed to perform 3D log generation, opening face determination, sawing simulation, and lumber grading. Lumber value could be increased 4.31% when optimal opening face cutting was used compared with average lumber value by any random opening face cuts. Lumber value recovery could be improved 10.01% using heuristic or 14.21% using dynamic programming optimization. Lumber grade could be improved significantly using the sawing optimization system. Although approximately 16% of lumber sawn in the sawmill is graded at Select or higher, this could be increased to 30% with the heuristic algorithm. Using multiple lumber thicknesses could further improve lumber value recovery compared with using a single lumber thickness. In this study, the use of multiple lumber thicknesses showed that average lumber value could be increased 4.9% from US $29.42 to US $30.87.

In this study, optimal opening face was determined by heuristic algorithm. In fact, the exhaustive search algorithm also can be used to determine the opening face. However, this process would be time-consuming because every degree of log rotation and opening face width needs to be considered simultaneously. Lumber value produced from the optimal opening face was not maximal in some cases. The reason may be that defect types and sizes were not fully considered in the opening face algorithm. For example, defect penetration depth and clear area between bark and pith of a log vary among defect types. Also, severe and large defects have more significant effects on lumber value than slight defects, thus severe defects must be given top priority and should be rotated to the edge of the log sawing planes. Future research is needed to combine internal defect information with external defect information to determine optimal opening face.

Fifty sample sawlogs at five typical hardwood sawmills in West Virginia were used to validate the system. Comparisons between actual lumber value and simulated sawing results from the same logs were conducted. Lumber value and grade were significantly improved in the optimization simulation compared with actual sawmilling production. Some measurement errors also existed in the data collection process because of equipment, operators' experience, and other factors. For example, there were only 7 external defects found for one log, but 10, 14, and 16 defects appeared in three pieces of lumber after sawing it and most of them were tiny or small defects. Areas of some logs had lost bark because of operations or long-time storage, which affected external defect identification. Logs were debarked in these five sawmills prior to the sawing process. Sawyers had difficulty identifying external defects, which could have affected their decisions on sawing. Also, accuracy of the defect prediction model also contributed to the difference between real production and simulations. Factors including experience, operator error, and mill equipment also have impacts on decision-making at the headrig.

Heuristic procedures are more easily adaptable to complex restriction, such as in log grade sawing process. However, they may not be proven to produce an optimal solution. A mathematically based optimization algorithm will be used to simulate log sawing to find the optimal solution. Average lumber value obtained by the dynamic programming algorithm was not always greater than the value generated by the heuristic algorithm, because precision of the dynamic programming optimization depends on the selected stage interval. When Tukey multiple comparison was used to test the difference of lumber value produced by actual sawmills, heuristic programming algorithms, and dynamic programming algorithms, it was found that there were significant differences. However, no significant difference existed in mean lumber values between heuristic and dynamic programming optimizations.

Although the log sawing optimization system has the potential to improve lumber value recovery, some limitations exist in the system. Accuracy of the log sawing simulation is limited because a circular cross-section model is used to represent real logs. The stage interval for the dynamic programming algorithm was chosen as 4 mm rather than 1 mm to increase system efficiency, and precision of the sawing results was affected accordingly. More sample logs of various species, shape, and defect should be tested to verify the system. All flitches produced from logs were edged to remove wanes. Maximum lumber value was not guaranteed because flitch edging and trimming also affect final lumber value. The optimum algorithm should be used to deal with flitch edging and trimming to increase total lumber value recovery.

Future improvements of the log sawing optimization system include 1) considering elliptical cross-sections in the 3D log model to improve model accuracy; 2) involving more variables including external defect type and size as well as internal defects to determine opening face; 3) improving the log sawing algorithm to increase system efficiency and accuracy; and 4) integrating log sawing with flitch edging and trimming optimization.

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