VALIDATION OF AN INTERNAL HARDWOOD LOG DEFECT PREDICTION MODEL

R. Edward Thomas[1]

Abstract.—The type, size, and location of internal defects dictate the grade and value of lumber sawn from hardwood logs. However, acquiring internal defect knowledge with x-ray/computed-tomography or magnetic-resonance imaging technology can be expensive both in time and cost. An alternative approach uses prediction models based on correlations among external defect indicators and internal defect features. Using external defect feature measurements, a prediction of internal defect size, shape, and depth can be generated. This paper examines the accuracy of the prediction models by comparing defect attributes on actual sawn board faces with the predicted defect attributes on virtual sawn boards. Although the models showed significant correlations in the model-testing dataset for most defect types and features, they were never tested by the sawing of new samples and comparing predicted to actual defect attributes. Results for a test sample of 41 boards with 83 observed knot defects show that the prediction models can predict the occurrence of approximately 80 percent of all knot-type defects.

INTRODUCTION

The grade and value of lumber sawn from hardwood logs depend on the type, size, and location of internal defects. The hardwood log grading rules are based on the relationship between defect occurrence and lumber recovery (Hanks and others 1980). The ability to use internal defect information such as location, size, and shape during the sawing process has been shown to significantly improve the value of hardwood lumber sawn by as much as 10 to 21 percent (Wagner and others 1990, Steele and others 1994). X-ray/computed-tomography (CT) and magnetic-resonance imaging (MRI) methods have been the traditional research approach to obtaining internal log defect information (Chang 1992). However, there are several problems associated with acquiring internal hardwood log defect data using these methods. For example, scanning a log can be costly due to equipment expenses and time-consuming, depending on resolution and processing speed (Schmoldt and others 2000).

Because of the importance of internal defect information to the sawing process, several studies have sought to link external features to internal defect characteristics. Schultz (1961) studied German beech (*Fagus sylvatica* L.) and found that the ratio of the bark distortion width to length was the same as the ratio of the stem when the branch stub was encapsulated to the current stem diameter. For species with heavier, irregular bark, such as sugar maple (*Acer saccharum* L.), however, Schultz (1961) found that it was difficult to judge the clear area above the defect using this method. Like Schultz (1961), Shigo and Larson (1969) found that for many hardwoods the ratio of defect length to width indicated the depth of the defect with respect to the radius of the stem at the defect. Hyvärinen (1976) studied external bark distortion measurements and defect encapsulation depth for sugar maple and found strong correlations among encapsulation depth and distortion

[1]Research Scientist, Northern Research Station, U.S. Forest Service, Forestry Sciences Laboratory, 241 Mercer Springs Rd., Princeton, WV 24740. To contact, call (304)-431-2324 or email ethomas@fs.fed.us.

width, length, and rise using linear regression methods. More recently, Lemieux and others (2001) examined knot defect correlations among external indicators and internal defect features for a sample of 21 black spruce (*Picea mariana* L.) trees collected in northern Quebec. They found correlations (r > 0.89) among the width and length of internal defect areas and external features such as branch stub diameter and length. The Lemieux and others (2001) study examined only branches that had not been dropped or pruned, thus preventing an examination of encapsulation depth.

An alternative approach to the x-ray/CT and MRI methods has been developed that uses high-resolution laser surface scanning. This approach uses intelligent software to locate and classify external log defects in the three-dimensional (3D) laser data (Thomas and others 2006). Once the external log defects are located, predictions of internal characteristics are made which estimate internal defect position, shape, and size based on measurements of the external indicator and log diameter (Thomas 2008, 2009). These models are based on correlations among internal and external defect features. Different models were created for different species, defect types, and defect type groupings. The models were created by statistically analyzing 842 red oak (*Quercus rubra* L.) and 1,000 yellow-poplar (*Liriodendron tulipifera* L.) defect samples collected from three sites in the central Appalachian region. These sites were the West Virginia University Experimental Forest; a forest near Rupert, WV; and the Camp Creek State Forest in West Virginia.

METHODS

A red oak tree was randomly selected from a site on the Fernow Experimental Forest near Parsons, WV. This experimental fire site had been subjected to fire twice in the last 15 years. The selected tree was bucked into four logs and a forked jump cut, which was discarded. Due to the site's burn history, the base of the tree had a large burn and decay area measuring approximately 66 x 26 inches with a maximum depth of 3.625 inches. The logs were graded to U.S. Department of Agriculture, Forest Service, log grades (Rast and others 1973). Despite the burn scar, the butt log was a grade 1 log. The second and third logs were grade 2 logs, and the fourth was a grade 3 log. Table 1 contains more detail about the size and defect characteristics of these logs. Because the butt log had no surface knot defects, it was omitted from the study.

Log surface data were collected using a high-resolution laser log scanner. The scanner is composed of three laser scan heads positioned at 120-degree intervals around the log. Each log is held on steel supports as the scanner mechanism traverses the length of the log. Each log scan is composed of series of scan lines around the circumference of the log. The distance between scan lines is 1/16 (0.0625) inch and each line is composed of approximately 300 to 600 points, depending on log size. The scan data, in their raw format, can be viewed as a dot cloud image (Fig. 1).

Table 1.—Characteristics of defect study logs.

					Defect characteristics			
Log	Grade	Length (feet)	Small end diameter (inches)	Large end diameter (inches)	Num. of knots	Num. of bark distortions	Num. of wounds	Num. of other defects
1	1	12	19.50	27.50	0	0	2	0
2	2	16	17.25	19.50	3	10	4	0
3	2	16	15.00	17.25	7	4	0	2
4	3	8	9.75	9.75	9	2	1	4

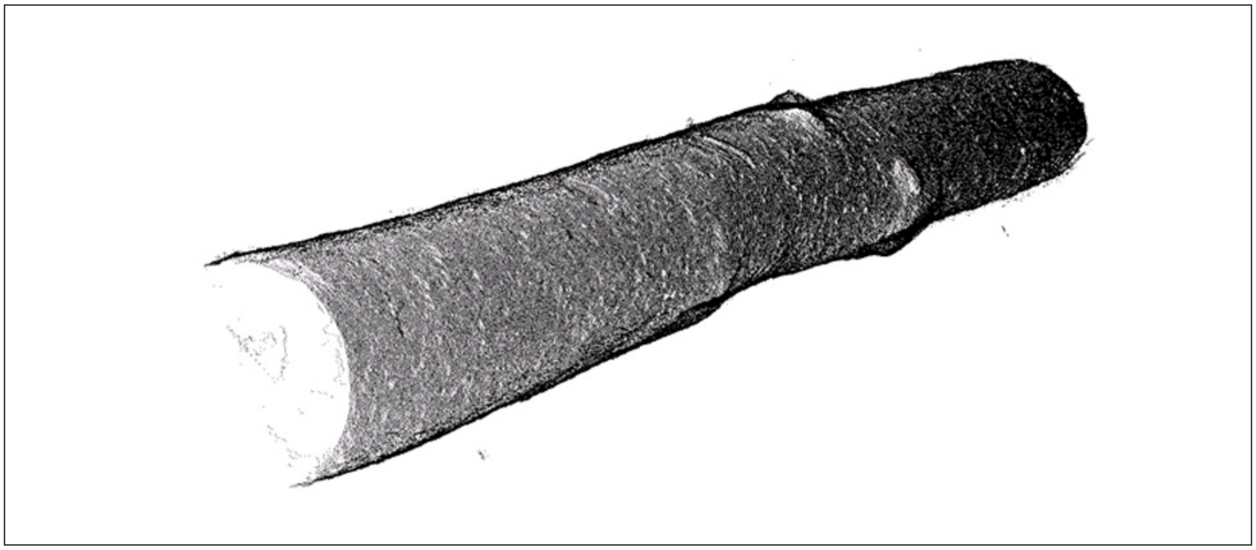

Figure 1.—Dot cloud image of a laser scanned log (Log 2).

After each log was scanned, all defect sizes and positions were recorded. This provided an accurate map of external defects and was used by the defect prediction program to generate internal defect size, shape, and position data. Defects are modeled as elliptical cones with two regions centered about the line from the center of the surface indicator to the predicted innermost endpoint determined using the predicted depth and penetration angle. The inner region extends from the predicted midpoint. The penetration angle is the angle at which a line through the center of the defect intersects the log surface. For some types of defects, most notably the bark distortions, the defects are grown over or encapsulated. Encapsulation depth is the amount of clear wood that has grown over the internal defect.

The internal and surface defect structure coordinates were overlaid with the scan data, creating a completely defined log dataset. These data were processed using the RAYSAW sawing program[2] (Thomas 2009), which reads a sawing pattern file and generates digital boards. Defects on the virtual boards are represented by boxes. The width and length of a box represent the size and approximate shape of the defect as it intersects the board face. To allow comparison of knots between actual and digital board faces, each log was sawn using the same sawing pattern as was used with its digital version.

The sawing patterns were designed to maximize the number of defects on the board faces rather than on the edges. This step was taken to simplify the comparison of defects on actual and digital board faces. To perform the comparison, defects were tracked from the surface indicator to their termination in both the digital and real-world logs. Only the knot-type defects on the board surfaces facing outward from the center of the log were compared. The specific defect types traced were:

Light Distortion	Medium Distortion	Heavy Distortion
Sound Knot	Sound Knot Cluster	Overgrown Knot
Overgrown Knot Cluster	Adventitious Knot Cluster	Unsound Knot

Given the 3/32-inch kerf, there is little difference in defect characteristics from the back side of the outermost board to the face side of the next board sawn.

[2]Thomas, R.E. 2009. RAYSAW: Ray-tracing based log sawing program for 3D laser profile data. Unpublished computer program. U.S. Forest Service, Northern Research Station, Princeton, WV.

RESULTS

Forty-one boards were sawn from three sample logs. Three categories of results were observed: 1) defect was observed on the board face, but not predicted by the models; 2) defect was predicted but was not observed on the board face; and 3) the observed defect was predicted by the models. If no defects were observed on the actual board face and no defects were predicted, this was counted as a match. This situation occurred on two boards.

The outermost or first face of the boards contained 83 knot defects. The length and width of all observed knots were measured and knots traced to their surface indicator. In addition, the lineal position of each defect was determined by measuring the distance from the center of defect to the end of the board. Of the 83 knot defects observed on the board faces, the model predicted the appearance of 67, or 80.7 percent of the population. The median of the absolute value of the difference between actual defect surface size versus predicted size was 5.6 square inches. However, in many cases the actual error was much smaller. In 15 instances (22.4 percent) the actual versus predicted size error was less than 1 square inch. In 22 instances (32.8 percent) the error was less than 2.5 square inches. The minimum size error observed was 0.02 square inch, and the maximum was 42.81 inches. The large maximum error size was due to a single overgrown knot cluster that appeared on four board faces which had a large surface indicator but a small internal defect. If these samples are omitted from the analysis, the median absolute size error becomes 4.94 square inches. This size of error corresponds approximately to 2.22 inches in defect width and length.

For the 67 defects which were predicted by the models, the median of the absolute value of the lineal position errors was 0.875 inch (measured from the center of the actual defect to the predicted location). In 35 instances or 52.2 percent of those predicted, the mean error was 1.0 inch or less. In 49 instances, or 73.1 percent of those predicted, the mean error was less than 2.5 inches. The minimum observed error was 0 inches while the maximum was 21.25 inches. The maximum error occurred on a sound knot which had a very slight rake. Here the penetration angle into the log was nearly vertical. The model predicted a more normal occurrence of the rake angle, thus the error in position.

The other types of errors in the analysis were instances where there was a defect predicted but not an actual defect, or vice-versa. These are summarized by defect and prediction error types in Table 2. In 14 instances, a defect was found on the board face but was not predicted. Ten of these occurrences were with distortion defects while the remainder occurred with sound and overgrown knots and clusters. A greater number of defects, 49 occurrences, were predicted but were not found on the actual board faces. Thirty-one instances of these errors were with the distortion-type defects; the model often predicted that the defect penetrated more deeply or that the defect was not encapsulated as deeply as it was in actuality.

DISCUSSION

This was the first test of the models in predicting the location and size of knot defects on a randomly selected tree. Overall, the models predicted the location of 67 of 83 board defects for an accuracy rate of 80.7 percent. While missing less than 20 percent of all defects, the models predicted 49 more defects which did not appear on the board faces. In these cases the models over-estimated the severity of the surface indicators and under-estimated the encapsulation depth of the defects, making the model predictions a conservative estimate of potential lumber quality and value.

Table 2.—Prediction error counts by defect and error type.

Defect type	Number of defects observed but not predicted	Number of defects predicted but not observed
Heavy distortion	6	19
Light distortion	4	3
Sound knot	1	1
Overgrown knot	2	11
Overgrown knot cluster	1	1
Medium distortion	0	9
Adventitious knot cluster	0	3
Unsound knot	0	2
Total	14	49

In general, the models performed well at predicting the location of knots within the tree, that is, the location of the defects on the resulting sawn board faces. The median error of the measured distance between the actual defect location and the predicted defect location was 0.875 inch. Given the sizes of the knot defects, the predicted and actual defect areas often overlapped. Thus, the impact of defect location error on predicted grade or yield should be small.

The models's predictions for internal defect size were not as accurate, but still acceptable in most instances. In 22 cases (32.8 percent) the error was less than 2.5 square inches. This error approximately corresponds to an error of 1.5 inches in defect length and width. The minimum size error observed was 0.02 square inch, and the maximum was 42.81 inches. Overall, the median error for predicted defect area on the board faces was 5.59 square inches. This size of error is approximately 2.4 inches in defect width and length.

The mean absolute error for all internal defect feature predictions was determined during model development. One question arises: Given these errors, what impact could they have on the predicted grade or value of the lumber sawn from logs with predicted defect sizes and locations? This question is currently being addressed and preliminary results indicate that in almost all cases the current prediction error level does not have a significant impact on lumber recovery value. In addition, this initial study needs to examine a greater sample pulled from a wider geographic location. This research will further test the prediction models and compare the value and yield of actual boards to predicted boards.

LITERATURE CITED

Chang, S.J. 1992. **External and internal defect detection to optimize the cutting of hardwood logs and lumber.** Transferring technologies to the hardwood industry: Handbook No. 3. Beltsville, MD: U.S. Department of Commerce.

Hanks, L.F.; Gammon, G.L; Brisbin, R.L.; and Rast, E.D. 1980. **Hardwood log grades and lumber grade yields for factory lumber logs.** Res. Pap. NE-468. Broomall, PA: U.S. Department of Agriculture, Forest Service, Northeastern Forest Experiment Station. 92 p.

Hyvärinen, M.J. 1976. **Measuring quality in standing trees -- depth of knot-free wood and grain orientation under sugar maple bark distortions with underlying knots.** Ann Arbor, MI: University of Michigan. 142 p. Ph.D. dissertation.

Lemieux, H.; Beaudoin, M.; Zhang, S.Y. 2001. **Characterization and modeling of knots in black spruce (*Picea mariana*) logs.** Wood & Fiber Science. 33(3): 465-475.

Rast, E.D., Sonderman, D.L.; Gammon, G.L. 1973. **A guide to hardwood log grading.** Gen. Tech. Rep. NE-1. Upper Darby, PA: U.S. Department of Agriculture, Forest Service, Northeastern Forest Experiment Station. 31 p.

Schultz, H. 1961. **Die Beurteilung der Qualitätsent wicklung junger Bäume.** Forstarchiv. XXXII (May 15): 89-99.

Schmoldt, D.L.; Scheinman, E.; Rinnhofeer, A.; Occeña, L.G. 2000. **Internal log scanning: research to reality.** In: Meyer, D.A., ed. Proceedings of the 28th annual hardwood symposium: West Virginia now-the future for the hardwood industry? 2000 May 11-13; Davis, WV. Memphis, TN: National Hardood Lumber Association: 103-114.

Shigo, A.L.; Larson, E.vH. 1969. **A photo guide to the patterns of discoloration and decay in living northern hardwood trees.** Res. Pap. NE-127. Upper Darby, PA: U.S. Department of Agriculture, Forest Service, Northeastern Forest Experiment Station. 100 p.

Steele, P.H.; Harless, T.E.G.; Wagner, F.G.; Kumar, L.; Taylor, F.W. 1994. **Increased lumber value from optimum orientation of internal defects with respect to sawing pattern in hardwood logs.** Forest Products Journal. 44(3): 69-72.

Thomas, L.; Milli, L.; Thomas, R.E.; Shaffer, C.A. 2006. **Defect detection on hardwood logs using laser scanning.** Wood & Fiber Science. 38(4): 682-695.

Thomas, R.E. 2008. **Predicting internal yellow-poplar log defect features using surface indicators.** Wood & Fiber Science. 40(1): 14-22.

Thomas, R.E. 2009. **Modeling the relationships among internal defect features and external Appalachian hardwood log defect indicators.** Silva Fennica. 43(3): 447-456.

Wagner, F.G.; Harless, T.E.G.; Steele, P.H.; Taylor, F.W.; Yadama, V.; McMillin, C.W. 1990. **Potential benefits of internal log scanning.** In: Faust, T.D., ed. Proceedings of process control/production management of wood products: technology for the 90's; 31 Oct. - 1 Nov. 1990; Athens, GA. Athens, GA: University of Georgia: 77-88.