ALPS—A potential new automated lumber processing system

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Abstract

During conventional production of solid wood furniture parts, logs are first sawed into lumber having defects randomly located throughout the board. The lumber is then remanufactured and the defects removed by ripping and crosscutting. The process is labor intensive, and saw kerf losses alone waste substantial volumes of lumber.

This paper proposes an *A*utomated *L*umber *P*rocessing *S*ystem (ALPS) which produces the same parts more efficiently. In ALPS, logs are scanned by computerized axial tomography to locate internal knots and establish log geometry without destruction. Using this data, the computer determines the log positions needed to maximize grade or value yield and automatically positions and turns the log as needed, activates the sawmill dogs and carriage stroke, and sets feed speeds. Many boards, however, will still contain defects (i.e., knots, wane, stain, worm holes, checks) which must be removed.

After drying and superficial surfacing, boards are scanned for defects by video image analysis methods. The computer identifies defect types, provides data on their location, and defines board geometry. ALPS then uses the image-derived defect data to compute an optimum cutting pattern for each board, thus yielding the maximum number of parts for a given cutting bill.

Parts are cut from the board by a numerically controlled high-power laser directed by the computer derived optimum cutting pattern data. Lastly, parts are automatically sorted for size. Residue material is chipped and used for fuel.

In the conventional process for producing solid wood parts for furniture and other assembled wood products, logs are first sawn into lumber having defects randomly located throughout the board. The lumber is then remanufactured into smaller parts and the defects removed by ripping and crosscutting. The process is labor intensive and saw kerf losses alone waste substantial volumes of valuable lumber. These factors, combined with a diminished supply of skilled labor, indicate the need for an entirely new processing system that can reduce overall costs and improve productivity.

This paper proposes such a computer-aided-manufacturing system to produce the same parts. The acronym ALPS (Automated Lumber Processing System) has been adopted to identify the process. ALPS combines elements suggested by Huber (9, 10) with recent advances in industrial tomography and computer vision, yield optimization, numerical control of machines, and laser technology. In the application described here, ALPS is expected to offer the following significant advantages:

- The value yield of lumber will be increased by using a computer derived optimal sawing strategy considering both log geometry and location of internal defects.
- The yield of usable parts from lumber will be increased by using computer vision technology to identify the type and location of surface defects and to develop an optimal cutting strategy.
- A laser cutting system will further improve yield and generate a higher percentage of longer parts because of reduced kerf and programmed blind (right angle) cutting.
- Manufacturers will be able to specify the type and extent of defects permissible in the laser cut parts.

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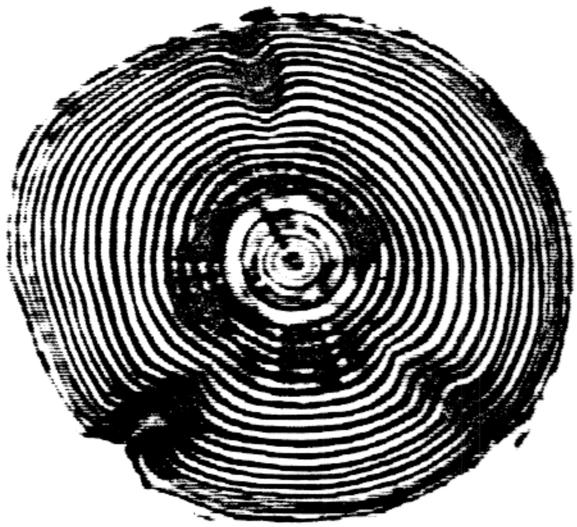

Figure 1 Computer tomograph of the cross section of a log.

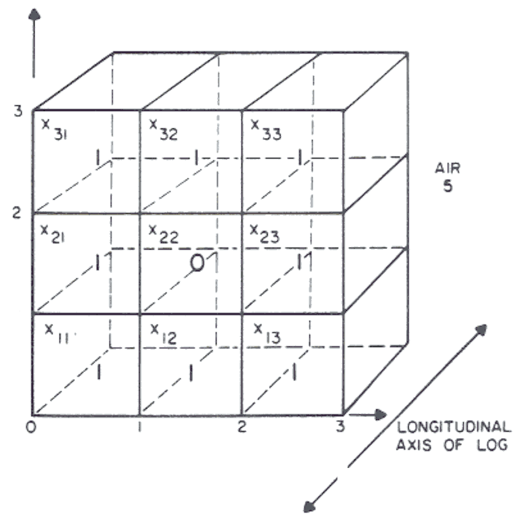

Figure 2. — Simplified cross section of a log with variable names and linear absorption coefficients indicated.

- Computer control of the process will reduce labor costs and minimize human error.
- The process will prove economical.

For discussion, ALPS is divided into sections.

Log processing

In ALPS, logs are conventionally felled, delimbed, and bucked to desired lengths. At the sawmill, the entire log is scanned with a specialized imaging technique termed industrial photon tomography (IPT). IPT uses computer reconstruction of axial projections to locate the position and extent of internal defects (i.e., knots) and establish log geometry without destruction (6, 15, 16). Figure 1 shows a tomograph of the interior of a southern pine log—no crosscut was made. Clearly visible are earlywood and latewood bands, pith, juvenile wood, pitch streaks, a knot located at the lower left periphery, and two areas of annual ring deviation near knots. A series of such tomographs would result in a three-dimensional image of the entire log.

Display of the visual image is not needed in the application proposed here. Rather, scan data would be stored in numerical arrays and manipulated directly using thresholding or pattern recognition techniques to establish knot locations. From the knot location and log geometry data, a second computer program calculates the log positions needed to maximize grade or value yield. One estimate indicates an increase of 15 percent or more, depending upon species; eliminating operator log turning error might increase yield an additional 7 percent (11).

Lastly, the computer, upon determination of an optimum sawing pattern, automatically positions and turns the log as needed, activates the sawmill dogs and carriage stroke, and controls feed speeds using a numerically controlled sawing system (not yet developed).

To understand how IPT detects defects in logs, consider the following simplified example. Let the 3 by 3 array of cubes shown in Figure 2 represent a log cross section and the large numbers in each cube the linear photon absorption coefficient of the log at that point. For simplicity, assume that solid wood has an absorption coefficient of 1 while the area with an absorption coefficient of zero represents a dense knot. Air surrounding the log is assumed to have an absorption coefficient of 5. Variable names (X_{11}, X_{12}, etc.) are assigned to each cube to establish their location with the array.

Consider now a photon source (i.e., Iridium-192) and a detector that moves in a direction perpendicular to the longitudinal axis of the log as in Figure 3A. At each of the three positions, the response of the detector is equal to the response in air, 5, minus the sum of the absorption coefficients of the cubes. Equations can now be written describing the response in terms of the variables at each position as follows:

$$\text{Position 1: } 5 - X_{31} - X_{32} - X_{33} = 5 - 3 = 2 \qquad [1]$$
$$\text{Position 2: } 5 - X_{21} - X_{22} - X_{23} = 5 - 2 = 3 \qquad [2]$$
$$\text{Position 3: } 5 - X_{11} - X_{12} - X_{13} = 5 - 3 = 2 \qquad [3]$$

The result represents the actual detector response. Equations [1], [2], and [3] can be simplified to yield

$$\text{Position 1: } X_{31} + X_{32} + X_{33} = 5 - 2 = 3 \qquad [4]$$
$$\text{Position 2: } X_{21} + X_{22} + X_{23} = 5 - 3 = 2 \qquad [5]$$
$$\text{Position 3: } X_{11} + X_{12} + X_{13} = 5 - 2 = 3 \qquad [6]$$

The difference between these equations and Equations [1], [2], and [3] is that the detector response is subtracted from a normalizing factor (the detector response when only air is between the source and the detector). The normalizing factor is determined by calibrating the scanner in an appropriate fashion.

The result does not satisfy all variables since there are more variables than there are linear equations (e.g., 3 equations and 9 unknowns). Hence, another scan is required at a different radial position as in Figure 3B.

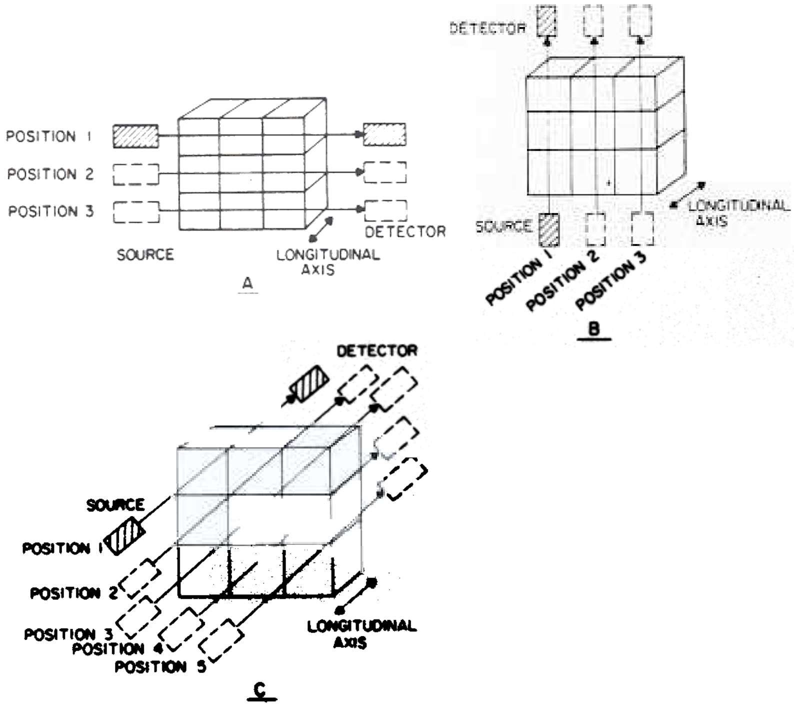

Figure 3. · Radial orientation of scans across sample.

This scan yields three additional equations as follows:

Position 1: $X_{11} + X_{21} + X_{31} = 3$ [7]

Position 2: $X_{12} + X_{22} + X_{32} = 2$ [8]

Position 3: $X_{13} + X_{23} + X_{33} = 3$ [9]

Equations [4] through [9] still cannot be solved as there are 9 unknowns and 6 equations.

An additional scan is made as in Figure 3C which yields the following equations:

Position 1: $X_{31} = 1$ [10]

Position 2: $X_{21} + X_{32} = 2$ [11]

Position 3: $X_{11} + X_{22} + X_{33} = 2$ [12]

Position 4: $X_{12} + X_{23} = 2$ [13]

Position 5: $X_{13} = 1$ [14]

Since there are now 11 equations and 9 unknowns, normal methods for solving linear equations can be used to show that the absorption coefficients of this slice are precisely as those shown in Figure 2. The process described above, repeated for adjacent slices, builds a three-dimensional data array of absorption coefficients for the entire log.

After collection of the absorption coefficient data, a computer program (currently under development) would examine the array to identify defects and establish their location. Slice planes containing only defect-free wood need not be considered in the analysis. While admittedly an over-simplification, cube X_{22} in Figure 2 would be interpreted as a knot since its computed linear absorption coefficient is zero. As another example, a cube with a computed linear absorption coefficient of 5 might be interpreted as a hole since its absorption coefficient is that of air.

The defect detection algorithm would not only compare the linear absorption coefficient pattern of adjacent cubes within a slice plane to assess the extent of defects but also the pattern between successive slice planes. For example, a series of adjacent high linear absorption coefficients repeated in successive slices could be interpreted as a radial crack extending along the longitudinal axis of the log.

Total exposure and processing times must be minimal in the industrial application proposed here. The number of scans needed to yield sufficient data is not yet known. As the resolution of the tomograph is improved, the number of equations and variables increases dramatically and requires prohibitively long processing times. Research is underway at the Southern Forest Experiment Station in cooperation with others to determine minimum exposure times, angular views, and slice plane spacing needed to yield tomographic data of sufficient resolution for the ALPS process.

Defect detection and optimum cutting strategy

After primary log breakdown, the random length random width lumber is dried in the conventional manner although the process could be automated by computer control. After grading, lumber selected for further processing is unstacked, conveyed to an abrasive planer, and lightly surfaced on both sides. Many boards will contain visible surface defects (i.e., knots, wane, stain, worm holes, checks, etc.) which must be removed before the material is suitable for furniture parts. Presently, this operation is performed by human crosscut and ripsaw operators. Frequently, the yield of usable

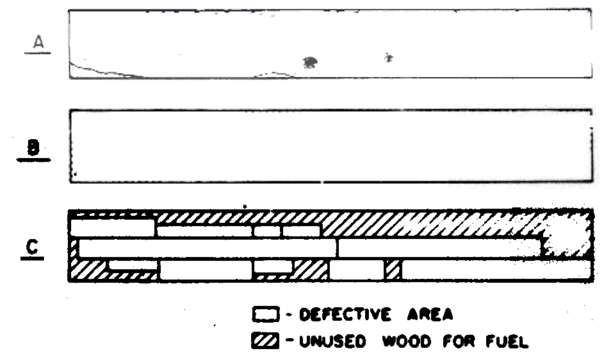

Figure 4. Sample board (A) showing computer image (B) and the best sawing solution (C).

parts is significantly diminished due to human error, inattention, inadequate supervision, or poor equipment design.

In the ALPS process, human operators will not locate defective areas on boards or devise crosscut and rip strategies. Rather, each board will be scanned with a video camera and the image information digitized. A computer rapidly analyzes the data for tonal and textural qualities to identify and locate types of defects. The image-derived defect data are then used to compute an optimum cutting pattern for each board, thus yielding the maximum number of parts for a given cutting bill (Fig. 4).

A summary of known methods for automated defect detection has been provided by Szymani and McDonald (20). Optical imaging devices using lasers or cameras seem to detect more surface defects than other methods. However, optical systems designed to date (13, 14, 18) and processing equipment, such as the Iggesund Opti-Edger, do not detect small defects important in furniture operations and other appearance-sensitive applications. Such marginal flaws require manual suppression or enhancement for the system to detect them. Additionally, these systems only differentiate between a limited number of defect types.

ALPS is similar to existing systems but more sophisticated. Like current systems, ALPS will automatically inspect boards to detect defects and compute an optimal cutting strategy based on defect location. However, unlike existing systems, ALPS will not only be able to detect a wide range of surface defects but also to classify them by type (i.e., check, knot, decay, etc.). Thus, ALPS will provide the capability to choose which defects may appear in each piece of a cutting bill. This enables the manufacturer to selectively leave certain defects in parts, such as defects which do not reduce marketability or adversely affect the mechanical strength of parts hidden from view.

A feasibility study has been executed to determine whether image analysis techniques exist which can accurately differentiate defects from clear wood and identify them by type (4). A brief summary is provided here.

A data base of approximately 350 2-foot-long by 6- to 8-inch-wide surfaced southern red oak boards was collected from trees grown in central Louisiana. One hundred and ninety-two of the boards contained only clear wood. The remainder contained one or more of the following defects: knots, mineral streak, decay, stain, wane, bark pockets, splits, checks, grub holes, and

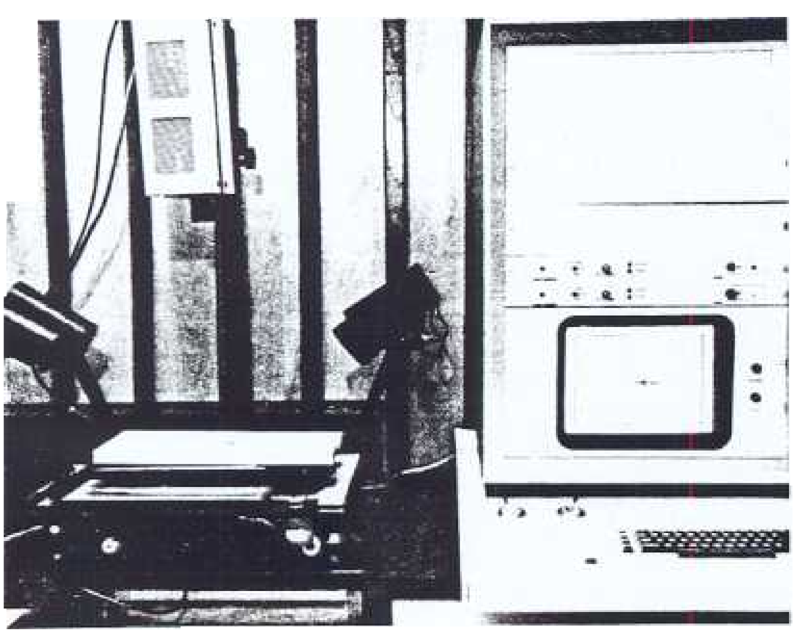

Figure 5. — Video camera scans the surface of boards (left). The image of clear wood and a knot appear on monitor (right).

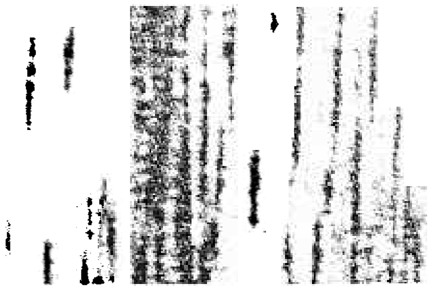

Figure 6. — Video image of clear wood containing 256 gray levels (left) and same image reduced to 8 gray levels (right). Note that most textural information is retained in the reduced image.

holes. These defects represent about 95 percent of those encountered in industrial operations.

Each sample board was scanned with a single video camera to create a 512 by 512 resolution black and white digital image containing 256 gray levels (Fig. 5). The spatial resolution was about 64 pixels (picture points) per inch. A shading correction was performed on each digital image to remove any nonuniformities in either response or lighting conditions across the scanner face.

A set of training data was selected from the data base. Each training sample was a square 64 by 64 pixel region (approximately 1 square in.) containing a defect or clear wood. The goal of the image analysis problem is to devise a set of measurements which accurately define the various classifications with a minimal number of calculations. Visual examination of the samples suggested that tonal properties of some defects show substantial differences. For example, knots are usually darker than clear wood but decay is lighter. Thus, statistical measures which gauge tonal properties would seem important in the computerized analysis. First-order tonal properties measured for each training sample were the mean, variance, skewness, and kurtosis of the distribution of gray levels in the digitized image.

However, tonal measures alone do not seem sufficient. Consider, for example, that checks and splits appear darker than clear wood. The difference is that checks and splits are long and narrow rather than round. Obviously, the pattern that defects present is important in differentiating the type of defect present. The patterns presented by clear wood or defect in a region are classic examples of texture patterns. Consequently, a texture algorithm (Spatial Gray Level Dependence Method) was used to gauge these qualities (5, 7, 8). Second-order measures used in the algorithm include inertia, cluster shade, cluster prominence, local homogeneity, energy, and entropy.

In the feasibility study, the first-order measures were computed from each 256 gray level training sample. An equal probability quantizer algorithm (3) was then applied to the region to reduce the number of gray levels from 256 to 8 and the second-order measures computed from the reduced image (Fig. 6).

Tonal measures, while useful, did not prove sufficiently accurate to classify most defect types—the overall correct classification was 63.4 percent. These measures were accurate in identifying clear wood from all classes of defective wood with an accuracy of 91.7 percent.

As expected, better results were obtained when both tonal and texture measures were combined in the analysis (Table 1). Overall correct classification increased to 88.3 percent; with two exceptions, all were classified with better than an 88 percent accuracy. Only light and dark bark were relatively low. It is also significant that only 3 of 810 defect samples were incorrectly labeled as clear (a 99.6% accuracy) while 93.8 percent of the clear wood samples were correctly classified.

While these results may not be sufficiently accurate for all industrial applications (studies are only now being executed to determine how well humans perform the task), they do suggest that a commercially useful system is possible.

A computer program for determining optimum yield of specified size pieces from a variable size board having randomly located defects has been written, tested, and used (9). The program provides for elimination of saw kerf and for determination of yield by location sensitivity or a punch press type of operation. Research is underway to modify and improve this program to provide direction to the computer numerically controlled cutting system envisioned in ALPS.

TABLE 1. — *Results obtained using both tonal and texture measures. Overall correct classification was 88.3 percent.*

Human computer	No. samples tested	Percent correct classification	Decay	Knots	Wane	Stain	Holes grub holes	Splits checks	Mineral streak	Light bark	Dark bark	Clear wood
Decay	100	98.0	98	0	0	0	0	1	1	0	0	0
Knots	86	88.4	1	76	1	0	5	1	0	1	1	0
Wane	100	96.0	0	3	96	0	1	0	0	0	0	0
Stain	99	92.9	0	0	1	92	0	2	0	3	0	1
Holes grub holes	81	92.6	0	3	0	0	75	1	1	0	1	0
Splits checks	100	95.0	1	0	0	0	0	95	1	1	0	2
Mineral streak	100	93.0	3	0	0	1	1	2	93	0	0	0
Light bark	76	76.3	0	2	4	4	3	4	0	58	1	0
Dark bark	68	57.4	0	7	3	0	15	1	1	2	39	0
Clear wood	192	93.8	3	0	0	7	0	1	1	0	0	180

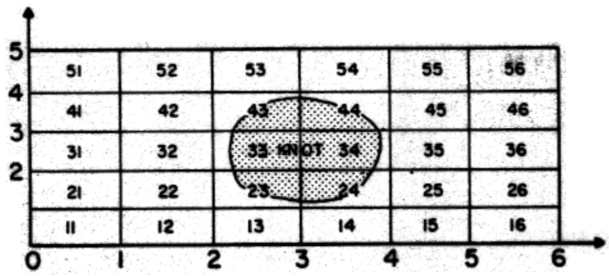

Figure 7. Coordinate system used to establish clear and defective areas on board surfaces.

In concept, the surface of a board is depicted by the computer as a number of rectangular regions within a coordinate system forming a two-dimensional array (Fig. 7). Because ALPS will cut with little kerf, it is desirable that each region be as small as possible within constraints imposed by computational time.

After scanning, each region is analyzed for tonal qualities to determine whether it contains clear wood. If defective wood is present, tonal and texture qualities are analyzed to establish the defect type. This sequential classification procedure is proposed since most of the board surface contains clear wood and tonal qualities can rapidly and accurately classify clear from defective wood. The region is then labeled as clear or defective (by type) and the procedure repeated for all remaining regions. Thus, in Figure 7, regions 23, 33, and 43 and regions 24, 34, and 44 would be labeled as knots while all other regions would be labeled as clear wood. The computer would also establish edge coordinates for the board.

The yield optimization program then analyzes the array for location, extent, and type of defects and, depending on preestablished limits, determines which defects are to be considered clear wood for cuttings. After locating the remaining clear wood areas, the computer establishes coordinates for cuttings of the desired size to give maximum yield in a manner that would duplicate a versatile and perfect rough mill operation.

Laser cutting

In the ALPS process, conventional crosscut and ripsaws used to cut parts from defective boards are replaced with a laser cutting system computer driven by the optimal cutting strategy program. Lasers emit a coherent beam of highly collimated monochromatic light that can be focused to very small diameters. At the focal point, the power density vaporizes most materials.

Use of a laser offers a number of advantages over conventional machining methods. Most important to the ALPS process is the small kerf (approximately 0.020 in. wide) and the ability to start and stop cutting at any location. The laser corresponds to a punch press with infinitely variable die sizes.

The feasibility of continuously cutting wood with a laser was demonstrated by McMillin and Harry (17). In this early experiment with an air-jet-assisted carbon-dioxide laser of only 240 watts output power, maximum feed speed was limited to about 1.5 feet per minute for 1-inch-thick southern pine. In a subsequent experiment, Peters and Banas (19) were able to cut 1-inch-thick dry Douglas-fir lumber at 33 feet per minute using 5 kW of laser output power.

For an ALPS rough mill cutting 32,000 board feet of southern red oak lumber a day in a single shift, the laser cutting system must cut 1-inch-thick lumber at a rate of about 80 feet per minute. Commercial lasers are available in the range of 12 to 15 kW. However, subsequent unpublished research by the author suggests that increasing laser power alone may not yield such high cutting speeds and maintain the desired surface quality and kerf width. High feed speeds may be obtained by splitting a 12 kW beam and directing each half to opposite sides of the board—each beam cutting halfway through the board thickness.

However, it is not yet clear whether the system should be designed with only one laser. Use of a multiple laser system is attractive since it reduces the speed that boards or the laser beam must be moved. This is important given the right angle punch press type of operation required to give maximum yield. Additionally, a two-laser system allows for continued mill operation, albeit at reduced throughput, given failure of one laser. If cutting speed were reduced to 40 fpm and two lasers of 5 to 8 kW power used, the same approximate throughput could be maintained.

Figure 8 (adapted from (1)) shows a conceptual drawing of one embodiment of the ALPS laser cutting system. In this system, a single multi-kilowatt laser is operated over two 8-hour shifts to maintain the desired throughput. The laser beam transfer unit (not illustrated) is located to the rear of the laser power supply and electrical controls. The beam is directed from the transfer unit via mirrors to a gas-jet-assisted focusing head attached to a gantry spanning the cutting station. The vertical position of the head (Z-axis direction) may be adjusted by the computer numerical control to accommodate boards of varying thickness. Additionally, the beam path can be moved in the y-axis direction by the servomotors in the housing assembly attached to the gantry.

Boards entering the process stream are placed in fixed positions on one of several carriages with their longitudinal axes parallel to the direction of carriage travel. Each carriage could contain several boards that are processed as a group. The self-driven, computer controlled carriages move along precision parallel ways to the various processing stations in an endless loop.

The carriage first advances through the defect detection station where the boards are scanned for defect type and location and the optimum cutting strategy for maximum yield computed. The carriage is labeled by the computer and coordinate data for the desired cuts transferred to the numerical control driving the laser cutting system.

The carriage then moves to the laser cutter where it oscillates bidirectionally in the x-axis plane under computer control to produce rip cuts along the grain. These

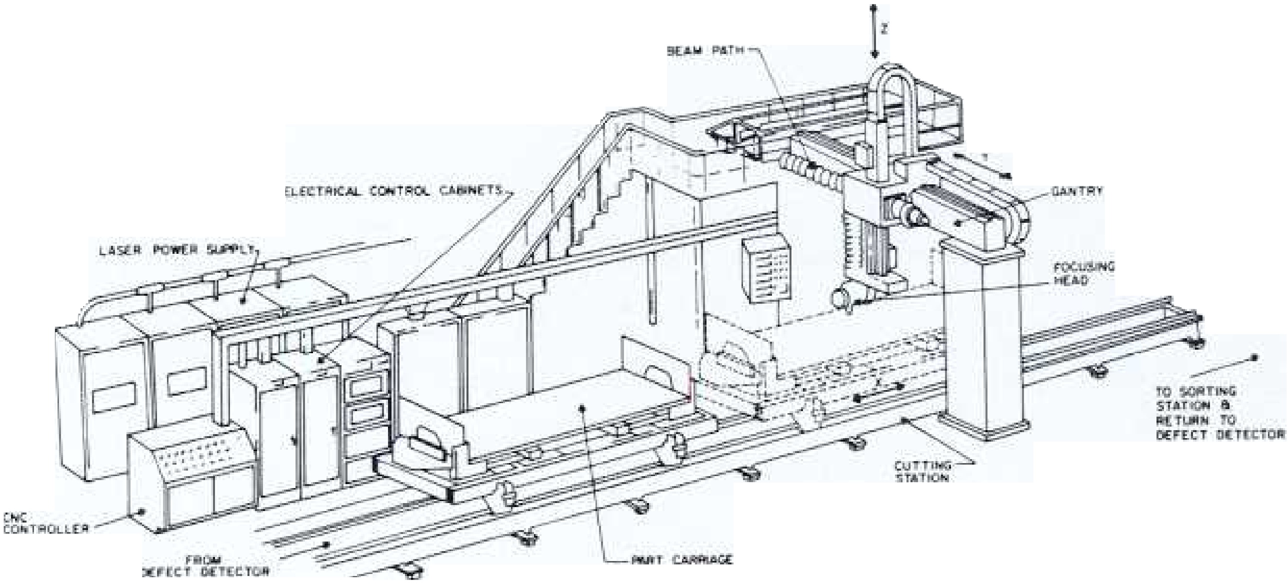

Figure 8. Conceptual drawing of the ALPS laser cutting system.

cuts need not extend the entire length of the board as a high-speed shutter in the beam transfer cabinet can instantaneously terminate cutting. At the end of each stroke, the laser head is moved to a new location along the y-axis to position the beam for the desired part width.

After completion of all rip cuts, the carriage returns to the exact point where rip cuts were terminated. The laser beam is then activated and crosscuts executed by motion of the focusing head assembly along the y-axis of the gantry and in a direction perpendicular to the longitudinal axis of the board. The carriage then moves to a station where the cuttings are automatically sorted by size. Residue material is chipped and used for fuel. The empty carriage is then returned to the defect detection station and the process repeated.

A financial analysis of the image analysis and laser cutting portions of ALPS has been executed using discounted cash-flow techniques (12). The analysis assumed only a 5 percent yield increase resulting from saw kerf reduction in a mill cutting 32 thousand board feet per day. With this conservative approach, calculated raw material savings for a furniture plant using red oak lumber were $1,210 per day and $1,198 per day when using sap gum.

The net present value of the $790,000 investment was $408,024 and the internal rate of return after tax was 22.5 percent.

Conclusion

Current tomographic scanners, optical defect analyzers, lasers, and computer systems can be used to design an automated lumber processing system. While technically and economically feasible, additional work is required to optimize equipment and develop computer hardware and software needed for a working system.

What has been described in this paper is a radical departure from current rough mill practice, but the future competitive nature of the wood industry may depend on such innovations.

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