Open access • Journal Article • DOI:10.1016/S0736-5845(02)00010-8

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Published on: 01 Jun 2002 - Robotics and Computer-integrated Manufacturing (Pergamon)

PERGAMON

Robotics and Computer Integrated Manufacturing 18 (2002) 197-203

Robotics
and
Computer Integrated
Manufacturing

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Impact of human error on lumber yield in rough mills

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Abstract

Rough sawn, kiln-dried lumber contains characteristics such as knots and bark pockets that are considered by most people to be defects. When using boards to produce furniture components, these defects are removed to produce clear, defect-free parts. Currently, human operators identify and locate the unusable board areas containing defects. Errors in determining a defect and its location, known as operator error, lead to lower lumber yield and increased product cost. Technology exists that would alleviate these problems and is a viable option to avoid wasting lumber because' of human error. This study was performed in a rough mill collecting data on the errors made by humans when marking defects. Computer-based simulation tools were used to assess the significance of these errors. It was found that three-quarters of the decisions made by human operators are erroneous in some way resulting in an absolute yield loss of approximately 16.1 %. Thus, automated defect detection systems that perform more accurately than do humans could have a payback period of 1 year or less. Published by Elsevier Science Ltd.

Keywords: Human error; Material loss; Lumber yield; Wood processing

1. Introduction

Solid wood dimension parts for furniture and cabinets are cut from rough sawn, kiln-dried, random length, and random width lumber. In a rough mill, boards are processed into rough-sized furniture parts utilizing two processing methods: rip-first or crosscut-first. Rip-first processing begins by ripping the board into narrow strips, then chopping the strips into part lengths. Crosscut-first processing chops the board to the part lengths, then rips the board segments to the correct widths. This paper is concerned only with rip-first processing. For a thorough discussion of rough mills see [1]. Furniture parts are mainly produced using hardwood lumber, however, the price of hardwood lumber has almost doubled during the last 20 years [2]. During this same period, domestic furniture manufacturers were competing with imported, low price, good quality, solid wood furniture in most retail market sectors. In fact, furniture imports have grown significantly over the last decade, comprising one-third of all furniture sales in the US [3]. Not surprisingly, US manufacturers are striving to minimize their production costs to compete with foreign producers.

Lumber costs are the single most important cost for furniture manufacturers. Between 12% and 15% of the furniture production cost, depending on style and quality of the furniture, is due to lumber costs [4]. A popular rule of thumb states that saving 1 % of the incoming raw material (i.e. lumber) reduces total production costs by as much as 2% [5]. As a result, manufacturers are aggressively trying to improve yield. Yield is defined as the ratio of aggregate part surface area output in relationship to aggregate lumber surface area input [6].

Wood is a non-homogeneous material with unusable areas randomly dispersed throughout the board. Each board is classified in appropriate quality classes based on defect sizes, locations, frequencies, and other geometric characteristics [7]. Boards of the same quality class are then processed in rough mills that either employ crosscut-first or rip-first sawing technology. Ripfirst technology is the most commonly used technology today [8]. Classifying all the different natural characteristics of lumber is a difficult task performed by human operators. Some board characteristics are considered acceptable, others as a defect. It is the responsibility of the operators, or "marker" as they are called in the wood industry, to determine which

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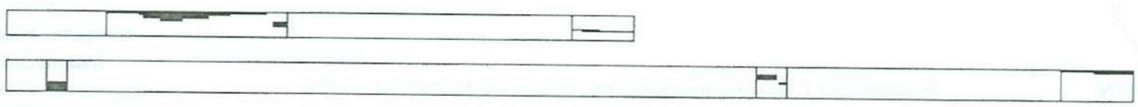

Fig. 1. Two strips with defects that are perfectly marked.

characteristics are acceptable and which are not. Operators are constantly fed narrow board strips from the ripsaw over roller conveyors. Both sides of each strip are inspected and defects are marked with a scanner-readable chalk. A computerized saw with a camera reads these marks and optimizes the fit of parts into the clear areas, then cuts the strips into segments of clear wood with no defects and unusable segments containing defects. Fig. 1 shows two strips as an operator could encounter them. The black areas symbolize defects and cannot be used for the finished product. The operator has to distinguish between clear areas of the strip and the areas containing defects. The marks encompassing the defects in Fig. 1 show the two strips marked perfectly, i.e marked such that no clear wood is wasted.

However, due to the difficulties in distinguishing some defects from sound wood, the high speed at which operators have to work, and the long hours on the job, human errors occur. Operators theoretically can make four decisions when marking strips. These decisions are shown in the decision matrix in Fig. 2.

As shown in the decision matrix, an operator has a choice of four decisions when marking strips. Two are correct and two incorrect (Fig. 2). Positive outcomes result under one of two conditions: a defect is identified and removed (Yes-Yes) and defect free wood is not marked for removal (No-No). Costly errors can result from the other two conditions. When a defect-free area is marked as a defect, then usable wood is wasted (Yes-No, Type II error). When a defect is not detected (No-Yes, Type I error), then this defective area will be used to produce a part that will either require costly remanufacturing or the part will be discarded later in the production process. Rejects are especially costly as they result not only in a loss of wood; but labor as well. In the last case, when the operator marks an area that contains no defect, (Yes-No, Type II error), then a negative outcome is achieved in that clear, usable wood is cut out and wasted.

Two other errors can occur: (1) incorrectly marking the end of a defect, leaving a small portion of the defect in the board to be used for a part (Fig. 3, A), and (2) marking the end of a defect beyond its true end resulting in wasted usable material (Fig. 3, B).

Both errors A and B are mistakes, which can lead to waste material and increased production costs. However, error A is of more concern since it may lead to a part containing a defect that will be rejected later in the production process. The loss of usable wood is an error, which is present regardless of human error in defect

		Defect exists	
		Yes	No
Marker perceives defect	Yes	correct	Type II error
	No	Type I error	correct

Fig. 2. Decision matrix for operator.

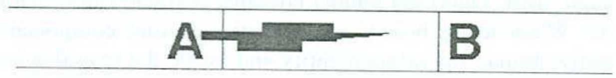

Fig. 3. Two special cases of operator error: (A) when mark is within defect, and (B) when mark is beyond defect.

identification since the optimization of a strip's clear areas is rarely able to find chop solutions that use 100% of the clear area. Since a minimal amount of usable wood is lost when optimizing the clear areas of a strip, error B is increasing costs only marginally. Therefore, we did not further investigate this error. In summary, there are three operator errors that are of significance and will lead to either a loss of usable, clear wood or to rejects because defects will be contained in the part:

(1) Type II error, detection of a defect where there is none.
(2) Type I error, when a defect goes undetected.
(3) Incorrect marking of a defect within its boundaries (Fig. 3, A). We will refer to this type of error as "partial Type I error."

Little knowledge exists concerning the amount of lumber or money lost due to operator error. However, Huber et al. published a paper in 1985 concerning the ability of operators to correctly detect and mark defects in boards [9]. This study assessed the performance of six experienced operators from three different plants by asking them to assess a board in 1 min and to memorize the location and type of defects. The operators then used an eight (length of the board) by two (width of the board) matrix to indicate the location and type of defects found in the board. This test was performed twice for each employee on 30-2A common southern red oak boards. The authors concluded that operators need to be able to (a) "see and recognize defects", (b) "have the mental aptitude to properly locate the cuts", (c) "possess the physical strength to position the board manually" , (d) "resist boredom and maintain an alert mental attitude", and (e) "be able to remember defect location on one side while marking on the other side". This study highlights the difficulty of the tasks performed by operators. Although all persons tested were experienced, motivated individuals, the average mean composite score (i.e. the combination of all individual parameters tested) was 68%, the minimum was 59%, the maximum 74%, respectively. Highest mean scores were achieved for location (75 percent), followed by number of defects (71 percent) with defect types being lowest (65%).

Although these tests demonstrated the magnitude of human error in marking, they did not assess yield effects resulting from operator errors. To fill this gap, the objective of this study was to evaluate the frequency of operator errors (Type I, Type II, and partial Type I errors) and the resulting yield losses in a state-of-the-art rip-first rough mill. By quantifying the potential yield increases, one can investigate the economics of automated scanning systems for reducing or eliminating yield losses due to operator error. Such vision-based lumber defect detection systems are becoming commercially available [10]. They recognize defective areas of boards with a high accuracy and thus allow computer-based yield optimization and saw control systems to efficiently use the clear areas of a board.

2. Methodology

Due to careful planning of an earlier study involving the validation of a computer-based rough mill simulation model called ROMI-RIP, previously ",ollected data could be used [7,11]. These two publications also contain more details about the rough mill and simulation setup used for this study. This study used randomly sampled kiln-dried red oak hardwood lumber from a sawmill in southeastern West Virginia. After digitization of the boards, they were cut to strips in a state-of-the-art rough mill and the strip solutions were recorded. Next, an experienced employee marked the strips. The results were compared to the digitized location of the individual defects to establish the number of inaccurate marks. Both datasets were then employed to perform simulation to assess yield losses associated with operator error.

2.1. Materials

Rough sawn, kiln-dried lumber was randomly sampled from the lumber grading conveyor of a large sawmill in West Virginia. Roughly 200 boards were collected and 158 were found to be usable for this study. The remaining 42 boards were discarded because they were either below grade or had excessive crook. Crook is when a board has a substantial arc from end to end across the grain. Thus, if you would lay a board flat and put one side against a wall, the middle of the board would not be touching the wall. The boards were digitized according to Anderson et al. [12]. Fig. 4 displays an example of a digitized board. The USDA Forest Service's computerized ultimate grading and remanufacturing system (UGRS) was employed to grade the selected boards into appropriate quality classes [13]. The material used in this study consisted of 8.3% FIF, 6.8% Selects, 51.6% 1 Common, 25.9% 2A Common, and 7.4% 3A Common. Appendix A shows the details of the lumber sample used.

Cutting bills, as shown by Buehlmann et al. [14], have a significant influence on yield. A cutting bill is the list of pieces that need to be produced during a given production run. To minimize the influence of cutting bill composition on this study, we used a cutting bill that is considered easy to complete [15]. Part quantities for this cutting bill were set such that all pieces could be obtained from the 158 boards available. Appendix B gives the details of the cutting bill used. The prioritization algorithm we used was length-square times width (L 2W) with the maximum part value set at 1000. Prioritization algorithms are necessary to allow the software to decide which parts to prefer over others in situations where different part-choices exist. The part values assigned help the prioritization algorithm determine which part is more preferable than others for a given situation. For a more complete discussion of part prioritization, see [15].

2.2. Rough mill

The first processing step is to rip the boards into narrow strips. An arbor, which is a steel rod holding the saw blades, is used to rip the boards into strips. The part widths are the distances between the saw blades. GRADS [16], the gang-ripsaw arbor design program, was used to determine the optimal arbor width spacing arrangement. The ripping process optimizes the placement of the board with respect to the saws such that the highest yielding strip combination is obtained.

The strips resulting from gang-ripping were then presented to the human operator. Since the relevance of our findings was directly connected with the abilities and

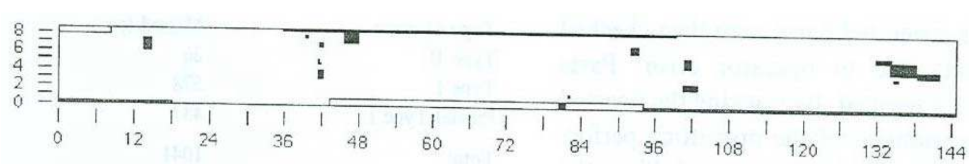

Fig. 4. Sample board with digitized defects

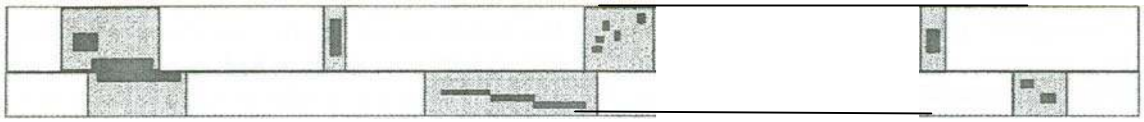

Fig. 5. Sample board showing the actual defects and the operator solutions.

motivation of the person doing the marking, a person with more than 5 years of experience was employed. The worker's ability to detect defects and react properly was tested using the Wais-R digit symbol recognition test used earlier in the Huber study [9]. For this test, a score of 40 points was achieved by the operator, which indicated that the worker's performance is comparable to the performance of the average rough mill operator. The tests were performed at the worker's regular workstation with no change to the workplace that could indicate testing was being done. The worker marked all areas of the strips. containing defects with a scanner readable crayon. The strips were directly fed to a Barr-Mullin Turbo Wondersaw crosscut saw, with the sawblade removed, allowing for the measurement and recording of the operator's marks. After this step, there were two sets of strip-data for the simulation: (a) the digitized board data, and (b) the defect-marking solution as done by the human operator. Fig. 5 displays the marking solutions by the operator shown in gray, with defects digitized before ripping shown in black.

3. Computer based rough mill simulation

The USDA Forest Service's ROugh Mill RIP (ROMI RIP) first simulator, Version 2.0, was employed [11,17].An additional computer program was written to assess the accuracy of the operator. This program overlaid the locations of the operator's grade marks with the actual defect locations on the board. From this comparison several important evaluation factors were determined including: (1) how close the marks were to the defect(s), (2) defect sizes and types not marked, (3) defects split, (i.e. defects not entirely in a marked area), (4) marked areas with no defects, and (5) defects properly marked and entirely included in a marked area. This information described the accuracy of the human operator.

A second test was designed to estimate yield losses due to operator error. Here the boards were processed on the ROMI RIP simulator using the marked area information from the operator, cutting clear parts and parts that contained defects. Using a special software tool, these computer generated parts were then checked for remaining defects due to operator error. Parts containing defects were rejected. By tracking the rejected parts, an accurate assessment of the operator's performance in respect to yield could be performed. Since the strip feeding sequence to the chop saw could not be simulated exactly as it occurred in the rough mill, the average of four repetitions from the simulation was used. The feeding sequence of strips influences yield, since the placement of individual parts within the available areas depends on the sequence in which the strips are processed. However, this effect, although discernible, is small and does not alter the conclusions of this study.

4. Results

A total of 1303 defects were present in the 158 boards used in the study (Table 1). Out of these boards, the ripsaw produced 404 strips: 59, 1.75in wide; 259,2.00 in wide; and 86, 3.50 in wide. The operator made 1331 marks on the strips or 3.45 marks per strip on average. No marks were necessary for defects located < 1 in from either end of the board since the system was set to make a I-in trim cut on both ends. The number of marks and the number of defects are loosely correlated. Often several defects in close proximity are marked together between two beginning and ending marks.

Twenty-six of all marks set were Type II errors, i.e. the operator marked areas where no defects were present. The operator also made 578 Type I marking errors, i.e. not marking a defect when there was one. Furthermore, 437 partial Type I errors, meaning that marks were placed inside the defective area, were made by the operator. Table 1 shows the test results obtained.

As these results show, 78.2% of the decisions made by the human operator deviated from the optimum decision. Type I error, not detecting a defect when one is present, was the most common error constituting 43.4% of the total number of errors committed (Table 1). Partial Type I errors, marking a defect inside the

Table 1
Results of the operator accuracy tests

Total boards used		158
Total strips marked		386
Total no. of defects registered		1303
Total marks placed		1331
Type of error	Missed (no.)	Missed (%)
Type II	26	20
Type I	578	43.4
Partial Type I	437	32.8
Total	1041	78.2
Average error/strip	2.7	78.2

Table 2
Rejected parts due to human marking error

Run	Input lumber area (m2)	Output parts area (m2)	Yield including rejects (%)	Reject parts area (m2)	Rejects as percentage of Input (%)	Rejects as percentage of Output (%)	Yield without rejects (%)
A	88.0	55.6	63.2	14.0	15.9	25.1	47.3
B	87.9	55.9	63.6	14.2	16.1	25.3	47.5
C	85.3	54.4	63.8	13.5	15.8	24.8	48.0
D	87.1	55.2	63.4	14.4	16.6	26.2	46.8
Average	87.1	55.3	63.5	14.0	16.1	25.4	47.4
std. dev.	1.3	0.7	0.3	0.4	0.3	0.6	0.5
Run	No. of boards (No.)	No. of parts (No.)		Rejected parts (No.)		Rejected parts (%)	
A	155	1485		330		22.2	
B	156	1494		323		21.6	
C	149	1441		324		22.5	
D	154	1463		316		21.6	
Average	153.5	1470.8		323.3		22.0	
std. dev.	3.1	23.7		5.7		0.4	

defective area, accounted for 32.8% of the errors made and Type II errors, identifying a defect when one is not present, only constituted 2.0% of the total number of errors.

Four repetitions of the simulation of the strip cuts were performed to detect yield rates associated with human operator error (Table 2). On average, 25.4%, or more than a quarter of the parts produced (output), would be rejected because they contained a defect or a partial defect resulting in a decrease of yield from 63.5% to 47.4% yield.

5. Discussion

Marking lumber in a rough mill is a truly challenging occupation. The average operator stands 8 hours a day in a noisy, often poorly lighted workplace and is required to mark hundreds of strips indicating defective areas. Also, what constitutes a defect is not clearly defined and a wide range of definitions exists within the industry and sometimes even within the same operation [18]. In addition, wood defects can have a wide variety of shapes and colors, often making it challenging to: (a) recognize the defect, and (b) determine the border between defect and clear wood. These factors, when combined, lead to a high error rate that costs the industry millions of dollars every year. Kline et al. [19] estimated that for an average rough mill, a 1 % yield increase results in estimated savings of $150,000 to $300,000 in lumber and operation costs per year.

This study's measurement quality standards were very demanding. The verification programs that compared a mark and the beginning/end of a defect did not allow any deviation from the optimum position, except if the mark was made outside of the defective area in the clear wood. If a mark was made one-sixteenth of an inch (1.6mm) inside the recorded defect area, the verification program registered that as an operator error. Therefore, the error rate indicated in Table 1, although true, is exceptionally rigorous. Since most furniture parts are cut slightly overlength in the rough mill, some of these "errors" would not be rejected.

Due to the traditionally high reject rates in furniture plants, rough mill operators should be taught to mark defects away from the apparent end of the defects in the clear wood to decrease the probability of part rejections. This will help decrease rejection rates due to partial Type I errors. It is hypothesized that the loss of 1-5 mm of clear wood for each defect will not significantly reduce yield due to the optimization schemes. Conversely, Type I errors will require more effort, such as increased operator training, better lighting, and easier to understand defect specifications, to be eliminated.

This phenomenon is also responsible for the significantly lower part reject rate compared to the much higher operator error rate. Although the operator error was 78.2%, a significantly fewer number of parts, 22% (25.4% on an area basis), were rejected. The excess clear area relative to part length required eliminates most, if not all, rejects from partial Type I operator errors. Additionally, Type II errors (2.0%), although they lower yield, do not lead to rejected parts.

Type I errors (43.4%) are the major contributors of rejected parts. The negative impact from these errors is lessened by two factors: (a) overlooked defects tend to be small, and (b) small defects are often clustered close together. Therefore, many rejected parts contained more than one Type I error. Also, some of these overlooked defects may have been adjacent to a defect that the operator marked correctly. Due to the excess clearance effect described above where the part optimization process usually wastes some clear wood, some defects were cut out in this process. The remaining undetected defects were responsible for the 22.0% reject rate of parts.

Vision-based lumber scanning systems exist and are being increasingly adopted by the industry [20,10]. With prices for such systems below $1,000,000, they seem to be an attractive investment for medium to large size rough mills. Although such systems currently are not perfect due to the difficulty of detecting and classifying wood defects, small yield improvements allow the investment to be recaptured within the required payback periods [19]. A system able to reduce part-reject rate to half would save an average rough mill approximately $1.2 million a year, making the simple payback period < 1 year (assuming 8% higher yield, an average saving of $ 150,000 per 1 % yield per year [19], and an annual interest of 10%). However, problems other than technology or financing, such as employee education, managerial capabilities, or facility environment, are barriers to implementation of these systems.

6. Conclusions

Using an experienced employee and computer simulation, this study researched the reliability and the accuracy of a human operator when marking defects on wooden strips prior to cut-up for furniture parts. Three types of operator error were investigated: (a) when the operator marked a defect when there was none, (b) when the operator missed a defect, and (c) when the operator marked a defect inside the defective area of the strip. Acknowledging that the test criteria were stringent, 78.2% of all defects were marked incorrectly. Two percent of all marks made were Type II errors, 43.4% were Type I errors, and 32.8% were partial Type I errors. This high error rate translated in a highdrate of rejected parts after the processing (22.0%). The overall yield was reduced from 63.5% before rejections to 47.4% after rejections.

Vision-based lumber scanning systems are able to solve many of the operator errors observed in this study. Due to the high rate of human errors, such systems do not need to be flawless. If their defect detection ability is 50% better than the one observed in the human case studied here, payback periods for such advanced systems could be as low as 1 year. However, as discussed above, problems other than technology or financing are barriers to implementation of these systems.

Future research will have to address the problems beyond financing and technology that slows the industry in adopting such systems. One major area of interest is the supply of well-educated and motivated employees, who are needed to run such complex vision and optimization systems. Research and development also will have to generate systems that are easier to setup and to manage and have a high degree of robustness and reliability. Furthermore, the data derived for this study will allow the creation of software, which will enable companies to simulate their yield losses due to human operator error.

Acknowledgements

We gratefully acknowledge the support of the USDA Forest Service for this research. The authors would also like to thank Debbie Butler and Neal Bennett from the USDA Forest Service for their contributions in performing this study. The support of the Wood Education and Resource Center in Princeton, WV for the use of their rough mill is very much appreciated. We also greatly appreciate the critical input of Dr. Jan Wiedenbeck and the helpful comments of Dr. Kari BabskiReeves and Dr. William G. Sullivan.

Disclaimer

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Appendix A

See Table 3 below.

Table 3
Quality classification of the lumber sample used

Lumber grade	Board footage	Board count	Board footage as percentage of total	Board count as percentage of total
FIF	77	11	8.3	7.0
Selects	63	17	6.8	10.8
I Common	480	77	51.6	48.7
2A Common	241	39	25.9	24.7
3A Common	69	14	7.4	8.8
Total	930	158	100%	100%

Appendix B

See Table 4.

Table 4

Cutting bill part size and quantity requirements

Part number	Part width (in)	Part length (in)	Quantity	Part prioritization value
1	3.50	67.00	12	1000
2	3.50	57.00	6	724
3	3.50	43.50	6	422
4	3.50	33.50	12	250
5	3.50	31.25	30	218
6	3.50	29.50	12	194
7	3.50	27.50	6	168
8	3.50	25.50	12	145
9	3.50	20.50	18	94
10	3.50	18.25	62	74
11	2.00	65.25	18	542
12	2.00	59.00	36	443
13	2.00	49.50	33	312
14	2.00	43.50	18	241
15	2.00	35.75	55	163
16	2.00	31.25	49	124
17	2.00	29.50	18	III
18	2.00	27.50	90	96
19	2.00	25.50	130	83
20	2.00	23.00	II3	67
21	2.00	20.50	204	54
22	2.00	18.25	36	42
23	1.75	65.25	30	474
24	1.75	43.50	30	211
25	1.75	27.50	30	84
26	1.75	25.50	30	72

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