ACOUSTIC SORTING MODELS FOR IMPROVED LOG SEGREGATION

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(Received October 2012)

Abstract. In this study, we examined three individual log measures (acoustic velocity, log diameter, and log vertical position in a tree) for their ability to predict average modulus of elasticity (MOE) and grade yield of structural lumber obtained from Douglas-fir (*Pseudotsuga menziesii* [Mirb. Franco]) logs. We found that log acoustic velocity only had a moderate correlation with average MOE of the lumber produced from the logs ($R^2 = 0.40$). Log diameter had a weak correlation with average lumber MOE ($R^2 = 0.12$). Log vertical position in a tree was found to have a relatively good relationship with lumber MOE ($R^2 = 0.57$). Our analysis also indicated that the combinations of log acoustic velocity and log diameter or log acoustic velocity and log position were better predictors of average lumber MOE and lumber visual grade yield than log acoustic velocity alone. For sorting best quality logs, multivariable models were more effective than the velocity-alone model; however, for sorting poorest quality logs, the velocity-alone model was as effective as multivariable models.

Keywords: Acoustic velocity, log diameter, log position, log sorting, lumber, modulus of elasticity, visual grade.

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Wood and Fiber Science, 45(4), 2013, pp. 343–352

INTRODUCTION

End product properties are dependent on the quality of incoming log supplies. It is well recognized that natural variation in wood properties is enormous within a pile of logs that has been visually sorted for similar grade (Tsehaye et al 1995, 2000). The same is true for logs from trees of the same age and from the same forest stand (Huang et al 2003). There are major commercial benefits to be gained by assessing wood properties of incoming logs and optimizing the use of wood resources through effective log sorting. Research has shown that log acoustic measures can be used to predict strength and stiffness of structural lumber that would be produced from a log (Aratake et al 1992; Aratake and Arima 1994; Ross et al 1997; Wang et al 2004b). Some early investigations by Aratake et al (1992) and Aratake and Arima (1994) explored the possibility of using the natural frequency of longitudinal compression waves in a log to predict strength and stiffness of the structural timber. They identified a close relationship between the fourth resonant frequency of the logs and modulus of elasticity (MOE) and modulus of rupture of the scaffolding boards and square timbers cut from the logs. A trial study in the US also revealed good correlation between acoustic wave-predicted MOE and mean lumber MOE (Ross et al 1997). This research opened the way for acoustic technology to be applied in mills for sorting logs and stems for structural quality.

To validate the usefulness of the resonance acoustic method for a practical sorting process, Wang et al (2004b) conducted a mill study and examined the effect of log acoustic sorting on lumber stiffness and lumber E-grades. After acoustically testing 107 red maple logs, they segregated the logs into four classes according to acoustic velocity. They found a significant differentiation and clear trend regarding average lumber MOE among the log acoustic classes. They further reported good correlation among log acoustic classes and lumber E-grades. Logs that had a high acoustic velocity contained higher proportions of high-grade lumber. A study in New Zealand revealed similar results when presorting unproved logs of radiata pine into three acoustic classes (Tsehaye et al 1997). Logs with the highest acoustic velocity (the top 30%) produced timber that was 90% stiffer than that from the group with the lowest velocity (the bottom 30%).

Currently, the companies implementing acoustic sorting strategies measure only the velocity of acoustic waves and segregate stems and logs into velocity classes using predetermined cutoff velocity values. Although this simple sorting strategy has been proven somewhat effective by several mill studies (Tsehaye et al 1997; Carter and Lausberg 2001; Wang et al 2004b; Carter et al 2005), the strength of the direct correlation between acoustic velocity in a particular log and the properties of wood products derived from that log are actually not very strong with a typical correlation coefficient (R^2) in the range of 0.38 and 0.54 (Aratake et al 1992; Farrell and Nolan 2008). Although still operationally useful, the precision of acoustic sorting is less than desired. The purpose of this study was to gauge the effect of combining additional variables with acoustic velocity to predict average MOE and grade yield of the structural lumber obtained from the logs. Specifically, we examined three individual log measures—acoustic velocity (V), average log diameter (D), and log vertical position in a tree (P)—for their ability to sort logs individually and then developed new acoustic sorting models that used diameter and/or log position as a second variable for improving log-sorting precision.

MATERIALS AND METHODS

Log Samples

The green logs used in this study were from Douglas-fir (*Pseudotsuga menziesii* [Mirb. Franco]) trees selected from a 70-yr-old stand on Pack Forest, the University of Washington's Research Forest in Eatonville, WA. Trees were naturally generated, resulting from a severe fire in 1922. The study site was established in the mid-1970s to test the effectiveness of using municipal waste to increase forest productivity

(Sonne 2001). The stand consisted of four treatments: control, thinned, biosolid fertilization, and thinned and biosolid fertilization, each with three replicates on 0.2-acre plots. Before treatment, the site was a heavily stocked stand with some plots having more than 1000 trees per acre, and approximately 75% were less than 17.8-cm diameter at breast height (DBH) (Edmonds and Cole 1980). The thinned plots were decreased to 250 trees per acre, which was a decrease in basal area of about 50% because most of the trees less than 17.8 cm in diameter were removed. In 1998, the US Forest Service and the University of Washington initiated a study to assess the effects of biosolid fertilization and thinning on log and lumber wood quality. Four trees were selected in each plot using a stratified random sample based on the plot quadratic mean diameter, resulting in a total sample of 48 trees ranging from 14.2 to 53.3 cm DBH.

The sampled trees were then harvested and bucked into 4.9-m-long mill-length logs. Each log was tagged with a number that identified the tree and the position in the tree from which it came. A P number was assigned to the logs to identify the vertical position in each tree based on the cutting sequence from ground level ($P =$ 1-6, with 1 representing the butt log, 2 the second log, etc). A total of 171 mill-length logs were obtained. Log position in each tree stem was recorded, and log length and diameters of both ends of each log were measured.

Acoustic Measurements

Each log was nondestructively tested using an acoustic resonance technique to obtain an acoustic velocity for the log. During log testing, an accelerometer was attached to one end of the log, near the center of the cross-section. An acoustic wave was introduced to the log with a hammer impact on the opposite end, and the resulting acoustic signals were recorded with a computer. The waveform of the signals consisted of a series of equally spaced pulses, which indicated the reverberation of the acoustic waves within the log. The V (m/s) in a log was determined by coupling measurements of the transmission time (Δt [s]) (time between two consecutive pulses of a waveform observed) and log length (L [m]):

$$V = 2L/\Delta t \tag{1}$$

Mill Process

Logs were then sawn into lumber using a Wood-Mizer (Wood-Mizer Products, Inc., Indianapolis, IN) at the yard site of Pack Forest. As each piece of lumber was sawn, it was labeled with the sawing number and its position within the sawing pattern was diagrammed. The lumber pieces produced were predominantly 51-mm dimensions (51 × 102, 51 × 152, and 51 × 203 mm) with some 25-mm jacket boards (25 × 102 and 25 × 152 mm) sawn from the outer portion of the logs. Green lumber thickness and width were measured on a randomly selected sample. All lumber was kiln-dried to less than 19% MC and surfaced at a local sawmill.

Transverse Vibration Test and Visual Grading

After sawing and kiln-drying, 1098 pieces of lumber were obtained and evaluated for stiffness and visual grade yield. The dynamic MOE (MOE_d) of each piece of lumber was measured using an E-computer (Metriguard Inc., Pullman, WA) according to ASTM (2003). The lumber under test was supported by tripods, and the load cell tripod was connected to a computer. Vibrations were initiated by gently striking the lumber by hand near the span center. The vibrational parameter measured was fundamental natural frequency f_0 (Hz). MOE_d of lumber was determined from the following equation:

$$MOE_d = \frac{f_0^2 w s^3}{K_d I g} \tag{2}$$

where MOE_d = dynamic MOE (GPa), f_0 = fundamental natural frequency (Hz), w = weight of specimen (N), s = span (mm), I = moment of inertia, $bh^3/12$, b = width (mm), h = height (mm), g = acceleration due to gravity (9807 mm/s^2), and

K_d = constant for free vibration of a simply supported beam (2.47).

All lumber was then visually graded according to structural light framing grading rules (WWPA 1998) under the supervision of a Western Wood Products Association-certified lumber inspector.

DATA ANALYSIS

We first evaluated log V, D, and P as individual predictors of lumber MOE and visual grade yield. We then gauged the effect of combining log diameter and log position with log acoustic velocity to predict MOE and grade yield of the lumber. Log diameters used in the analysis were the averages of the large and small end diameters of the logs. For each log, we obtained a simple unweighted average of the MOEs of lumber extracted from the log. SAS (SAS Institute Inc., Cary, NC) Version 8 MEANS and UNIVARIATE procedures were used to generate descriptive statistics for log and lumber properties. The SAS REG procedure was used to perform the linear regressions. The simple unweighted average MOE of all lumber in a log was the response being predicted.

In preliminary analysis, we identified five influential outliers in the regression of MOE on log acoustic velocity and log position. These outliers had large externally studentized residuals and large dffits values, which indicated that they were both outliers and influential in the fit. The dffits value is a regression diagnostic that provides a measure of how the deletion of a particular point affects regression results (Belsley et al 1980). We were interested in using the true underlying relationships among log acoustic velocity, log position, and average MOE to identify logs that should or should not be selected for a particular sorting strategy. We realized that fits that were based on data that included influential outliers might yield poorer log selections, therefore we compared prediction equations from fits that did not include the outlying logs and fits that did. Prediction equations from regressions that did not include the outlying logs performed better in subsequent sorts of all 171 logs, therefore we report those prediction equations here.

RESULTS AND DISCUSSION

Log and Lumber Properties

Table 1 provides descriptive statistics for diameter, acoustic velocity, and average lumber MOE of the Douglas-fir logs. Because the sampled trees were from four different treatment plots, the resulting logs exhibited a wide diameter range, from 10.2 to 40.6 cm with a coefficient of variation (COV) of 27.4%. The large-diameter logs were primarily from trees harvested in thinned and thinned and biosolid-treated plots. In a separate study, Sonne (2001) reported that the thinned, biosolids, and thinned–biosolids treatment produced 45, 14, and 104% increases in volume, respectively.

Acoustic velocity of the Douglas-fir logs ranged from 3.3 to 4.9 km/s with a COV of 7.9%. The mean velocity (4.2 km/s) of the Douglas-fir logs in this study was much higher than mean velocities observed for other softwood species (such as Sitka spruce, western hemlock, ponderosa pine, red pine, and radiata pine) (Wang 2013). This was probably because of the relatively old stand age of the Douglas-fir trees in this study (compared with the young stands [8-43 yr old] in Chauhan and Walker [2006], Grabianowski et al [2006], Wang et al [2007], and Mora et al [2009]). Because acoustic velocity has been generally accepted as an effective measure of wood stiffness, the higher mean acoustic velocity and lower COV observed for the Douglas-fir logs in this study indicated a better quality of

Table 1. Descriptive statistics of log diameter, log acoustic velocity, and average modulus of elasticity (MOE) of lumber on a per-log basis.

Property	Mean	Minimum	Maximum	COV (%)
Log diameter (cm)	23.5	10.2	40.6	27.4
Log acoustic velocity (m/s)	4212	3255	4886	7.9
Average lumber MOE (GPa)	14.8	8.9	21.6	18.4

COV, coefficient of variation.

wood for the forest stands in terms of structural properties.

On a per-log basis, average MOE of dried lumber for the Douglas-fir logs ranged from 8.9 to 21.6 GPa with a COV of 18.4%. A total of 1098 pieces of lumber was obtained from the logs. Of these, 12.5% were select structural (SS), 24.1% were No. 1, 57.1% were No. 2, and 6.3% were No. 3.

Acoustic Sorting Models

Table 2 shows the results from the regressions of average lumber MOE on log V, D, P, and the combinations of log acoustic velocity and log diameter or log acoustic velocity and log position. Prediction equations were derived using the following two functional forms:

$$MOE = \beta_0 + \beta_1 \cdot x_1 \quad (3)$$

$$MOE = \beta_0 + \beta_1 \cdot x_1 + \beta_2 \cdot x_2 \quad (4)$$

where MOE is average lumber MOE being predicted; x_1 and x_2 are predicting variables (V, D, and P); and β_0, β_1, and β_2 are regression coefficients.

Log acoustic velocity had a positive correlation with lumber MOE, but the relationship was not very strong ($R^2 = 0.40$). Figure 1 shows observed lumber MOE (average lumber MOE on a log basis) vs predicted MOE for the regression in which MOE is regressed only on log acoustic velocity. This result is consistent with findings in other species (Aratake et al 1992; Farrell and Nolan 2008). Two wood processing procedures could have contributed to this less than satisfactory correlation. The first was the sawing process.

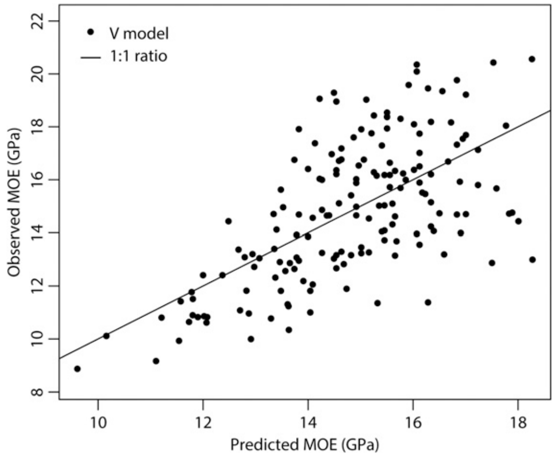

Figure 1. Observed modulus of elasticity (MOE) vs predicted MOE for a regression in which MOE is regressed on log acoustic velocity (V).

After a log was sawn into pieces of lumber, a significant outer portion of the log was removed as slabs and trimmings. The property information of these removed waste materials was subsequently lost, causing the overall log property change after lumber conversion. The second was the wood drying process. The moisture content of wood in green logs was well above the FSP when logs were acoustically tested. Moisture content was decreased to less than 19% after kiln-drying, causing a significant increase in lumber MOE, also inducing warp and uneven moisture content in lumber.

Log diameter was found to have a weak relationship with lumber MOE ($R^2 = 0.12$). Although not suited for predicting lumber MOE, log diameter was found to have a significant effect on acoustic wave propagation (Wang et al 2004a).

Table 2. Regressions of average lumber modulus of elasticity (MOE) on log acoustic velocity (V), log diameter (D), log position (P), and the combination of V, D, and P.[a]

Predictors		Coefficients								
x_1	x_2	β_0	p value	β_1 (x_1)	p value	β_2 (x_2)	p value	R^2	Adjusted R^2	RMSE
V	—	−7.70	0.0005	0.001621	0.0001	—	—	0.400	0.396	2.06
D	—	11.37	0.0001	0.374	0.0001	—	—	0.122	0.116	2.49
P	—	18.72	0.0001	−1.48	0.0001	—	—	0.587	0.584	1.70
V	D	−10.39	0.0001	0.001606	0.0001	0.316	0.0001	0.501	0.495	1.88
V	P	6.53	0.0014	0.000823	0.0001	−1.19	0.0001	0.672	0.668	1.52

[a] Average MOE of all lumber in a log is the response being predicted. Average coefficients and RMSE are for MOE measured in GPa.
RMSE, root mean squared error.

After examining 201 logs of mixed softwood species with acoustic wave and static bending testing, Wang et al (2004a) concluded that the diameter of logs had an interactive effect that contributed significantly to MOE prediction when used in conjunction with the fundamental wave equation. In this study, we examined a simple acoustic sorting approach in which density of logs was not measured and thus prediction of log MOE through the fundamental wave equation was not considered. However, the effect of log diameter on acoustic wave measures cannot be neglected.

Log vertical position in a tree was found to have a relatively good but negative relationship with lumber MOE ($R^2 = 0.59$). Lumber MOE was highest at the first and second logs and decreased with increasing position. This finding is similar to what Iangum et al (2009) reported for 20-yr-old Douglas-fir and western hemlock trees. They observed that flexural stiffness and strength decreased with increasing vertical position. This was caused by the influence of the crown, in which the proportion of juvenile wood is known to be relatively high. Figure 2 shows observed lumber MOE vs predicted MOE for a regression in which MOE is regressed only on log position.

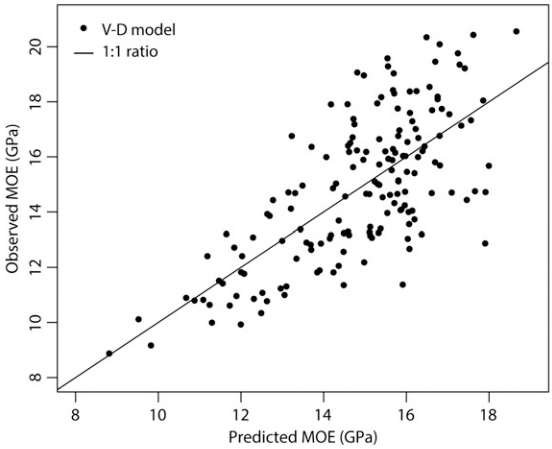

Figure 3. Observed modulus of elasticity (MOE) vs predicted MOE for a regression in which MOE is regressed on both log acoustic velocity (V) and log diameter (D).

Regressions of average lumber MOE on the combination of log acoustic velocity and log diameter or log acoustic velocity and log position show significant improvement as evidenced by the increase of coefficient of determination (Table 2). Figure 3 shows observed MOE vs predicted MOE for a regression in which MOE is regressed on both log acoustic velocity and log diameter ($R^2 = 0.50$). Figure 4 shows observed MOE vs predicted MOE for a regression in which MOE is regressed on both log acoustic velocity

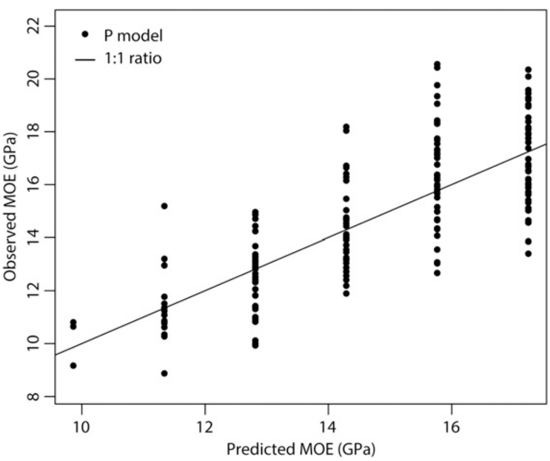

Figure 2. Observed modulus of elasticity (MOE) vs predicted MOE for a regression in which MOE is regressed on log position (P).

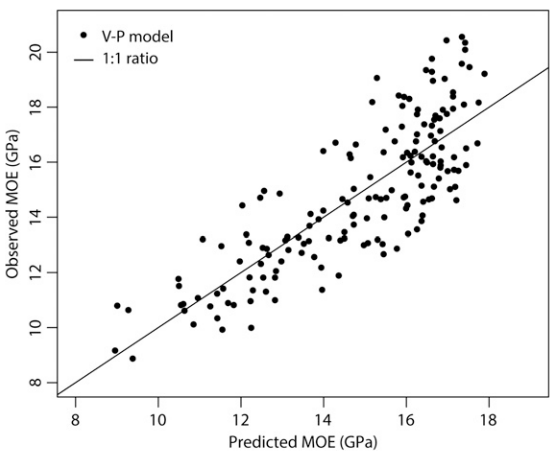

Figure 4. Observed modulus of elasticity (MOE) vs predicted MOE for a regression in which MOE is regressed on both log acoustic velocity (V) and log position (P).

and log position ($R^2 = 0.67$). The results indicated that log acoustic velocity by itself was not as good a predictor as the combination of log acoustic velocity and log diameter or the combination of log acoustic velocity and log position. The practical implications of these sorting models are illustrated through the following two sorting strategies.

Illustration of Acoustic Sorting Strategies

In a practical log-sorting process, companies can achieve benefits by implementing one of the following sorting strategies based on log sources and desired end products: 1) sorting best quality logs, and 2) sorting poorest quality logs.

Sorting best quality logs. Figure 5 demonstrates the outcomes of sorting best quality logs in terms of lumber MOE. Suppose we used the regression equation to identify logs that would produce lumber with the highest average MOE. If we selected, for example, the predicted top 20% of the logs, average MOE of the lumber produced from the logs identified by the log acoustic velocity and log position equation (*V-P* model) would be about 17.5 GPa, whereas average MOE of the lumber produced from the logs identified by the velocity-alone equation (*V* model) would be about 16.5 GPa. If we used no prediction equation, the resulting average MOE would be about 15.3 GPa. Thus, selecting the "best" 20% of the logs based on the *V-P* and *V* models yielded 14.5 and 8% increases in average lumber MOE, respectively. When less than 10% of the logs were selected, average lumber MOE for the logs selected by the *V* model showed large variations, which indicated the uncertainties of the *V* model when only a small sample size of logs was selected. The *V-P* model, conversely, showed a consistent trend in MOE improvement between 0 and 50% log selection.

Figure 6 shows the results of sorting best quality logs in terms of visual grades. The fraction of No. 1 & Better lumber in selected logs fluctuated significantly when log selection was less than 50%. This could be contributed to the fact that visual grading is a subjective procedure and does not fully reflect the stiffness of individual pieces of lumber. There appeared to be no difference between the *V-P* and *V* models if less than 10% or greater than 30% of the logs were selected. However, the results did show a clear difference between the two acoustic sorting models for log selection between 10 and 30%. For example, if we selected the predicted top 20% of logs, the fraction of No. 1 & Better lumber in the lumber produced from the logs identified by the *V-P* model would be about

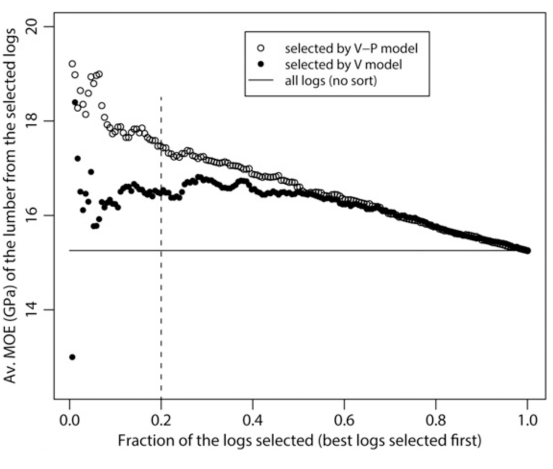

Figure 5. Average modulus of elasticity (MOE) of lumber from the selected logs vs fraction of the logs selected (best logs selected first) (*V*, velocity; *P*, position).

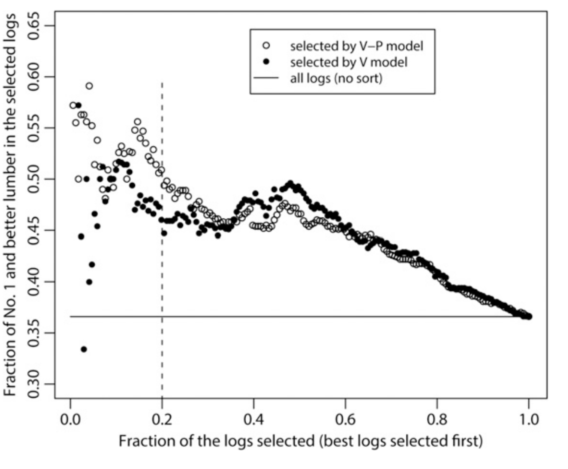

Figure 6. Fraction of No. 1 & Better lumber among lumber produced from selected logs vs fraction of the logs selected (best logs selected first) (*V*, velocity; *P*, position).

51%, whereas the fraction of No. 1 & Better lumber in the lumber produced from the logs identified by the *V* model would be about 46%. If we used no prediction equation, the fraction of No. 1 & Better lumber in the lumber produced from the logs would be about 37%. Thus, selections of the "best" 20% of the logs based on the *V-P* and *V* models yielded 39 and 26% increases in the fraction of No. 1 & Better lumber, respectively.

Sorting poorest quality logs. Figures 7 and 8 demonstrate the outcomes of sorting poorest quality logs. Figure 7 plots both average MOE of the lumber produced from the selected logs and average MOE of the lumber produced from the logs that are not selected vs the fraction of logs that are selected. If we used the *V-P* model to select the predicted poorest (lowest stiffness) 34 of the 171 logs (the poorest 20%), average MOE of the resulting lumber was approximately 12.0 GPa. The corresponding average MOE of the lumber from the 137 logs not selected (the remaining 80%) was approximately 15.8 GPa. If we used the *V* model to select the predicted poorest 34 of the 171 logs (the poorest 20%), average MOE of the resulting lumber was approximately 12.4 GPa. The corresponding average MOE of the lumber from the 137 logs not selected (the remaining 80%) was approximately 15.8 GPa. Thus, sorting out the predicted 20% poorest logs using either the *V-P* or the *V* model enhanced average lumber MOE of the remaining log population by about 3.3% (recall that average lumber MOE for all logs was approximately 15.3 GPa).

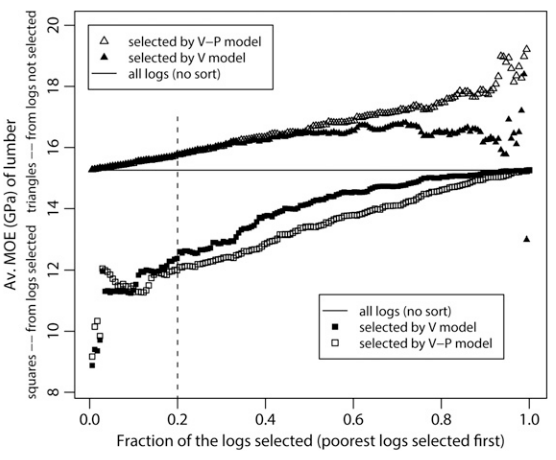

Figure 7. Average modulus of elasticity (MOE) of lumber from selected and unselected logs vs fraction of the logs selected (poorest logs selected first). Squares correspond to selected logs. Triangles correspond to unselected logs (*V*, velocity; *P*, position).

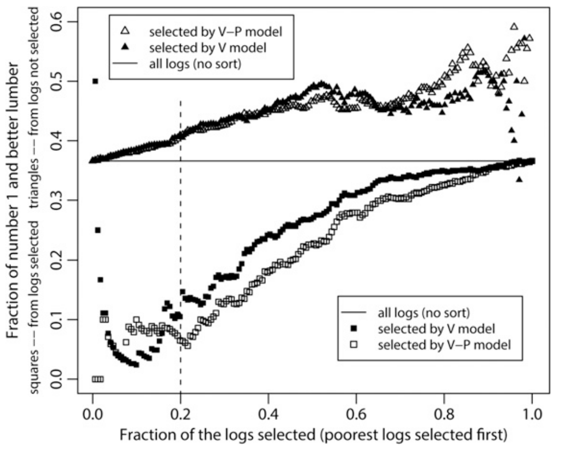

Figure 8. Fraction of No. 1 & Better among lumber produced from selected and unselected logs vs fraction of the logs selected (poorest logs selected first). Squares correspond to selected logs. Triangles correspond to unselected logs (*V*, velocity; *P*, position).

Figure 8 shows the fraction of No. 1 & Better lumber among the lumber produced from the selected and unselected logs vs the fraction of the logs that were selected. Similarly, if we used the *V-P* model to select the predicted poorest 34 of the 171 logs (the poorest 20%), the fraction of No. 1 & Better lumber in the resulting lumber was approximately 7%. The corresponding fraction of No. 1 & Better in the lumber from the 137 logs not selected (the remaining 80%) was approximately 41%. If we used the *V* model to select the predicted poorest 34 of the 171 logs (the poorest 20%), the fraction of No. 1 & Better in the resulting lumber was approximately 11%. The corresponding fraction of No. 1 & Better in the lumber from the 137 logs not selected (the remaining 80%) was still about 41%. Thus, sorting out the 20% poorest logs using the *V-P* model or *V* model resulted in an increase from 37 to 41% in the fraction of No. 1 & Better lumber in the remaining log population (recall that the average for all logs was about 37%).

Two observations can be made from this analysis. First, the increase in lumber MOE or visual grade yields as a result of sorting poorest logs might be minimal and could be offset by the prediction errors of the acoustic sorting models. The main benefit of sorting out the poorest quality logs prior to mill processing is to avoid cutting low MOE or low-grade lumber from the poorest quality logs, thus decreasing the cost of misallocation of resources. Second, the effectiveness of the *V-P* and *V* model for sorting the poorest quality logs is about the same, which implies that the simpler *V* model could be used to segregate the poorest logs in mill operations.

CONCLUSIONS

In this study, we examined three log measures (acoustic velocity, log diameter, and log position) for their ability to predict average MOE and grade yield of the structural lumber obtained from Douglas-fir logs. Based on the results from this mill study, we conclude the following:

1. Acoustic velocity of the Douglas-fir logs had a relatively good correlation with average MOE of all the lumber extracted from each log, but the relationship was not very strong ($R^2 = 0.40$);
2. No good relationship was found between log diameter and average lumber MOE ($R^2 = 0.12$);
3. Log vertical position in a tree was found to have a relatively good but negative relationship with lumber MOE ($R^2 = 0.57$). Lumber MOE was highest at the first and second logs and decreased with increasing position;
4. The combinations of log acoustic velocity and log diameter or log acoustic velocity and log position were better predictors of average lumber MOE and lumber visual grade yield than log acoustic velocity alone. The log acoustic velocity and log position model performed better than the log acoustic velocity and log diameter model in this study;
5. For sorting best quality logs, multivariable models were more effective than the velocity-alone model; however, for sorting poorest quality logs, the velocity-alone model was as effective as multivariable models. In the first case, we were focusing on the properties of the 20% of the logs that were selected as best. In the second case, we were focusing on the 80% of the logs that were not selected; and
6. In sawmill operations, a real threshold for sorting logs should be determined based on incoming log sources, end products, and the sorting strategy for the specific operation. Also, it can be fine-tuned to maximize the product value.

ACKNOWLEDGMENTS

This study was supported in part by funds provided by Michigan Technological University, Houghton, Michigan, and Fibre-gen, Inc., Christchurch, New Zealand.

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