Acoustic Sorting Models for Log Segregation

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Abstract

Acoustic resonance technique has been recognized as a robust nondestructive testing tool for raw material evaluation in the wood industry. Acoustic velocity is currently the primary sorting parameter for mills to segregate in-coming stems and logs into classes that suit structural or nonstructural applications. Although this simple sorting strategy has been proved somewhat effective by several mill studies, the direct correlation between acoustic velocity of logs and properties of wood products derived from the logs was actually low. In this paper we examine three individual log measures (acoustic velocity (AV), average log diameter (ALD), and log order (LO)) for their ability to predict the average modulus of elasticity (MOE) and grade yield of the structural lumber obtained from Douglas-fir logs. We find that, in addition to log acoustic velocity, log diameter and log order are important physical parameters that should be incorporated into log sorting models. In three different acoustic sorting models (AV alone, AV and ALD, AV and LO) developed for Douglas-fir logs, the velocity and log order model and the velocity and log diameter model perform better than the velocity-alone model. The results of this study indicate that using a second variable can improve the precision of log sorting. The two-parameter acoustic sorting models can be used either to select best quality logs or to segregate worst quality logs, depending on the needs of mills and material applications.

Introduction

End product properties are dependent upon 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. The same is true for logs from trees of the same age and from the same forest stand (Huang et al. 2003). At a keynote presentation of the 2nd International Precision Forestry Symposium, Dyck stated that "all logs are different even if they are clonal and even if they come from the same tree" (Dyck 2002). Clearly, there are major commercial benefits to be gained by assessing wood properties of incoming logs and optimizing the use of resources through appropriate log sorting.

The ability to sort incoming logs with acoustic resonance technique has been well recognized in the wood industry. This technology is based on the observations of hundreds of acoustic pulses resonating longitudinally in a log and provides a weighted average acoustic velocity. Because the modulus of elasticity (MOE) of the log is simply equal to density times the acoustic velocity squared, the technology is basically measuring fiber properties that influence macro properties such as stiffness, strength, and stability. The challenge is to interpret log acoustic measures into meaningful product values.

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Currently, the companies implementing acoustic sorting strategies measure only the velocity of acoustic waves and segregate stems and logs into velocity classes using predetermined cut-off velocity values. Although this simple sorting strategy has been proved somewhat effective by several mill studies (Addis et al. 1997, Wang and Ross 2000, Carter and Lausberg 2003, Carter et al 2005), the direct correlation between the acoustic velocity in a log and the properties of wood products derived from that log are actually not very strong. Consequently the precision of acoustic sorting is rather low. The purpose of this study was to gauge the effect of combining additional variables with acoustic velocity to predict the average modulus of elasticity (MOE) and grade yield of the structural lumber obtained from the logs. Specifically, we examined three individual log measures - acoustic velocity (AV), average log diameter (ALD), and log order (LO) - for their ability to sort logs individually and then developed new acoustic sorting models that used diameter and/or log order as a second variable for improving log sorting precision.

Materials and Methods

Forty eight Douglas-fir (Pseudotsuga menziesii) trees ranging from 14.2 to 53.3 cm (5.6 to 21 in) diameter at breast height (DBH) were selected from a 70 year-old stand on Pack Forest, the University of Washington's Research Forest near the town of Alder, WA. The sample matrix consisted of eight 5-cm (2-in) diameter classes and 6 trees from each class, which resulted in a total sample of forty-eight trees. The trees were nondestructively tested using a time-of-flight acoustic wave method to obtain acoustic wave velocities for the standing trees. The DBH of each sampled tree was also measured.

The sampled trees were harvested and bucked into mill-length logs (4.9-m (16-ft) long). The logs were tagged with a number that identified the tree and the position in the tree from which it came. A total number of 171 mill-length logs were obtained. Each log was nondestructively tested using an acoustic resonance technique to obtain an acoustic velocity for the log. The log order (cutting sequence from the butt) in each tree stem was recorded, and the log length and diameters of both ends of each log were measured.

The mill-length logs were then sawn into lumber using a Wood MizerTM at the yard site of Pack Forest. As each board 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 (2-in. dimension with some 25-mm (1-in.) jacket boards sawn from the outer portion of the logs. Green lumber thickness and width were measured on a randomly selected sample. All boards was kiln dried and surfaced at a local sawmill.

After sawing and kiln drying, 1098 pieces of lumber were obtained and evaluated for stiffness and visual grades yield. The MOE of each piece of lumber was measured using a transverse vibration method. 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

Figure 1 shows the data structure of the overall study. The data sets collected through the process included the following:

- Tree - acoustic velocity (AV) and diameter at breast height (DBH).
- Logs - acoustic velocity (AV), small end diameter (SED), large end diameter (LED), and log order (LO) (cutting sequence from the butt).
- Lumber - modulus of elasticity (MOE) and visual grades.

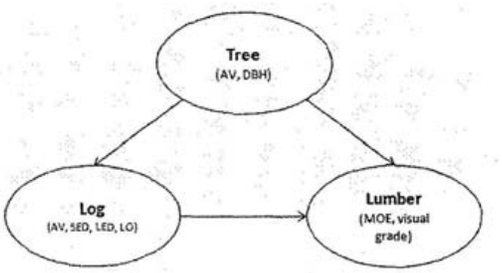

Figure 1. *—Data structure*

Our analysis in this paper focused on mill-length logs and dimension lumber produced from the logs. We first evaluated log acoustic velocity (AV), average log diameter (ALD), and log order (LO) as individual predictors of lumber stiffness and visual grade yield. We then gauged the effect of combining log diameter and log order with the log acoustic velocity to predict the stiffness and grade yield of the dimension lumber.

Results and Discussion

Table 1 shows the results from the regressions of average lumber MOE on log acoustic velocity, average log diameter, and on the Combination of log acoustic velocity and average log diameter after seven "outliers" have been removed from the data set. Average log diameter was found not having a strong relationship with lumber MOE. Log acoustic velocity had a relatively good correlation with lumber MOE, but the relationship was not very strong either (R^2 = 0.455). However, a regression of average lumber MOE on the combination of log acoustic velocity and average log diameter showed a moderate improvement with R^2 = 0.533.

Table 1. - *Regressions of average lumber MOE on log acoustic velocity, average log diameter, and on the combination of log acoustic velocity and log diameter (Outliers removed).*

Predictor(s)	R^2	Adjusted R^2	RMSE[a]
Acoustic velocity (AV)	0.455	0.452	0.289
Avg. log diameter (ALD)	0.123	0.118	0.365
Acoustic velocity (AL) and avg. log diameter (ALD)	0.533	0.527	0.267

[a] Root mean squared error

Table 2 shows the results from the regressions of average lumber MOE on log acoustic velocity, log order, and on the combination of log acoustic velocity and log order after seven "outliers" have been removed from the data set. It was found that log order had a very good correlation with the lumber MOE (R^2 = 0.561). Regressions of average lumber MOE on the combination of log acoustic velocity and log order showed a significant improvement in terms of correlation coefficient (R^2 = 0.667).

Table 2. *—Regressions of average lumber MOE on log acoustic velocity, log order, and on the combination of log acoustic velocity and log order (Outliers removed).*

Predictor(s)	R^2	Adjusted R^2	RMSE[a]
Acoustic velocity (AL)	0.455	0.452	0.289
Log order (LO)	0.561	0.558	0.258
Acoustic velocity (AL) and log order (LO)	0.667	0.663	0.226

[a] Root mean squared error

Figure 2 plots observed MOE versus predicted MOE for a regression in which MOE is regressed only on log acoustic velocity. **Figure 3** plots observed MOE versus predicted MOE for a regression in which MOE is regressed only on log order. **Figure 4** plots observed MOE versus predicted MOE for a regression in which MOE is regressed on both log acoustic velocity and log order.

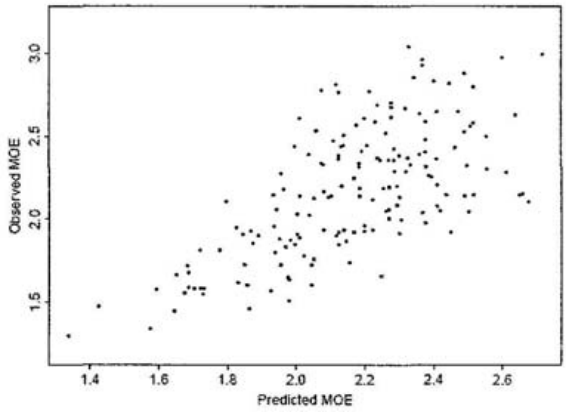

Figure 2. *—Observed MOE versus predicted MOE for a regression in which MOE is regressed only on log acoustic velocity (AV). (Seven outliers were removed)*

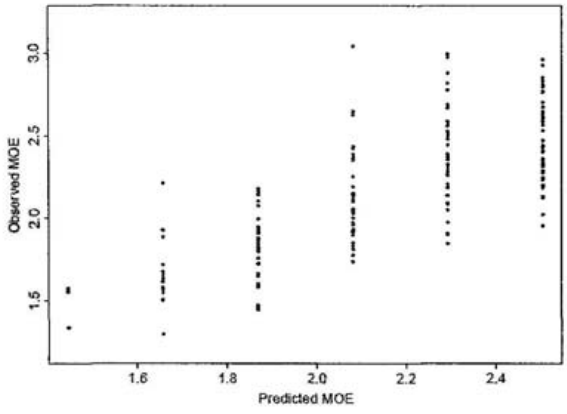

Figure 3. *—Observed MOE versus predicted MOE for a regression in which MOE is regressed only on log order (Seven outliers were removed).*

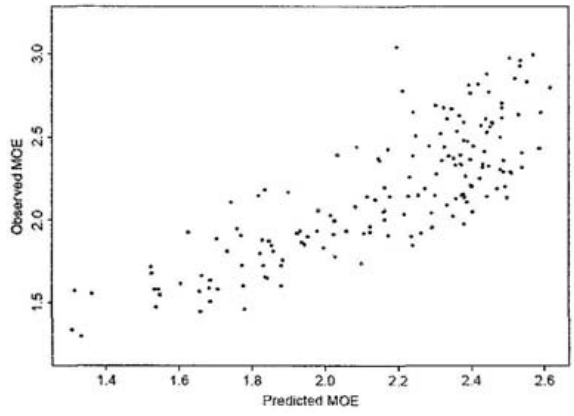

Figure 4. *- Observed MOE versus predicted MOE for a regression in which MOE is regressed on both log AV and log order (Seven outliers were removed).*

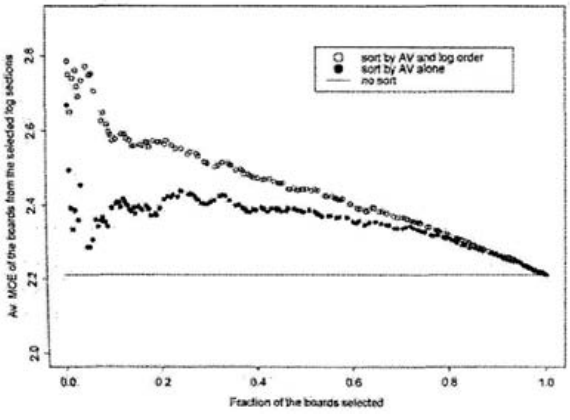

Figure *5. —Average MOE of the lumber from the selected logs versus fraction of the lumber in the selected logs (best predicted logs selected first).*

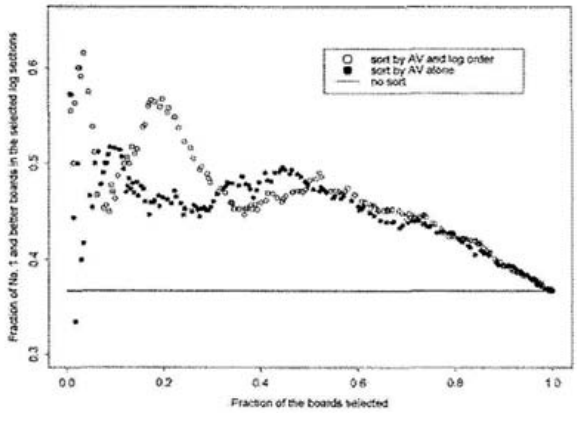

Figure 6. *—Fraction of No. 1 and Better lumber among the lumber produced from the selected logs versus fraction of the lumber in the selected logs (best predicted log sections selected first).*

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 order. The practical implications are illustrated in **Figure** 5 and **Figure 6.**

Figure 5 demonstrates the followings. Suppose we used the regression equation to identify the logs that would produce the lumber with the highest average MOE. If we selected, for example, the predicted top 20 percent of the logs, the average MOE of the lumber produced from the logs identified by the log acoustic velocity and log order equation would be about 17.6 GPa (2.55 Mpsi), while the average MOE of the lumber produced from the logs identified by the AV (alone) equation would be about 16.6 GPa (2.4 Mpsi). If we used no prediction equation and just obtained a random sample of logs, the resulting average MOE would be a bit above 15.2 GPa (2.2 Mpsi).

Similarly, in **Figure 6,** if we selected the predicted top 20 percent of the logs, the fraction of No. 1 & Better lumber among the lumber produced from the logs identified by the AV and log order equation would be about 0.57, while the fraction of No. 1 & Better lumber among the lumber produced from the logs identified by the AV (alone) equation would be about 0.47. If we used no prediction equation and just obtained a random sample of logs, the fraction of No. 1 & Better lumber among the lumber produced from the logs would be about 0.37.

Another strategy for mills to increase profit is to isolate worst quality logs prior to processing. **Figure 7** plots both the average MOE of the lumber produced from the selected logs and the average MOE of the lumber produced from the logs that are not selected versus the fraction of logs that are selected.

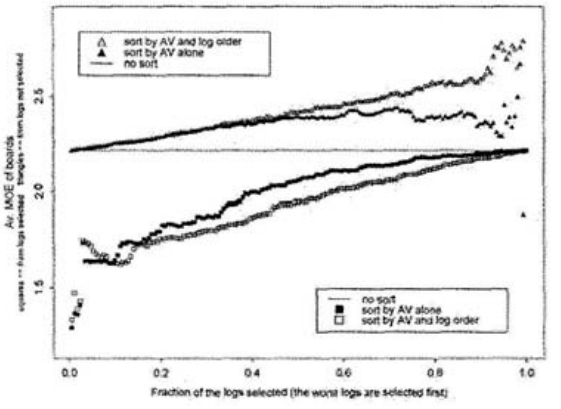

Figure 7. —*Average MOEs of the lumber from the selected and unselected logs versus the fraction of the logs selected (worst predicted logs selected first). The squares correspond to the selected logs. The triangles correspond to the unselected logs.*

If we used the AV and log order model to select the predicted worst (lowest stiffness) 34 of the 171 logs (the worst 20%), the average MOE of the resulting lumber is approximately 12.1 GPa (1.76 Mpsi). The corresponding average MOE of the lumber from the 137 logs not selected (the remaining 80%) is approximately 15.7 GPa (2.28 Mpsi).

If we used the AV alone model to select the predicted worst 34 of the 171 logs (the worst 20%), the average MOE of the resulting lumber is approximately 12.4 GPa (1.80 Mpsi). The corresponding average MOE of the lumber from the 137 logs not selected (the remaining 80%) is approximately 15.8 GPa (2.29 Mpsi).

Figure 8 plots the fraction of No. 1 & Better lumber among the lumber produced from the selected and unselected logs versus the fraction of the logs that are selected.

If we used the AV and log order model to select the predicted worst 34 of the 171 logs (the worst 20%), then the fraction of No. 1 & Better lumber among the resulting lumber is

approximately 0.065. The corresponding fraction of No. 1 & Better lumber among the lumber from the 137 logs not selected (the remaining 80%) is approximately 0.409.

If we used the AV alone model to select the predicted worst 34 of the 171 logs (the worst 20%), the fraction of No. 1 & Better lumber among the resulting lumber is approximately 0.105. The corresponding fraction of No. 1 & Better lumber among the lumber from the 137 logs not selected (the remaining 80%) is approximately 0.409.

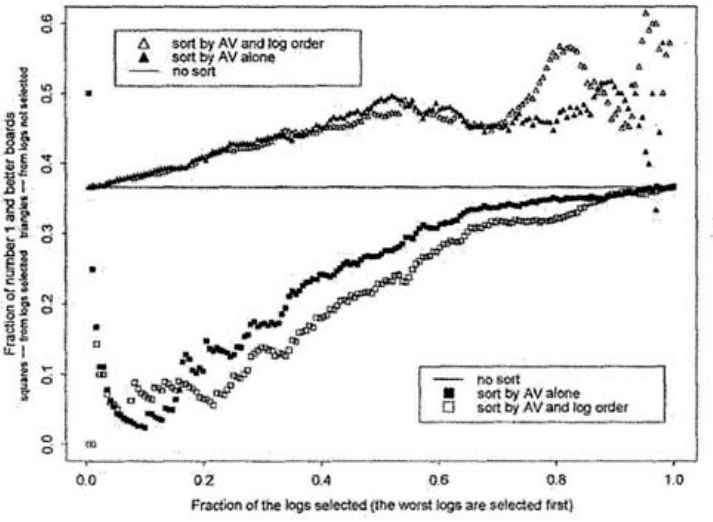

Figure 8. —*Fraction of No. 1 and Better boards among the boards produced from the selected and unselected log sections versus the fraction of the log sections selected (worst predicted log sections selected first). The squares correspond to the selected log sections. The triangles correspond to the unselected log sections.*

Conclusions

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

1. Log acoustic velocity has a relatively good correlation with average lumber MOE, but the relationship is not very strong (R^2 = 0.455);
2. No good relationship was found between average log diameter and average lumber MOE, but log order was found to have a very good correlation with average board MOE (R^2 = 0.558);
3. The combination of log acoustic velocity and average log diameter is a better predictor of average lumber MOE and lumber visual grade yield than log acoustic velocity alone.
4. The combination of log acoustic velocity and log order is a better predictor of average lumber MOE and lumber visual grade yield than log acoustic velocity alone.
5. The log acoustic velocity and log order model performed better than the log acoustic velocity and log diameter model in this study. Both models can be used to select best quality logs or used to segregate worst quality logs, depending on the needs of mills and material applications.

Acknowledgement

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