Estimating Upper Percentiles of Strand Thickness for Oriented Strand Board

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Abstract

Statistical reliability methods are applied to estimate the upper percentiles of strand thickness for the face layers of oriented strand board (OSB) panels manufactured from six mills in the Eastern United States. The influence of thick strands on OSB properties (thickness swell, TS; internal bond, IB; and modulus of rupture, MOR) has been well documented. However, there is an absence in the literature of characterizing wood strand thickness for OSB mills in the context of statistical reliability methods. With induced percentile left censoring for improved model fitting, bootstrapping methods are employed for better estimating the upper percentiles and confidence intervals for strand thickness. The upper percentiles of flakes may be costly, damage equipment, or cause dimensional instability in OSB.

The distributions of wood strands were nonnormal, and best-fit distributions varied from the log-logistic, largest extreme value, lognormal, and Weibull. The mean and median strand thicknesses for all mills were 0.0322 inches (0.8179 mm) and 0.0310 inches (0.7874 mm), respectively. The coefficient of variation for all mills was 39.1 percent. Parametric bootstrap confidence intervals for the 95th percentile with no censoring varied in length from 0.0009 inches (0.0229 mm) to 0.0145 inches (0.3683 mm). Nonparametric bootstrap confidence intervals for the 95th percentile with no censoring varied in length from 0.0005 inches (0.0127 mm) to 0.0225 inches (0.5175 mm). Study results were strengthened from the validation study in that the training intervals were either contained within, or overlapped, the validation intervals.

Oriented strand board (OSB) is an important engineered wood product in the US economy. Dimensional stability of OSB panels is critical in defining product quality. Current, unprecedented economic conditions require OSB manufacturers to maintain a strong focus on reliability, quality, and costs (Wang 2007). Modern OSB manufacturers have the ability to control the quality of manufactured feedstocks in the context of statistical methods (compare Young and Guess 1994). This study assesses the critical input of strand thickness for OSB panels. Green wood strand thicknesses for the face layers of OSB panels for six mills in the Eastern United States were evaluated using statistical reliability methods.

The influence of the thickness of wood strands on the dimensional stability of OSB panels was documented by Brochmann et al. (2004). OSB manufacturers generally target a strand thickness of 0.030 inches (Boyer et al. 2007). As Brochmann et al. (2004) noted, early studies by Brumbaugh (1960), Post (1961), and Jorgenson and Odell (1961) found that particles and strands that are too thick produce increased thickness swell (TS). Brochmann et al. (2004) also documented the effect of thinner face strands on reducing 24-hour TS, while the thicker strands produced higher internal bond (IB) but had the lowest surface area for resin bonding. Given the confidentiality requested by the OSB manufacturers sampled in this study, it was not possible to reveal strand thickness targets specific to any of the mills.

Strand thickness variability also influences mat formation and OSB dimensional stability (Canadido et al. 1990, Sharma and Sharon 1993, Paul et al. 2005, Hermawan et al. 2006, Tackie et al. 2008). Tackie et al. (2008) discuss variation in the thickness of the strands during formation on the top layer of the mat, i.e., more strands may overlap in

Table 1.—OSB strand thickness descriptive statistics for each mill's complete data.

Statistic	Mill A	Mill B	Mill C	Mill D	Mill E	Mill F	All mills
Mean	0.0357	0.0311	0.0288	0.0318	0.0364	0.0291	0.0322
Median	0.0335	0.0310	0.0275	0.0308	0.0365	0.0268	0.0310
SD	0.0124	0.0058	0.0127	0.0137	0.0151	0.0134	0.0122
CV (%)	34.7	18.7	44.1	43.1	41.5	46.1	39.1
IQR	0.0135	0.0040	0.0140	0.0159	0.0222	0.0162	0.0143
Minimum	0.0130	0.0210	0.0045	0.0070	0.0085	0.0067	0.0101
Maximum	0.0955	0.1030	0.0715	0.1155	0.0890	0.0876	0.0937
Skewness	1.0293	9.3936	0.9477	1.7258	0.2927	1.3612	2.4583
Kurtosis	2.2333	116.4694	1.6523	8.3946	0.0281	2.9531	21.9551
Sample size	300	200	140	150	150	304	—

one area of the mat than another, which can potentially cause dimensional instability for the OSB panel.

Using induced percentile left censoring for improved model fitting, bootstrapping methods were used for better estimating the upper percentiles (90th, 95th, and 99th) and confidence intervals for green wood strand thickness for the face layer of OSB panels.[1] Improved estimates of confidence intervals for the upper percentiles of wood strands promote OSB product quality and provide OSB manufacturers with potential competitive benchmarks.

Methods

Data sets

Green wood strands (*Pinus* spp.) were collected from six Southeastern US OSB mills during the fall of 2007. Even though the mills used a variety of species (e.g., *Populus* spp. and mixed hardwoods), the mills sampled in this study used primarily *Pinus* spp. in the face layer. Softwood/hardwood species mix of the face strands varied between mills, and species mix varied even within mills depending on species availability during the procurement process. Species mix information from the mills was not available to the researchers and was considered confidential information by the companies owning the mills. Green wood strand thicknesses were measured on-site at five of the six mill sites using a wireless caliper and PC-based data collection system. In one instance (Mill A), strands were immediately sealed in plastic bags after collection and were shipped to the laboratory for measurement. The thicknesses of individual strands were measured once at the centroid of the strand along the longest edge where the edge of the strand was placed at the base of a Mitutoyo digital micrometer. The green wood strands were collected at the mill sites at the drop chutes of the conveyors near the output of the flaker machines before screening. A shovel was inserted into the drop chutes three to four consecutive times over an approximate 10-minute interval to collect the strands. Undersized material (''fines'') and overcut material

that may occur as the flaker nears the end of the log (''beaver tails'') were not sampled in this study. Such material is typically screened before entering the OSB forming and pressing process.

Sample size varied from 140 to 304 strands among the six mills. The unequal sample sizes were the result of safety concerns for the researchers during sampling at the drop chutes near the flakers, i.e., employees of each mill collected the strands for the researchers, and the workers did not sample the same volume of flakes. The sample sizes obtained were large enough for the parametric statistical methods used in the study, see central limit theorem (Lindgren 1976). Given that most OSB mills have different brands of stranding machines, knife configurations, preventive maintenance schedules, operators, etc., wood strands were collected at the approximate midpoint of the maintenance cycle for the stranding machine at each mill. All of the mills had radial disk flakers. Descriptive statistics and sample size for each mill's strand thicknesses are displayed in Table 1.

Bootstrapping

Bootstrapping is a computationally intensive statistical method that simulates the sampling process a specified (large) number of times on an existing data set to obtain an empirical (''bootstrap'') distribution for a desired population parameter. This bootstrap distribution is then used to estimate characteristics (e.g., standard error, bias, and confidence intervals) of the population. Bootstrap intervals for the same sample size can have smaller standard errors than traditional parametric intervals and, thus, better precision (Efron and Tibshirani 1994, DiCiccio and Efron 1996, Meeker and Escobar 1998, Young et al. 2008). The bootstrap standard confidence interval is given by

$$\left[\hat{\theta} - z^{(\alpha/2)} \widehat{se}_{\hat{\theta}}, \ \hat{\theta} + z^{(1-\alpha/2)} \widehat{se}_{\hat{\theta}} \right] \quad (1)$$

where

$\widehat{se}_{\hat{\theta}} =$ the standard error found by calculating the SD of the bootstrap estimates of θ, and

$z^{(\alpha/2)} =$ the $\alpha/2$nd quantile of the standard normal distribution (e.g., $\alpha = 0.01, 0.05, 0.10$); see Chernick (1999) and Polansky (2000).

As Edwards et al. (in press) note, asymptotic intervals are often criticized for not being as realistic for smaller or even moderate sample sizes. Bootstrapping provides an alternative strategy that can realistically inform the practitioner by a more accurate assessment of the variability inherent in a system or process. Although this procedure might lead to

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[1] In statistics, censoring is conducted when the value of an observation is only partially known. In this study, induced ''left censoring'' (data points below a certain value) at the lower percentiles (e.g., 100th percentile where $P = 0.10, 0.15, 0.20, 0.25$) was conducted to improve the fit of the distribution for the upper percentiles and the estimates of confidence intervals for upper percentiles (e.g., 90th, 95th, and 99th). This ''induced percentile left censoring'' helps prevent the lower portion of the data from unduly influencing the modeling and estimating of the upper percentiles.

Table 2.—AIC scores for nine distributions for six mills using the complete data.

Distribution	Mill A	Mill B	Mill C	Mill D	Mill E	Mill F
Exponential	−1,395.8	−983.8	−708.8	−730.4	−689.8	−1,538.8
Frechet	−1,748.6	−1,662.4	−768.0	−824.6	−762.0	−1,775.6
LEV	−1,819.8	−1,673.4	−837.8	−884.6	−823.6	−1,831.6
Logistic	−1,798.2	−1,705.8	−832.0	−878.2	−824.6	−1,781.2
Log-logistic	−1,820.8	−1,725.4	−834.8	−883.8	−813.8	−1,829.6
Lognormal	−1,819.0	−1,699.8	−826.8	−878.0	−813.6	−1,833.6
Normal	−1,781.8	−1,714.0	−823.2	−857.8	−829.0	−1,755.4
SEV	−1,620.2	−1,713.0	−760.0	−794.2	−789.6	−1,579.6
Weibull	−1,783.2	−1,717.6	−833.0	−868.8	−835.0	−1,793.0

potentially wider confidence intervals over asymptotic approaches, one should understand clearly the advantages of bootstrapping being more accurate (Edwards et al., in press).

Left censoring and bootstrapping of upper percentiles

Upper percentiles of wood strands are of interest to quality control managers (i.e., influence on OSB properties) and maintenance managers of OSB manufacturers (i.e., potential damage to press platens or continuous press belts). In this study, induced percentile left censoring and bootstrapping were invoked to provide better estimates of the upper percentiles of wood strands. Each data set was left censored at the 0.10, 0.15, 0.20, and 0.25 quantiles; no censoring was also used for comparison. Nine distributions were fit to each data set without and with induced percentile left censoring, and the best distribution for each mill according to Akaike's information criterion (AIC) was used for bootstrapping (Akaike 1973), see Tables 2 and 3 for without censoring and with censoring, respectively. The distributions tested were the exponential, Frechet, largest extreme value, logistic, log-logistic, lognormal, normal, smallest extreme value, and Weibull. AIC was used as a quantitative method to score each of these distributions, i.e., the lowest AIC defines the best-fit distribution (Akaike 1973). See also the insightful, helpful work of Bozdogan (2000). Probability plots were also examined to assess the fit of the distributions. However, given that probability plots are subjective for interpretation by the user, the plots were more helpful in identifying potential outliers than a parametric model.

For example, the best-fitting distribution for Mill A when censoring at the 0.10 percentile is the logistic distribution, while with no censoring it is the log-logistic distribution. The distribution was then assumed for the appropriate data set, and next bootstrapping was used to find confidence intervals for the 0.95 quantile. This procedure was repeated for every mill using the best distribution for the particular data set. Also, a nonparametric approach was used not assuming any parametric model. Confidence intervals for the 0.90, 0.95, and 0.99 quantiles were estimated; see Table 4. Splida and Matlab software were used for distribution fitting and the censoring analyses (Mathworks 2009, Tibco 2009).

Validation study

A validation of the results for Mill B (least variability, coefficient of variation [CV] = 18.7%) and Mill F (most variability, CV = 46.1%) was performed where each data set was divided into 75 percent for training and 25 percent for validation. The training and validation data were selected at random. Nine distributions were fit to the training data sets and AIC was used to determine the best-fitting model. Parametric and nonparametric bootstrap confidence intervals for the complete and censored data sets were estimated for the 0.90, 0.95, and 0.99 quantiles for both the training and validation data sets, which coincided with previous study methods.

Results and Discussion

Descriptive statistics and distributions of strand thickness without censoring

The grand mean and median for all mills were 0.0322 inches (0.8128 mm) and 0.0310 inches (0.7874 mm), respectively (Table 1); recall Boyer et al. (2007). The CV ranged from 18.7 percent (Mill B) to 46.1 percent (Mill F). The average CV for all six mills was 39.1 percent. Mill B had the lowest interquartile range (IQR) of 0.004 inches (0.1016 mm) when compared with the other five mills. Mill E had the highest IQR of 0.022 inches (0.5588 mm).

For the complete data set for each mill, the log-logistic distribution was the best fit for Mills A and B, while the largest extreme value (LEV) distribution was the best fit for

Table 3.—AIC scores for six mills using the complete data excluding highest outlier.

Distribution	Mill A	Mill B	Mill C	Mill D	Mill E	Mill F
Exponential	−1,394.6	−983.4	−706.8	−731.0	−688.2	−1,537.8
Frechet	−1,748.6	−1,675.6	−766.4	−825.4	−760.8	−1,775.4
LEV	−1,823.8	−1,708.2	−838.2	−892.4	−824.0	−1,835.4
Logistic	−1,806.4	−1,766.2	−835.0	−892.8	−827.4	−1,788.4
Log-logistic	−1,823.6	−1,759.0	−834.6	−888.0	−813.6	−1,831.4
Lognormal	−1,823.4	−1,756.4	−826.4	−884.2	−813.6	−1,836.2
Normal	−1,799.4	−1,768.2	−828.2	−894.2	−835.2	−1,768.4
SEV	−1,677.6	−1,767.0	−768.8	−851.6	−814.4	−1,602.8
Weibull	−1,800.0	−1,774.0	−836.0	−898.2	−840.0	−1,801.4

Table 4.—Confidence intervals for the 0.90, 0.95, and 0.99 quantiles for nonparametric bootstrap, parametric bootstrap with censoring and without censoring.

	Mill A[a]	Mill B[b]	Mill C[c]	Mill D[c]	Mill E[d]	Mill F[e]
0.90 Quantile						
No censoring	0.0492–0.0544	0.0337–0.0346	0.0431–0.0503	0.0466–0.0539	0.0526–0.0602	0.0438–0.0501
0.25 censoring	0.0499–0.0551	0.0339–0.0347	0.0424–0.0498	0.0460–0.0534	0.0532–0.0625	0.0440–0.0495
0.20 censoring	0.0414–0.0489	0.0339–0.0348	0.0414–0.0489	0.0453–0.0528	0.0545–0.0616	0.0433–0.0489
0.15 censoring	0.0413–0.0486	0.0338–0.0347	0.0413–0.0486	0.0448–0.0520	0.0536–0.0611	0.0426–0.0481
0.10 censoring	0.0403–0.0475	0.0338–0.0347	0.0403–0.0475	0.0443–0.0514	0.0529–0.0600	0.0447–0.0504
Nonparametric	0.0485–0.0535	0.0335–0.0340	0.0400–0.0475	0.0425–0.0510	0.0515–0.0590	0.0425–0.0500
0.95 Quantile						
No censoring	0.0563–0.0635	0.0344–0.0354	0.0499–0.0587	0.0536–0.0626	0.0579–0.0671	0.0510–0.0595
0.25 censoring	0.0557–0.0621	0.0346–0.0356	0.0478–0.0572	0.0516–0.0613	0.0574–0.0682	0.0501–0.0571
0.20 censoring	0.0465–0.0560	0.0346–0.0356	0.0465–0.0560	0.0506–0.0602	0.0614–0.0702	0.0491–0.0561
0.15 censoring	0.0463–0.0554	0.0345–0.0355	0.0463–0.0554	0.0501–0.0590	0.0602–0.0692	0.0481–0.0549
0.10 censoring	0.0449–0.0539	0.0345–0.0355	0.0449–0.0539	0.0493–0.0580	0.0593–0.0677	0.0519–0.0591
Nonparametric	0.0530–0.0620	0.0340–0.0360	0.0430–0.0655	0.0465–0.0630	0.0555–0.0650	0.0488–0.0591
0.99 Quantile						
No censoring	0.0755–0.0892	0.0354–0.0367	0.0650–0.0776	0.0695–0.0822	0.0674–0.0802	0.0678–0.0823
0.25 censoring	0.0682–0.0779	0.0357–0.0369	0.0596–0.0737	0.0639–0.0787	0.0640–0.0776	0.0636–0.0740
0.20 censoring	0.0665–0.0755	0.0357–0.0370	0.0574–0.0714	0.0622–0.0768	0.0762–0.0898	0.0616–0.0720
0.15 censoring	0.0651–0.0737	0.0356–0.0368	0.0570–0.0704	0.0614–0.0745	0.0745–0.0876	0.0601–0.0699
0.10 censoring	0.0638–0.0725	0.0355–0.0367	0.0551–0.0678	0.0600–0.0728	0.0731–0.0850	0.0683–0.0791
Nonparametric	0.0625–0.0815	0.0350–0.0370	0.0590–0.0715	0.0560–0.1155	0.0635–0.0890	0.0591–0.0854

[a] Mill A has log-logistic distribution without censoring and logistic distribution with censoring.
[b] Mill B without the largest outlier has Weibull distribution without censoring and smallest extreme value (SEV) distribution with censoring.
[c] Mills C and D have largest extreme value (LEV) distribution without censoring and logistic distribution with censoring.
[d] Mill E has Weibull distribution without censoring, logistic distribution with censoring (0.10, 0.15, 0.20), and SEV with censoring at 0.25.
[e] Mill F has lognormal distribution without censoring, LEV with censoring (0.10), and logistic distribution with censoring (0.15, 0.20, 0.25).

Mills C and D. The Weibull was the best fit for Mill E, and the lognormal was the best fit for Mill F. If the highest outlier for each data set was excluded, the distributions for Mills A, B, and D changed. The best fit for Mill A was the LEV distribution, and the best fit for Mills B and D was the Weibull distribution (Table 3).

There was evidence of a lack of normality for all mills for both the complete data and the data set when the highest outlier was excluded. This lack of normality is an important consideration for both wood scientists and practitioners in the appropriate application of statistical methods.

Distributions of strand thickness with induced percentile left censoring

Mill B was interesting because the data set had the least variability relative to the other mills but contained an extreme outlier (very thick strand) that was about three times the value of the second highest data point. The outlier was removed after discussions with mill management in that extremely thick strands (i.e., known as ''beaver tails'' from the end of the log during processing at the flaker) are usually detected in the screening process. However, mill management noted that in some instances screening equipment for wood strands has failed or was operationally inefficient, allowing extremely thick strands into the process, resulting in damage to the press platens or expensive continuous press belts. At all censoring percentiles with the highest outlier removed, the data from Mill B followed a smallest extreme value (SEV) distribution.

For Mills A, C, and D at these censoring values (0.10, 0.15, 0.20, and 0.25 quantiles) the data best fit the logistic distribution. For Mill E when censoring was applied at the

0.10, 0.15, and 0.20 quantiles, the best-fit distribution was the logistic. When censoring at the 0.25 quantile, the data best fit the SEV distribution. For Mill F at 0.10 quantile censoring, the best distribution was the LEV. The best distribution at the 0.15, 0.20, and 0.25 quantiles was the logistic.

Confidence intervals of strand thickness

Without censoring.—Mill B had the narrowest confidence intervals (excluding the extreme outlier) when compared with the other five mills for the complete data set. However, Mill B did not have the thinnest strands (as measured by the median $M = 0.0310$ inches, 0.7874 mm; see Table 1). The intervals for Mill B in inches were 0.0337 to 0.0346 for the 0.90 quantile, 0.0344 to 0.0354 for the 0.95 quantile, and 0.0354 to 0.0367 for the 0.99 quantile (Table 4).[2]

Mill E had the thickest strands ($M = 0.0365$ inches, 0.9271 mm) and had the widest intervals without censoring at the 0.90 and 0.95 quantiles which were 0.0526 to 0.0602 inches and 0.0579 to 0.0671 inches, respectively.[3] Mill F had the thinnest median strand thickness (0.0268 inches) but had the widest interval at the 0.99 quantile of 0.0678 to 0.0823 inches.[4] The comparison of confidence intervals without and with censoring indicated that Mill B produced a

[2] Intervals in millimeters were 0.8560 to 0.8788 for the 0.90 quantile, 0.8738 to 0.8992 for the 0.95 quantile, and 0.8992 to 0.9322 for the 0.99 quantile.
[3] Intervals in millimeters were 1.3360 to 1.5291 for the 0.90 quantile and 1.4707 to 1.7043 for the 0.95 quantile.
[4] The interval in millimeters for the 0.99 quantile was 1.7221 to 2.0904.

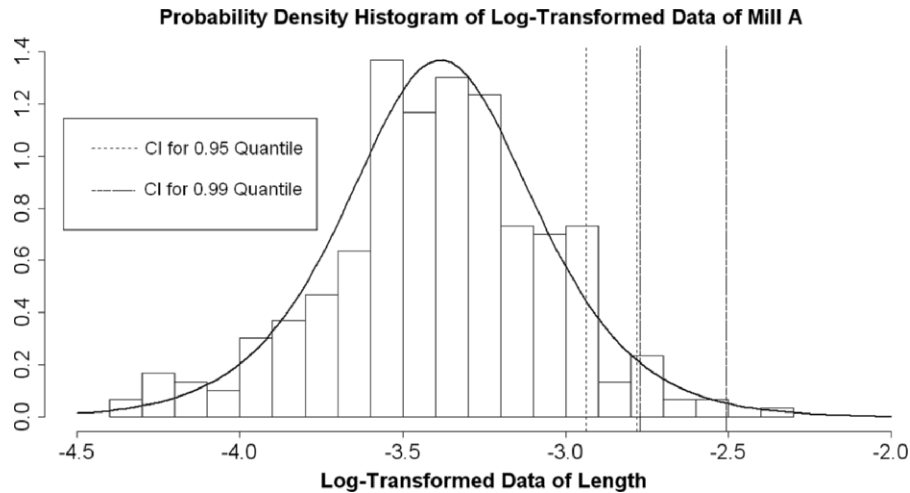**Probability Density Histogram of Log-Transformed Data of Mill A**

Figure 1.—Histogram and density function plot for Mill A (no censoring) with bootstrap confidence intervals for the 0.95 and 0.99 quantiles (with logarithm scale on x-axis).
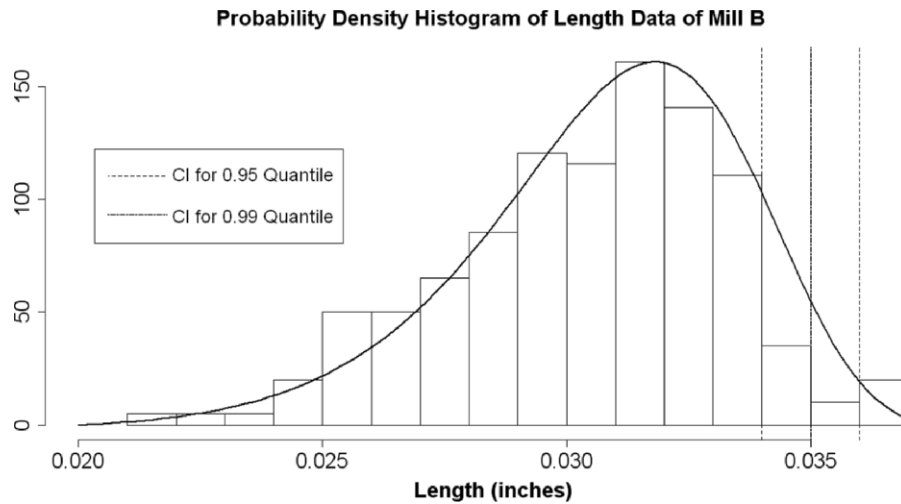
Probability Density Histogram of Length Data of Mill B

Figure 2.—Histogram and density function plot for Mill B (no censoring) with bootstrap confidence intervals for the 0.95 and 0.99 quantiles.

face layer strand that was more consistent in thickness relative to the other five mills.

Nonparametric.—Mill B also had the narrowest confidence intervals from nonparametric bootstrapping (excluding the extreme outlier) when compared with the other five mills for the complete data set derived. Intervals in inches were 0.0335 to 0.0340 for the 0.90 quantile, 0.0340 to 0.0360 for the 0.95 quantile, and 0.0350 to 0.0370 for the 0.99 quantile (Table 4).[5] Mill D had the widest intervals derived from nonparametric bootstrapping for the 0.90 and 0.99 quantiles with 0.0425 to 0.0510 inches and 0.0560 to 0.1155 inches, respectively.[6] Mill C had the widest confidence interval derived from nonparametric bootstrap-

ping for the 0.95 quantile with 0.0430 to 0.0655 inches.[7] Histograms of the raw data for Mills A, B, C, D, E, and F with the best-fit distributions and the bootstrapping intervals for the 0.95 and 0.99 quantiles are displayed in Figures 1, 2, 3, 4, 5, and 6, respectively.

With censoring.—As Chen et al. (2006) and Guess et al. (2004) noted, when induced percentile censoring impacts the underlying distribution of a data set, it can provide more reliable estimates of the percentiles, depending on the data sets. Clearly, the best censoring point depends on the data set and the practitioner's use of the results. The user is advised to pick the confidence interval with the highest upper limit if the practitioner wants to be conservative in the estimates, whether that is from the percentile censoring or the nonparametric interval at times. In the majority of cases, one or more of the induced censoring intervals was more

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[5] Intervals in millimeters were 0.8509 to 0.8636 for the 0.90 quantile, 0.8636 to 0.9144 for the 0.95 quantile, and 0.889 to 0.9398 for the 0.99 quantile.

[6] Intervals in millimeters were 1.0795 to 1.2954 for the 0.90 quantile and 1.4224 to 2.9337 for the 0.99 quantile.

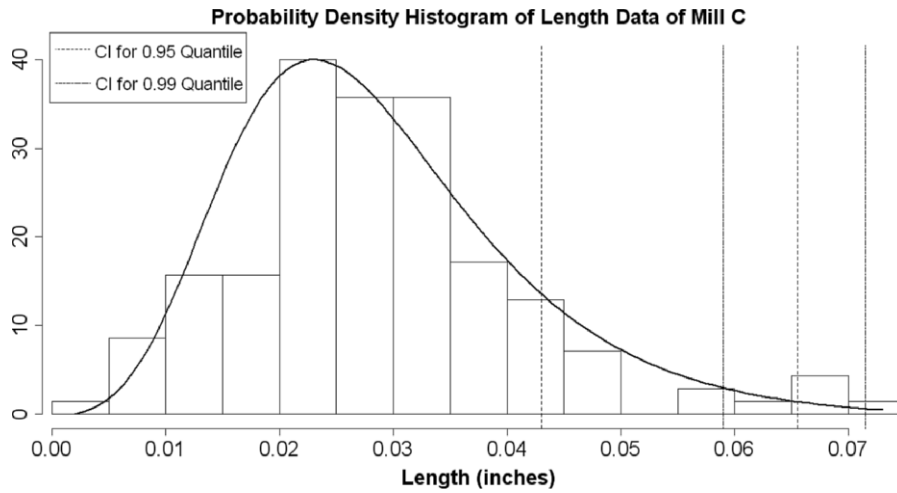[7] The interval in millimeters was 1.0922 to 1.6637 for the 0.95 quantile.

Probability Density Histogram of Length Data of Mill C

Figure 3.—Histogram and density function plot for Mill C (no censoring) with bootstrap confidence intervals for the 0.95 and 0.99 quantiles.
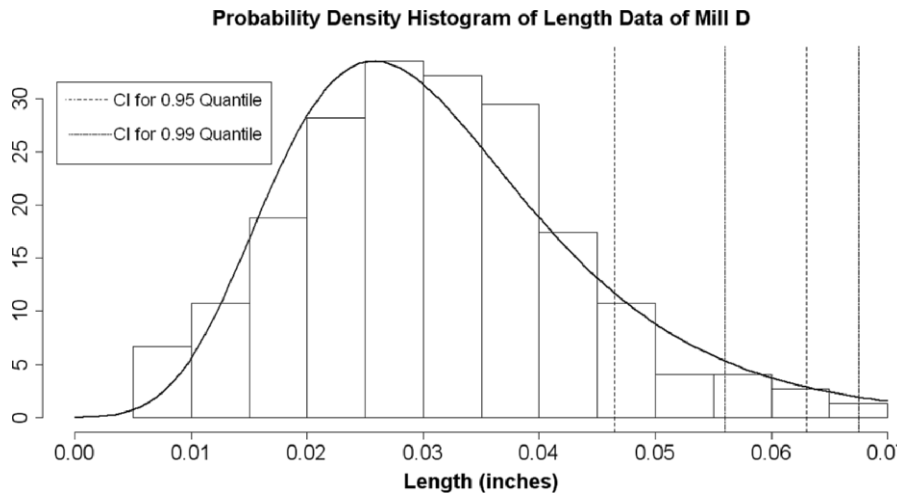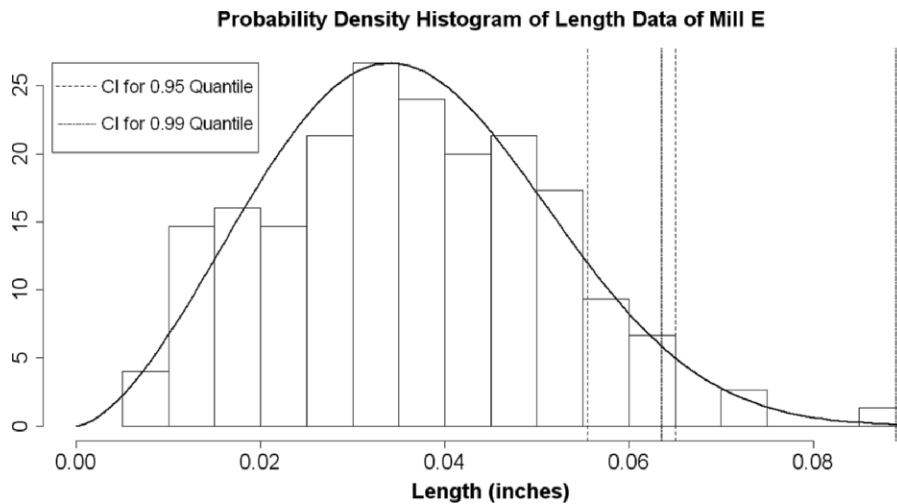
Probability Density Histogram of Length Data of Mill D

Figure 4.—Histogram and density function plot for Mill D (no censoring) with bootstrap confidence intervals for the 0.95 and 0.99 quantiles.

Probability Density Histogram of Length Data of Mill E

Figure 5.—Histogram and density function plot for Mill E (no censoring) with bootstrap confidence intervals for the 0.95 and 0.99 quantiles.

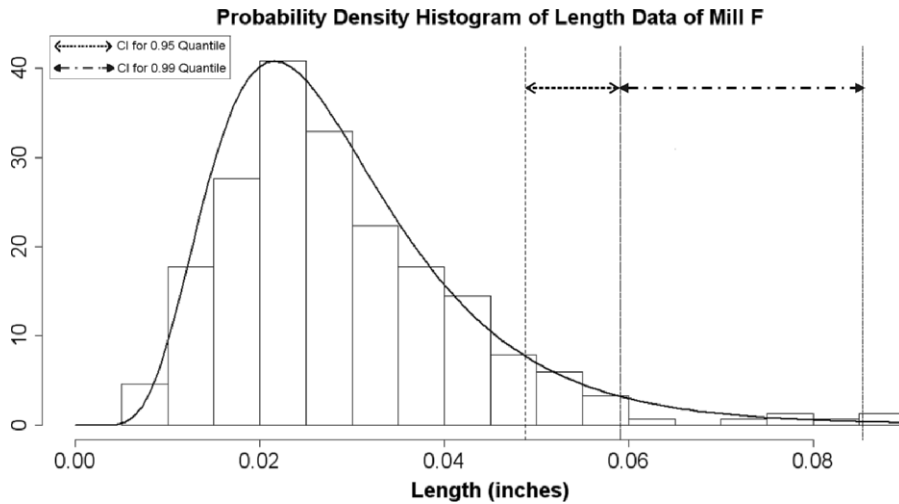**Probability Density Histogram of Length Data of Mill F**

Figure 6.—Histogram and density function plot for Mill F (no censoring) with bootstrap confidence intervals for the 0.95 and 0.99 quantiles.
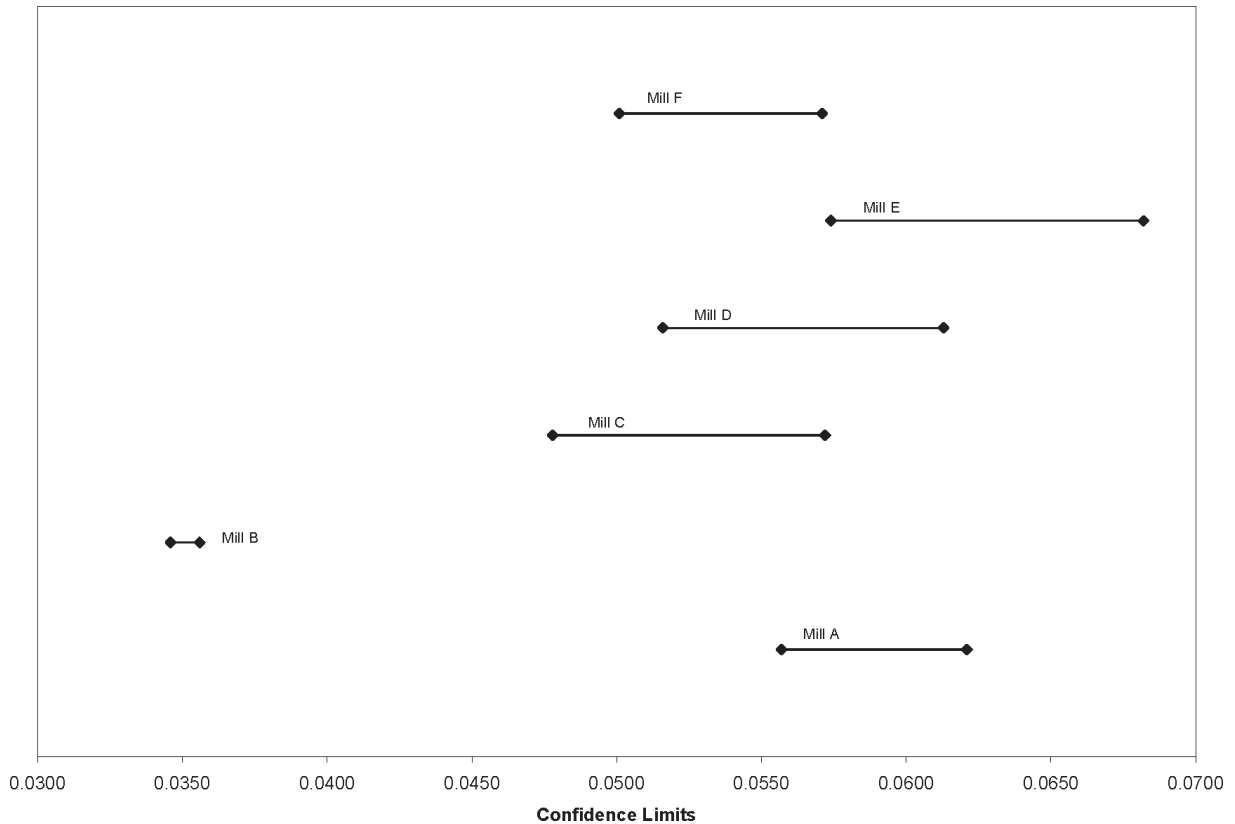

Figure 7.—Nonparametric bootstrap 0.95 quantile confidence intervals for induced left censoring at the 0.25 quantile.

conservative than the nonparametric interval. When the practitioner feels that ''early infant mortality'' (in this context of thickness, an undue preponderance of smaller thickness) will have an effect on the distribution chosen for a data set, then induced censoring at the quantiles say between the 0.10 and 0.25 quantiles can be helpful in removing potential effects of infant mortality or undue preponderance of smaller thicknesses. We mention very briefly that censoring at the 0.75 quantile tended to produce usually even more conservative (upper end of the confi-

dence interval being higher) than censoring at the lower values. At the same time this would be essentially weighting the upper 25 percent of the data, while discounting too much data from the lower 75 percent.

Mill B clearly has the narrowest confidence intervals after accounting for the extreme outlier. It appears that Mill B has a very effective process control in place at its manufacturing facilities. For Mill B, induced percentile censoring did not help much. The less variation the strands have, the less likely that an outlier that might damage equipment or
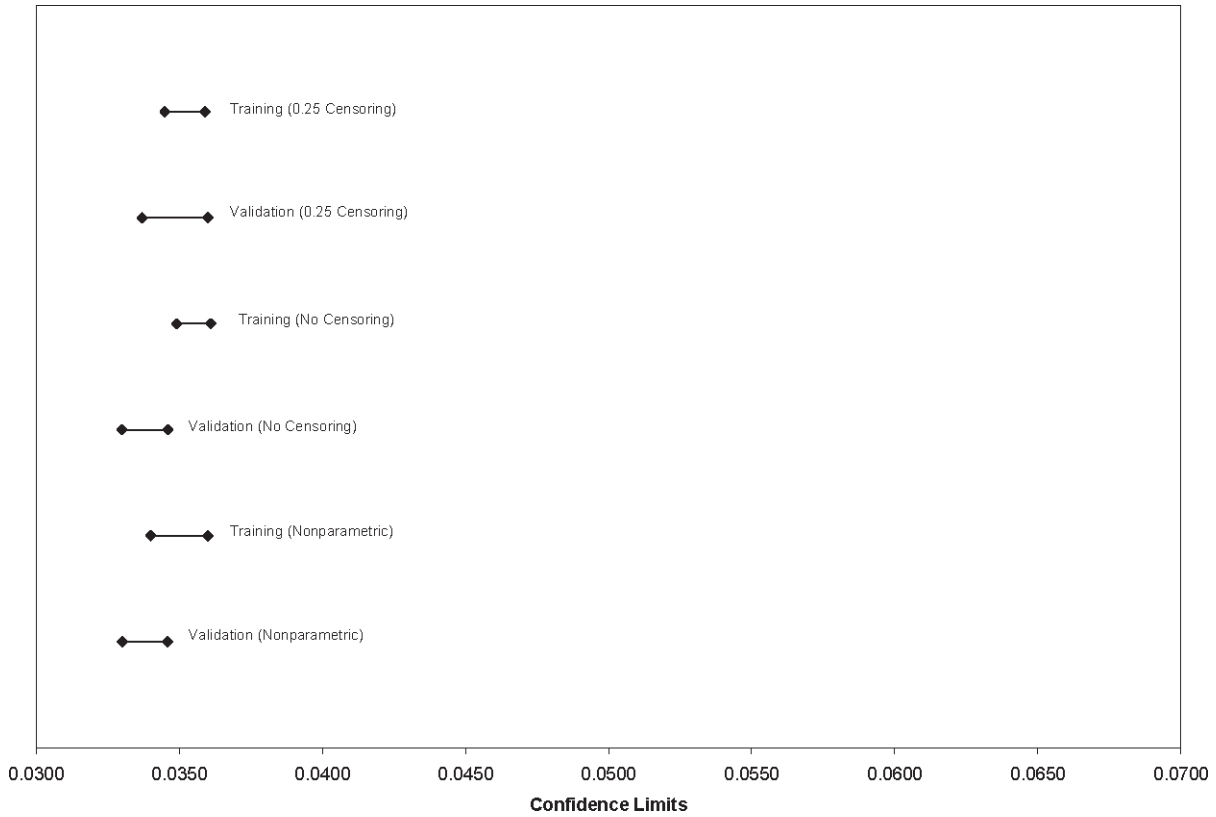
Figure 8.—Mill B (no outlier) validation and training data sets nonparametric and parametric bootstrap confidence intervals for the 0.95 quantile without and with censoring at the 0.25 quantile.
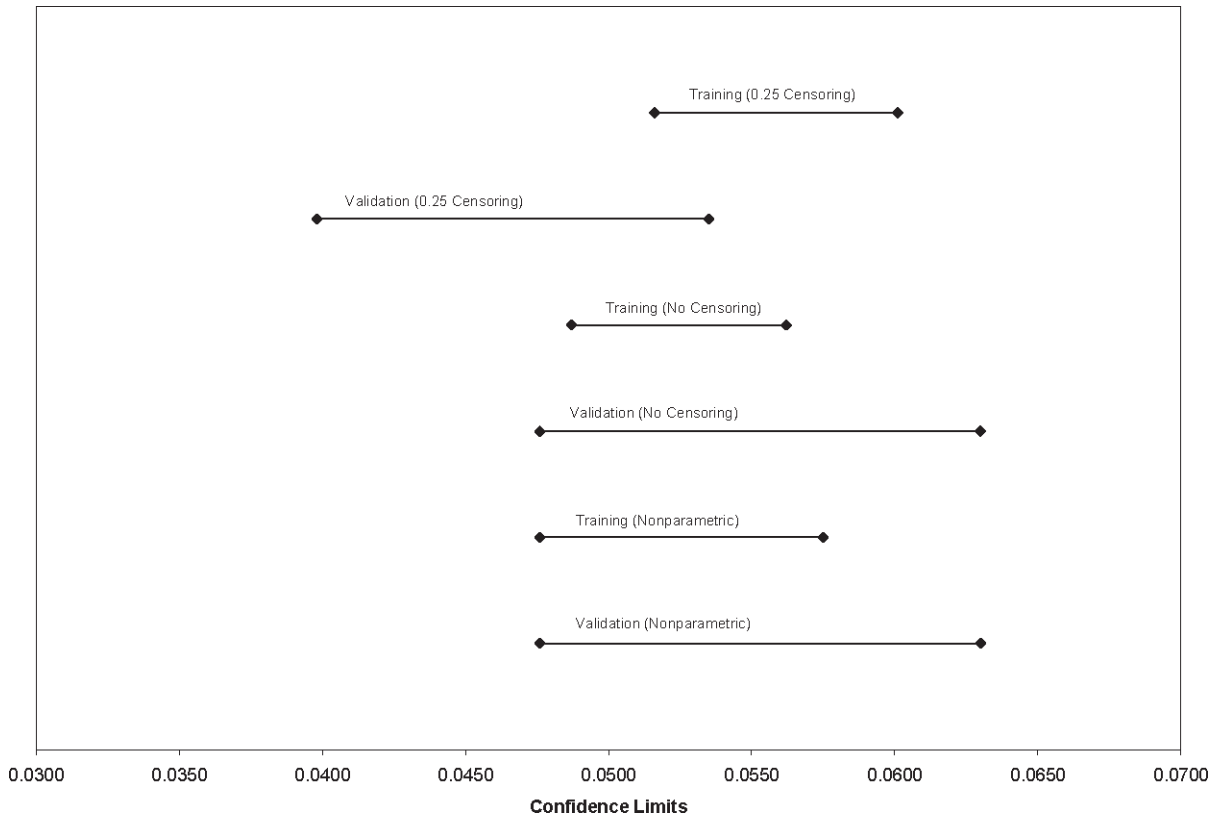

Figure 9.—Mill F (no outlier) validation and training data sets nonparametric and parametric bootstrap confidence intervals for the 0.95 quantile without and with censoring at the 0.25 quantile.

produce dimensional instability of OSB occurs. Less variation also promotes higher OSB quality and improves customer value.

Note for Mill B, censoring at any level (0.10, 0.15, 0.20, and 0.25) did not significantly affect the length of the confidence interval, see Table 4. Induced percentile left censoring may not offer improvement in the interval estimates for a mill with such small variability (Fig. 7).

For Mill F, induced percentile left censoring reduced the length of the confidence interval for the upper percentiles (i.e., 0.0006 inches or 0.0152 mm for the 0.90 quantile and to 0.0047 inches or 0.1194 mm for the 0.99 quantile). For Mills A, C, D, and E, induced percentile left censoring created confidence intervals that increased or decreased in length depending on the quantile censoring level.

Validation of confidence intervals

For Mill B (lowest CV of strand thickness) the validation intervals of the nonparametric bootstraps, with and without censoring, tended to be slightly left of the training sets (Fig. 8), which means the training sets were more conservative. As censoring quantiles increased, the validation intervals moved left of the training data sets, meaning the training set were more conservative. For Mill F (highest CV of strand thickness) the validation intervals were wider and to the left of the training intervals for the nonparametric, with censoring and without censoring (Fig. 9). For Mill F, as censoring quantiles increased, the validation intervals moved left of the training data sets. Study results are strengthened from the validation study in that the training intervals were either contained within, or overlapped, the validation intervals.

Conclusions

The influence of the thickness of wood strands on the dimensional stability of OSB panels has been well documented. An assessment of wood strand thickness variability for the face layers of OSB panels for six Southeastern US mills indicated dissimilarities among the mills. The grand mean and median for all mills were 0.0322 inches (0.8179 mm) and 0.0310 inches (0.7874 mm), respectively. The COV ranged from 18.7 to 46.1 percent among the six mills. There was evidence of a lack of normality for the strand thickness data from all mills. For the complete data sets the log-logistic distribution was the best fit for Mills A and B, LEV distribution was the best fit for Mills C and D, Weibull was the best fit for Mill E, and lognormal was the best fit for Mill F.

The upper percentiles are of interest to the practitioner, since too large flakes can produce OSB that is dimensionally unstable and may damage expensive equipment. Parametric bootstrap confidence intervals for the 95th percentile with no censoring varied in length from 0.001 inches (0.0254 mm) for Mill B to a maximum of 0.0092 inches (0.2337 mm) for the other mills. Clearly, the best censoring point depends on the data set and the practitioner's use of the results. The user is advised to pick the confidence interval with the highest upper limit if the practitioner wants to be conservative in the estimates, whether that is from the percentile censoring or even from not censoring (complete, original data) and using the nonparametric interval. In the majority of cases, one or more of the induced censoring intervals was more conservative than the corresponding nonparametric interval.

Note empirically, when being conservative is most important, this helps for deciding which to use.

Induced percentile left censoring slightly reduced the length of the confidence interval estimates for Mill B (0.0008 to 0.0013 inches; 0.0203 to 0.0330 mm) with minor increases in the lower bound of the interval (0.0001 to 0.0003 inches; 0.0025 to 0.0076 mm). This may imply that censoring does not offer much improvement in the estimate of the upper percentiles for a mill that has a stranding process with low variability. For Mill F, left censoring reduced the length of the confidence interval for the upper quantiles (0.0006 inches or 0.0152 mm for the 0.90 quantile and to 0.0047 inches or 0.1194 mm for the 0.99 quantile).

As the OSB industry undergoes unprecedented change, continuous improvement and competitive benchmarking become paramount for the manufacturer. Confidence intervals of the upper quantiles of strand thickness may help technical directors of OSB mills improve the effectiveness of quality control management by facilitating the use of statistical intervals or even control charts of the flaking process. The statistical reliability methods used in this study may provide both manufacturers and wood scientists with key insights for quantifying the variability of strand thickness.

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