International Journal of Reliability and Applications
Vol. 4, No. 4, pp.157-170, 2003

Exploring Graphically and Statistically the Reliability of Medium Density Fiberboard

Frank M. Guess, David J. Edwards and Timothy M. Pickrell
Department of Statistics, 338 Stokely Management Center,
University of Tennessee, Knoxville, TN 37996-0532 USA

Timothy M. Young*
Tennessee Forest Products Center, 2506 Jacob Drive,
University of Tennessee, Knoxville, TN 37996-4570 USA

Abstract. In this paper we apply statistical reliability tools to manage and seek improvements in the strengths of medium density fiberboard (MDF). As a part of the MDF manufacturing process, the product undergoes destructive testing at various intervals to determine compliance with customer's specifications. Workers perform these tests over sampled cross sections of the MDF panel to measure the internal bond (IB) in pounds per square inches until failure. We explore both graphically and statistically this "pressure-to-failure" of MDF. Also, we briefly comment on reducing sources of variability in the IB of MDF.

Key Words : *exploring reliability graphically and statistically, reliability, internal bond, medium density fiberboard, Weibull, normal, destructive tests, forest products.*

1. INTRODUCTION

Medium Density Fiberboard (MDF) is used internationally in a host of building needs and furniture construction. It is a superior engineered wood product with great strength, reliability and grooving ability for unique designs. In addition, MDF offers superior qualities on consistency of finish and density, plus freedom from knots and natural irregularities.

MDF has characteristics of strength, durability and uniformity not always found in natural timber or standard particleboard. It has excellent machinability due to its homogenous consistency and smaller variation in needed characteristics compared to natural wood. These features make MDF particularly suited for use in flooring, paneling,

* Corresponding Author
E-mail address: tmyoung1@utk.edu

manufacturing of furniture, cabinets, and moldings. It, also, has environmentally friendly properties of using wood waste to manufacture useful byproducts. This does not happen as easily with traditional wood products.

Figure 1 and Figure 2 demonstrate the marked differences between particleboard, natural timber, and MDF. We have observed the common usage in writing particleboard or fiberboard (or fibreboard). This is used by most companies or timber associations, which we sampled. Our sample ranged from Georgia-Pacific, Sabah Timber Industries Association of Malaysia, to an Association of New Zealand Forestry Companies. In some settings, however, you will see it written as two words "particle board." We followed the more typical industrial usage of writing as one word "particleboard" or "fiberboard."

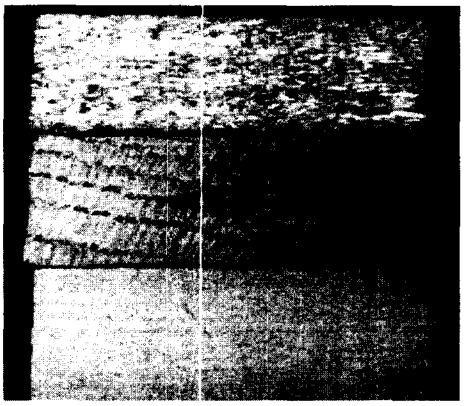

Figure 1. Cross sections from width view blown up to show details: top is particleboard, middle is natural wood, and bottom is MDF.

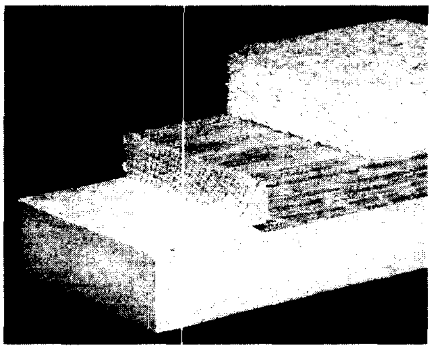

Figure 2. Cross sections from diagonal view: top is particleboard, middle is natural wood, and bottom is MDF.

Suchsland and Woodson (1986) and Maloney (1993) cover manufacturing practices of MDF. See, also, for more general and specific information: http://web.utk.edu/~tfpc/ and http://www.spcforwood.com.

Young and Guess (2002) present modern high technology approaches to managing the manufacturing of MDF and related data with real time process data feedback. They employ regression prediction of MDF strengths using knowledge on more than 230 process variables.

Here, we are interested in the statistical reliability properties of the strength to failure as opposed to the time to failure. The strength to failure data will give us a clear idea of the utility of the product. It allows the producer to make assurances to customers about the useful life of the product. The key measure of MDF's reliability and quality is its internal bond (IB), which is measured in pounds per square inch (or equivalent metric units) until breaking.

For a number of reasons, testing the MDF product types over any extended time, under a variety of operating conditions is not economically feasible. Instead of an elaborate procedure of designing and implementing life tests, a "pull apart" destructive approach provides an instantaneous measurement of the IB. Destructive "pull apart" test samples are taken periodically to determine IB. Due to the cost and loss of products from destructive testing, manufacturers obviously want to keep such tests to a minimum.

Another advantage to destructive testing is immediate feedback into the manufacturing process leading to rapid process improvement. Also, it can help modify or stop the manufacturing process; thus, preventing great waste of materials. The cost of unacceptable MDF was as large as 5% to 10% of total manufacturing costs, which can mean 10 to 15 million dollars per plant per year. In 2003 to 2004, ten such high production plants are anticipated to be built in Asia.

We present new results on different IB data regarding the statistical distributions for various product types of IB. This is important for studying potential warranty issues, understanding wearing over time, failure of products under misuse, and variation in IB between product types. This is, also, needed within particular product types of MDF. Our data covers the time period from March 19, 2002 to September 10, 2002.

We explore graphically and statistically the distributions of the strengths of this material. It would be natural to consider first the standard Weibull model for strengths of materials. Indeed, the researcher Weibull himself first analyzed strengths of different materials, ranging from cotton to metal. From his data sets, he found the primary available distribution of the normal did not fit his examples well in the 1930's. The alternative parametric model he originally proposed is what we now call the "three parameter" Weibull. See Weibull (1939 and 1951).

The original three parameter Weibull is often reduced and written today as a two. parameter distribution. Recall this two parameter Weibull density function can be written in the following parameterization as

$$f(x) = \lambda\beta x^{\beta-1}e^{(-\lambda x^{\beta})}, \text{ where } x \geq 0 \text{ (and } f(x) = 0, \text{ for } x < 0),$$

while the reliability function is

$$\overline{F}(x) = e^{(-\lambda x^{\beta})}, \text{ where } x \geq 0 \text{ (and } \overline{F}(x) = 1 \text{ for } x < 0).$$

Another common reason for modeling data with a Weibull distribution is that it may be suitable for either increasing, constant (i.e., an exponential) or decreasing hazard functions. For MDF subject to destructive "pull apart" tests, we would conjecture an increasing failure rate. This would lead us to hypothesis, a priori, that the shape parameter $\beta > 1$ for any MDF product type that might be Weibull.

See, for example, the excellent book of Meeker and Escobar (1998) for a thorough treatment of the Weibull, other reliability functions and validating/exploring graphically these models. Also, compare texts by O'Connor (1985), Barlow and Proschan (1981), etc.

Although the Weibull can sometimes fit parts of our IB data for some categories of MDF, it is surprisingly not a valid model for this data for the total IB range. Other parametric distributions of strengths are employed and a nonparametric approach needed. See Meeker and Escobar (1998) for reliability parametric/nonparametric models and the insightful Hollander and Wolfe (1999) on nonparametrics, in general.

The spirit of this paper is that of an exploratory analysis via graphs, descriptive statistics, and tests. See the excellent overview on graphics by Scott (2003) and his references. Section 2 covers the types of MDF and ways these types are determined. Section 3 explores both graphically and statistically particular types of MDF, while Section 4 provides concluding comments.

2. CATEGORIZING TYPES OF MDF

We begin the analysis by sorting the IB data by three key characteristics:

- density (lbs/ft^3)
- thickness (inches)
- and width (inches).

These three characteristics differentiate the MDF's for various applications. Since MDF in this particular study was produced in continuous length of sheets, length was not a crucial variable for our purposes. Further, for the purpose of analysis, the MDF was separated into two main groups:

- Group I: standard density
- Group II: high density.

The *high density* type is MDF with densities on the upper end of the scale 47-48 pounds per cubic foot. The standard density type is the MDF with densities ranging from 45-46 pounds per cubic foot.

Within each group the IB was measured in accordance with classification by density, thickness and width. The type numbers (with density, thickness, and width after each type number) are listed in Table 1.

Table 1. Group and type numbers for different MDF products with (A, B, C) where A = density, B = thickness, and C = width where for example Type 1 in Group I represents A = 46 pounds per cubic foot, B = 0.625 inches thickness, and C = 61 inches (or the equivalent metric units).

Group I: standard density Type #	Group II: high density Type #
1 (46,0.625,61)	2 (48,0.75,61)
3 (46, 0.75,49)	5 (48,0.625,61)
4 (46,0.75,61)	9 (48,0.75,49)
6 (45,1,61)	10 (48,0.375,61)
7 (46,0.625,49)	11 (48,0.5,61)
8 (45,1,49)	14 (48,0.5,49)
12 (46,0.688)	15 (48,0.625,49)
13 (46,0.688,49)	16 (47,1,61)
17 (45,1.125,61)	18 (48,0.4379,49)
20 (46,0.875,61)	19 (48,0.375,49)
22 (45,1.12549)	21 (48,0.563,61)
	23 (48,0.4379,61)
	24 (48,0.688,61)

Since there were a number of types in each group, we select the primary types, which sold the most, for a more detailed analysis. These were types 1 and 3 from Group I (standard density) and types 2 and 5 from Group 2 (high density). See Table 1 for more details.

Another reason behind our splitting into two distinct groups was that the destructive testing of the MDF is concerned mainly with the IB strength. A priori, this is reasonably hypothesized to be mainly a function of density. Furthermore, from the nature of the destructive testing, which involved the cutting of many cross sections from different pieces of MDF, the lengths and widths were not the major factors effecting strengths. In the next section graphs and statistical tests will demonstrate strikingly this hypothesis to be true.

3. EXPLORING GRAPHICALLY AND STATISTICALLY IB IN TYPES OF MDF

The initial analysis began with the assessment of the underlying distribution of the internal bond strengths, categorized by the density, thickness and width measurements. We want to first understand means, medians, and percentiles of the strengths of MDF. See, for example, Guess, Walker, and Gallant (1992) for how different measures of reliability can be used.

Table 2. Descriptive Statistics comparison of Types 1 and 2.

	Type 1 IB (psi)	Type 2 IB (psi)
Mean	120.2	180.0
Median	120.2	179.0
Std. Dev.	9.9	12.3
IQR	12.3	17.6
Min	87.2	140.6
Max	164.5	214.5

These numbers have been rounded to one decimal place. Note that both the mean and median in Type 1 are 120.2, while for Type 2 the mean and median are close at 180.0 and 179.0. Type 1 has less variation as measured by the IQR and standard deviation, but Type 1 has a bigger range of 77.3 when compared to Type 2 being 73.9. This bigger range for Type 1 can be understood by its outliers, boxplots, and the histograms in Figures 3 and 4.

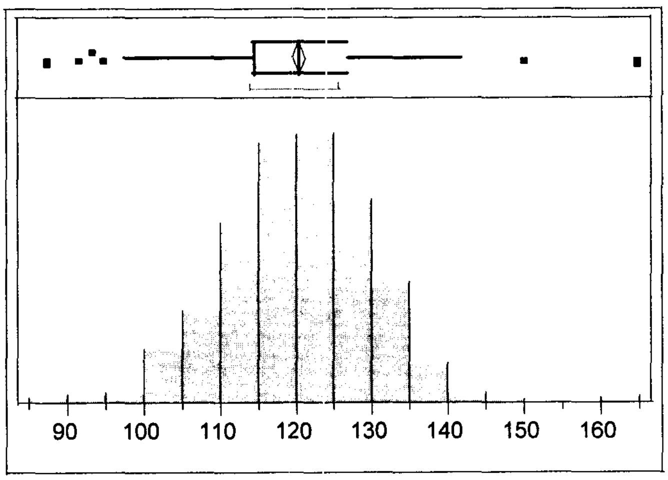

Figure 3. Histogram and Boxplot of Primary Product (Type 1) from JMP

From the histogram in Figure 3, we see that the distribution of the primary product, Type 1, is approximately normal. Recall the mean and median being the same.

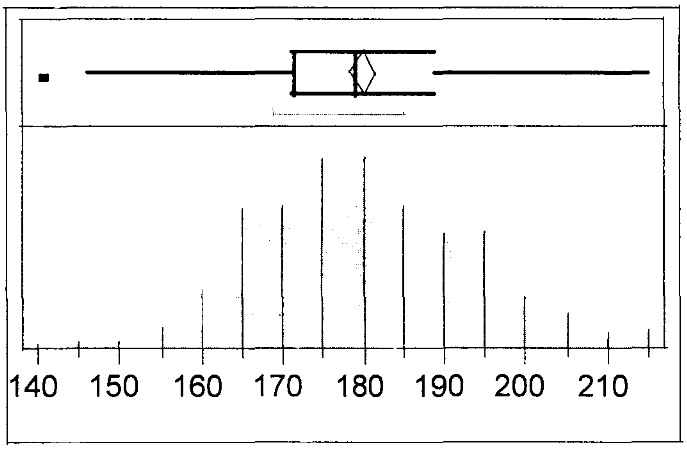

Figure 4. Histogram and Boxplot of Type 2 from JMP

Figure 4 suggests that we explore the reasons behind the weakness of the units in the 140 to 150 psi bins, plus understand the much better strengths in the higher bins overall, especially for the 190 to 210+ psi bins, in order to improve the reliability.

Recall the exploratory flavor of Tukey of examining many views of the same data. See, also, Scott (2003). Figure 5 is an overlay plot that gives another look at the differences and similarities between Types 1 and 2. Notice it can be a little misleading when compared to the actual raw data or the histogram. The plot shows quite a distinction between the two product types, providing evidence that Type 2 is much stronger than Type 1. That is, heavier products or products requiring more load bearing strength, such as shelving, would make use of Type 2 MDF. Type 1, with less strength, would be used more extensively in products not requiring large strength, such as picture frames.

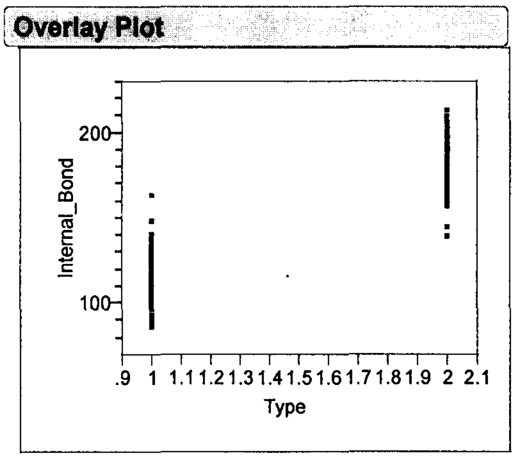

Figure 5. Overlay Plot of Types 1 and 2 from JMP

Probability plots were used extensively in this analysis because they give a clear demonstration of how a particular data set conforms to a specific candidate probability distribution. The data are ordered and then plotted against the theoretical order statistics for a desired distribution. If the data set "conforms" to that particular distribution, the points will form a straight line. Simultaneous confidence bands provide objective bounds of deviation from the line or not. Those data points outside the confidence bands are shown to deviate from the candidate probability distribution in question. See Chapter 6 of Meeker and Escobar (1998) for further information. Normal and Weibull probability plots were produced for Types 1 and 2 as shown in Figures 6 and 7.

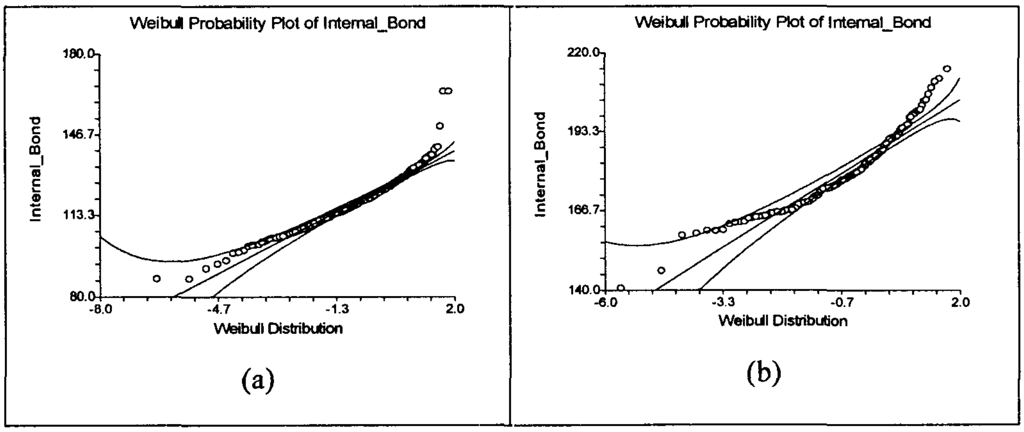

Figure 6. (a) NCSS Weibull plot for Type 1; (b) NCSS Weibull plot for Type 2

In Figure 6(a) for Type 1, there is clear departure from the Weibull in the upper tail, but appears to be following this distribution in the middle and the lower tail. Fitting in the lower tail can be important for estimating percent fall out of specification limits. Figure 6(b) for Type 2 shows clear departure from the Weibull distribution overall. The snake-like meandering is a systemic pattern that strongly suggests the Weibull does not fit at all

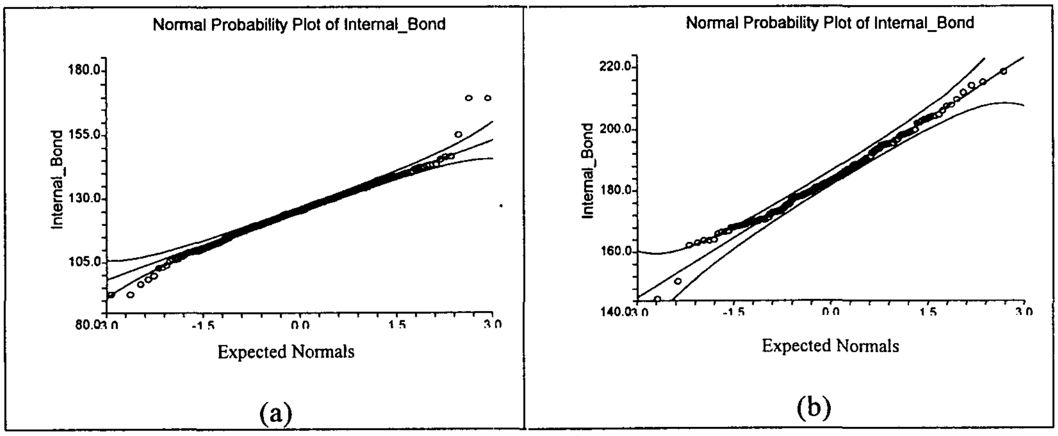

Figure 7. (a) NCSS Normal plot for Type 1; (b) NCSS Normal plot for Type 2

for Type 2.

Recall that the histogram of Type 1 as well as the mean and median being the same provides some evidence for normality. Figure 7(a) shows a normal plot with points that fall mostly within the simultaneous bounds, except for some outliers. There is some clear departure in the tails that may not be following so perfectly a normal distribution. Again, recall the lower tail is important in estimating lower percentiles. Thus, as shown in Figure 6(a), the Weibull may prove to be a better model for estimating these lower percentiles for Type 1.

Figure 7(b) shows less departure from normality and certainly appears to be a better fit of the data than the corresponding Weibull distribution for Type 2. In fact, as we will see later, large p-values will not allow for normality to be rejected for Type 2. Overall, neither model appears to be the best, thus; a nonparametric approach may be more appropriate.

As seen, the probability plots have been a very visual and indeed subjective method for assessing the underlying distribution for the different product types. In particular, the normal distribution was determined to be the reasonable fit compared to Weibull for some cases overall. (We do not show all cases here to save space.) Therefore, it is natural to ask if the data truly follows a normal distribution and if this is statistically significant by testing. Tests such as the Shapiro-Wilk, Kolmogorov-Smirnov, and others exist to help answer these questions more objectively. These tests will produce different p-values, as seen the Tables 3 and 4.

Table 3. Normality Test Comparisons for Type 1

		Test Statistic / p-value	
	Shapiro-Wilk	**Kolmogorov-Smirnov**	**Anderson-Darling**
JMP	0.97947 / <0.0001	N/A	N/A
SAS	0.97947 / <0.0001	0.0357 / >0.15	0.802126 / 0.0393
Minitab	0.9880 / <0.01	0.035 / >0.15	0.802 / 0.038
NCSS	0.979469 / 0.000021	0.03317 / N/A	0.8021374 / 0.037865

For Type 1, we clearly reject normality using the Shapiro-Wilk and Anderson-Darling test for alpha level of 0.05. The Kolmogorov-Smirnov test has bigger p-values, but recall it tends to have low power. Notice that four different software packages were used for checking the consistency of the tests statistics and p-values.

Table 4. Normality Test Comparisons for Type 2

		Test Statistic / p-value	
	Shapiro-Wilk	**Kolmogorov-Smirnov**	**Anderson-Darling**
JMP	0.990482 / 0.2514	N/A	N/A
SAS	0.990482 / 0.2514	0.044945 / >0.15	0.4855228 / 0.2311
Minitab	0.9947 / >0.1	0.045 / >0.15	0.485 / 0.224
NCSS	0.990482 / 0.251420	0.0449 / N/A	0.4852587 / 0.226802

Table 4 with its larger p-values for all three tests shows we can not reject normality for any reasonable alpha levels. Still we may want to seek better understanding by other plots. Walker and Guess (2003) stress the need for more nonparametric plots and analysis, when the parametric models may be weak or not the strongest. Nonparametric plots known as Kaplan-Meier estimators, survival plots, or reliability plots will now be shown for various product types.

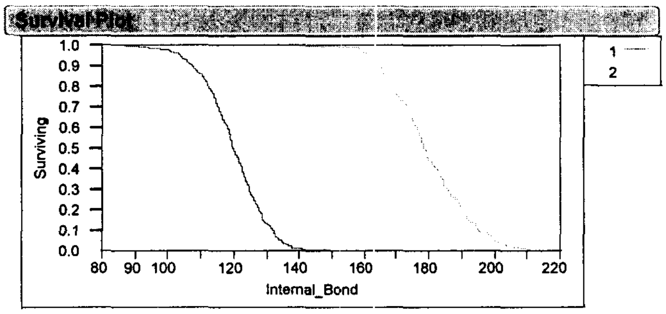

Figure 8. Survival Plot of Types 1 and 2 from JMP

Immediately, one should notice the large gap present between Type 1 and 2 in the Kaplan-Meir nonparametric survival plots in Figure 8. Recall further that the medians are very different. That is, 120.3 and 179.0 psi for Types 1 and 2, respectively. Based on this, Type 2 has even more evidence of being significantly stronger than Type 1. A two sample t-test was conducted with variances assumed unequal. This assumption was based on a test for unequal variances provided by SAS which yielded a p-value of $p=0.0004$. This is quite a significant result and allows us to proceed with the stated t-test. In particular, the t-test gives a p-value of $p<0.0001$ which is also soundly statistically significant and allows for the conclusion that Types 1 and 2 are significantly different and thus, Type 2 is significantly stronger than Type 1.

Suppose that interest lies in comparing two product types of the same thickness, but with a different density. Here, we compare product Types 1 and 5. That is, Type 1 has a smaller density of 46 lbs/ft^3 while Type 5 has a higher density of 48 lbs/ft^3. However, they both have a thickness of 0.625 inches. The survival plot comparing these two products is shown in Figure 9. As with Figure 8, notice the large gap separating the two product types

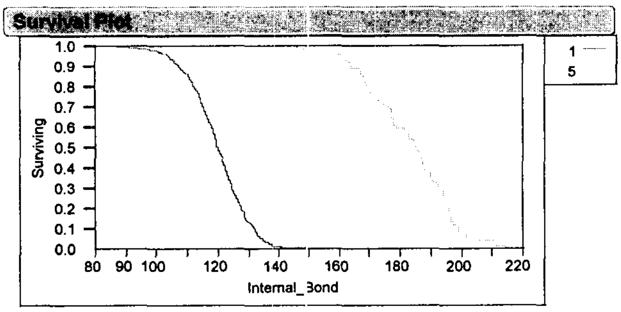

Figure 9. Survival Plot for Types 1 and 5 from JMP

allowing for evidence that Type 5 is a much stronger product. Thus, we are seeing that product types of a higher density appear to be stronger than those at a lower density.

Instead, now suppose that interest lies in comparing product types of the same density, but with a different thickness. Then, in this case, comparison is between product Types 1 and 3. Types 1 and 3 both have a density of 46 lbs/ft^3, but Type 1 has a thickness of 0.625 inches and Type 3 has a thickness of 0.75 inches. The survival plot showing this comparison is shown in Figure 10.

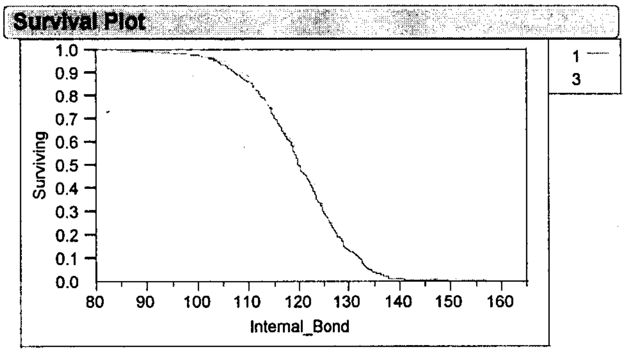

Figure 10. Survival Plot for Types 1 and 3 from JMP

Notice that the gap we have been seeing in the plots is no longer present. This provides evidence that there are no differences among these two product types. That is, when density is held constant, thickness does not appear to have any effect on IB. However, it is important to verify this statistically. Figure 11 is an overlay plot of Types 1 and 3. A two-sample t-test was conducted (again, assuming unequal variances) and a p-value of $p=0.1988$ was obtained. Thus, our suspicions are confirmed and it can be concluded that there are no statistically significant differences between Types 1 and 3 at particular levels.

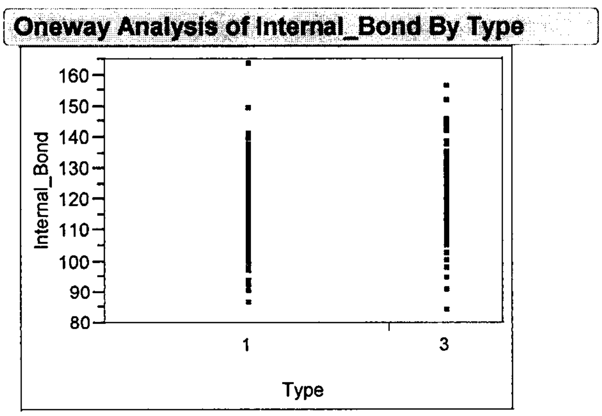

Figure 11. Overlay Plot of Types 1 and 3 from JMP

A summary survival plot showing Types 1, 2, 3, and 5 is shown in Figure 12. From this plot, it is relatively easy to see which product types had the higher density and which had a lower density. However, it is not as obvious which product types had the higher or lower thickness making it clear that density is the main driver in determining MDF strength whereas thickness is not a large contributor to IB.

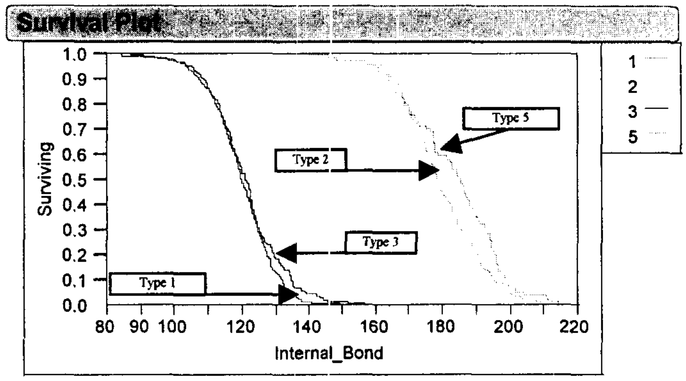

Figure 12. Summary Survival Plot for Types 1, 2, 3, and 5 from JMP

One noticeable attribute of the survival plot shown in Figure 12 is that the survival curves at the same density are crossing each other at some point. The explanation is quite simple. The significance of this crossing is that one product has a greater strength at lower pressures whereas the other product will surpass at higher pressures. For example, Type 2 starts out with a greater strength than Type 5 at the extreme lower pressures. However, as pressure increases, we see the survival curve for Type 5 cross that of Type 2 and thus, surpass it in strength at the higher pressures.

4. SUMMARY

In conclusion, we find that exploring graphically and statistically the MDF's reliability as measured by IB means, medians, and other percentiles readable from survival plots are helpful ways for understanding each product type better. Recall Type 1 had more outliers, which suggests more need for process improvements there and similar types in Group 1. Density is a key driver in improving IB average, which is naturally expected a priori. In fact, it was the key source of variation in IB. Changes in thickness (or width) do not affect IB as much as changes in the density.

One should be aware that quality and reliability are more than just one number (not just the mean or median). We need to explore these and other descriptive statistics as well as graphs of the data. Also, be careful of potential software differences on some tests, which may be mild or sometimes severe in certain instances. Validation with a different software package than the first software analysis might be advisable. Besides histograms, survival curves are a very helpful and insightful way to view your data. These different views may surprise you, suggesting places for real world process improvements. Compare Deming (1986 and 1993). Future work on estimating C.I.'s on the lower percentiles and other sources of variation will be explored later.

ACKNOWLEDGEMENTS

Dr. Frank M. Guess appreciates funding from the competitive Scholarly Research Grant Program of the College of Business Administration at the University of Tennessee during academic year 2003-2004 and the Department of Statistics at the University of Tennessee. Timothy M. Young appreciates funding from the United States Department of Agriculture, Special Wood Utilization Research Grants which is administered by The University of Tennessee Agricultural Experiment Station and the Tennessee Forest Products Center.

REFERENCES

Barlow, R. E. and Proschan, F. (1981). *Statistical Theory of Reliability and Life Testing: Probability Models,* To Begin With, Silver Spring, MD.

Deming, W.E. (1986). *Out Of The Crisis,* Massachusetts Institute of Technology's Center for Advanced Engineering Design, Cambridge, MA.

Deming, W.E. (1993). *The New Economics,* Massachusetts Institute of Technology's Center for Advanced Engineering Design, Cambridge, MA.

Guess, F., Walker, E., and Gallant, D. (1992). Burn-in to improve which measure of reliability?, *Microelectronics and Reliability*, 32, 759-762.

Hollander, M. and Wolfe, D. (1999). *Nonparametric Statistical Methods*, 2nd Ed. Wiley & Sons, New York, NY.

Maloney, T. M. (1993). *Modern Particleboard and Dry-Process Fiberboard Manufacturing*, Miller Freeman Inc., San Francisco, CA.

Meeker, W. Q. and Escobar, L. A. (1998). *Statistical Methods for Reliability Data.* Wiley & Sons, New York, NY.

O'Connor, P. D. T. (1985). *Practical Reliability Engineering*, 2nd Ed., John Wiley & Sons: Chichester, Great Britain.

Scott, D.W. (2003). The Case for Statistical Graphics, *AmStat News*, 315, 20-22.

Suchsland, O. and Woodson, G. E. (1986). *Fiberboard Manufacturing Practices in the United States*, U.S. Department of Agriculture Forest Service's Agriculture Handbook No. 640, Washington, D.C.

Walker, E. and Guess, F. (2003). Comparing Reliabilities of the Strength of Two Container Designs: A Case Study, *Journal of Data Science*, 1, 185-197.

Weibull, W. (1939). A Statistical Theory of the Strength of Materials, *Ing. Vetenskaps Akad. Handl.*, 151, **1**, 1-45.

Weibull, W. (1951). A Statistical Distribution Function of Wide Applicability, *Journal of Applied Mechanics*, 18, **1**, 293-297.

Young, T. and Guess, F. (2002). Mining information in automated relational databases for improving reliability in forest products manufacturing, *International Journal of Reliability and Applications*, 3, **4**, 155-164.