Statistical Process Control for Residential Treated Wood

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ABSTRACT

This paper is the first stage of a study that attempts to improve the process of manufacturing treated lumber through the use of statistical process control (SPC). Analysis of industrial and auditing agency data sets revealed there are differences between the industry and agency probability density functions (pdf) for normalized retention data. Resampling of batches of treated wood without replacement appears to affect the pdf of the industrial data. The best-fitting pdf for the agency data is the Largest Extreme Value (LEV) pdf. Assumptions of a normal or a Gaussian pdf may not be valid. The process of treated residential lumber is hard to predict due to special-cause variation. A capability analysis revealed that from 2.25% to 3.16% of the charges are below the AWPA Lower Confidence Limit (LCL) for an industrial data set and 1.57% to 6.63% are below the LCL for an agency data set, with both varying by product type.

Keywords: Residential treated lumber, statistical process control, probability density function, Largest Extreme Value, natural variation, capability analysis

INTRODUCTION

Improving product quality and reducing sources of process variation that lead to unnecessary costs (*e.g.,* reducing higher than necessary operating targets for chemical additives) are common goals for many forest products companies. Fundamental to the improvement process of reducing product and process variations is to first quantify variation and then to take remedial action (Lawless *et al.* 1999, Young 2008). A focus on improvement and variation reduction is essential for ensuring long-term business success of the forest products industry (Young and Winistorfer 1999).

Statistical methods play a vital role in the quality improvement process in manufacturing and service industries (Woodall 2000). Many enumerative and analytical statistical methods exist for quality improvement through the quantification and understanding of sources of variation (Hahn 1995, Lawless *et al*. 1999, Woodall 2000). Deming (1975) urged us to distinguish between *enumerative* and *analytical* studies. *Enumerative studies* deal with characterizing an existing, finite, unchanging target population by sampling from a well-defined frame, *e.g.,* ANOVA, Design of Experiments, confidence intervals, etc. (Hahn 1995). In contrast, the *analytical studies* most frequently encountered in industrial applications focus on action that is taken on a process or cause system, the aim being to improve practice in the future, *e.g.,* statistical process control (SPC), prediction statistical intervals, control charts, etc. (Deming 1975, Hahn 1995). SPC uses control charting and other statistical methods to improve product quality (Stoumbos *et al*. 2000, Woodall 2000, Young 2008). Predicting short-term process outcomes is a powerful aspect of the control chart (Deming 1975). Shewhart control charts (Shewhart 1931) have been used extensively for over 50 years. A plethora of literature is available on SPC and control charts, but as noted by Stoumbos *et al*. (2000), the diffusion of research to application is sometimes slow (Bischak and Trietsch 2007). The aim of this paper is to improve this diffusion towards application of SPC for the wood treating industry.

Problem Definition

Currently, wood treatment facilities must meet a '*passing standard*' for wood preservative penetration and retention of treated wood (as standardized by the American Wood Protection Association - AWPA, and governed by the American Lumber Standards Committee - ALSC). This paper focuses on the preservative retention aspect of quality control for treated lumber. Treating facilities determine the retention of each charge by removing 20 or more increment cores from different pieces in the charge and combining them to obtain a single composite assay sample. The key metric used for evaluating retention compliance with the standard is the Lower Confidence Limit (LCL).[1] This standard LCL or *minimum specification* is derived as a statistical lower bound assuming the *Standard Normal Distribution* and the theory of parametric confidence intervals (*i.e.,* $\bar{x} \pm$

[1] LCL – Lower confidence limit of the median retention of recent charges calculated using a one-tailed 95% critical value. The LCL is compared to the standardized minimum retention.

$\frac{s}{\sqrt{n}} z_{\alpha,\ n-1}$). The LCL standard is based on a *Z-score* of 1.729 which would contain a cumulative probability of p(Z) = 0.958095 above the LCL. One could argue that the application of statistical methods common to *enumerative studies,* such as confidence intervals that attempt to describe population parameters like the population mean, is inappropriate for the establishment of specification limits in industrial processes. Confidence limits were developed for a frame of reference that is not changing, while prediction intervals assume the frame of reference is continuously changing, *i.e.,* an industrial manufacturing process. Each preservative component will have an LCL and also an LCL for the total retention. This may lead to LCLs that are narrower than those developed from prediction intervals common to *analytical studies,* which tend to be wider from incorporating variation due to future sampling (see Deming 1975, Hahn 1995).

There are approximately 140 plants and roughly 700 active production categories in the treated wood industry that are monitored by inspection agencies using this LCL standard. The LCL standard and producer metrics of performance are used as a quality control technique and not part of a proactive continuous improvement process (*i.e.,* SPC); therefore, the system is reactive to problems discovered and of an antidotal nature in that the solutions are generally not preventative. An example of this reactive approach to manufacturing is the re-treatment of treated lumber (*i.e.,* rework) that occurs for batches that are below the LCL after initial and sometimes repeated sampling. The additional cost of rework and resampling increases the cost of the final product and diminishes business competitiveness. SPC methods can benefit the industry by identifying common sources of variation that influence product quality and by promoting proactive actions for continuous improvement. The fundamental premise of continuous improvement is the reduction of product and process variation.

The goal of this study is to quantify the natural variation (also called *common-cause* variation) and special-cause variation associated with the measure of the average retention for treated residential lumber by different parties. Necessary precursors to achieving this goal are to examine the quality of charge assay retention data sets and then to estimate the most appropriate probability density function (pdf) for the data.

MATERIALS AND METHODS

The data for this study were obtained, in confidence, from ALSC accredited treating facility auditing agencies. The agencies provided paired, normalized assay retentions for charges that had been inspected by both the treating facility and the auditing agencies. Retention was normalized around the AWPA standard retention; the analyses were performed by product type and did not reveal the industry source. The sample sizes were: 1) N = 4,259 records for product type UC3B; 2) N = 2,942 records for product type UC4A; 3) N = 196 records for product type UC4B.

Estimating and Selecting the Probability Density Functions

The statistical metrics used in this study for selecting the best pdf were the Akaike Information Criteria (AIC) and Bayesian Information Criteria (BIC). The AIC (Akaike 1974) value of the model is:

$$AIC = 2k - 2\ln(\hat{L}) \qquad [1]$$

where $\hat{L}$ = the maximized value of the likelihood function of the model and k = the number of free parameters to be estimated. The preferred model is the one with the minimum AIC value. AIC rewards goodness of fit (as assessed by the likelihood function), but it also includes a penalty that is an increasing function of the number of estimated parameters. The BIC (Findley 1991) or Schwarz criterion (also known as the SBC, SBIC) value is:

$$BIC = \ln(n)k - 2\ln(\hat{L}) \qquad [2]$$

where $\hat{L}$ = the maximized value of the likelihood function of the model, n = number of observations, and k = the number of free parameters to be estimated. The preferred model is the one with the minimum BIC value. Estimated parameters for each density were obtained as part of the maximum likelihood procedures in JMP® software (SAS®, Cary, NC). The first term in the BIC penalizes distributions that contain more parameters. In general, distributions with an AIC within a magnitude of two of the minimum AIC or a BIC within a magnitude of two of the minimum BIC can be considered contenders. Probability plots were also evaluated to assess conformance to distributions.

Control Charting Methods

The Shewhart control chart, primarily the "*Individuals and Moving Range*" (ImR) chart, was used to quantify the natural variation (also known as *common-cause* variation) and special-cause variation from the industrial measured retention values of residential treated lumber charges (Shewhart 1931). The Shewhart control chart is based on the theory of the statistical prediction interval for real-time data (*i.e.,* analytical studies), and is defined in its general form as:

$$\bar{X} \pm 3s \qquad [3]$$

where, $\bar{X}$ is the process average and s is the process standard deviation. Given that s is a biased estimator for the population standard deviation (σ), the unbiased estimator of σ is used $\frac{\overline{mR}}{d_2}$, where d_2 =1.128 for a subgroup size of two for estimating a moving range value. Therefore, equation [3] reduces to:

$$\bar{X} \pm 2.66\ (\overline{mR}) \qquad [4]$$

where, $\bar{X}$ is the process average and $\overline{mR}$ is the average moving range.

Capability Analysis

Capability analysis is a common tool in statistical process control (SPC) methods for estimating conformance to specifications (or engineering tolerance - ET) given the natural tolerances (NT) of the process, where ET = USL – LSL (or upper specification limit – lower specification limit) and NT = $6 \cdot s$, where s is the process standard deviation. All methods of capability analyses require that the data are statistically stable. Capability analysis is summarized in indices where these indices show a system's ability to meet its numerical requirements. Common capability indices are:

$$C_p = \frac{USL-LSL}{6\times(\overline{mR}/d_2)} \qquad [5]$$

$$C_{pk} = \min\left[\frac{\bar{X}-\mathrm{LSL}}{3\times(\overline{mR}/\mathrm{d}_2)}, \frac{\mathrm{USL}-\bar{X}}{3\times(\overline{mR}/\mathrm{d}_2)}\right] \qquad [6]$$

and the Taguchi index (Boyles 1991, Taguchi 1993),

$$C_{pm} = \frac{USL-LSL}{6\sqrt{(\bar{X}-T)^2+(\overline{mR}/d_2)^2}} \qquad [7]$$

where T = target. Note: process performance indices (P_p, P_{pk} , P_{pm}) are similar to those of equations [5], [6], and [7], where s is used instead of $\frac{\overline{mR}}{d_2}$ (*i.e., s* represents long term variation). Both types of indices are presented in this paper. The indices were estimated for the previously defined data set. The capability analyses were also used to estimate the increase in operating targets for chemical dosing necessary to achieve a 100% conformance above the AWPA LCL.

RESULTS

Probability Density Functions

There were distinct differences between the industry and agency values of normalized retention as illustrated by the histograms of each (Figure 1). Industry treating plants calibrate their instruments to agency standards; however, it is plausible that there may be additional variability due to plants that the agency does not experience with measurements made on their instruments. The differences may be due to the resampling without replacement that occurs with the industry samples when the first, second, or third sample falls below the LCL and additional samples are taken from the same batch of treated wood. The difference may also be due to a batch of treated lumber that is re-treated. Both data sets contained statistical outliers as illustrated in the box plots. Given resampling that occurs with the industry data, probability density functions were estimated in this paper only for the agency data.

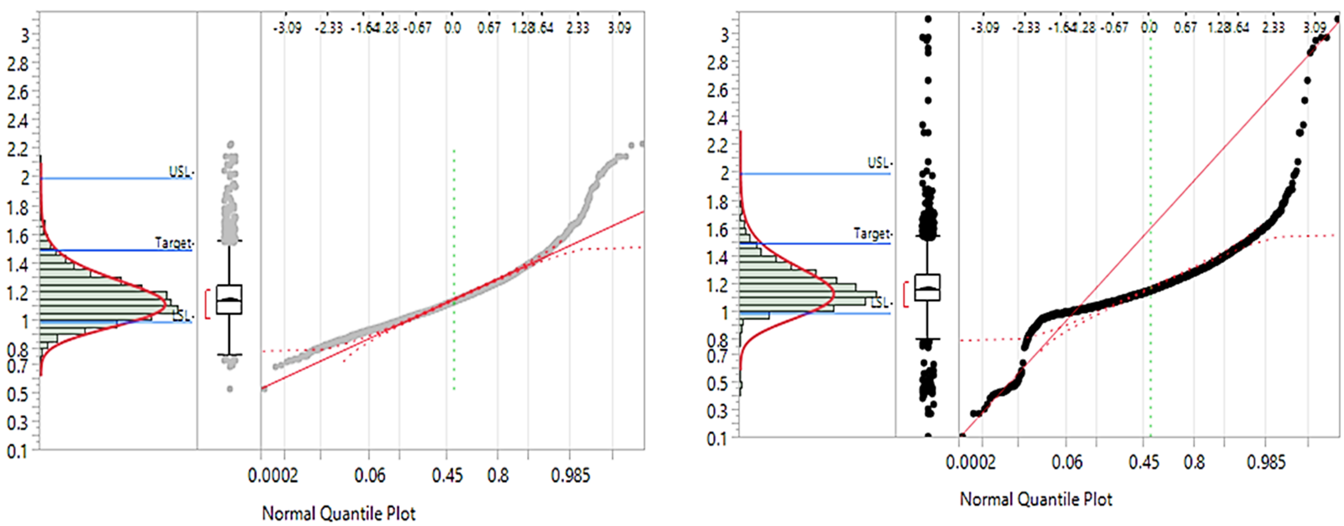


Figure 1. Histograms, box plots, and quantile plots of normalized retention relative to the AWPA LCL; agency data (left), industry data (right).

Based on the minimum AIC and BIC values, the best pdf for each of the product types UC2, UC3B, UC4A, and UC4B was the Largest Extreme Value (LEV) (Table 1). For each product group, the commonly assumed normal, or Gaussian, pdf was ranked 15th out of the 19 different distributions that were tested and exceeded the minimums by at least six units providing strong evidence against normality. The lack of normality of normalized retention samples from the agency data set is important when statistical methods that have stringent assumptions of normality are used for analyses. Depending on the goal, methods robust to the normality assumption or methods that directly address an underlying distribution may need to be considered. Also, further investigation of the sampling process, treatment process, and sources of process variation (*e.g.,* components of variance) are required to explain the reason for the somewhat rare LEV pdf and to determine whether actions can be taken such that the process may be modeled by assuming an underlying normal distribution.

Quantifying the Natural Process Variation

Sample data were normalized to better quantify the natural variation of the process. As examples for this paper of the application of control charts, charts were developed for product types UC3B and UC4B. The natural variation of the industry data differs with product type and exhibits some special-cause variation (Figures 2 and 3). Eliminating or reducing special-cause variation is typically the starting point of any continuous improvement effort where root-cause analyses should reveal the 'events' that are not part of the system variation, *e.g.,* shift change, startup from downtime, sensor failure, etc. Special-cause variation usually contributes to excessive costs and poor product quality. Even though the process as exhibited by these control charts is not predictable (i.e., out-of-control points or special-cause variation are present), the natural variation is approximately 30% of the average without special cause variation. Control charting may represent a useful starting point for this industry to quantify variation and monitor process performance and improvements.

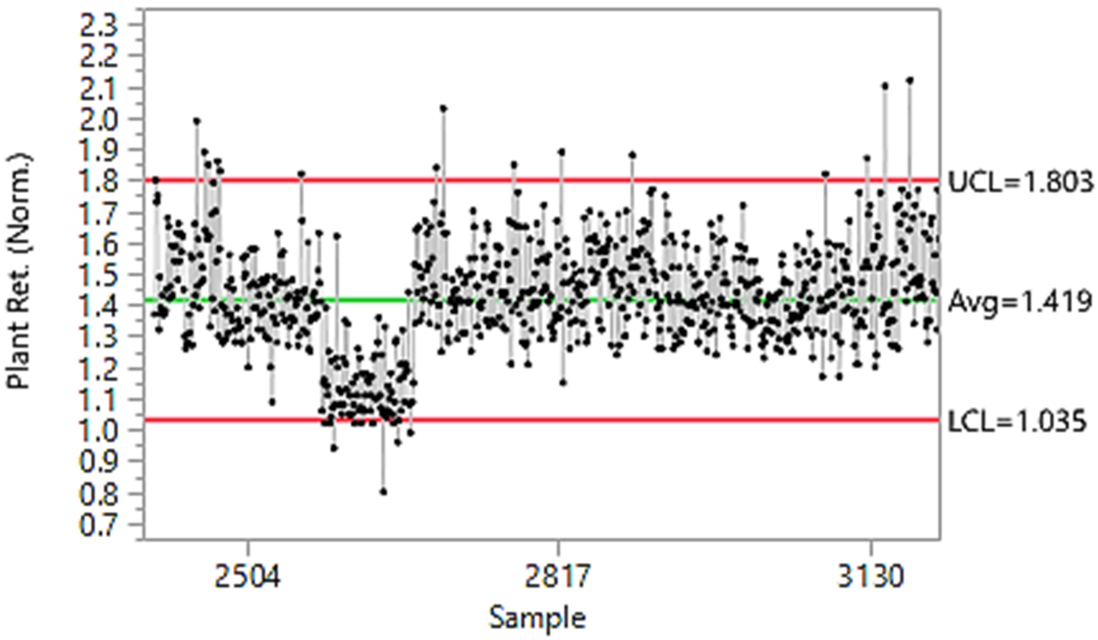


Figure 2. Individuals control chart for UC3B (normalized industry retention data).

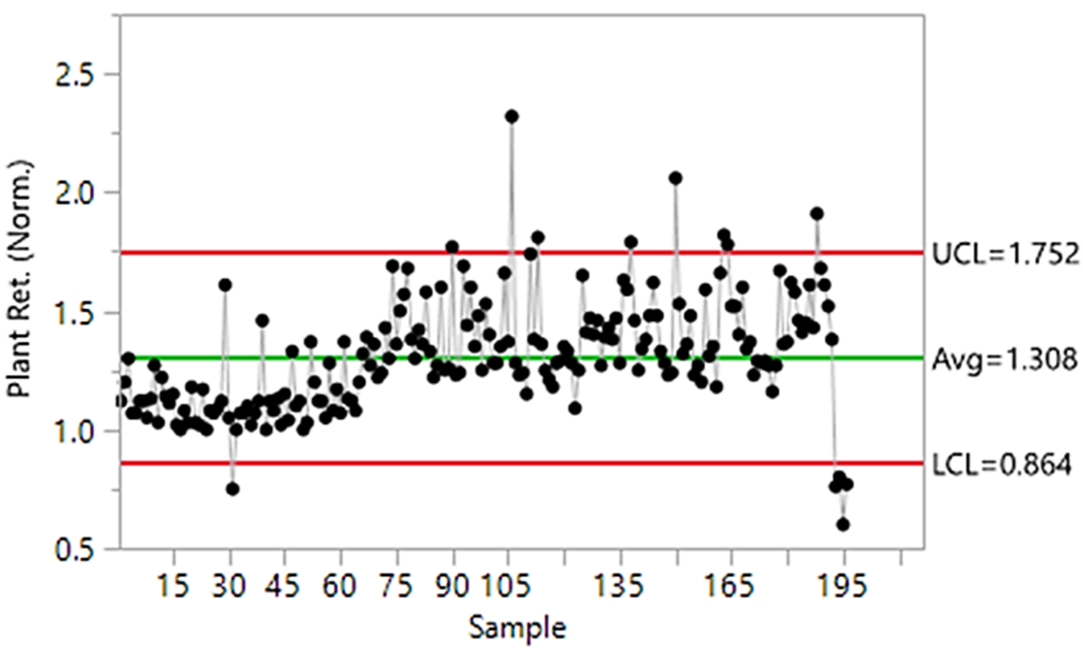


Figure 3. Individuals control chart for UC4B (normalized industry retention data).

Table 1. Probability density functions of normalized retention and corresponding AIC and BIC metrics by product group for the agency data set.

Rank	Probability Density Function	UC2		UC3B		UC4A		UC4B	
		AIC	BIC	AIC	BIC	AIC	BIC	AIC	BIC
1	Largest Extreme Value (LEV)	26.37	29.37	-177.63	-167.97	-247.06	-237.66	-10.39	-9.97
2	Frechet	27.46	30.46	-176.69	-167.03	-244.31	-234.90	-9.71	-9.29
3	Loglogistic	27.56	30.56	-163.70	-154.03	-241.38	-231.97	-8.10	-8.16
4	Threshold Loglogistic	27.74	32.04	-159.54	-149.88	-239.06	-232.77	-7.59	-7.17
5	Log Generalized Gamma	28.37	32.68	-132.96	-126.49	-237.00	-227.59	-7.57	-7.63
6	Threshold Frechet	28.38	32.68	-130.89	-121.23	-234.68	-225.27	-7.48	-7.54
7	Generalized Gamma	28.50	32.81	-123.52	-113.86	-230.81	-221.40	-7.44	-7.50
8	Lognormal	28.82	31.82	-94.28	-84.62	-215.83	-209.54	-7.40	-7.46
9	Threshold Lognormal	28.89	33.20	-61.92	-55.46	-199.56	-193.27	-7.38	-7.44
10	DS Frechet	29.82	34.12	-59.86	-50.20	-197.49	-188.08	-7.20	-7.26
11	DS Loglogistic	29.92	34.22	-50.38	-43.92	-183.11	-173.70	-6.65	-6.23
12	DS Lognormal	31.18	35.48	40.04	46.51	-160.47	-154.18	-5.87	-5.45
13	Threshold Weibull	31.44	35.74	42.11	51.77	-139.66	-133.36	-4.41	-4.46
14	Logistic	33.90	36.89	42.47	48.93	-137.60	-128.18	-4.20	-3.78
15	Normal	37.50	40.49	253.74	260.21	-42.53	-36.23	-3.47	-3.52
16	Weibull	41.42	44.41	260.61	267.07	50.75	57.04	-0.20	0.22
17	DS Weibull	43.77	48.08	262.68	272.34	52.81	62.22	2.99	2.93
18	SEV	55.34	58.33	491.76	495.00	211.51	217.80	3.27	3.69
19	Exponential	111.65	113.20	551.86	558.32	427.33	430.49	40.33	40.73

Process Capability

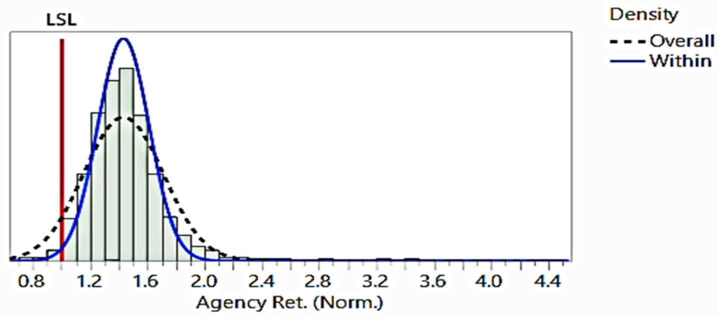
Capability analyses were performed by product type to assess the capability of the retention samples relative to the 'AWPA LCL' (also known as the lower specification limit or LSL in capability analysis terminology). Since there is only a one-sided AWPA defined LCL, the C_{pl} index is used to determine capability. For the agency data set the indices were: product type UC3B, C_{pl} = 0.807 (1.57% out-of-specification); product type UC4A, C_{pl} = 0.724 (2.55% out-of- specifcation); UC4B, C_{pl} = 0.588 (6.63% out-of-specification) (Figures 4, 5, and 6). For the industry data set, the indices were: product type UC3B, C_{pl} = 0.937 (2.77% out-of- specification); product type UC4A, C_{pl} = 0.803 (3.16% out-of-specification); UC4B, C_{pl} = 0.694 (2.25% out-of-specification) (Figures 7, 8, and 9). The differences in the C_{pl} indices between the industry and agency data sets is unexplained at this point in the study. It would be expected that the industry C_{pl} indices should be higher with less out-of-specification data due to resampling and retreating batches of treated wood below the LCL. However, this only occurred for product type UC4A. A limitation of any capability analysis is the assumption of normality, which was not exhibited in either of the industry or agency data sets. The capability analysis attempted to transform the data set towards a normal pdf (see histograms in Figures 4 thru 9).

Process Capability Use Category=UC3B

Individual Detail Reports

Agency Ret. (Norm.) Capability

Histogram



Process Summary

LSL	1
N	4259
Sample Mean	1.435095
Within Sigma	0.179666
Overall Sigma	0.278521
Stability Ratio	2.403173

Within sigma estimated by moving range.

Within Sigma Capability

Index	Estimate	Lower 95%	Upper 95%
Cpk	0.807	0.783	0.831
Cpl	0.807	0.783	0.831

Overall Sigma Capability

Index	Estimate	Lower 95%	Upper 95%
Ppk	0.521	0.506	0.536
Ppl	0.521	0.506	0.536

Nonconformance

Portion	Observed %	Expected Within %	Expected Overall %
Below LSL	1.5731	0.7724	5.9125
Total Outside	1.5731	0.7724	5.9125

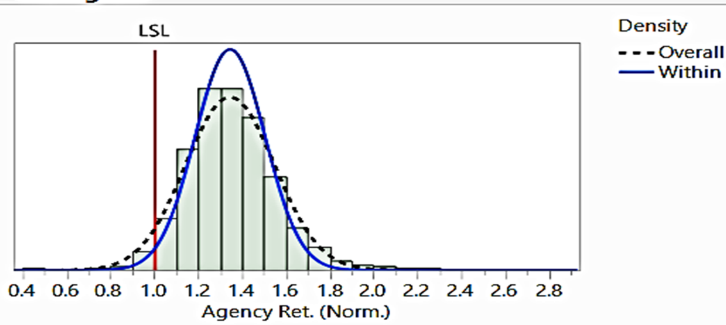
Figure 4. Capability analysis for agency data product type UC3B.

Process Capability Use Category=UC4A

Individual Detail Reports

Agency Ret. (Norm.) Capability

Histogram



Process Summary

LSL	1
N	2942
Sample Mean	1.346207
Within Sigma	0.159461
Overall Sigma	0.203604
Stability Ratio	1.630288

Within sigma estimated by moving range.

Within Sigma Capability

Index	Estimate	Lower 95%	Upper 95%
Cpk	0.724	0.697	0.750
Cpl	0.724	0.697	0.750

Overall Sigma Capability

Index	Estimate	Lower 95%	Upper 95%
Ppk	0.567	0.548	0.586
Ppl	0.567	0.548	0.586

Nonconformance

Portion	Observed %	Expected Within %	Expected Overall %
Below LSL	2.5493	1.4961	4.4528
Total Outside	2.5493	1.4961	4.4528

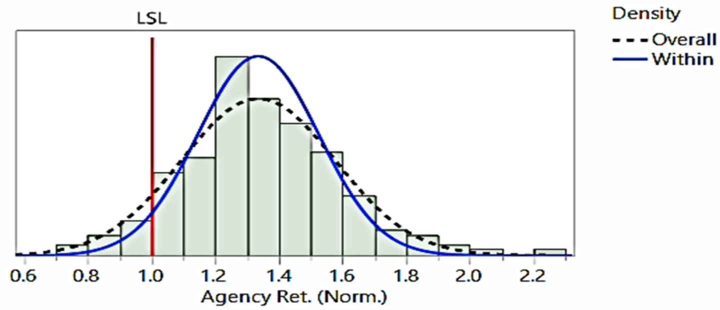
Figure 5. Capability analysis for agency data product type UC4A.

Process Capability Use Category=UC4B

Individual Detail Reports

Agency Ret. (Norm.) Capability

Histogram



Process Summary

LSL	1
N	196
Sample Mean	1.335459
Within Sigma	0.190289
Overall Sigma	0.24177
Stability Ratio	1.614274

Within sigma estimated by moving range.

Within Sigma Capability

Index	Estimate	Lower 95%	Upper 95%
Cpk	0.588	0.500	0.675
Cpl	0.588	0.500	0.675

Overall Sigma Capability

Index	Estimate	Lower 95%	Upper 95%
Ppk	0.463	0.397	0.528
Ppl	0.463	0.397	0.528

Nonconformance

Portion	Observed %	Expected Within %	Expected Overall %
Below LSL	6.6327	3.8959	8.2642
Total Outside	6.6327	3.8959	8.2642

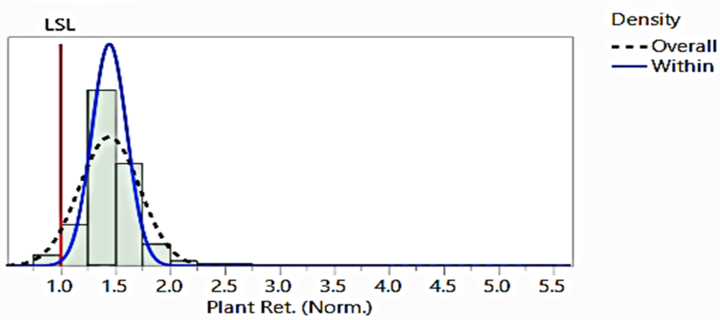
Figure 6. Capability analysis for agency data product type UC4B.

Process Capability Use Category=UC3B

Individual Detail Reports

Plant Ret. (Norm.) Capability

Histogram



Process Summary

LSL	1
N	4259
Sample Mean	1.450787
Within Sigma	0.160297
Overall Sigma	0.276602
Stability Ratio	2.977548

Within sigma estimated by moving range.

Within Sigma Capability

Index	Estimate	Lower 95%	Upper 95%
Cpk	0.937	0.910	0.965
Cpl	0.937	0.910	0.965

Overall Sigma Capability

Index	Estimate	Lower 95%	Upper 95%
Ppk	0.543	0.528	0.558
Ppl	0.543	0.528	0.558

Nonconformance

Portion	Observed %	Expected Within %	Expected Overall %
Below LSL	2.7706	0.2460	5.1579
Total Outside	2.7706	0.2460	5.1579

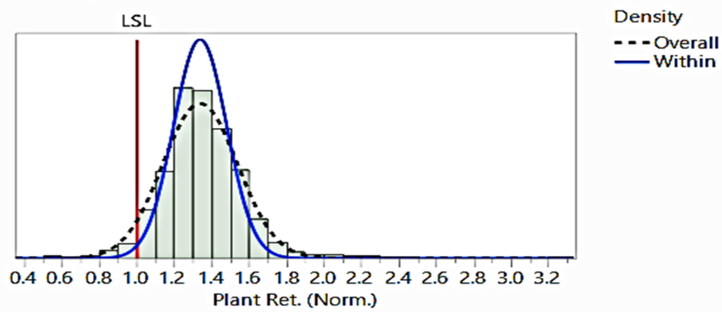
Figure 7. Capability analysis for industry data product type UC3B.

Process Capability Use Category=UC4A

Individual Detail Reports

Plant Ret. (Norm.) Capability

Histogram



Process Summary

LSL	1
N	2942
Sample Mean	1.341044
Within Sigma	0.141622
Overall Sigma	0.200415
Stability Ratio	2.002628

Within sigma estimated by moving range.

Within Sigma Capability

Index	Estimate	Lower 95%	Upper 95%
Cpk	0.803	0.774	0.831
Cpl	0.803	0.774	0.831

Overall Sigma Capability

Index	Estimate	Lower 95%	Upper 95%
Ppk	0.567	0.548	0.586
Ppl	0.567	0.548	0.586

Nonconformance

Portion	Observed %	Expected Within %	Expected Overall %
Below LSL	3.1611	0.8017	4.4407
Total Outside	3.1611	0.8017	4.4407

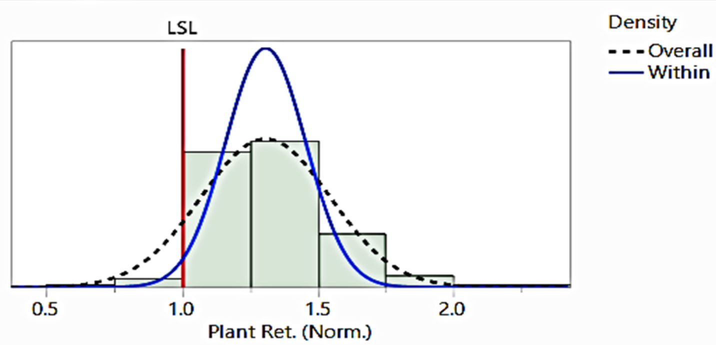
Figure 8. Capability analysis for industry data product type UC4A.

Process Capability Use Category=UC4B

Individual Detail Reports

Plant Ret. (Norm.) Capability

Histogram



Process Summary

LSL	1
N	196
Sample Mean	1.308214
Within Sigma	0.147932
Overall Sigma	0.238595
Stability Ratio	2.601357

Within sigma estimated by moving range.

Within Sigma Capability

Index	Estimate	Lower 95%	Upper 95%
Cpk	0.694	0.595	0.793
Cpl	0.694	0.595	0.793

Overall Sigma Capability

Index	Estimate	Lower 95%	Upper 95%
Ppk	0.431	0.367	0.494
Ppl	0.431	0.367	0.494

Nonconformance

Portion	Observed %	Expected Within %	Expected Overall %
Below LSL	2.5510	1.8603	9.8215
Total Outside	2.5510	1.8603	9.8215

Figure 9. Capability analysis for industry data product type UC4B.

Capability analyses are a useful tool for estimating the shift in operating target to attain 100% conformance. Even though this *'shift'* is inappropriate as a long-term continuous improvement strategy, it is sometimes a necessary short-term business strategy for survival. It is not a sustainable strategy in the long-term and continuous improvement should focus on variation reduction.

As an example, a shift in the process mean of 1.85288 (30% increase) for the normalized agency data set for product type UC3B should result in 100% conformance to LCL (Figure 10). A shift in the process mean of 1.69811 (27% increase) for the normalized agency data set for product type UC4B should result in 100% conformance to LCL (Figure 11). However, we repeat: increasing the process mean by adding more chemical is not a continuous improvement strategy and is not recommended.

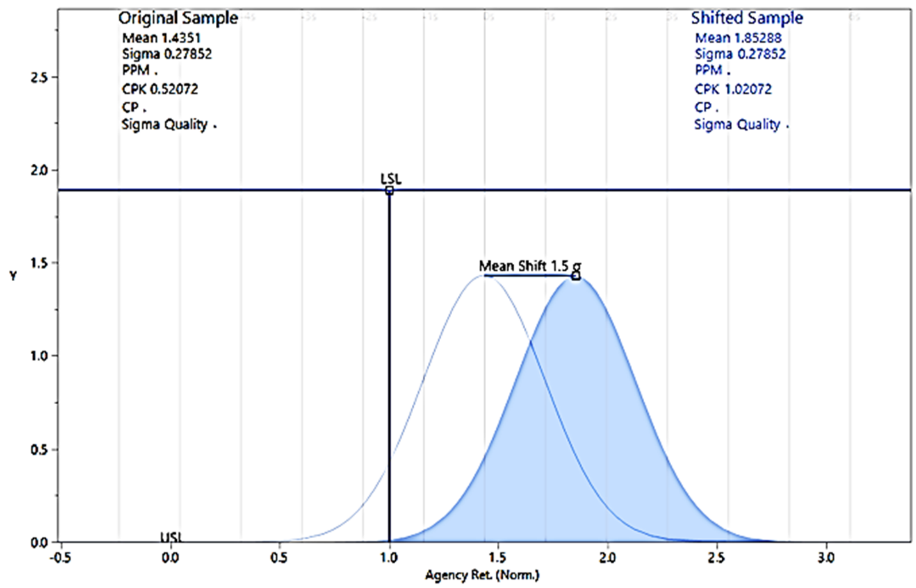


Figure 10. Shift in mean of 1.85288 for normalized agency data set to attain 100% conformance to LCL for product type UC3B.

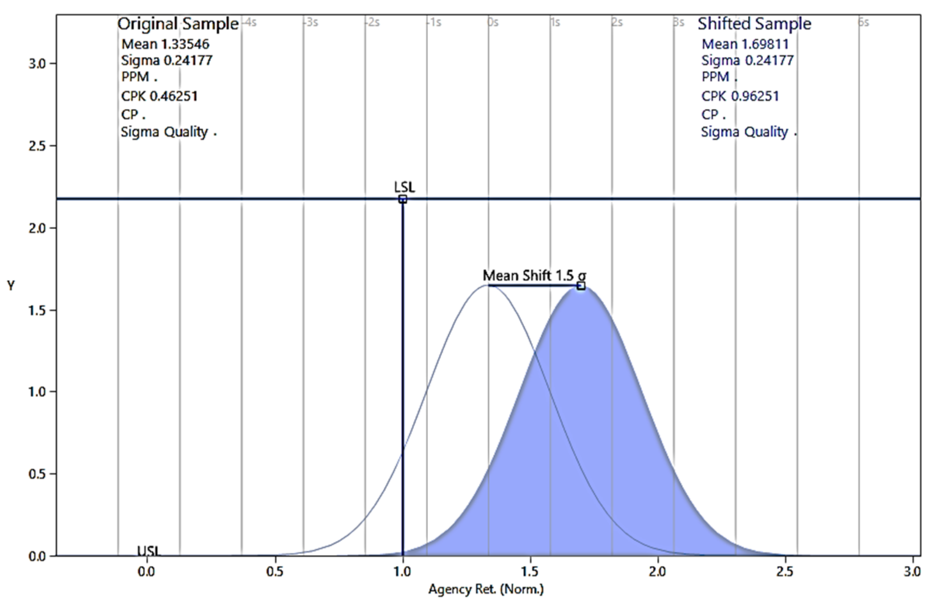


Figure 11. Shift in mean of 1.69811 for normalized agency data set to attain 100% conformance to LCL for product type UC4B.

CONCLUSIONS

This paper is the first stage of a study that attempts to improve the process of treating residential treated lumber through statistical process control. Key findings were:

- There are differences between the industry and auditing agency normalized retention probability density functions (pdf); this may be due to the resampling, and possible retreatment, of batches of treated wood that occur with industry data;
- The best-fitting pdf for the auditing agency retention data is the Largest Extreme Value (LEV);
- The process of treated residential lumber is not predictable, *i.e.,* special-cause variation exists; in the absence of special-cause variation the natural variation of the treated wood process is approximately 30% from the process mean;
- A capability analysis revealed that from 2.25% to 3.16% is below the LCL for an industrial data set, and 1.57% to 6.63% for an agency data set, both vary by product type;
- Based on two product types (UC3B and UC4B) for the data sets analyzed in this study, a shift in the operating process mean of 30% for UC3B and 27% for UC4B would yield 100% conformance to LCL; this is not recommended as long-term sustainable business practice.

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PROCEEDINGS

One Hundred Thirteenth Annual Meeting

of the

AMERICAN
WOOD PROTECTION
ASSOCIATION

Encore at Wynn Las Vegas
Las Vegas, Nevada
April 9-11, 2017

VOLUME 113

AMERICAN WOOD PROTECTION ASSOCIATION
P O BOX 361784 • BIRMINGHAM, ALABAMA 35236-1784 • USA

ISSN 0066-1198

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