A Protocol for Implementing Statistical Process Control in the Treated Wood Industry

Timothy M. Young
The University of Tennessee
Knoxville, Tennessee

Patricia K. Lebow
Grant Kirker
U.S. Forest Service Forest Products Laboratory
Madison, Wisconsin

Adam Taylor
The University of Tennessee
Knoxville, Tennessee

ABSTRACT

Statistical process control (SPC) is an important strategy for manufacturing organizations seeking improved profitability in highly competitive businesses such as the treated wood industry. SPC is a well-established methodology that focuses on reducing variation of key process parameters. Such variation reduction can result in lower manufacturing costs, improved product quality, and enhanced environmental stewardship. This paper outlines a protocol for establishing SPC for the treated-wood industry.
Keywords: Statistical process control, treated wood, reduced variation, lower targets

INTRODUCTION

Reducing variation in the wood treatment process by using quantitative techniques has positive financial and improved product value implications for the industry (Young *et al.* 2017). The use of statistical process control (SPC) has a well-documented history of success for both the manufacturing and service sectors throughout the global economy (Young and Winistorfer 1999, Young 2008). As we noted in our previous paper (Young *et al.* 2017), "*Improving product quality and reducing sources of process variation that lead to unnecessary costs (e.g., higher than necessary operating targets for chemical additives) are common goals for many forest products companies*." Sources of process variation include inherent variability in wood structure (Zobel and Buijtenen 1989, Kretschmann *et al.* 2006), as well controllable factors such as species, geographic source, pre-treatment moisture content and pressure-treatment parameters (Kleinknecht, 1999, Lebow, *et al.* 2007). The application of SPC to wood treatment may be of fundamental importance for the industry's long-term success and competitiveness with alternative products.

The wood treatment industry is aware of process variation and it establishes minimum chemical-additive targets based on an estimate of variation across the industry. However, increased efforts could be focused on reducing variation using SPC methods; justification for the use of SPC is given below in the Rationale section. The purpose of this paper is to outline a protocol for reducing variation in the treated wood industry.

The Importance of a 'Proactive Culture' for Implementing SPC

As Deming (1975) and many others have noted, management philosophies within an organization are the key determinants of success of SPC programs. Implementing SPC is successful only when it has support from the highest levels within an organization, and when a clearly-defined strategy is developed for the entire organization prior to implementation. Implementing SPC within a company will vary given different manufacturing systems/configurations, and different data management systems. However, the fundamental statistical methods for implementation will be similar across the industry. The protocol below is intended to be a guide for companies.

Rationale

Statistical methods have played a key role in the improvement process for manufacturing 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, *analytical studies* most frequently encountered in industrial applications focus on *real-time* analysis of a process or system, the aim being to improve the process in the future from the predictions, *e.g.,* prediction intervals, SPC, and control charts (Deming 1975, Hahn 1995). SPC involves the implementation of control charts to improve product quality by predicting outcomes of manufacturing applications. Such charts can also aid in sustaining the process improvement effort (Shewhart 1931, Stoumbos *et al*. 2000, Woodall 2000). SPC is a fundamental statistical method in the era of '*Six Sigma*' and '*Lean Six Sigma*' quality improvement philosophies (Harry and Schroeder 2000).

PROTOCOL FOR IMPLEMENTING SPC

Even though there is no universal template for implementing SPC, Deming's (1975), 'Plan-Do-Check-Act' (PDCA) cycle is a very good general framework. We have refined this framework with a four-phase, series-based approach to implementing SPC. Even though each phase is important, it is not feasible here to go into an in-depth discussion for all four phases. Phases I, II and IV are discussed briefly, while emphasis is given to Phase III, the SPC phase.

Phase I – Define the Problem

General Assessment

Accurately defining the problem for continuous improvement, or for any research endeavor, is essential to a successful outcome. Many continuous improvement projects fail because the problem is poorly defined, or it is not aligned with the overall mission and goal for improvement. Some useful steps, or questions, for accurately defining the problem are presented in Figure 1, *i.e.,* is the problem clearly defined, and is it aligned to the customer requirements? It is essential in Phase I to clearly define the objectives required to satisfy the problem. Given these objectives, the variable(s), *i.e.,* dependents or ***Y***s, for SPC should be defined. The variable(s) for improvement (variation reduction) are typically associated with cost-savings (Taguchi, 1993). Once the variable for improvement is defined, successful projects typically develop a time-frame to accomplish the objectives. As (Ohno, 2014) noted, many continuous improvement endeavors fail because the problem is too broad with too many variables (***Y***s) associated to the SPC initiative. As Juran (1951) articulated, if variation of the variable ***Y*** is reduced, will it lower operational targets and reduce costs.

Phase II – Assess Measurement Variation and Data Quality

General Assessment

Many SPC projects in industry do not succeed because the measurement error is not quantified for the variable ***Y***. There is a plethora of literature on assessing measurement error, see Wheeler (2006). It is beyond the scope of this paper to go in depth into the study of measurement error. However, it is vital in the initial phases of implementing SPC (Figure 2). If the measurement error is unacceptable, steps to reduce the error and control the error must be developed.

Data quality is also fundamental to SPC. An initial review of the data quality for ***Y*** should be done to determine if there concerns. A key issue for many industries is resampling when an initial test sample is out of specification. Data from resamples should not be included in the original set of data (Lebow *et al.* 2015). Histograms (in the context of specification limits) are a very helpful tool to assess the data quality for ***Y***. This is very important if data are manually collected and entered in a database. If data that one would expect to be normally distributed show a 'shoulder' at the specification limit, one you explore reasons for this pattern (Figure 3).

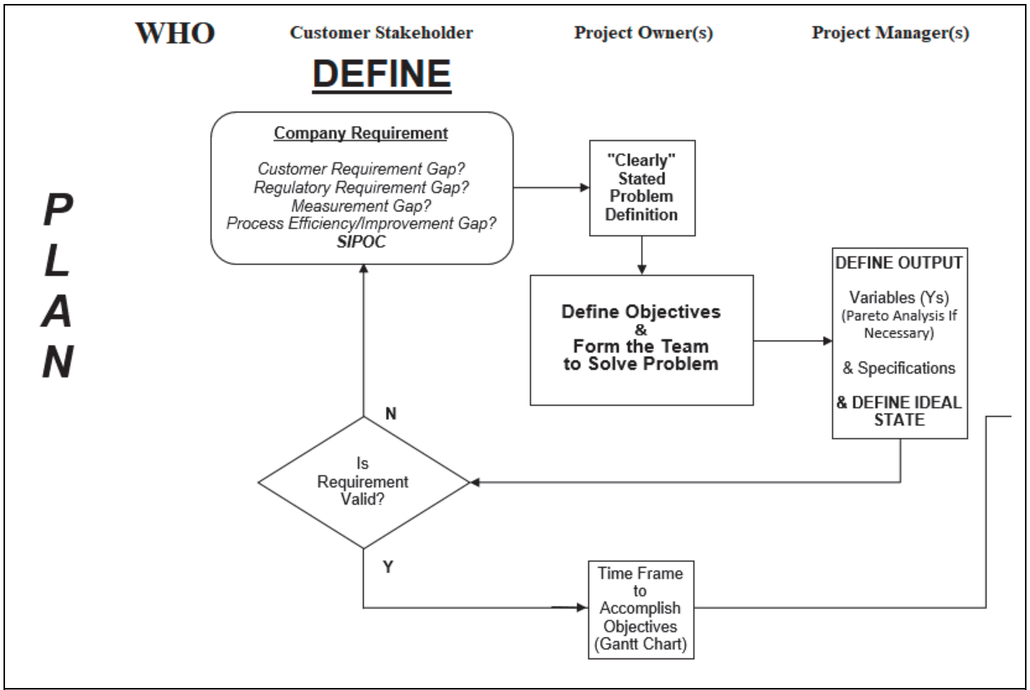

Figure 1. Illustrative flow chart of clearly-stated problem definition.

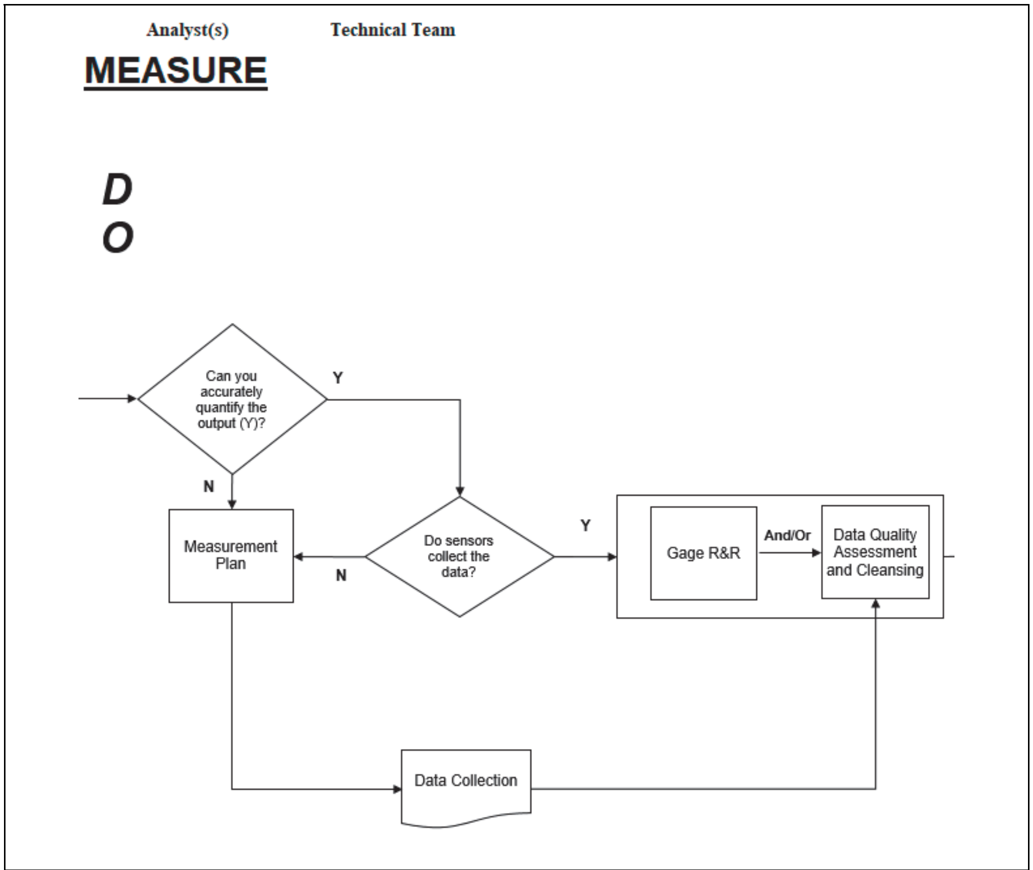

Figure 2. Illustrative flow chart of measurement assessment and plan.

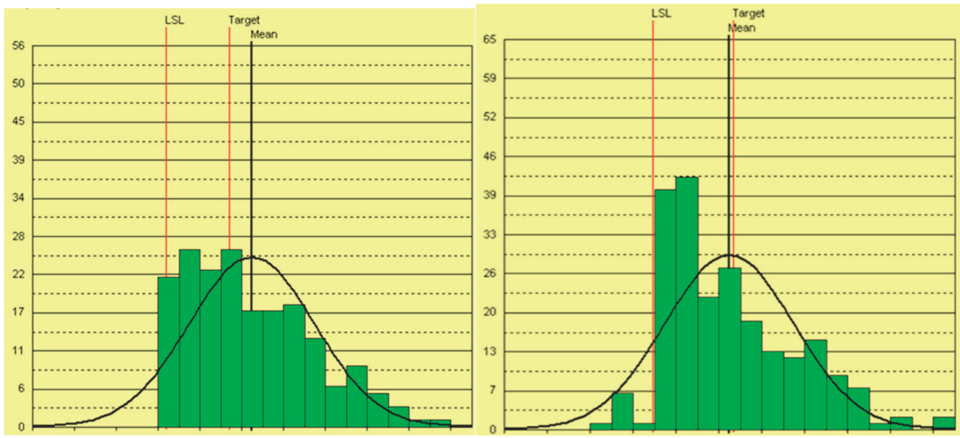

Figure 3. Illustration of histograms with suspect data quality with a 'shoulder' at the specification limit.

Phase III – Analyze and Investigate the Problem

Detailed Assessment

The initial step in Phase III is defining the state of statistical control (Figure 4). A Shewhart control chart for ***Y*** should be developed to quantify the currents state of control (Figure 5). The Shewhart control chart estimates upper and lower control limits as: $\bar{Y} \pm 3 \cdot \boldsymbol{s}$, where $\bar{Y}$ is the process average, and ***s*** is the standard deviation. Control charts are a time series of data and provide useful signals for special-cause variation ('*out-of-control*' points) and overall process stability (Figure 4). Special-cause variation are '*events*' and should be analyzed, *i.e.,* in most cases '*events*' are a cost. Pareto charts are an excellent tool for summarizing the '*events*' for ***Y***. Pareto charts prioritize which '*events*' require root-cause analysis and corrective action (Figure 6).

In the early stage of Phase III, a capability analysis is essential. The capability analysis compares the natural tolerance of ***Y*** (six standard deviations) with the engineering tolerance for ***Y*** (upper specification minus lower specification). For example, in the case of preservative retention values, there is typically only a lower specification limit. The capability analysis sets the benchmark for reducing variation relative to specification limits (Figure 7). In some instances, it may be necessary in the short-term to shift the process mean to attain specification, *i.e.,* reducing variation takes more time than shifting the process mean. However, this is not an acceptable long-term business strategy, because increasing the process mean increases cost.

The final stages of Phase III are iterative root-cause analyses that may involve Ishikawa or Fishbone diagrams, cause-mapping, correlation analyses, and planned experimentation. Ishikawa diagrams are helpful for initial brainstorming, and categorizing ideas for sources of variation. Ishikawa diagrams are generally developed as a team exercise where personnel that understand the process associated ***Y*** (*e.g.,* retention value) list all the possible factors (independent variables ***X***) that may induce variation in ***Y*** (Ishikawa 1976). Cause-mapping is another useful tool that is more prescriptive in that a solution to the problem is sought (Rooney 2016), see Figure 8.

In many instances, the Ishikawa diagram from the organized brainstorming session can lead to a complex diagram (Figure 8). Some companies have been successful when team members rank the top five ***X***s before proceeding with further root-cause analysis. If data exist for the ***X***s, it is effective to develop ***XY*** scatter plots and conduct correlation analyses (Figure 9). The ***XY*** scatter plots highlight if a relationship exists between ***X*** and ***Y***. The correlation coefficient measures the strength of the linear relationship between ***X*** and ***Y***. The correlation coefficient is defined by:

$$r = \frac{\sum_{i=1}^{n}(X_i-\bar{X})(Y_i-\bar{Y})}{\sqrt{\left[\sum_{i=1}^{n}(X_i-\bar{X})^2\right]\times\left[\sum_{i=1}^{n}(Y_i-\bar{Y})^2\right]}} = \frac{S_{x\,y}}{S_x S_y}. \qquad -1 \le r \le 1 \qquad [1]$$

The independent variables ***Xs*** that are influencing ***Y*** should be ranked by strength of correlation coefficient. The ***Xs*** with the largest magnitude correlation coefficients (near -1 or 1) should be investigated given that they have the largest influence on the variation in ***Y***. Root-cause analyses should continue in an iterative manner until there is evidence of variation reduction in ***Y***. The control chart of ***Y*** will reveal whether or not variation reduction has occurred. If variation reduction in ***Y*** has occurred, the process mean can be shifted towards the specification limit. This is the point where true cost savings occurs (Taguchi 1993). The control chart is a fundamental tool to use in the operations control room to monitor and sustain variation reductions in ***Y***. The above procedure may be suboptimal, however, as there can be dependencies between the independent variables, that could have an impact on the control variable and on the iterations determining the importance of the independent variables.

Phase III may also involve designed experimentation known as '*Design of Experiments*' (DOE) that can help address multifactorial process control (Box *et al.* 1978, 2005 and Montgomery, 2013).

Plans for implementing new techniques should be developed by management but proper training of plant personnel in the use and interpretation of SPC is fundamental to attaining uniform adoption across the organization. In some instances, '*standard operating instructions*' (SOI) or '*standard operating procedures*' (SOP) may need to be developed to ensure long term success. Documentation of improvements is essential for long term success of the variation reduction effort. Phase III is an iterative process that involves all levels of the organizations, *e.g.,* cost accountants will document costs savings.

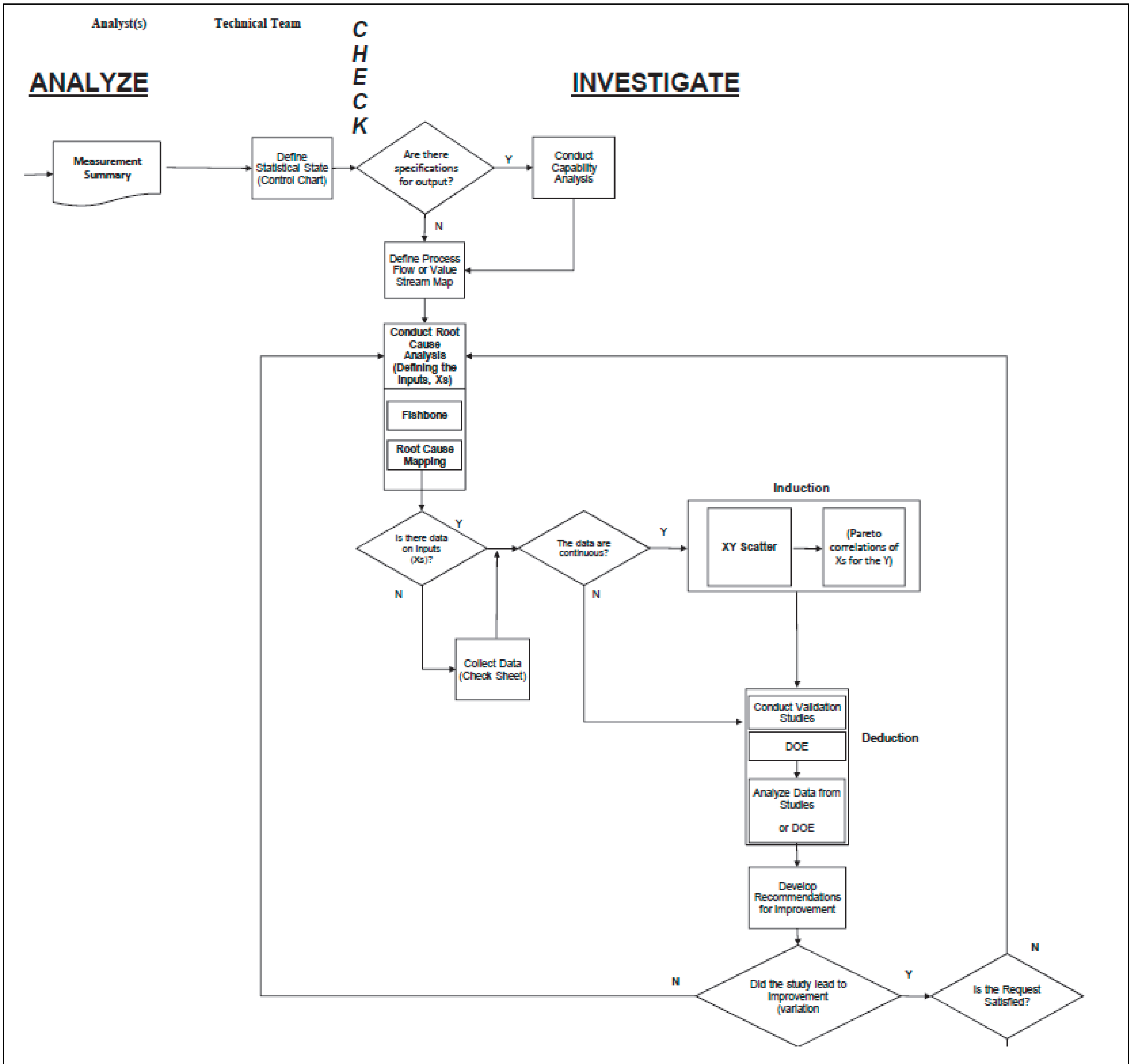

Figure 4. Illustrative flow chart of analyze and investigate phase.

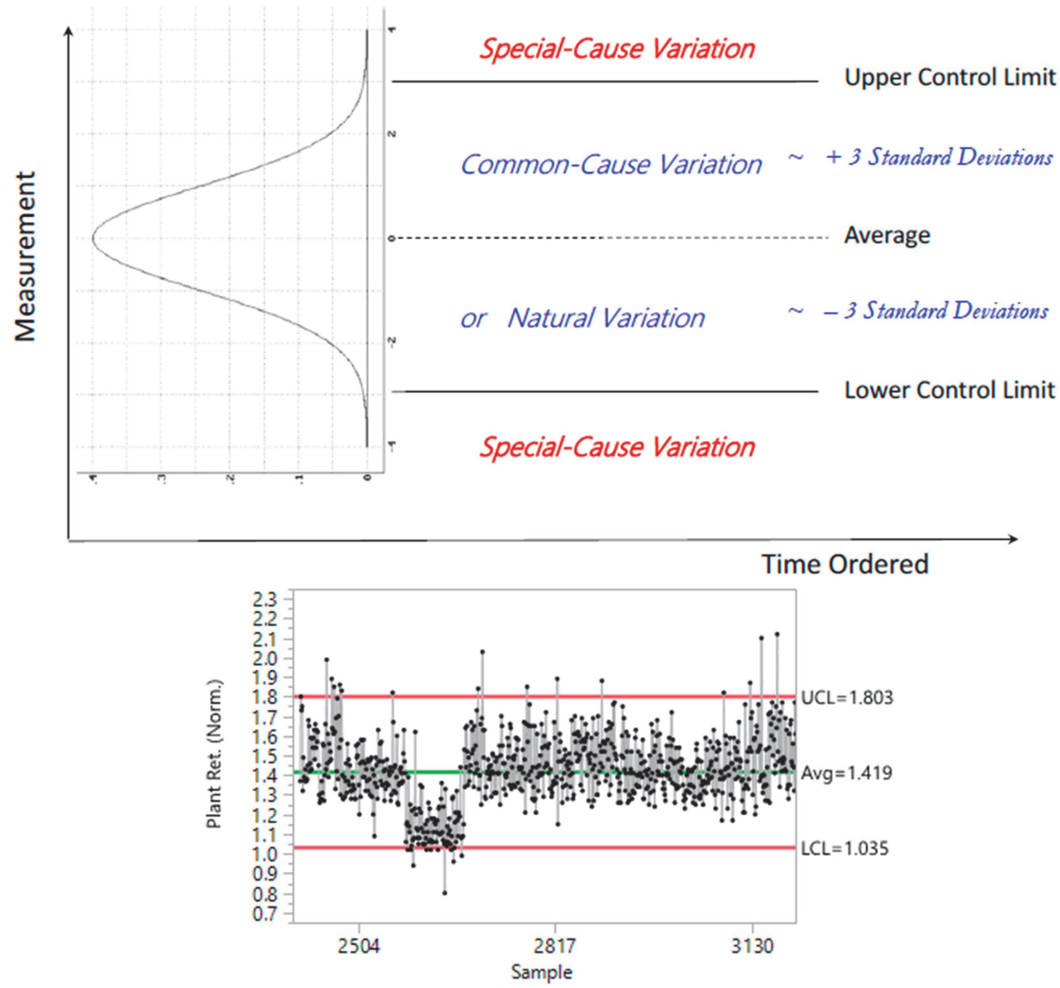

Figure 5. Shewhart control chart structure and examples for plant retention values.

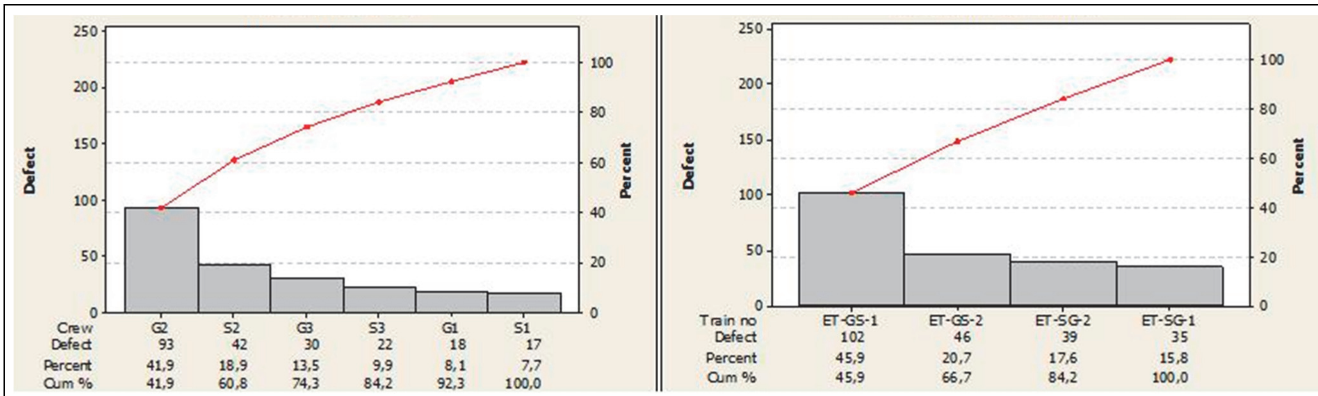

Figure 6. Illustration of Pareto Charts as an ordered histogram with individual and cumulative percentages of defects.

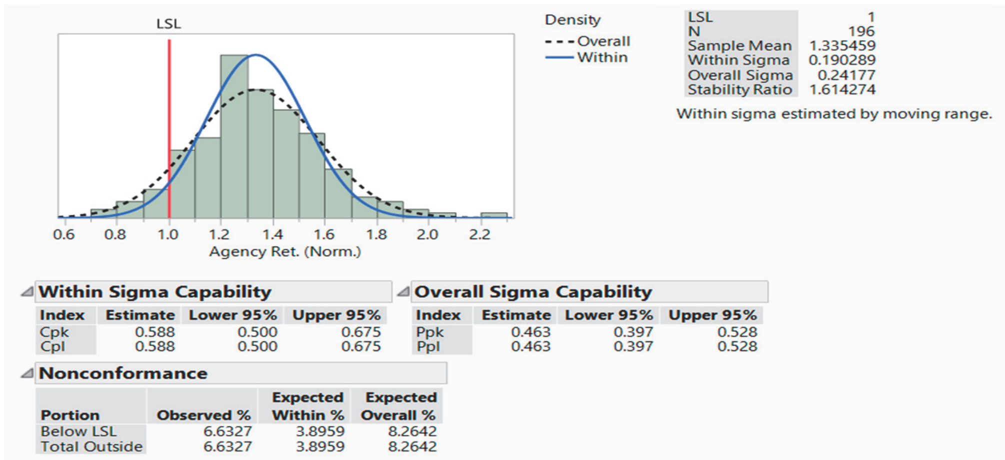

Figure 7. Example of capability analysis for retention values relative to lower specification limits.

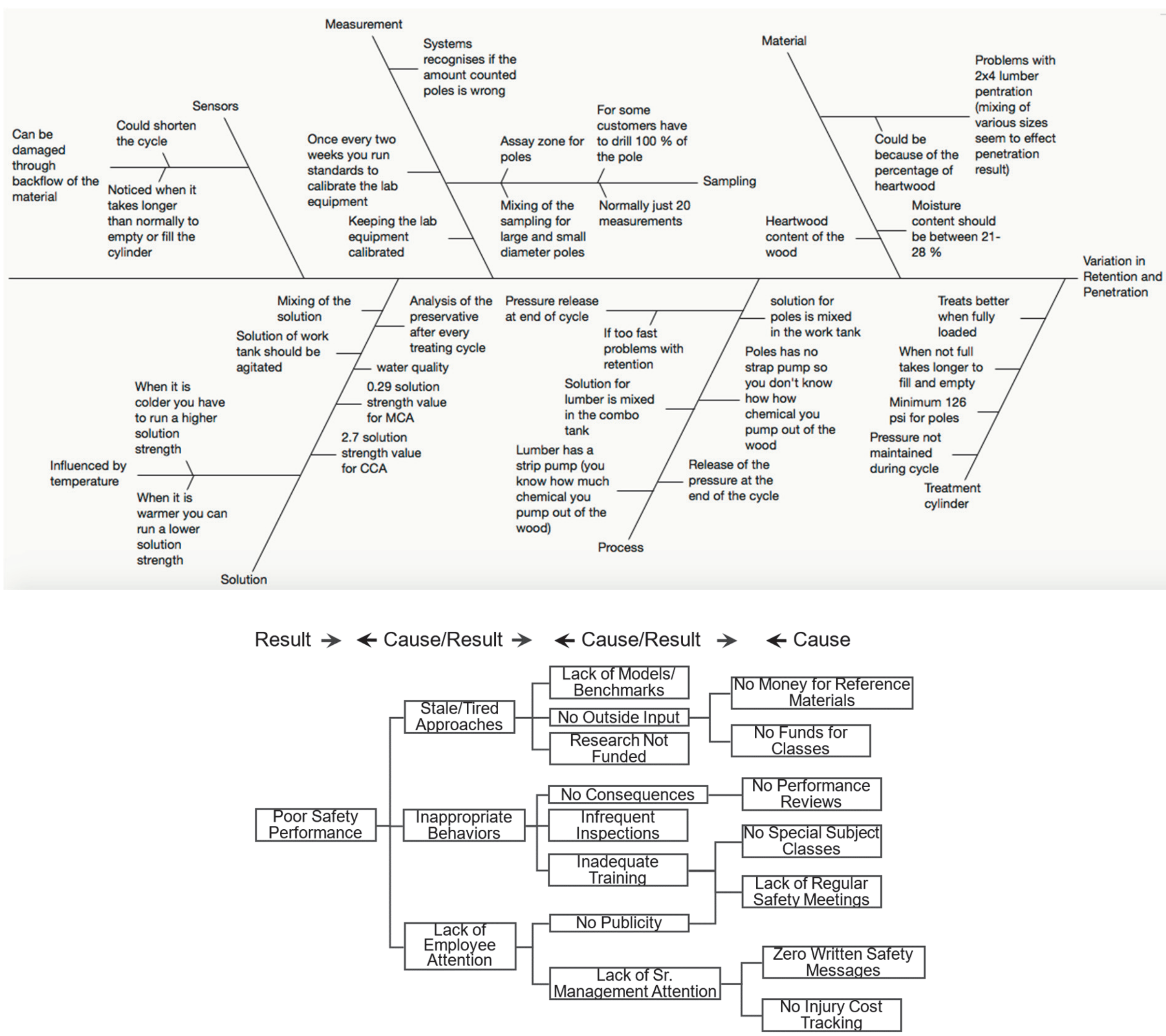

Figure 8. Illustration of Ishikawa diagram (top graph) and cause map (bottom graph).

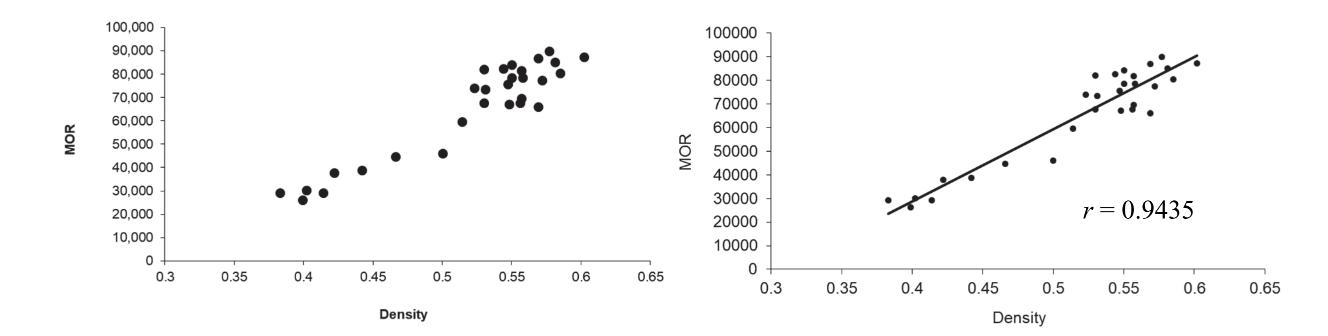

Figure 9. Example of *XY* scatter plot (left diagram) and straight-line fit with correlation coefficient (right diagram).

Phase IV – Implement and Control Strategy for Improvement

General Assessment

Once the analyses and investigations are completed in Phase III, the key question is '*has the defined-problem been solved*'? This usually implies variation reduction of ***Y***. If so, implementation of SPC as a long term strategy should occur (Figure 10). If there is a financial risk for implementing the control strategy for ***Y***, a risk assessment should be conducted. If the control strategy is approved by management, it should be implemented and monitored using control charts. Statistics for ***Y*** may be in the form of daily or weekly reports with control charts. It is vital at this final stage that communication of the control strategy to critical operational and management personnel occur. Periodic audits for ***Y*** will be required.

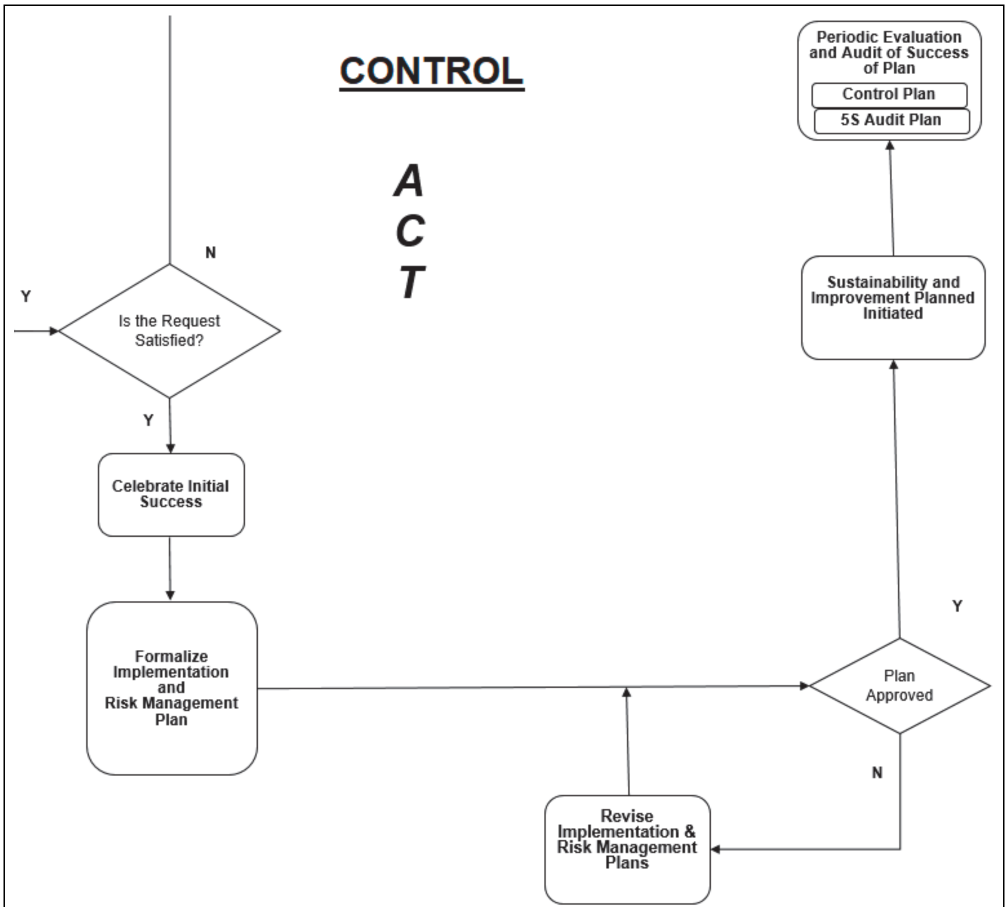

Figure 10. Illustrative flow chart of '*Do*' or '*Control*' phase for implementation.

CONCLUSIONS

A protocol for implementing SPC was provided. The protocol highlights a series-based approach to implementing SPC and provides well recognized statistical methods for reducing variation and cost savings.

Management culture has a strong influence on the success of implementing SPC. In some instances, the company's culture may not be suitable for SPC. Data quality is paramount to the success of implementing SPC and variation reduction.

REFERENCES

1. Box, G.E.P., W.G. Hunter, and J. Stuart. (1978). Statistics for experimenters: An introduction to design, data analysis, and model building. New York: Wiley.
2. Box, G.E.P.; Hunter, William G.; Hunter, J. Stuart. (2005). Statistics for experimenters: design, innovation, and discovery (2 Ed). Hoboken, N.J.: Wiley.
3. Deming, W.E. (1975). On probability as a basis for action. The American Statistician 29:146-152.
4. Hahn, G.J. (1995). Deming's impact on industrial statistics: some reflections. The American Statistician 49(4):336-341.
5. Harry, M.J. and R. Schroeder. (2000). Six sigma: The breakthrough management strategy revolutionizing the world's top corporations. New York: Currency.
6. Ishikawa, Kaoru (1976). Guide to Quality Control. Asian Productivity Organization.
7. Juran, J.M. (1951). Quality-control handbook. New York, McGraw-Hill.
8. Kleinknecht, D. 1999. The influence of variability in treated wood samples on "accept/reject" decisions. In: Proceedings, American Wood Preservers' Association Annual Meeting. May 16-19, Fort Lauderdale, FL. American Wood Preservers' Association, Granbury, TX. 95:105-115.
9. Kretschmann, D.E., Cramer, S.M., Lakes, R. and T. Schmidt. 2006. Selected mesostructure properties in loblolly pine from Arkansas plantations. In: Characterization of the cellulosic cell wall. Blackwell, Oxford, UK, D. Stokke and L. Groom, (Ed), pp. 149-170, Blackwell Publishing: Ames, IA.
10. Lawless, J.F., R.J. Mackay, and J.A. Robinson. (1999). Analysis of variation transmission in manufacturing processes – part I. Journal of Quality Technology 31(2):131-142.
11. Lebow, P., A. Taylor, and T.M. Young. (2015). Estimating variability in wood preservative treatment retention. Forest Products Journal. 65(5/6):278-284.
12. Lebow, S.T., Hatfield, C.A., and Halverson, S. 2007. Effect of source, drying method, and treatment schedule on treatability of Red Pine. Proceedings, 2006 American Wood-Preservers Association Annual Meeting, April 9 – 12, Austin TX. 102:39-43
13. Montgomery, D. (2013). Design and analysis of experiments (8th Ed). Hoboken, NJ: John Wiley & Sons, Inc.
14. Ohno, T. (2014). Toyota production system: beyond large-scale production. CRC Press. London.
15. Rooney, J. (2016). Root Cause Analysis for Beginners. Asq.org. Available at: http://asq.org/quality-progress/2004/07/quality-tools/root-cause-analysis-for-beginners.html [Accessed 17 Apr. 2016].
16. Shewhart, W.A. (1931). Economic control of quality of manufactured product. New York: D. Van Nostrand Company. pp. 501 p.
17. Stoumbos, Z.G., M.R. Reynolds, Jr., T. P. Ryan, and W. H. Woodall. (2000). The state of statistical process control as we proceed into the 21st century. Journal of the American Statistical Association 95:992-998.
18. Taguchi, G. (1986). Introduction to quality engineering: Designing quality into products and processes. Asian Productivity Organization, available in the USA from American Supplier Institute. Dearborn MI.
19. Taguchi, G. (1993). Taguchi on robust technology development. The American Society of Mechanical Engineers. American Society of Mechanical Engineers (ASME) Press, New York, NY.
20. Wheeler, D.J. (2006). EMP III Using Imperfect Data. SPC Press, Inc. Knoxville, TN.
21. Woodall, W.H. (2000). Controversies and contradictions in statistical process control. Journal of Quality Technology 32(4):341-350.
22. Young, T.M. and P.M. Winistorfer. (1999). Statistical process control and the forest products industry. Forest Products Journal 49(3):10-17.
23. Young, T.M. (2008). Reducing variation, the role of statistical process control in advancing product quality. Engineered Wood Journal. 11(2):41-42.
24. Young, T.M., P.K. Lebow, and S. Lebow. 2017. Statistical process control for residential wood. American Wood Protection Association (AWPA) conference, Las Vegas, NV. April 9-12, 2017. Vol. 113: 234-244 Birmingham, AL.
25. Zobel B.J., van Buijtenen J.P. 1989. Wood Variation and Wood Properties. In: Wood Variation: Its Causes and Control. Springer Series in Wood Science. Springer, Berlin, Heidelberg. 363p.

PROCEEDINGS

One Hundred Fourteenth Annual Meeting

of the

AMERICAN WOOD PROTECTION ASSOCIATION

Marriott Seattle Waterfront
Seattle, Washington
April 22-24, 2018

VOLUME 114

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

ISSN 0066-1198

Colin McCown, *Editor*
Kathryn Branton, *Assistant Editor*