# On 100 Years of the Shewhart Control Chart

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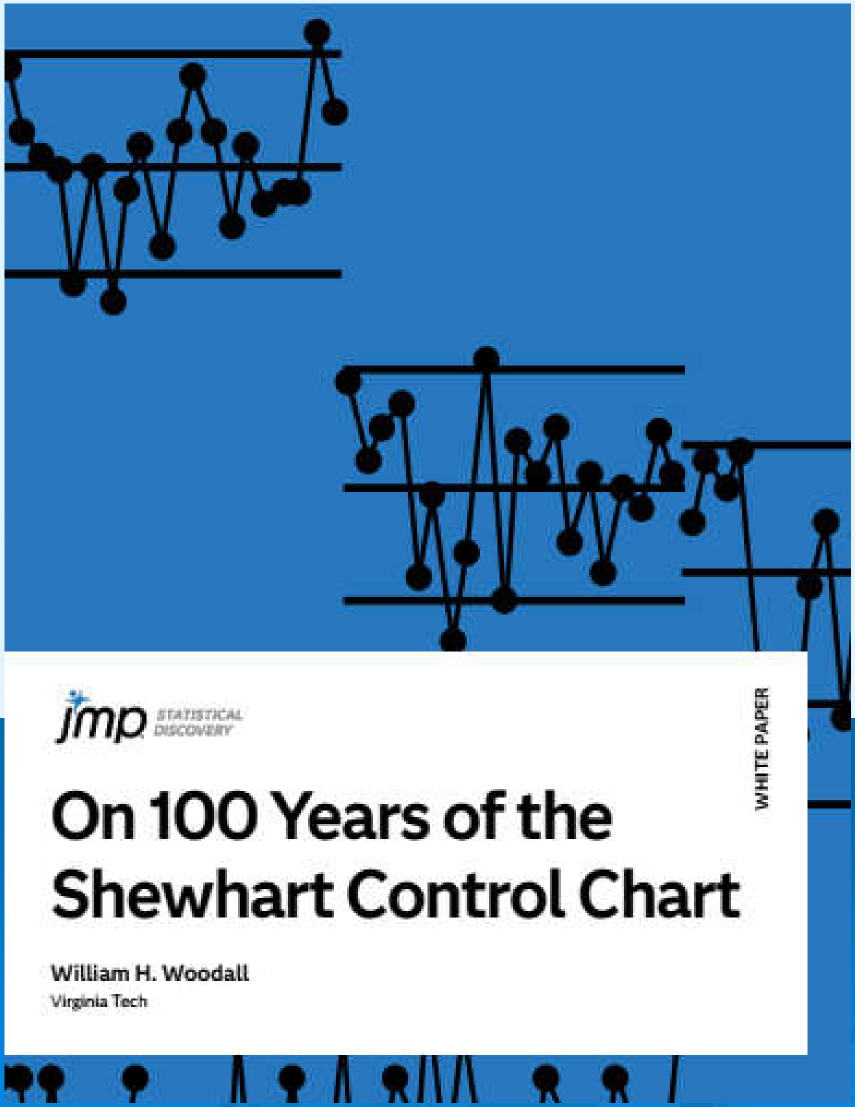

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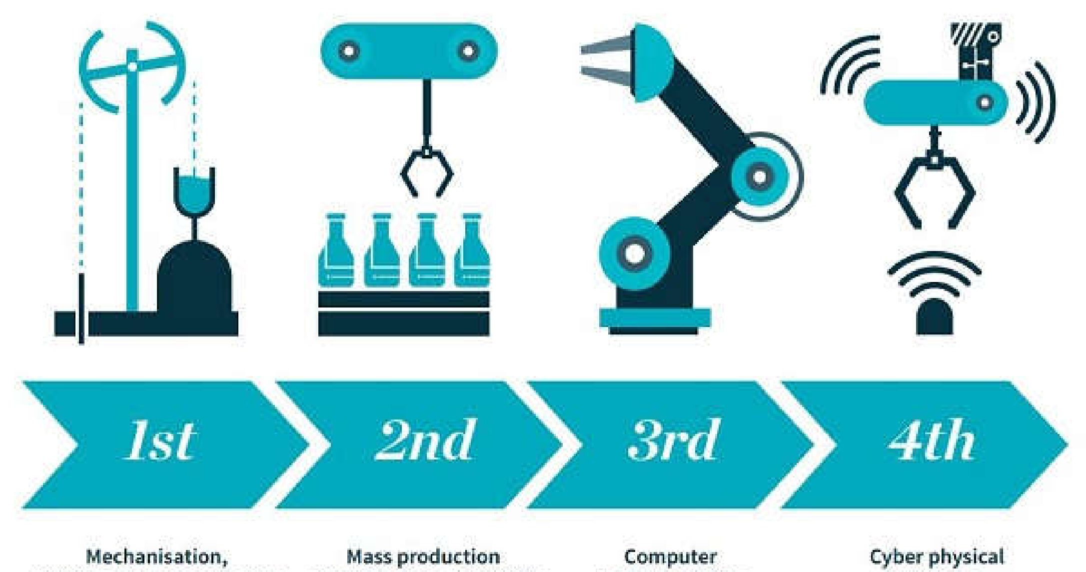
WHITE PAPER

# On 100 Years of the Shewhart Control Chart

**William H. Woodall**

Virginia Tech

| | | |
|---|---|---|
| Industry 1.0 | Water and steam power, mechanization | 1800 - |
| Industry 2.0 | Electricity, mass production | 1900 - |
| Industry 3.0 | Automation and information technology | 1970 - |
| Industry 4.0 | Cyber-physical systems, big data | 2011- now |



# Walter A. Shewhart 1891 – 1967

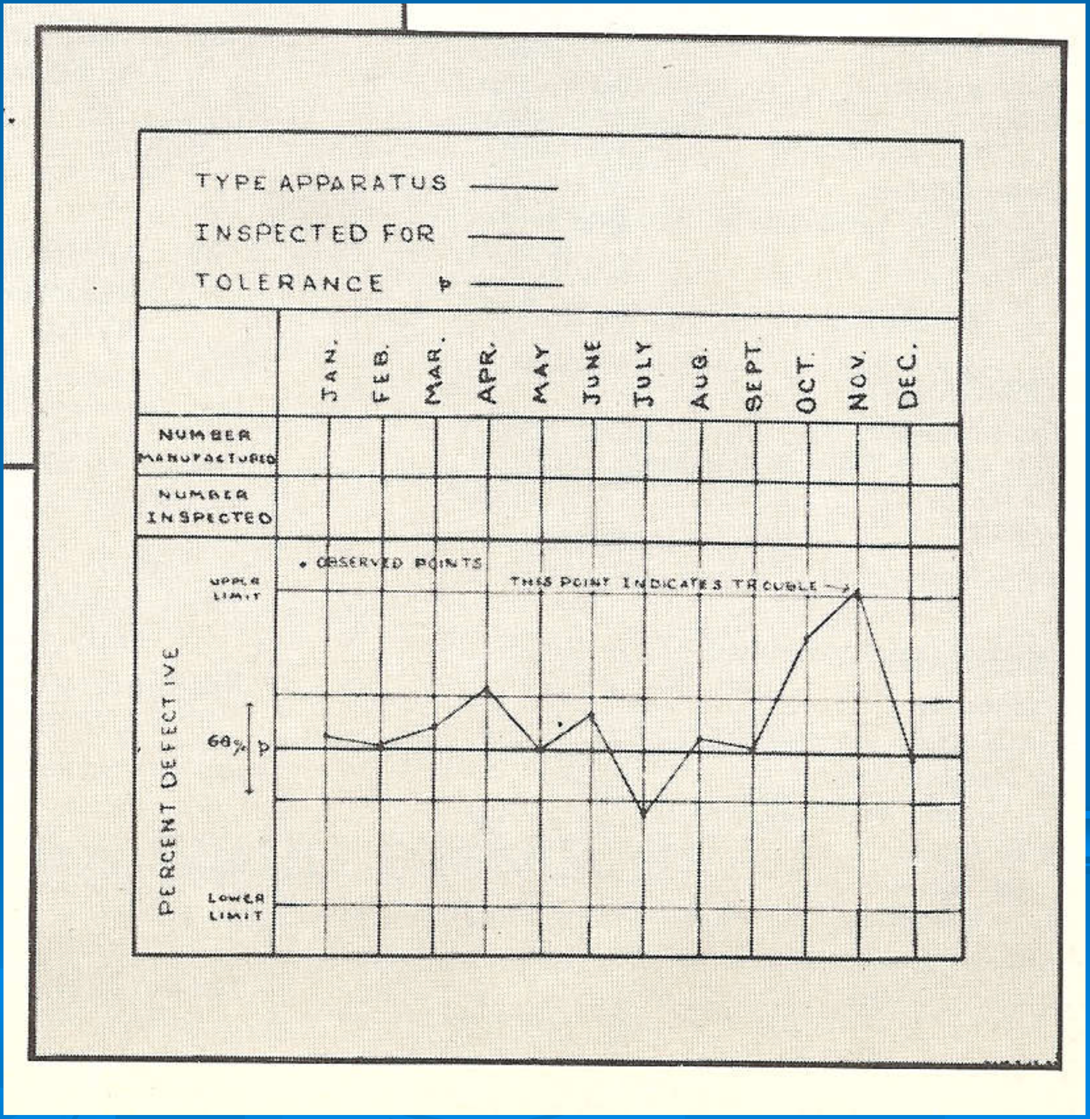
Considered the *Father of Statistical Quality Control*

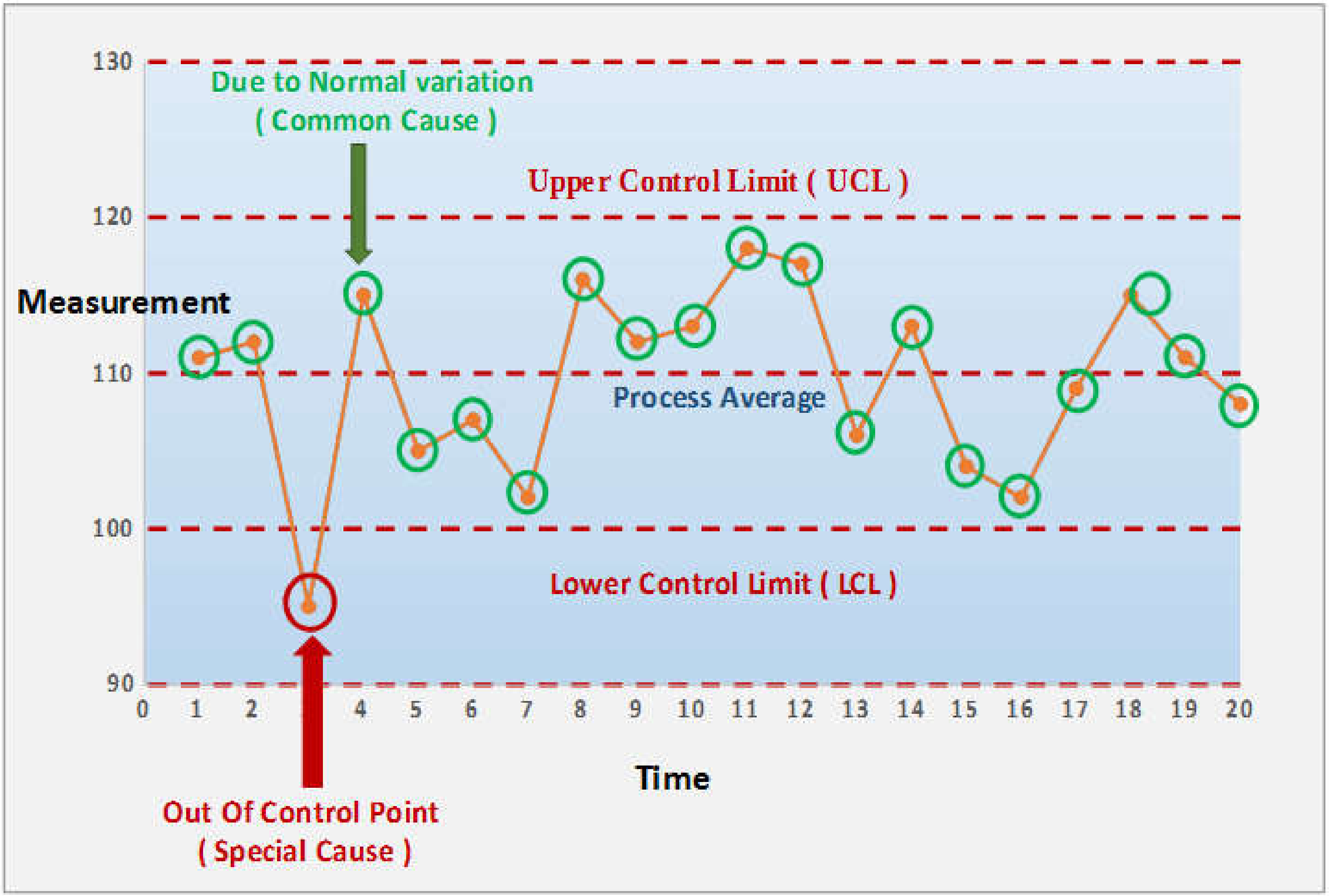
Western Electric employee

Stressed the importance of considering the time order of data.

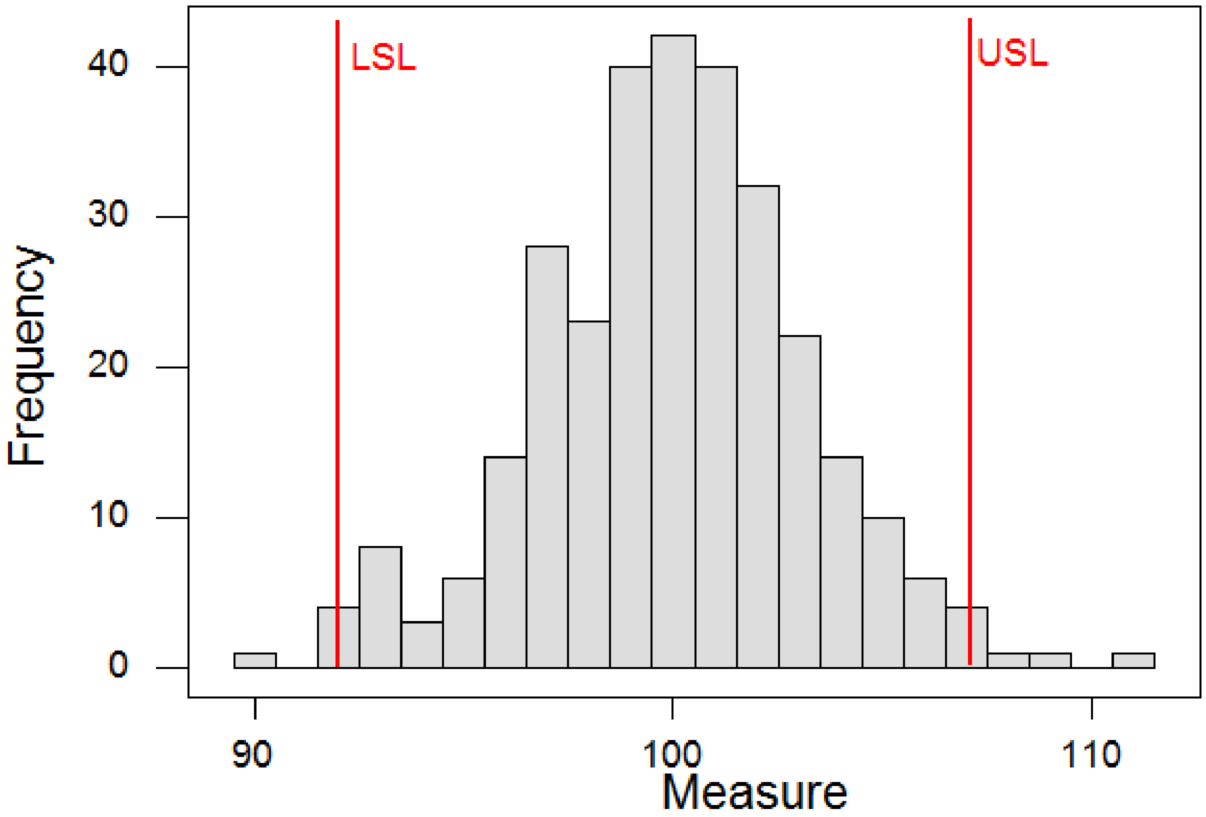
His Plan/Do/Check/Act cycle was a precursor to Six Sigma DMAIC process.

# The first control chart
# June 6,  1924





# Illustrative Control Chart



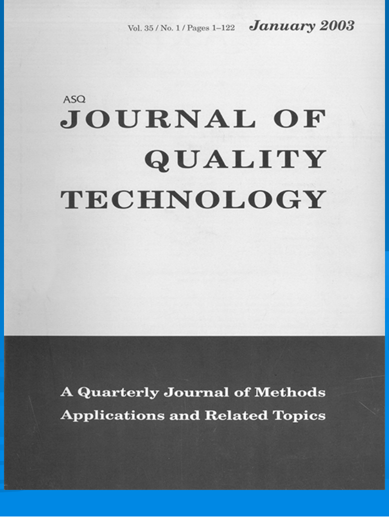
Histogram of Quality Measure with Specification Limits

# Process Monitoring

**Phase I** – Historical baseline time series data are used to characterize and understand process variation and improve the process.

A model is fitted to data and the in-control parameters estimated.

Jones-Farmer LA, Woodall WH, Steiner SH, and Champ CW. 2014. An Overview of Phase I Analysis for Process Improvement and Monitoring. *Journal of Quality Technology* 46(3), 265-280.



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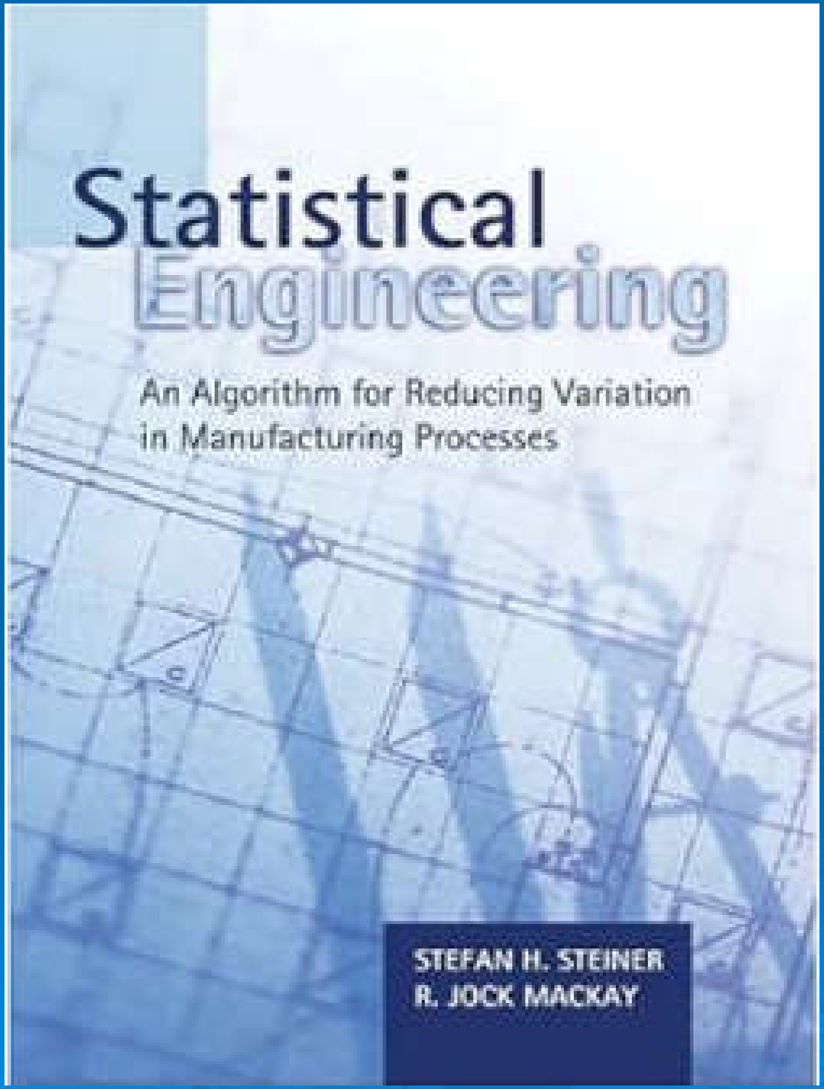


Statistical Engineering

An Algorithm for Reducing Variation in Manufacturing Processes

STEFAN H. STEINER
R. JOCK MACKAY

# Phase II – Data are collected sequentially and changes from the baseline model are to be detected.

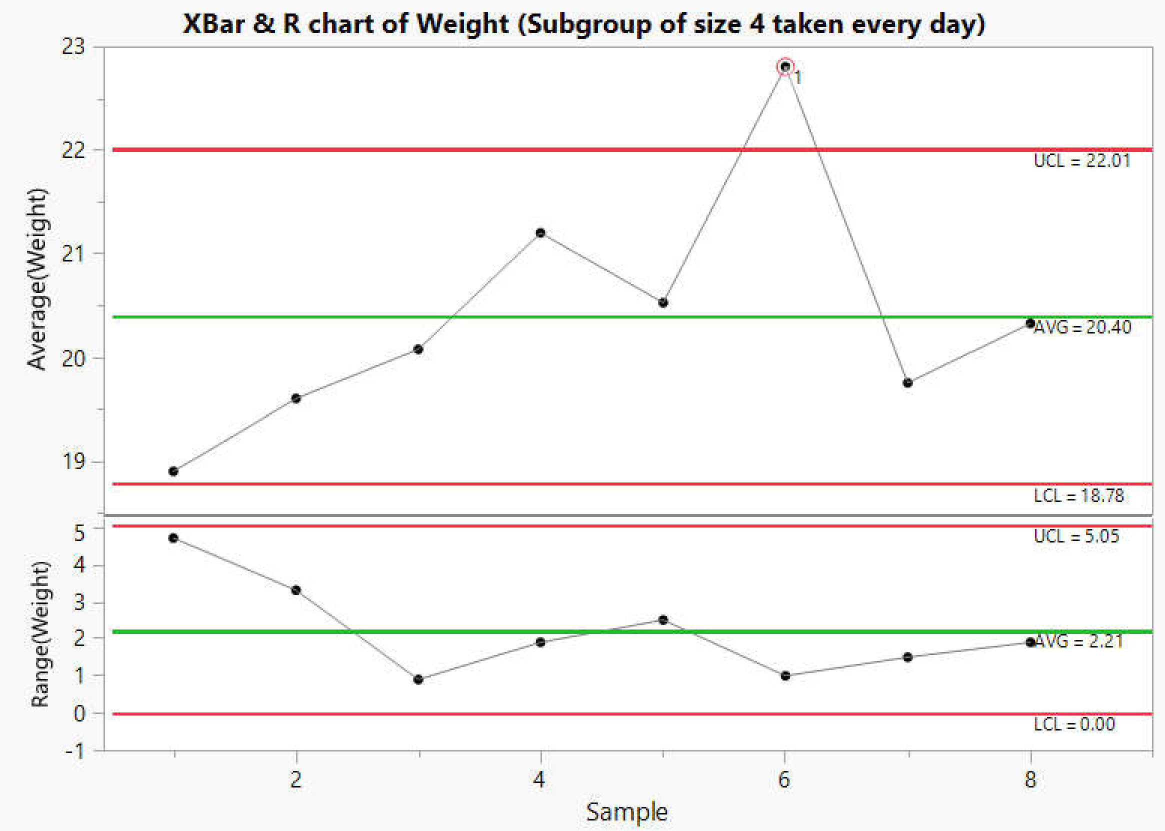
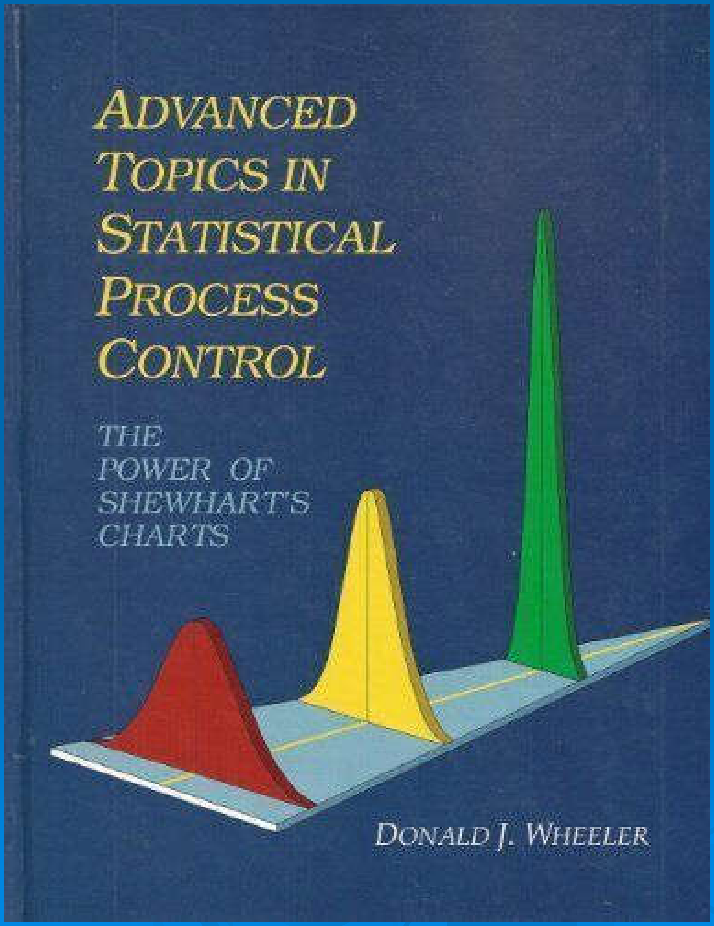


Figure 2: Shewhart X-bar and R charts

# The basic Shewhart X-bar chart allows only one component of variation. Sometimes we need a three-way chart.

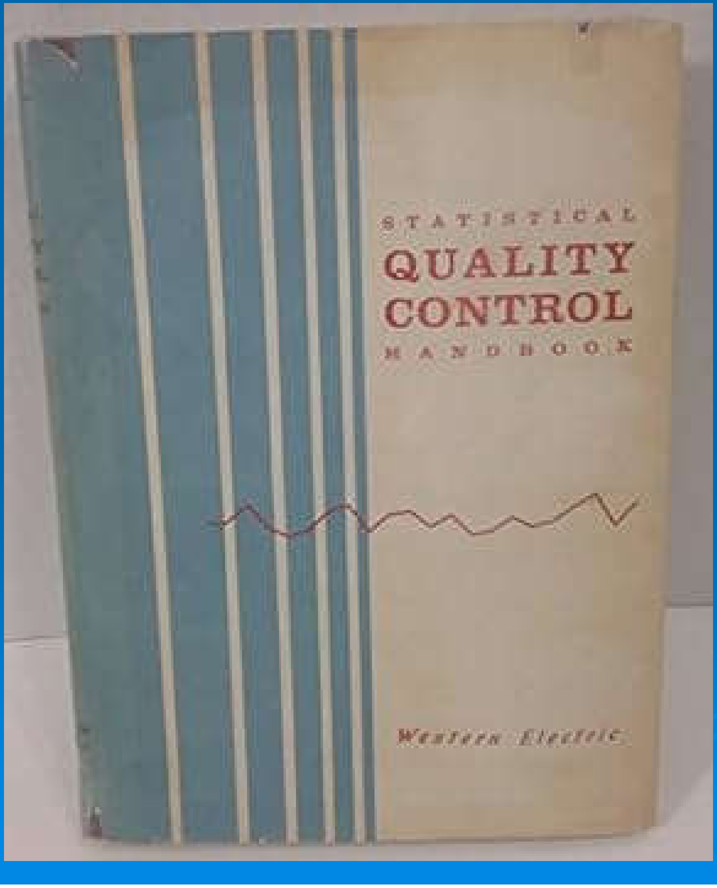


ADVANCED
TOPICS IN
STATISTICAL
PROCESS
CONTROL

THE
POWER OF
SHEWHART'S
CHARTS

DONALD J. WHEELER

# Sometimes we need to incorporate an influential covariate.



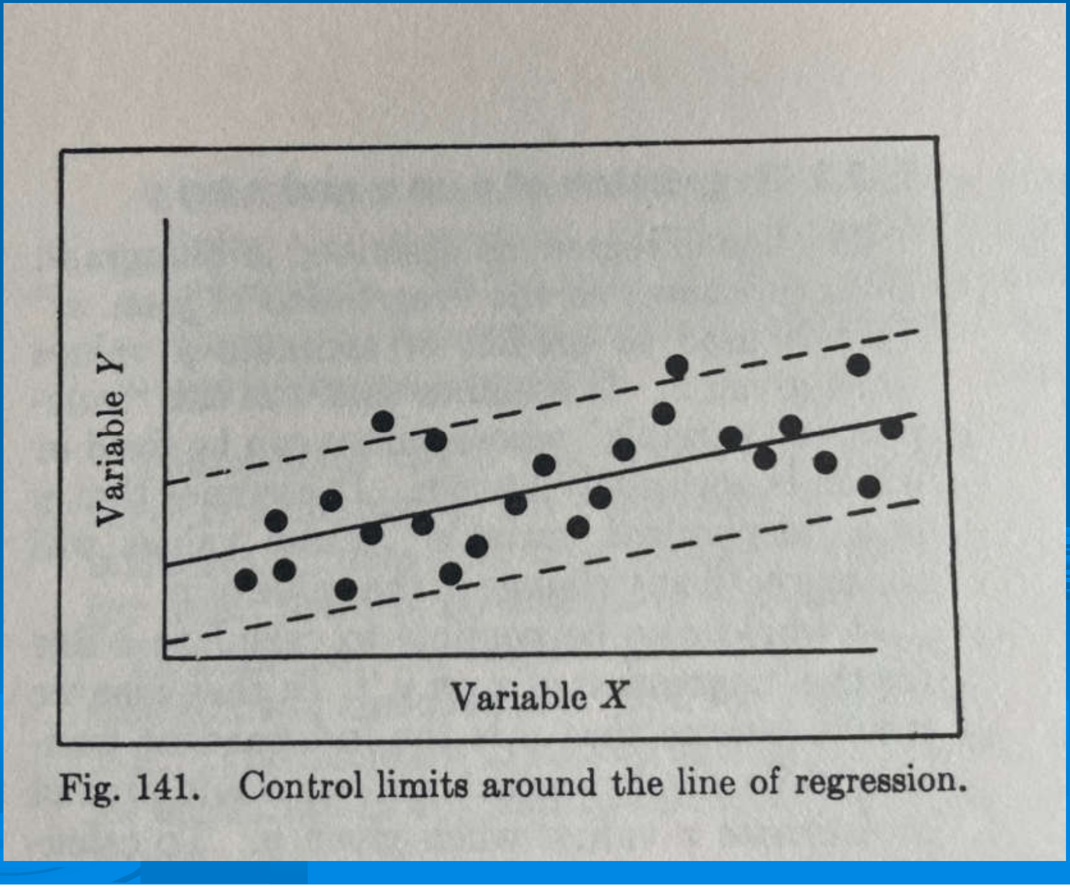
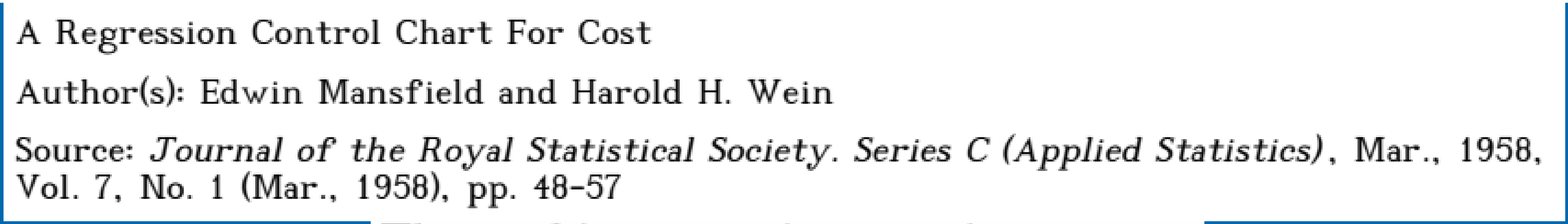


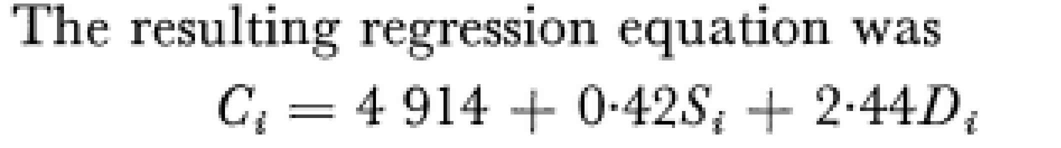
Fig. 141. Control limits around the line of regression.



A Regression Control Chart For Cost

Author(s): Edwin Mansfield and Harold H. Wein

Source: *Journal of the Royal Statistical Society. Series C (Applied Statistics)*, Mar., 1958, Vol. 7, No. 1 (Mar., 1958), pp. 48-57



The resulting regression equation was

$$C_i = 4\,914 + 0{\cdot}42S_i + 2{\cdot}44D_i$$

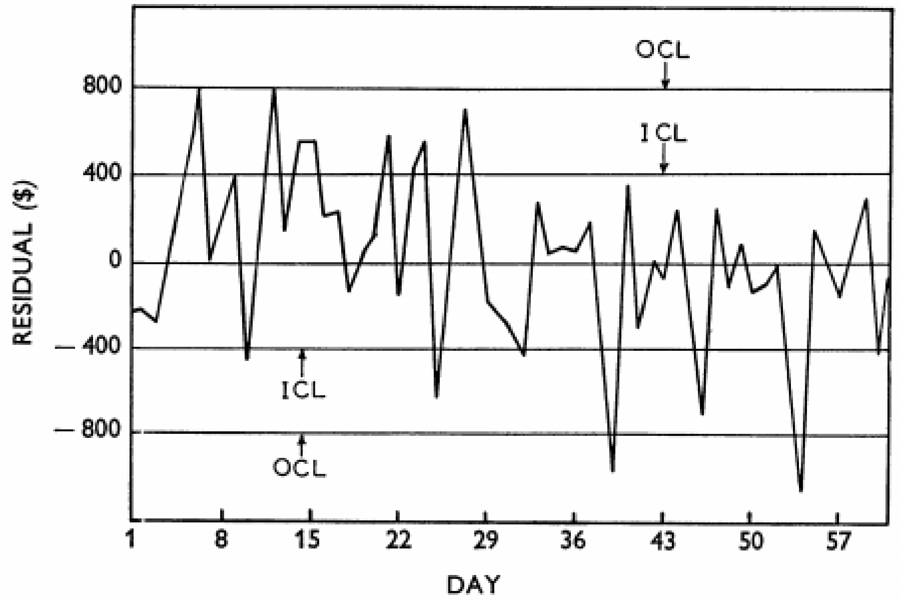
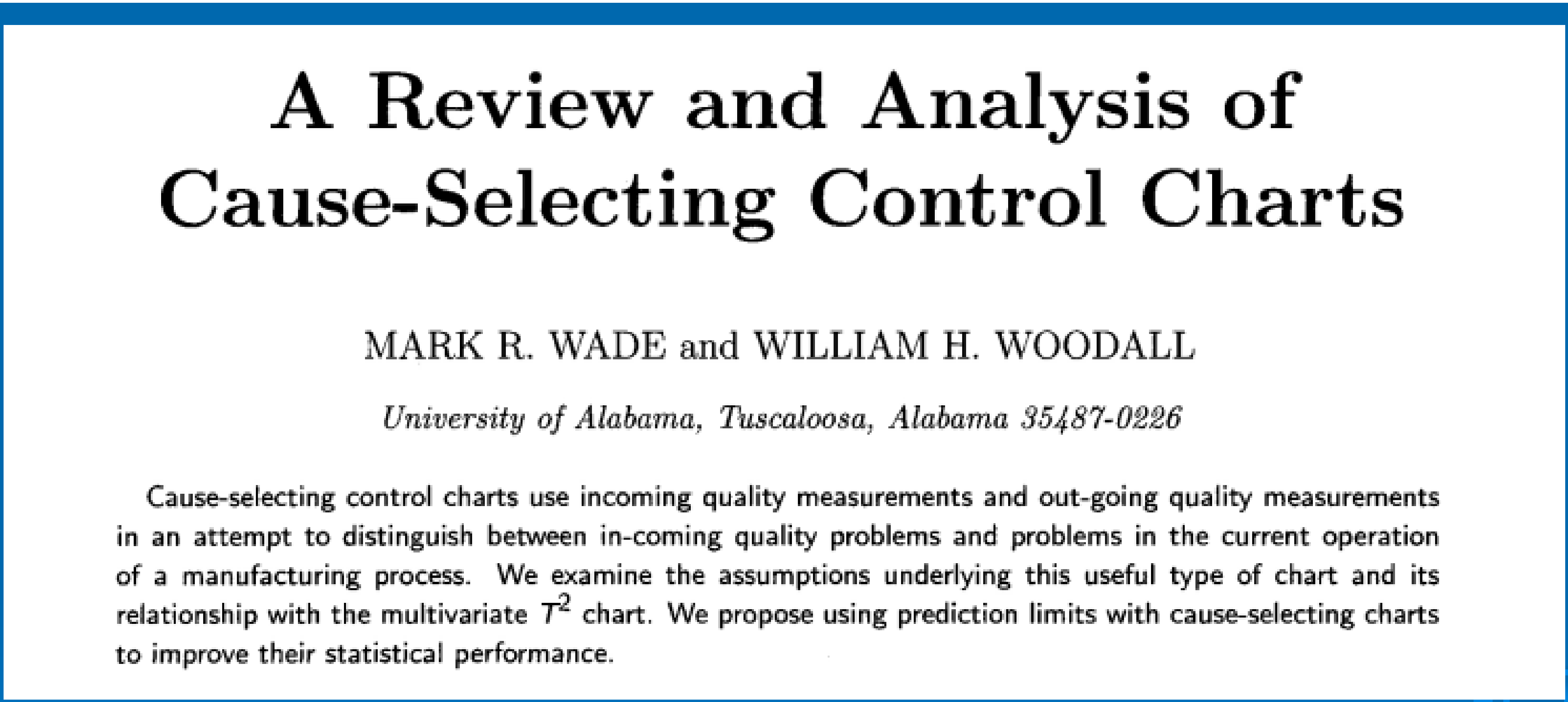


Fig. 1. Residuals from regression of cost on output: freight yard, 61 days, 1956. (Source: records of co-operating railroad.)

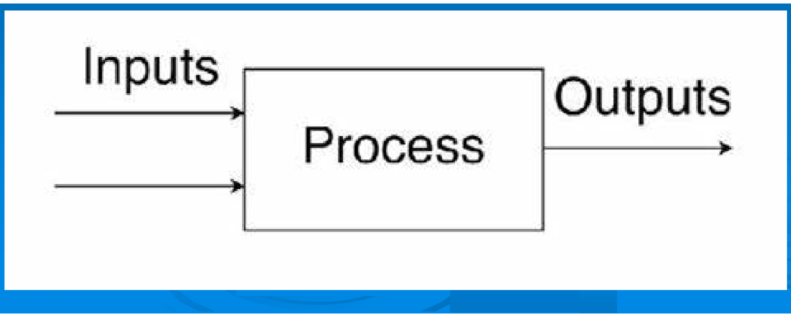


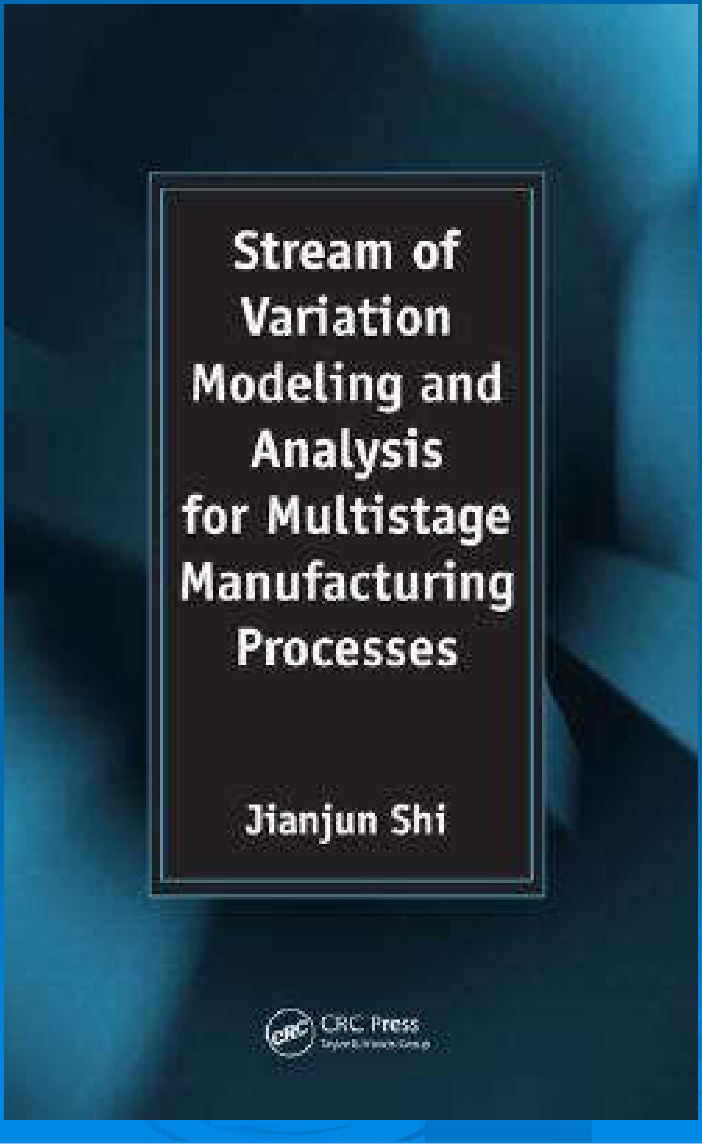
# A Review and Analysis of Cause-Selecting Control Charts

MARK R. WADE and WILLIAM H. WOODALL

*University of Alabama, Tuscaloosa, Alabama 35487-0226*

Cause-selecting control charts use incoming quality measurements and out-going quality measurements in an attempt to distinguish between in-coming quality problems and problems in the current operation of a manufacturing process. We examine the assumptions underlying this useful type of chart and its relationship with the multivariate $T^2$ chart. We propose using prediction limits with cause-selecting charts to improve their statistical performance.





Stream of
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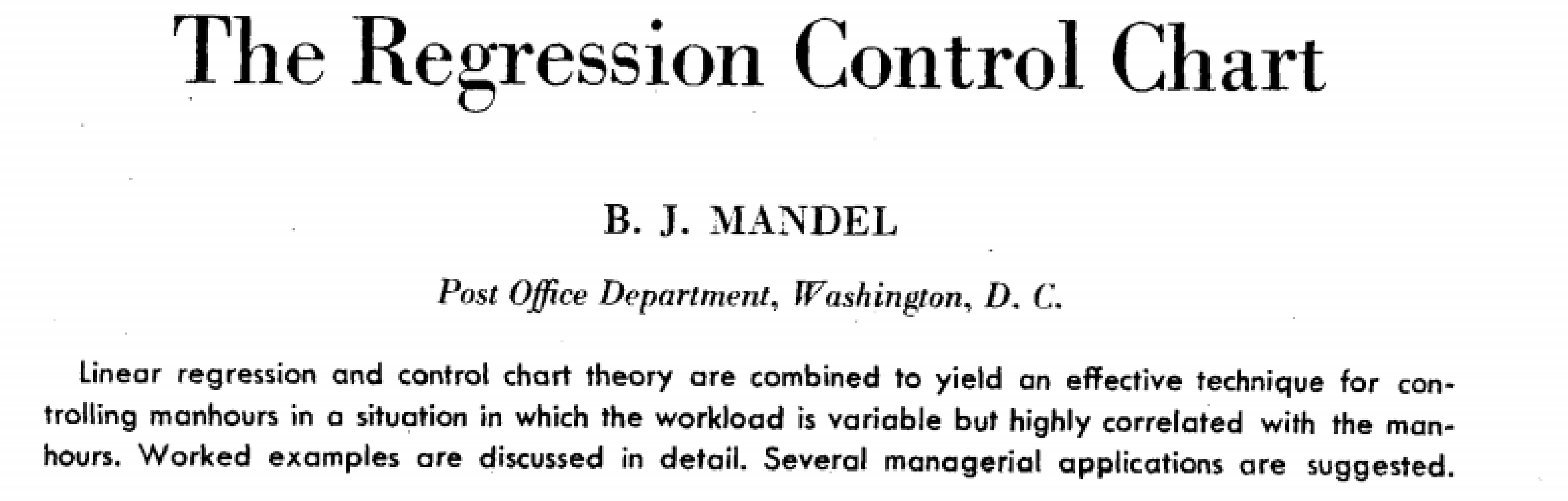
Modeling and
Analysis
for Multistage
Manufacturing
Processes

Jianjun Shi

CRC Press



# The Regression Control Chart

B. J. MANDEL

*Post Office Department, Washington, D. C.*

Linear regression and control chart theory are combined to yield an effective technique for controlling manhours in a situation in which the workload is variable but highly correlated with the manhours. Worked examples are discussed in detail. Several managerial applications are suggested.

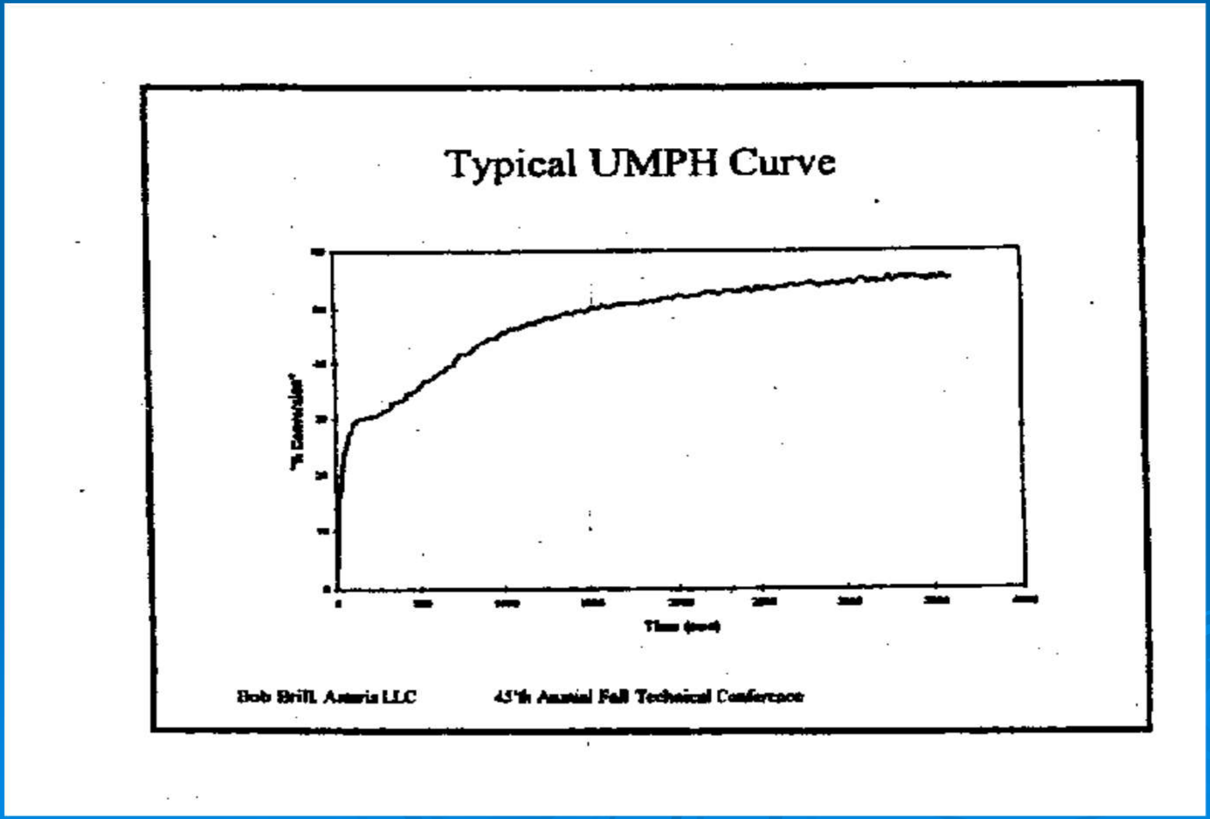
# Profile Monitoring

**If we have enough data, we can monitor the function itself over time.**

## Using Control Charts to Monitor Process and Product Quality Profiles

WILLIAM H. WOODALL and DAN J. SPITZNER
*Virginia Tech, Blacksburg, VA 24061-0439*
DOUGLAS C. MONTGOMERY and SHILPA GUPTA
*Arizona State University, Tempe, AZ 85287-5906*

**Brill RV (2001). “A Case Study for Control Charting a Product Quality Measure That is a Continuous Function Over Time”. Presentation at the 45th Annual Fall Technical Conference, Toronto, Ontario.**

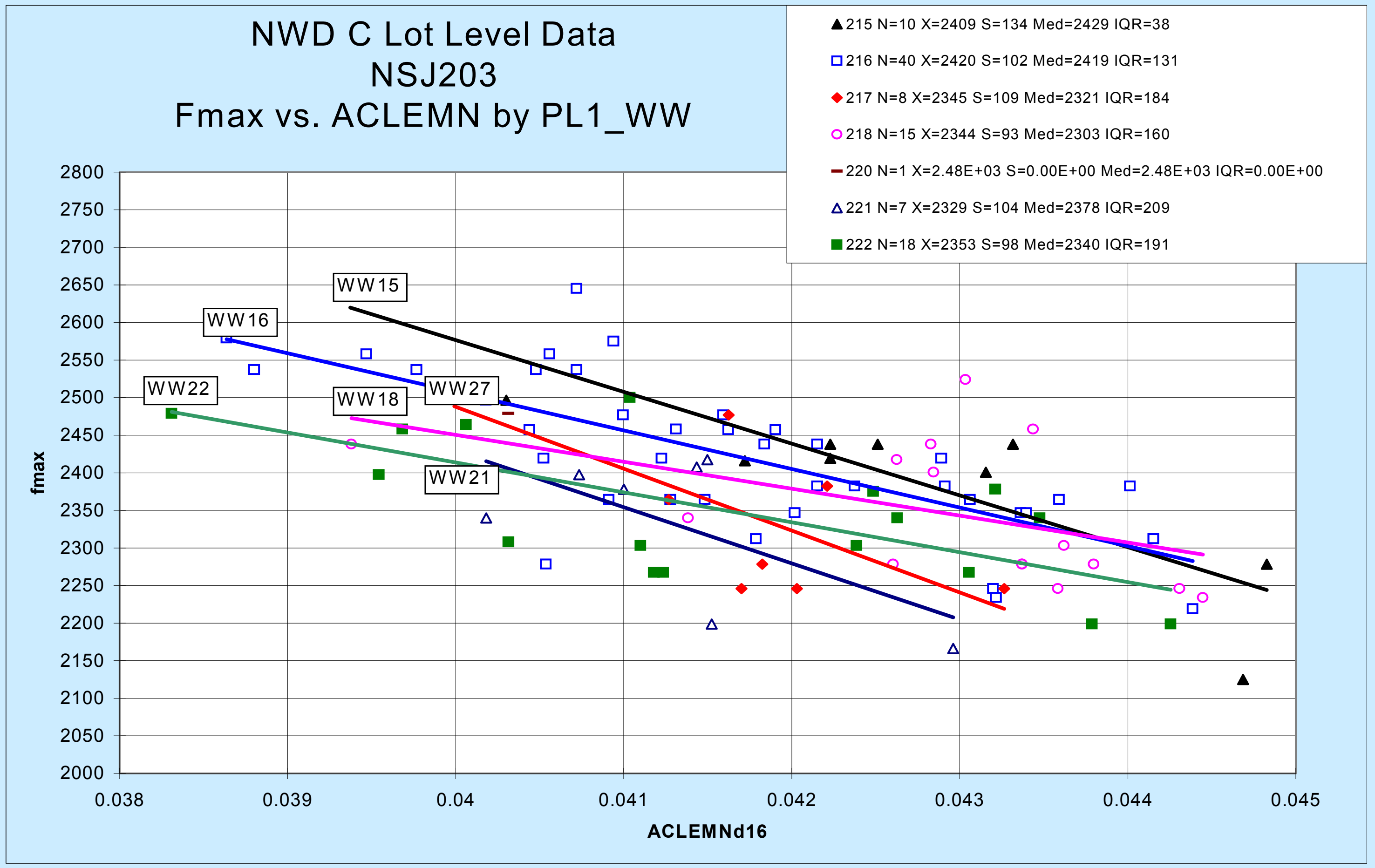


Typical UMPH Curve

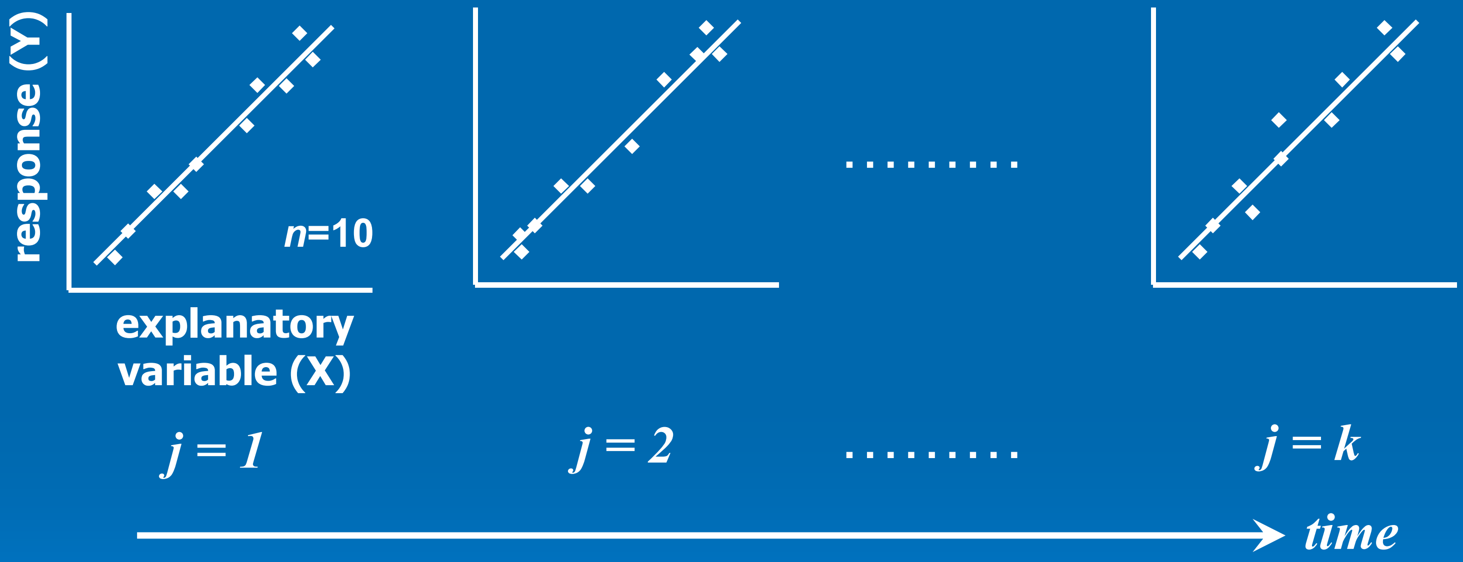
Bob Brill, Asteria LLC 45'th Annual Fall Technical Conference

# Profile Monitoring

## Example: Semiconductor Manufacturing (from Vivek Ajmani)



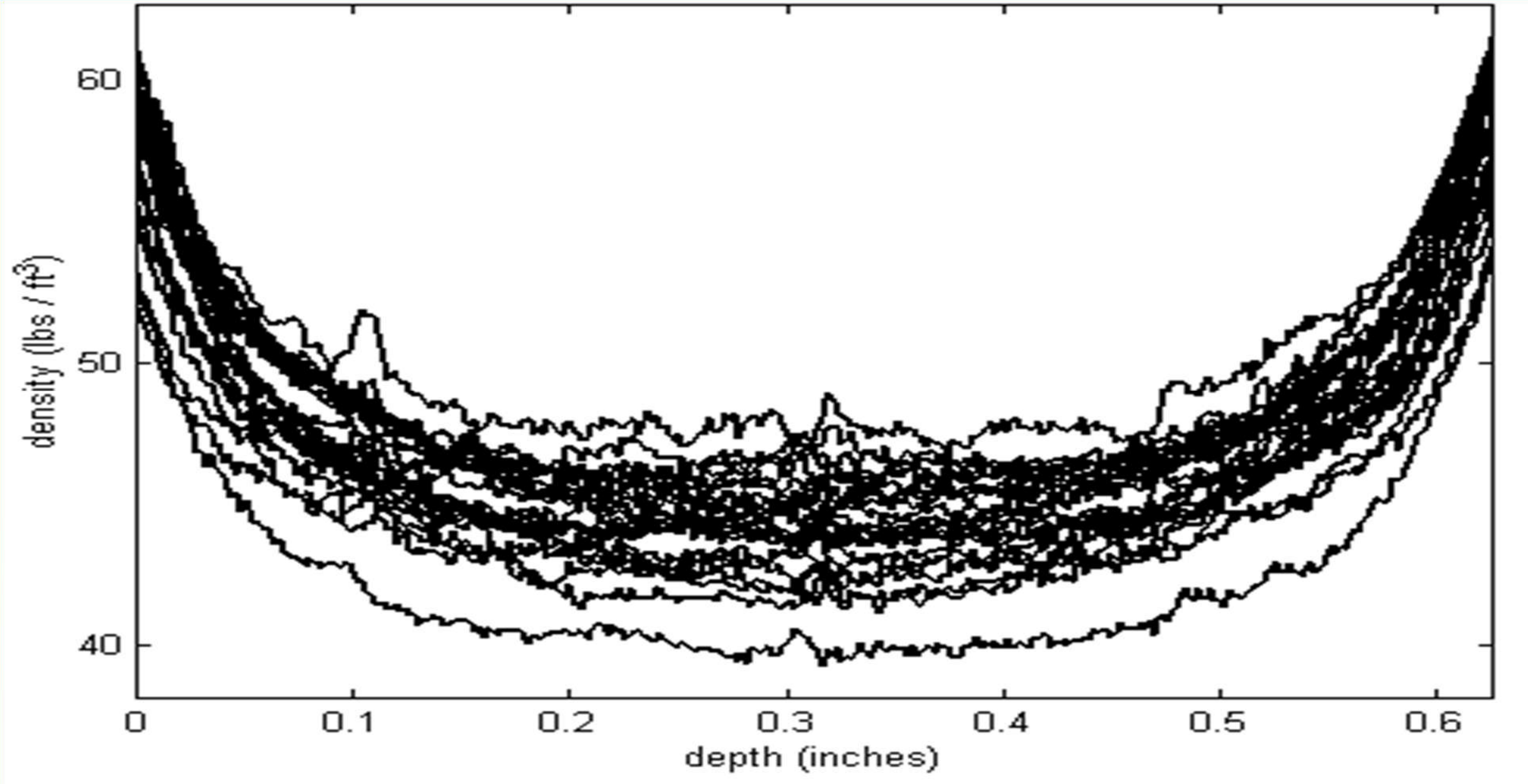
# Linear Profile Data Framework



$j = 1,2,\ldots,k$ **sample profiles with $n$>1 observations in each profile**

# Example: Board Vertical Density Profile Data from Walker and Wright (*JQT*, 2002)

**We have 24 profiles of vertical density, each profile consists of *n* =314 measurements.**



# Example: Another density profile

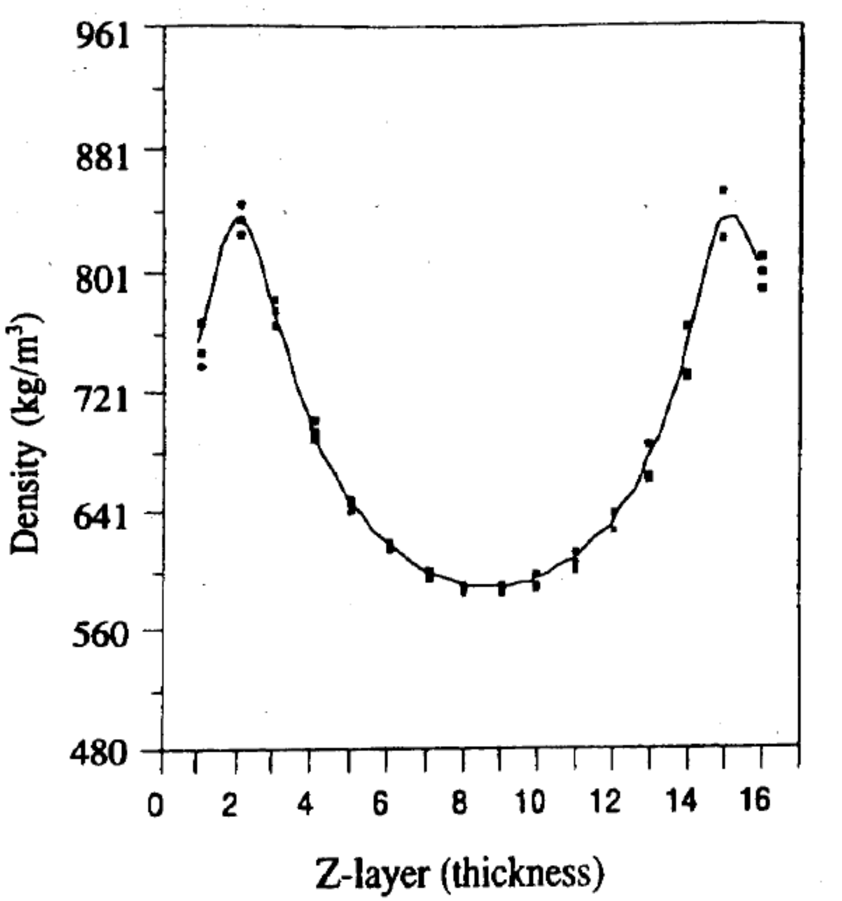
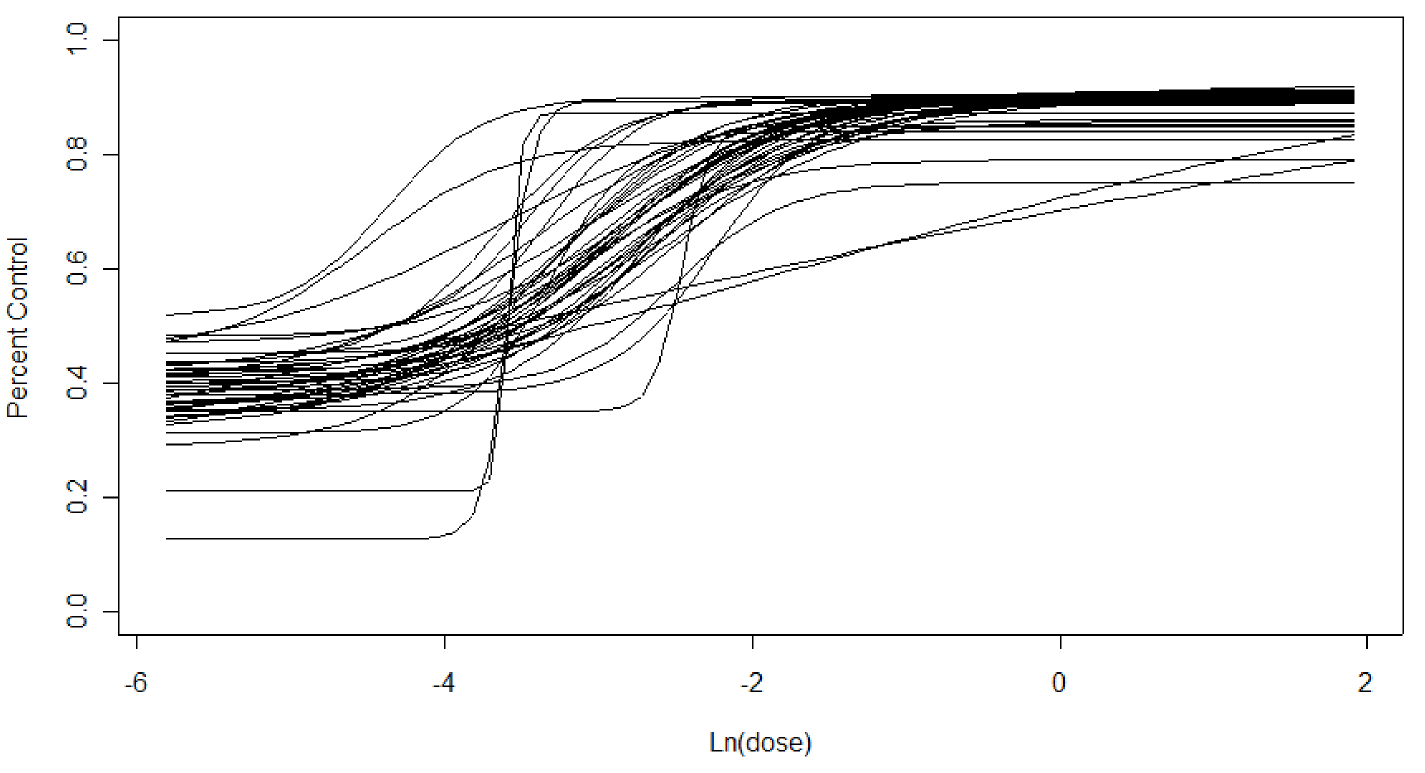
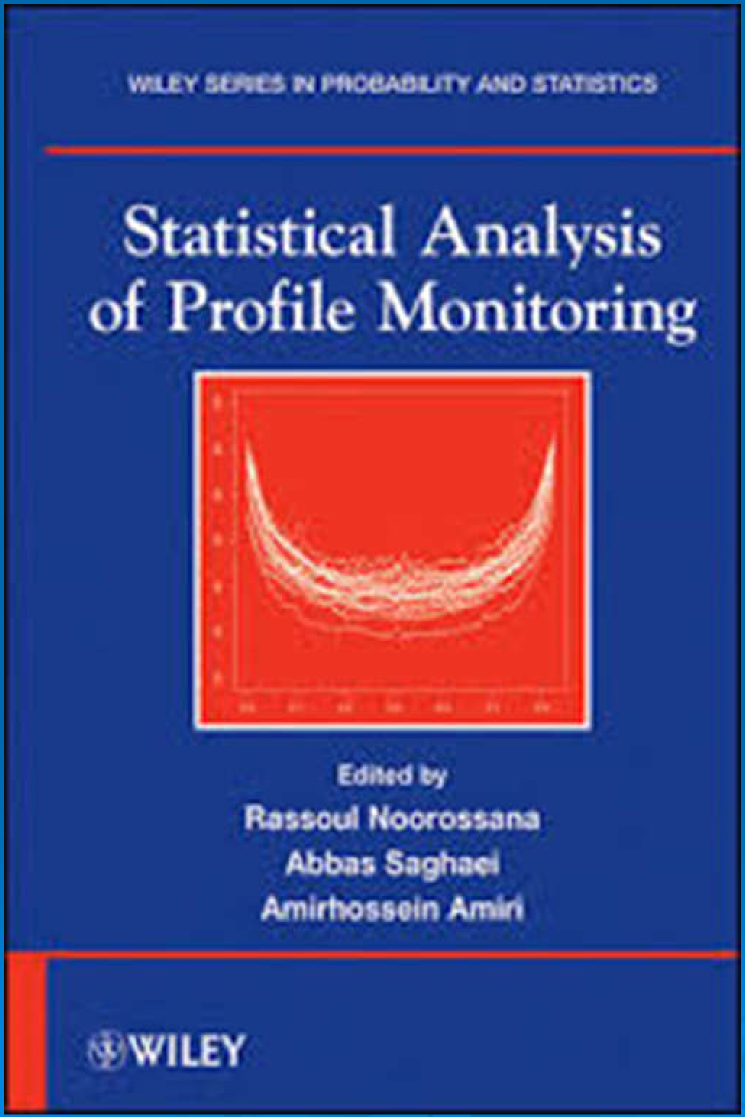


FIG. 3. Spline estimate for mean density (kg/m$^3$) across panel $Z$-layers for 8% furnish moisture content treatment.

# Example: Dose-Response Profile of a Drug (DuPont)





WILEY SERIES IN PROBABILITY AND STATISTICS

# Statistical Analysis of Profile Monitoring

Edited by
Rassoul Noorossana
Abbas Saghaei
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Sometimes control charts are too sensitive. As Freund (1960, *IQC*) wrote:

*Many assignable causes produce effects that are real, but small and unimportant. In fact, it is often completely uneconomical to detect these effects, much less worry about how to correct them.*

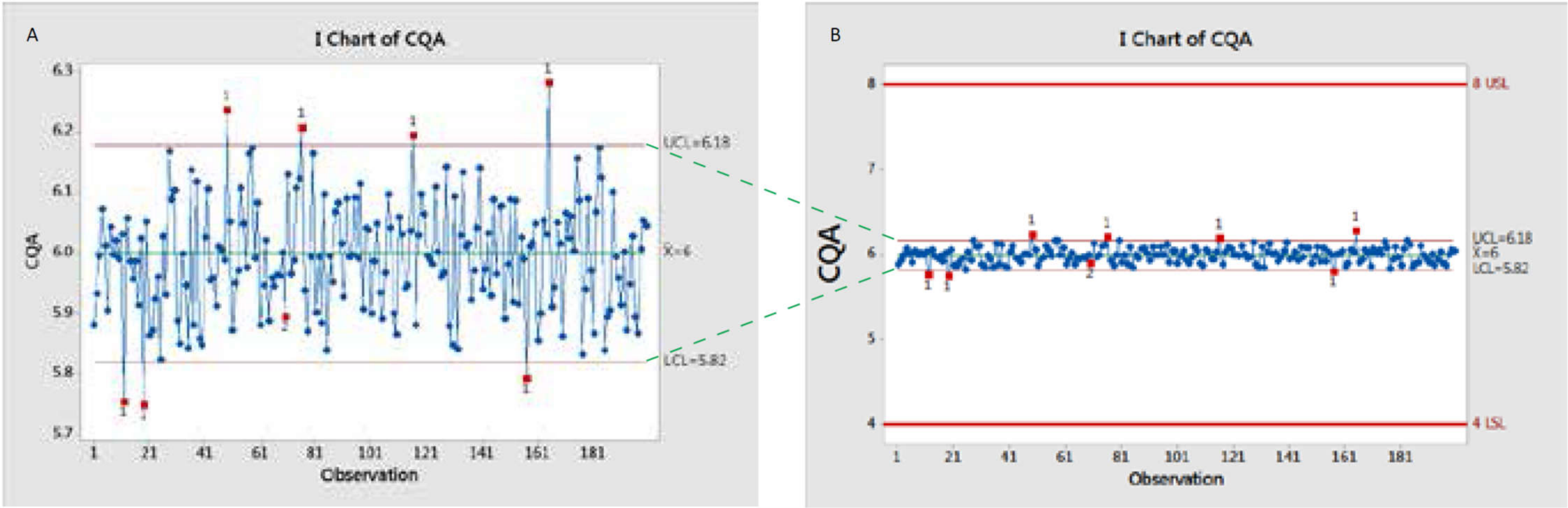
# Some consequences of false and nuisance alarms

With too many such alarms, the monitoring is ignored or abandoned.

Adjusting a process unnecessarily increases variation.

Investigations of such alarms cost time and money.

One can be distracted from more important problems.



**An I-Chart shown without (left) and with (right) plotted specification limits.** **(Reproduced from Crichton and Faltin, *Pharmaceutical Engineering*, 2018)**

# Solution: Increase width of Shewhart chart limits (an acceptance control chart) or increase the reference value of a cumulative sum (CUSUM) chart.

Taylor & Francis
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Quality Engineering

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Rethinking control chart design and evaluation

William H. Woodall & Frederick W. Faltin

# Industry 4.0 is characterized by

- Use of sensor technology in multistage processes
- High dimensional data (Volume)
- High and varied sampling frequencies (Velocity)
- Use of process and quality data in many forms (Variety)
- Complicated relationships among variables
- Monitoring, diagnosis, root cause determination
- Necessity of AI and machine learning methods (see, e.g., processminer.com)

Colosimo BM, Jones-Farmer LA, Megahed, FM, Paynabar K, Ranjan C, and Woodall WH (2024). “Statistical Process Monitoring from Industry 2.0 to Industry 4.0: Insights into Research and Practice.” To appear in *Technometrics*.

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American Statistical Association

# Some other process monitoring applications:

- Public health surveillance
- Monitoring surgical outcomes
- Monitoring shapes and surfaces
- Monitoring social network communications
- Monitoring machine learning algorithms
- Personalized health monitoring

# Conclusions

- SPM methods evolved in order to handle changes in the amount and types of available data in Industry 3.0.
- SPM methods will need much more development in Industry 4.0. In some cases machine learning and AI will be needed. See processminer.com.
- Academic/industry cooperation is increasingly important.