The State of Statistical Process Control: An Update

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1949

Stoumbos ZG, Reynolds MR Jr, Ryan TP, and Woodall WH (2000), "The State of Statistical Process Control as We Proceed into the 21st Century," *JASA*, 95(451), 992-998.

Zachary Stoumbos
1993 VT Ph.D.
2007 ASA Fellow

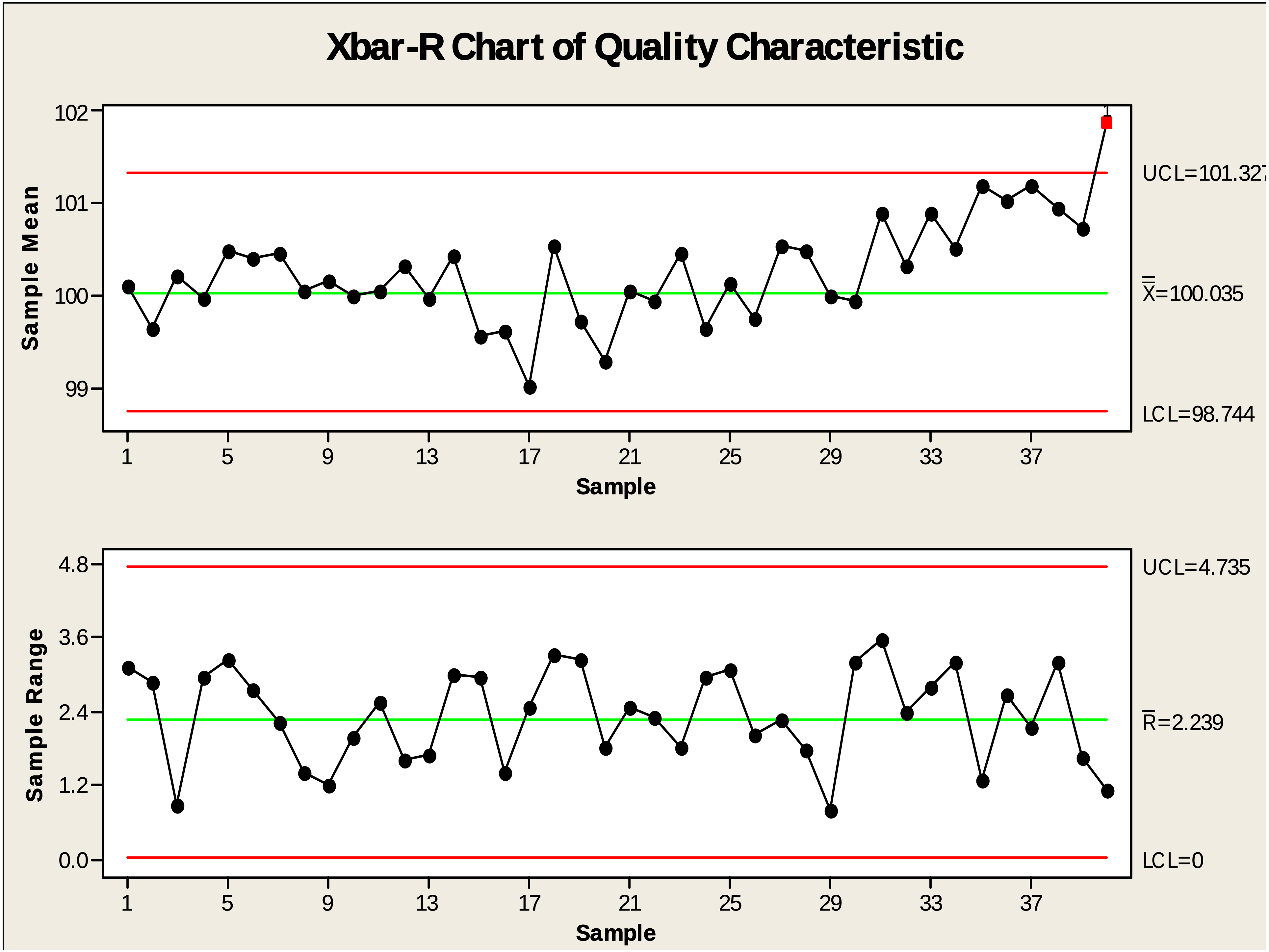
Topics

- Brief introduction
- Profile monitoring
- Health-related surveillance
- Contrasts between industrial and health-related surveillance
- Other areas of research and application

Keys Aspects of Statistical Process Monitoring

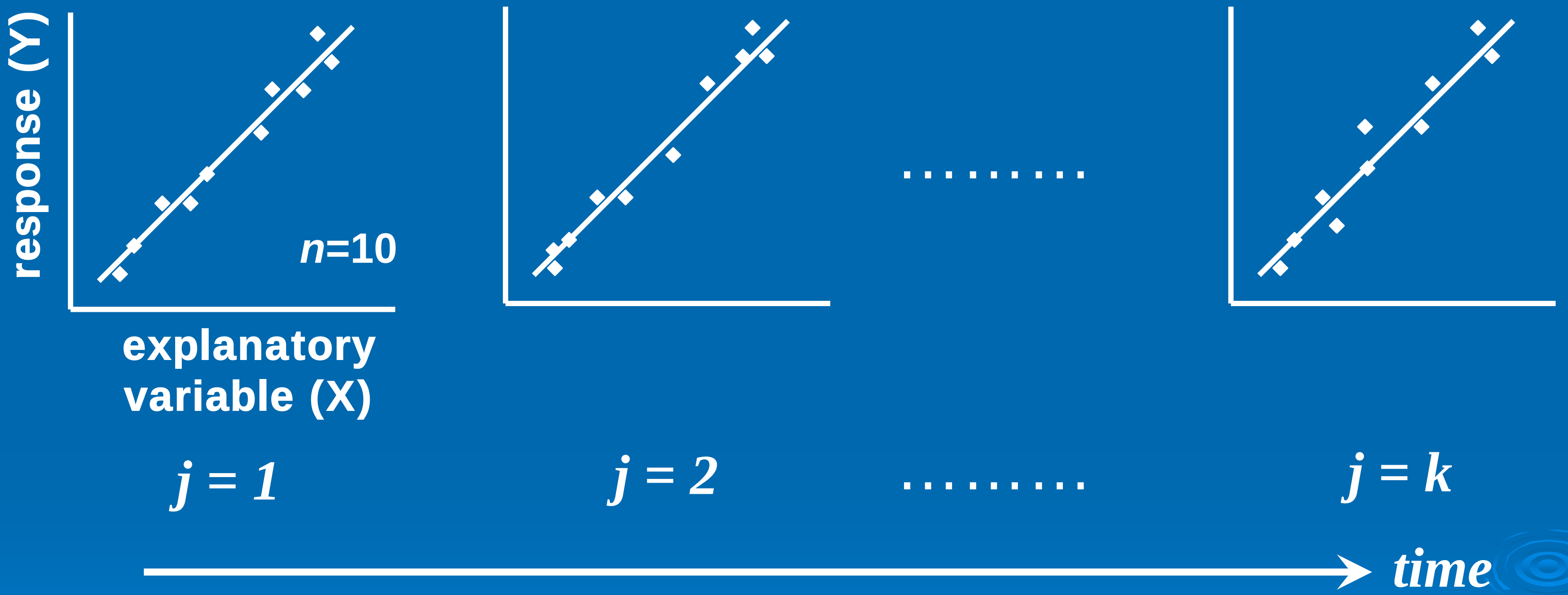
1. **Data are collected over time.**
2. **Shifts in parameters of underlying models are to be detected as quickly as possible.**
3. **A “signal” is given that a change from the baseline has occurred.**

4. **One wants to control the “false alarm rate”.**


Xbar-R Chart of Quality Characteristic
Sample Mean
102
101
100
99
UCL=101.327
X̿=100.035
LCL=98.744
1
5
9
13
17
21
25
29
33
37
Sample
Sample Range
4.8
3.6
2.4
1.2
0.0
UCL=4.735
R̄=2.239
LCL=0
1
5
9
13
17
21
25
29
33
37
Sample

Profile Monitoring: The objective is to monitor functional data over time.

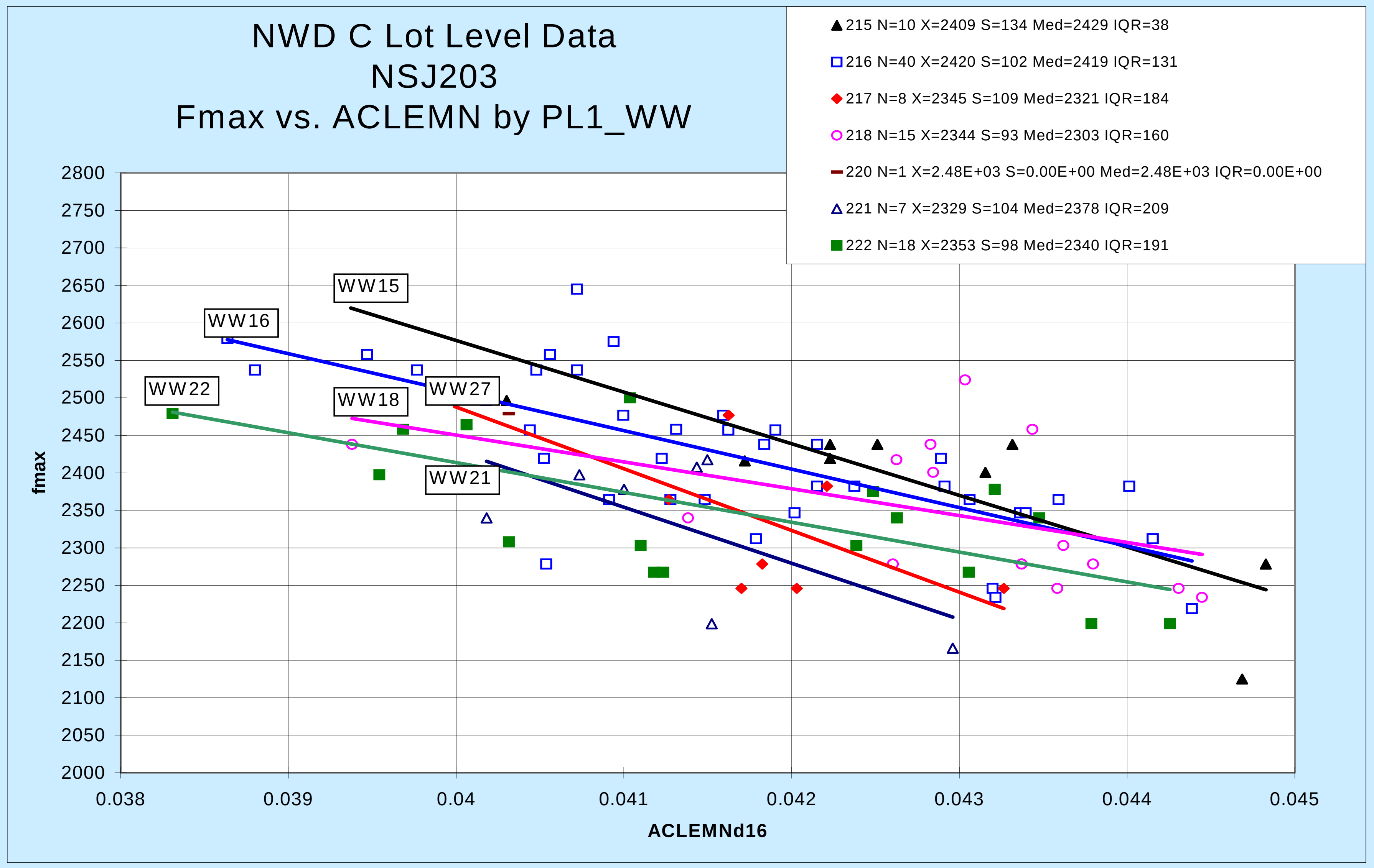
Linear Profile Data Framework:



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

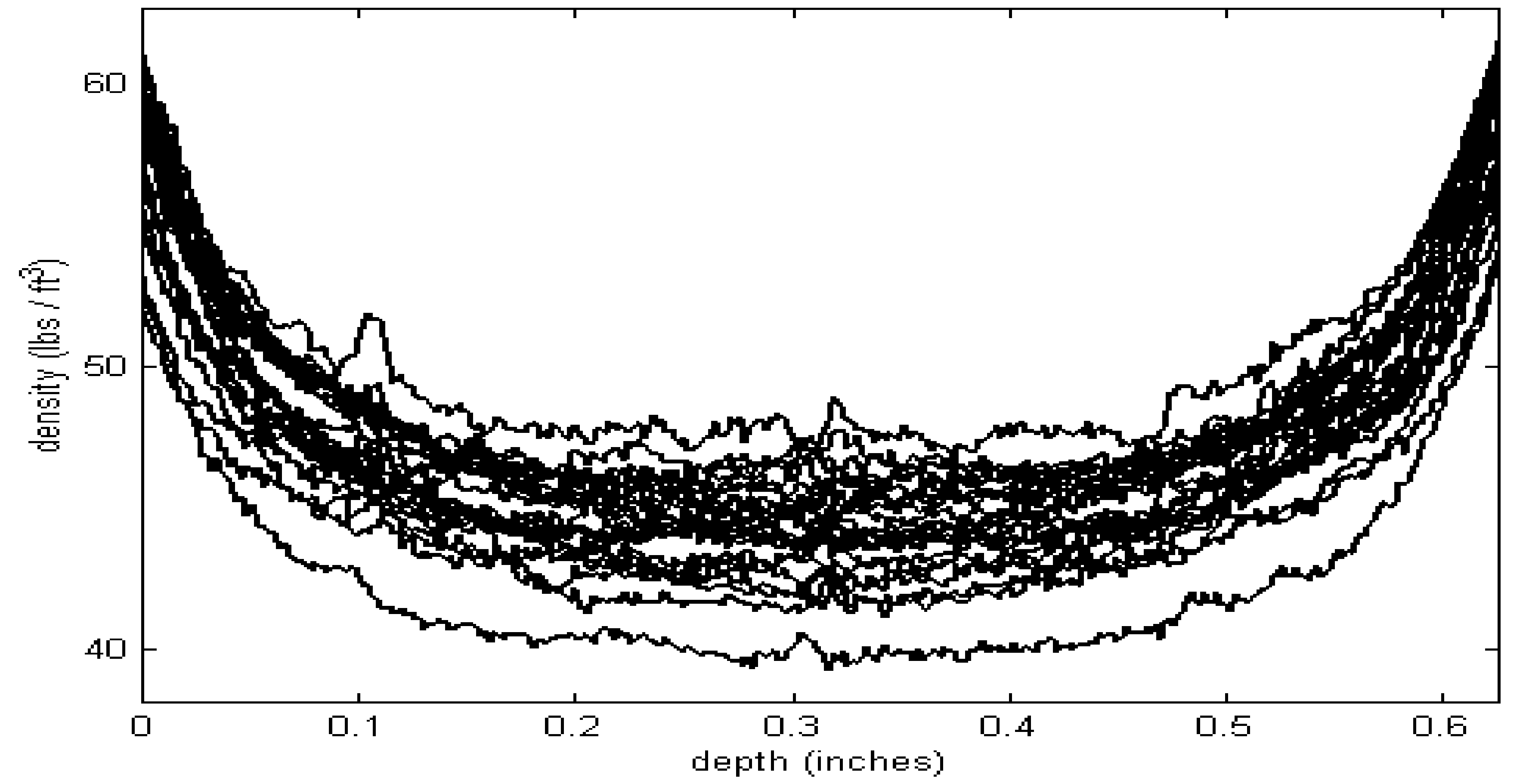
Profile Monitoring

Example 1: Semiconductor Manufacturing (from Vivek Ajmani)



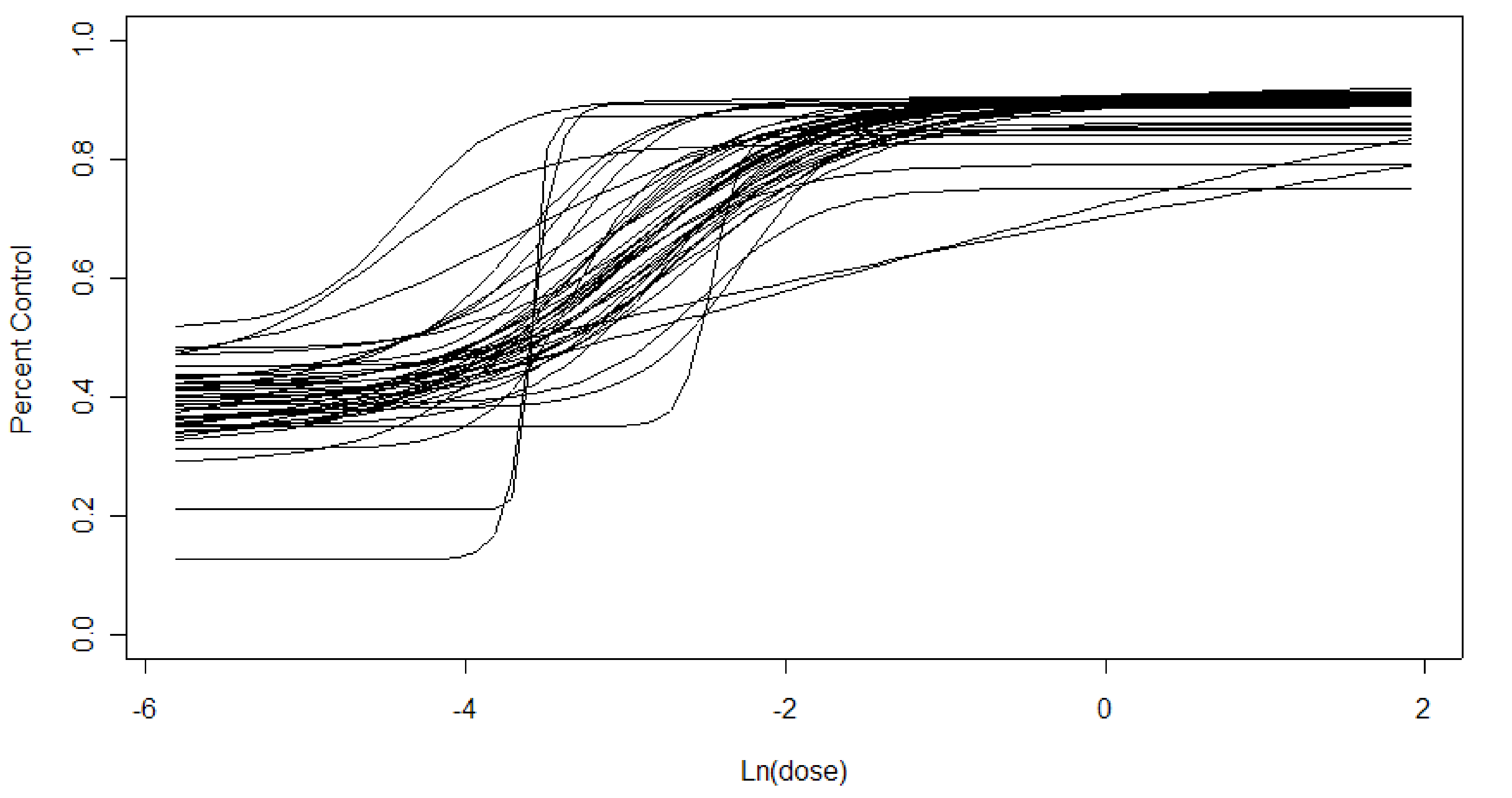
Example 2: Vertical Board Density Profile Data from Walker and Wright (*JQT*, 2002)

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

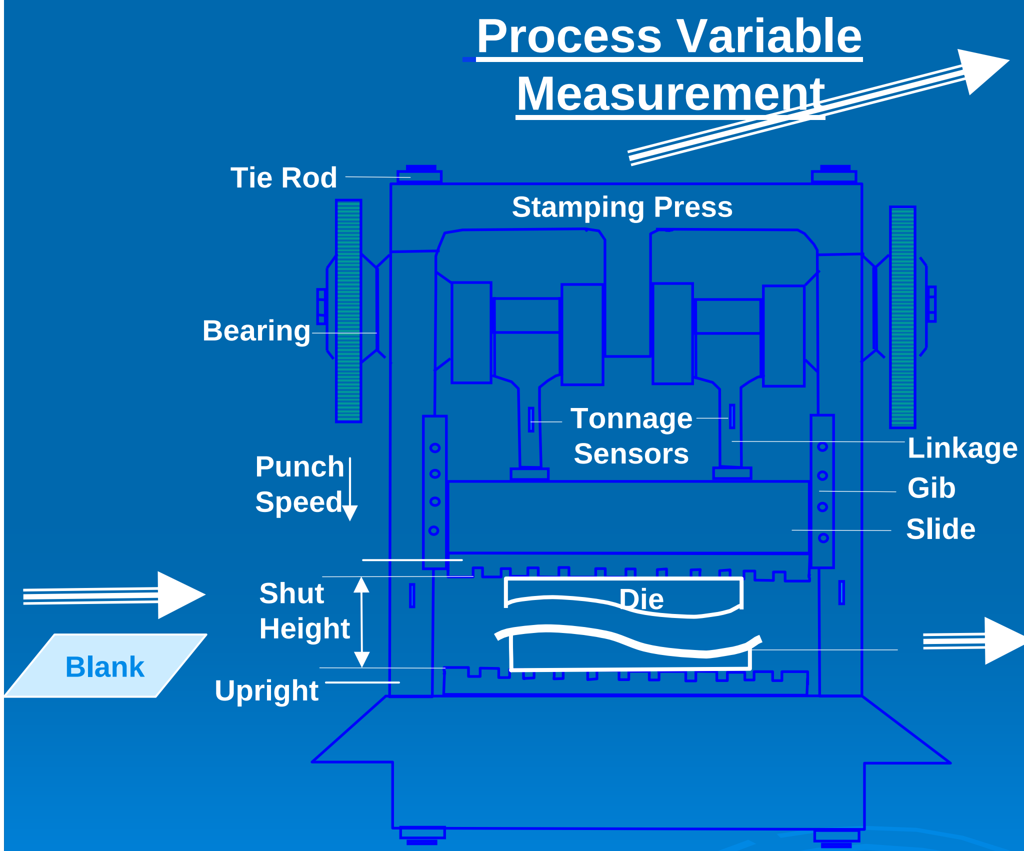


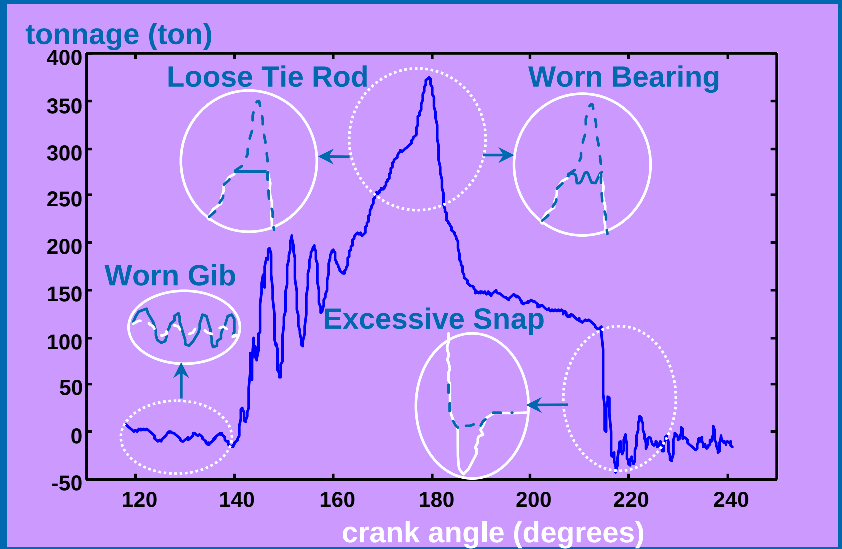
Profile Monitoring

Example 3: Fitted Dose-Response Profiles of a Chemical (DuPont)

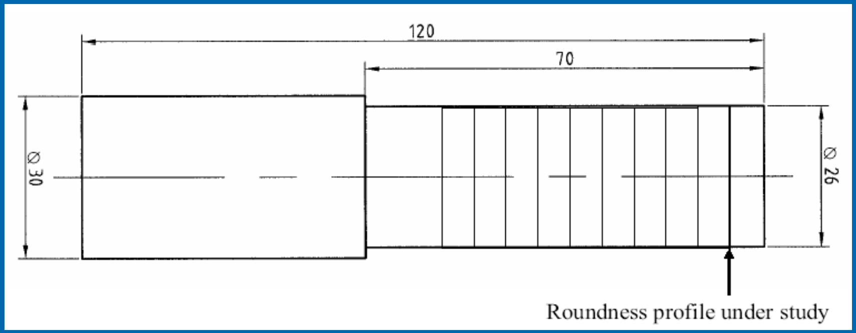


Example 4: Signature Analysis for Stamping Process Monitoring and Diagnosis (from Jan Shi, Georgia Tech)



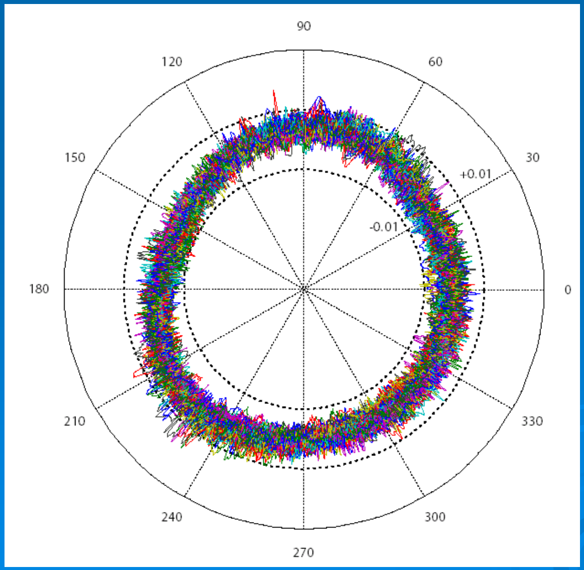


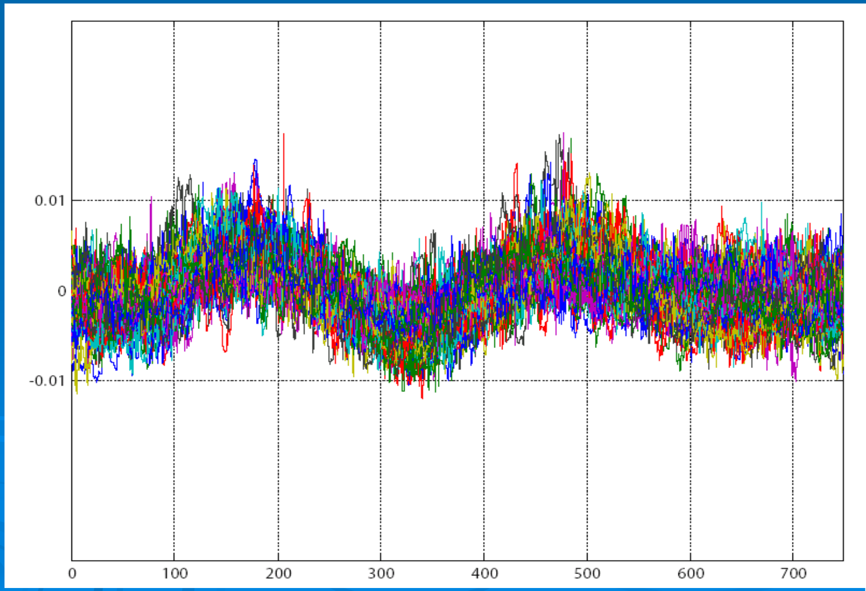
Example 5: Roundness profiles obtained by turning
(from Bianca Colosimo, Politecnico di Milano, Italy)



100 cast C20 carbon steel cylinders (supplied in Ø30 mm rolled bars) machined to nominal Ø26 mm.

Each profile was sampled 748 times by a CMM.





Applications of Profile Monitoring

- Stamping processes
- Calibration of measurement devices
- Dimensional and shape control
- Paper quality
- Spectroscopy
- Laser sensor data in lumber manufacturing
- Automobile air bag quality
- Wind turbine power curves
- Asphalt quality ……………………………

Some Models for Profiles

- Simple linear regression
- Polynomial regression
- Multiple regression
- Nonlinear regression, including logistic regression
- Mixed models
- Wavelets
- Nonparametric smoothing
- …

Review papers on Profile Monitoring

Woodall WH, Spitzner DJ, Montgomery DC, and Gupta S. (2004). "Using Control Charts to Monitor Process and Product Quality Profiles", *JQT* 36, 309-320.

Woodall WH (2007), "Current Research in Profile Monitoring", *Revista Producão* 17(3), 420-425.

Biosurveillance

Healthcare Monitoring

- **Individual patient monitoring (univariate and multivariate) See Tennant et al. (2007) *International Journal for Quality in Healthcare.***
- **Hospital and physician performance tracking (often risk-adjusted) See Thor et al. (2007) *Quality & Safety in Health Care.***

Public Health Surveillance

- **Monitoring of incidence rates (temporal and spatiotemporal, chronic disease and infectious disease)**
- **Syndromic surveillance – involves use of multiple dissimilar data streams to detect outbreaks or attacks**

Examples of health care variables

- Lab turnaround time
- Days from positive mammogram to definitive biopsy
- Patient satisfaction scores
- Medication error counts
- Emergency service response times
- Infection rates
- Mortality rates
- Number of patient falls
- Post-operative length of stay
- “Door-to-needle” time ……and many others…

Risk adjustment is most often necessary in comparing rates between hospitals and doctors due to differences in patient mix, i.e., varying health risk factors of patients.

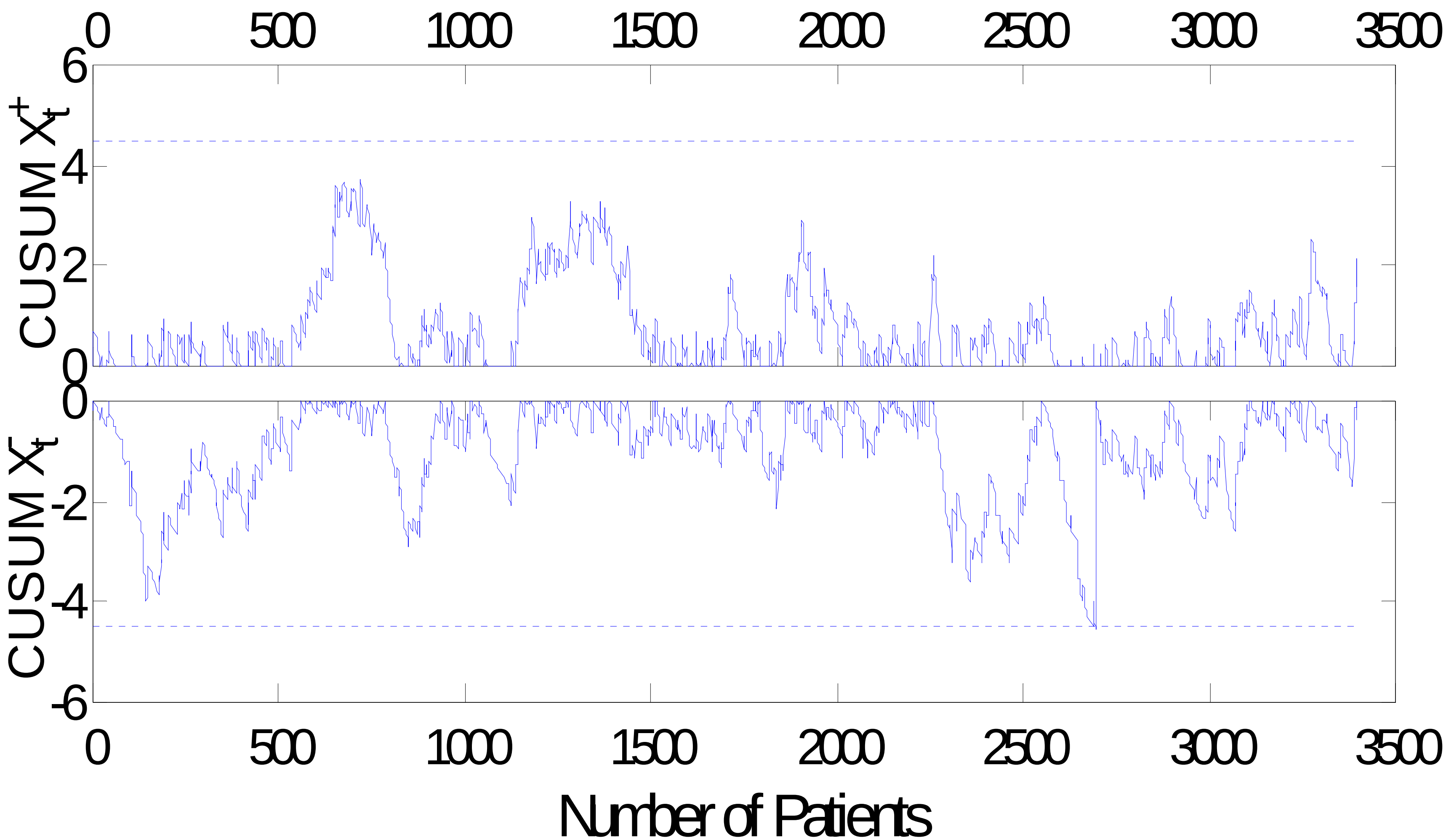
See http://www.sfar.org/t/spip.php?article60 for information on various ICU and surgical risk scoring methods.

Table 1 Parsonnet risk factors[7]*

Parsonnet factor	Weight (%)
Patient factors	
Female sex	1
Left ventricular ejection fraction 30-49%	2
Preoperative balloon pump	2
Weight ⩾1.5 times ideal	3
Diabetes	3
Hypertension (systolic pressure >140 mm Hg)	3
Left ventricular ejection fraction <30%	4
Age 70-74	7
Dependent on dialysis	10
Emergency due to failure in cardiac catheter laboratory†	10
Age 75-79	12
Age ⩾80	20
Catastrophic state	30
Procedural factors	
CABG at time of valve surgery	2
Valve replacement:	
Tricuspid valve	3
Aortic valve (gradient ⩽120 mm Hg)	5
Mitral valve (PASP <60 mm Hg)	5
Congenital heart disease	5
Left ventricular aneurysm	5
First reoperation	5
Valve replacement:	
Aortic valve (gradient >120 mm Hg)	7
Mitral valve (PASP ⩾60 mm Hg)	8
Second or subsequent reoperation	10
Heart transplantation	15

CABG=coronary artery bypass grafting. PASP=pulmonary artery systolic pressure.
*Add all weights that apply to patient and type of operation—for example, female patient having tricuspid valve replacement has estimated risk of 1+3= 4%.
†For example, cardiac perforation.

http://www.sfar.org/scores2/parsonnet2.html



Example of a two-sided risk-adjusted CUSUM chart (provided by Stefan H. Steiner)

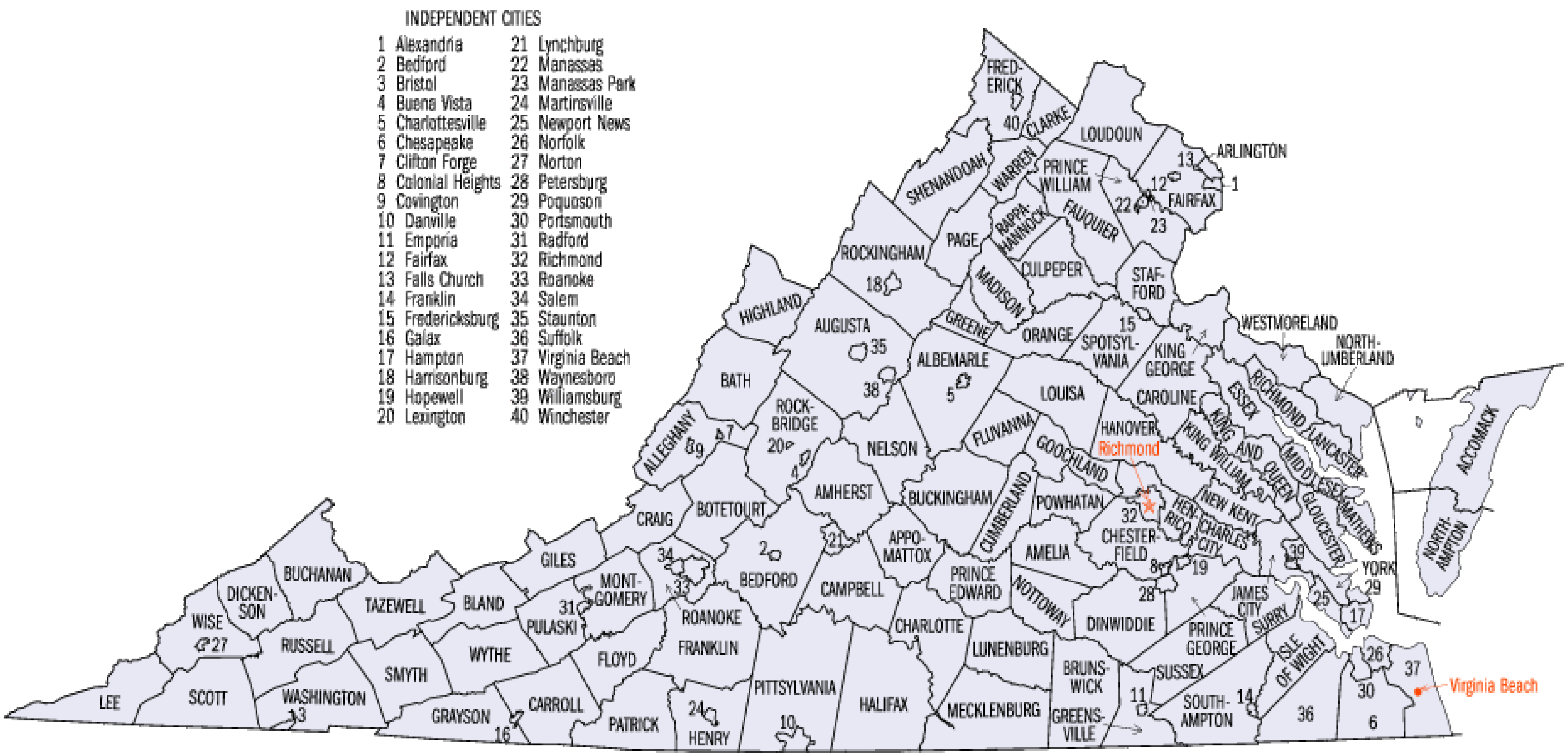
The CUSUM chart is the best option.

- It can be risk-adjusted.
- It has optimality properties in detecting sustained shifts in the process.
- It has good inertial properties.
- It can be designed based on meaningful performance measures such as average run length (ARL).
- It can be run in the background with a more interpretable chart if necessary.

Cluster Detection in Public Health Surveillance

There are some new methods for detecting clusters prospectively, i.e., as they are forming with spatiotemporal data.

This is a very challenging problem.


INDEPENDENT CITIES
1 Alexandria
2 Bedford
3 Bristol
4 Buena Vista
5 Charlottesville
6 Chesapeake
7 Clifton Forge
8 Colonial Heights
9 Covington
10 Danville
11 Emporia
12 Fairfax
13 Falls Church
14 Franklin
15 Fredericksburg
16 Galax
17 Hampton
18 Harrisonburg
19 Hopewell
20 Lexington
21 Lynchburg
22 Manassas
23 Manassas Park
24 Martinsville
25 Newport News
26 Norfolk
27 Norton
28 Petersburg
29 Poquoson
30 Portsmouth
31 Radford
32 Richmond
33 Roanoke
34 Salem
35 Staunton
36 Suffolk
37 Virginia Beach
38 Waynesboro
39 Williamsburg
40 Winchester
FREDERICK
CLARKE
LOUDOUN
ARLINGTON
SHENANDOAH
WARREN
PRINCE WILLIAM
FAIRFAX
RAPPAHANNOCK
FAUQUIER
ROCKINGHAM
PAGE
CULPEPER
MADISON
STAFFORD
HIGHLAND
AUGUSTA
GREENE
ORANGE
SPOTSYLVANIA
KING GEORGE
WESTMORELAND
NORTHUMBERLAND
ALBEMARLE
BATH
LOUISA
CAROLINE
ESSEX
RICHMOND
LANCASTER
ROCKBRIDGE
ALLEGHANY
NELSON
FLUVANNA
HANOVER
Richmond
GOOCHLAND
KING AND QUEEN
KING WILLIAM
MIDDLESEX
ACCOMACK
AMHERST
BUCKINGHAM
CUMBERLAND
POWHATAN
HENRICO
NEW KENT
GLOUCESTER
MATHEWS
CRAIG
BOTETOURT
APPOMATTOX
AMELIA
CHESTERFIELD
CHARLES CITY
YORK
NORTHAMPTON
BUCHANAN
GILES
MONTGOMERY
BEDFORD
CAMPBELL
PRINCE EDWARD
NOTTOWAY
JAMES CITY
DICKENSON
TAZEWELL
BLAND
PULASKI
ROANOKE
WISE
RUSSELL
WYTHE
FRANKLIN
CHARLOTTE
LUNENBURG
DINWIDDIE
PRINCE GEORGE
SURRY
ISLE OF WIGHT
SMYTH
FLOYD
BRUNSWICK
SUSSEX
LEE
SCOTT
WASHINGTON
GRAYSON
CARROLL
PATRICK
HENRY
PITTSYLVANIA
HALIFAX
MECKLENBURG
GREENSVILLE
SOUTHAMPTON
Virginia Beach

Scan Methods

Kulldorff's (2001, *JRSS-A*) SaTScan™ methods (available at www.satscan.org) are very popular.

A window moves and varies in space and time. It is a likelihood ratio-based method that incorporates simulation to determine decision rules.

Properties and issues are discussed by Sonesson (2007, *Statistics in Medicine*) and Woodall et al. (2008, *JRSS-A*).

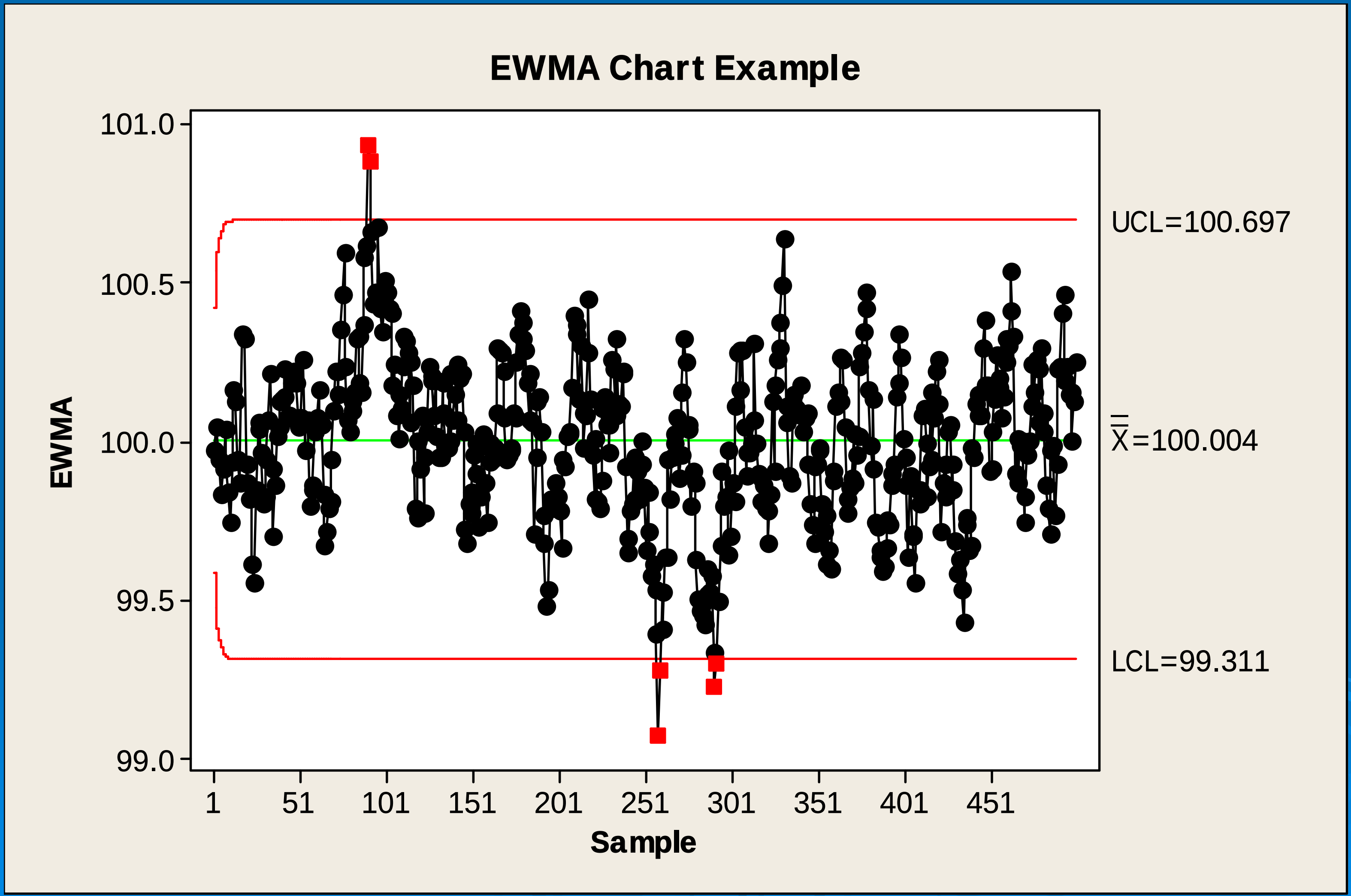
Performance Metrics

In industrial SPC the key performance metrics are based on the time-to-signal.

Health-related metrics include sensitivity, specificity, probability of a false alarm, probability of successful detection, predictive value, recurrence interval, etc., etc.

(See Fraker et al., 2008, *Quality Engineering*)

In industrial applications the focus is on the time to the first alarm, whereas in public health surveillance monitoring is ongoing and methods are not reset after an alarm.



The *recurrence interval* (RI) is the fixed number of time periods such that the expected number of signals is one. It is estimated as the reciprocal of the proportion of plotted points beyond the control limits.

The *average time-to-signal* (ATS) is the expected number of time periods to obtain the first signal.

With on-going monitoring the average time between false alarms becomes important.

If consecutive signals over time are considered as only one signal event, the RI value contains little information on time-to-signal or time-between-alarms performance.

The clustering of signals is ignored with use of the recurrence interval.

Health-related vs. Industrial Applications

In health-related applications…

- …data are more often attribute (yes/no) data with 100% inspection with an assumed underlying Bernoulli, Poisson, geometric or exponential distribution.

- … methods are frequently evaluated only on an example case study dataset. Data models are rarely used relative to the industrial SPC literature.

In health-related applications…

- … outbreaks are most often of limited duration.
- … methods are usually one-sided.
- … monitoring schemes are usually not reset after a signal.

In health-related applications…

- … *p*-values and scan methods are more often used in surveillance.

- … baselines, often seasonal, change frequently even for “in-control” processes.

- … control limits are updated frequently, although “guard-bands” are sometimes used.

Some Healthcare Monitoring Review Papers

Grigg O and Farewell V (2004). "An Overview of Risk-Adjusted Charts". ***Journal of the Royal Statistical Society*** **A 167, 523-539.**

Shmueli G and Burkom HS (2009). "Statistical Challenges in Modern Biosurveillance", to appear in ***Technometrics*****.**

Sonesson C and Bock D (2003). "A Review and Discussion of Prospective Statistical Surveillance in Public Health". ***Journal of the Royal Statistical Society*** **A 166, 5-21.**

Woodall WH (2006). "Use of Control Charts in Health Care Monitoring and Public Health Surveillance" (with discussion), ***Journal of Quality Technology 38(2), 89-104*****.**

The profile monitoring and spatiotemporal surveillance research done in the last ten years is in line with the recommendations of

Nair V, Hansen M, and Shi J (2000), "Statistics in Advanced Manufacturing", *JASA*, 95 (451), 1002-1005.

Some Other Areas

- Adaptive Control Charting (Tsung and Wang, 2009)
- Autocorrelated Data (Psarakis et al. 2007,*QTQM*)
- Change-point Methods (Work by Emmanuel Yashchin, Joe Pignatiello, and Doug Hawkins)
- Effect of Parameter Estimation (Jensen et al. 2006, *JQT*)
- Financial/Economic Applications (Emmanuel Yashchin, Marianne Frisén, and Wolfgang Schmid)
- Multi-stage Processes (Tsung et al. 2008, *International Journal of Operations and Informatics)*
- Multivariate Charts (Bersimis et al. 2007, *QREI*)
- Sampling Issues (by Marion Reynolds, Zachary Stoumbos, and others)
- …….

There are many important applications and research opportunities in the process monitoring area, especially in profile and health-related monitoring.

References

Bersimis S, Psarakis S, and Panaretos J (2007), “Multivariate Statistical Process Control Charts: An Overview”, *Quality and Reliability Engineering International*, 23, 517-543.

Fraker SE, Woodall W H, and Mousavi S (2008). “Performance Metrics for Surveillance Schemes”, *Quality Engineering,* 20, 451-464.

Jensen WA, Jones-Farmer LA, Champ CW, and Woodall WH (2006), “Effects of Parameter Estimation on Control Chart Performance: A Literature Review”, *Journal of Quality Technology 38(4), 349-364*.

Joner MD Jr, Woodall WH, and Reynolds MR Jr (2008). “Detecting a Rate Increase Using a Bernoulli Scan Statistic”, *Statistics in Medicine 27, 2555-2575.*

Psarakis S and Papaleonida GEA (2007), “SPC Procedures for Monitoring Autocorrelated Processes”, *Quality Technology and Quantitative Management* 4(4), 501-540.

Tsung F, Li Y, and Jin M (2008). “Statistical Process Control for Multistage Manufacturing and Service Operations: A Review and Some Extensions”, *International Journal of Operations and Informatics*, 3, 191-204 .

Tsung F and Wang K (2009), "Adaptive Charting Techniques: Literature Review and Extensions, to appear in *Frontiers in Statistical Quality Control 9*, edited by HJ Lenz and P-Th Wilrich.

Steiner SH, Cook RJ, Farewell VT, and Treasure T (2000). "Monitoring Surgical Performance Using Risk-Adjusted Cumulative Sum Charts". *Biostatistics* 1, 441-452.

Tennant R, Mohammed MA, Coleman JJ, et al. (2007). "Monitoring Patients Using Control Charts: A Systematic Review", *International Journal for Quality in Healthcare*, Vol. 19 (4), pp. 187-194.

Thor J, Lundberg J, Ask J, Olsson J, Carli C, Härenstam, KP, and Brommels M (2007), "Application of Statistical Process Control in Healthcare Improvement: Systematic Review", *Quality and Safety in Health Care*, 16, pp. 387-399.

Woodall WH, Grigg OA, and Burkom HS (2009), "Research Issues and Ideas on Health-Related Monitoring", to appear in *Frontiers in Statistical Quality Control 9*, edited by HJ Lenz and P-Th Wilrich.

Woodall WH, Marshall JB, Joner MD Jr, Fraker SE, and Abdel-Salam AG (2007). "On the Use and Evaluation of Prospective Scan Methods in Health-Related Surveillance", *JRSS-A* 171(1), 223-237.

Woodall WH and Montgomery DC (1999), "Research Issues and Ideas in Statistical Process Control," *Journal of Quality Technology*, 31, 376-386.