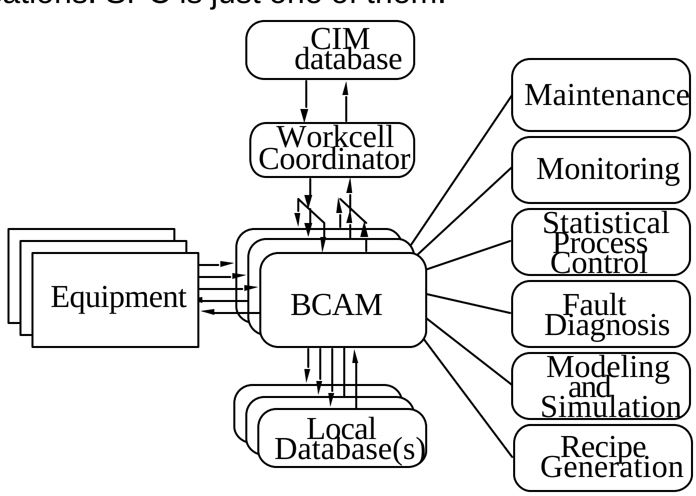
Statistical Process Control
and
Computer Integrated Manufacturing

Run to Run Control, Real-Time SPC, Computer Integrated Manufacturing.

The Equipment Controller

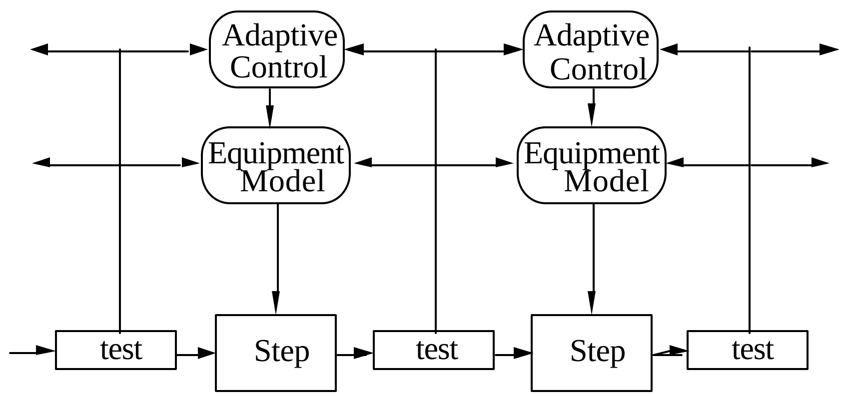
Today, the operation of individual pieces of equipment can be streamlined with the help of external software applications. SPC is just one of them.



The Workcell Controller

Most process steps are so interrelated that must be controlled together using feed forward and feedback loops.

Crucial pieces of equipment must by controlled by SPC throughout this operation.



Model Based Control

All actions are based on the comparison of response surface models to actual equipment behavior.

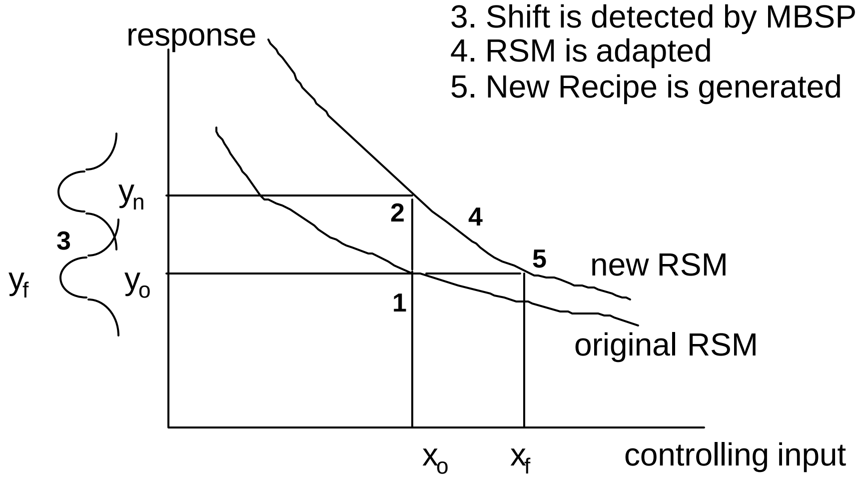
<u>Malfunction alarms</u> are detected using a multivariate extension of the regression chart on the prediction residuals of the model.

<u>Control alarms</u> are detected with a multivariate CUSUM chart of the prediction residuals.

Control limits are based on experimental errors as well as on the model prediction errors due to regression. Hard limits on equipment inputs are also used.

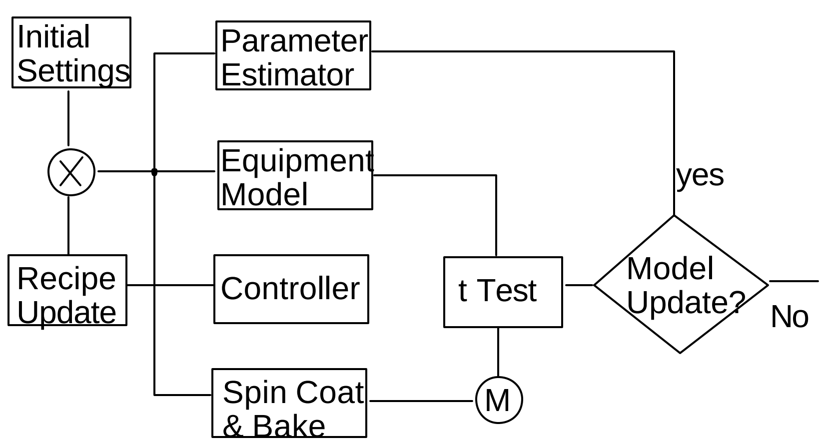
The Idea of Statistically Based Feedback Control

1. Original Operation
2. Process Shifts
3. Shift is detected by MBSPC
4. RSM is adapted
5. New Recipe is generated

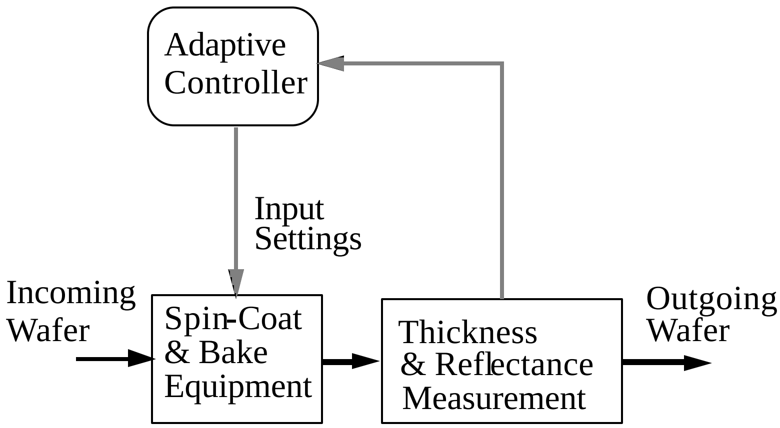


Feedback Control

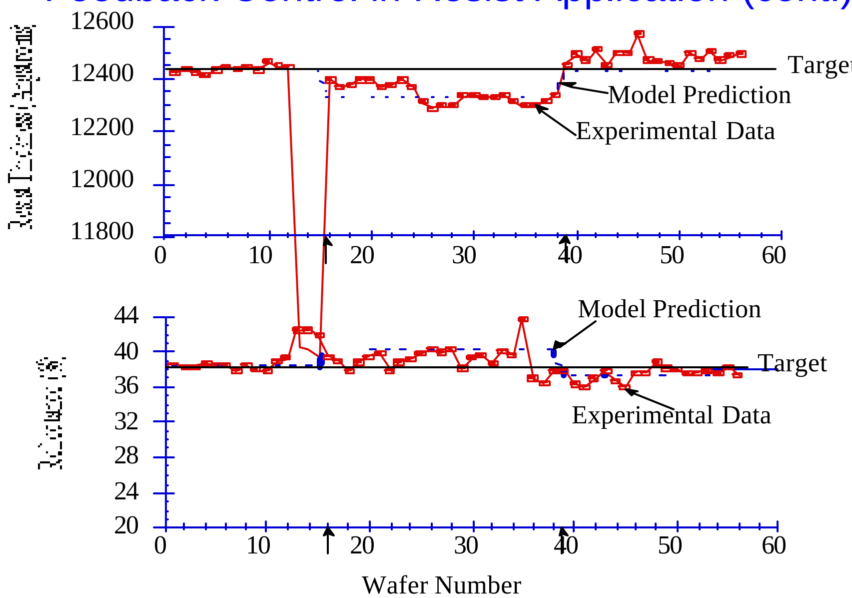
Model-based, adaptive Feedback Control has been employed on several processes.



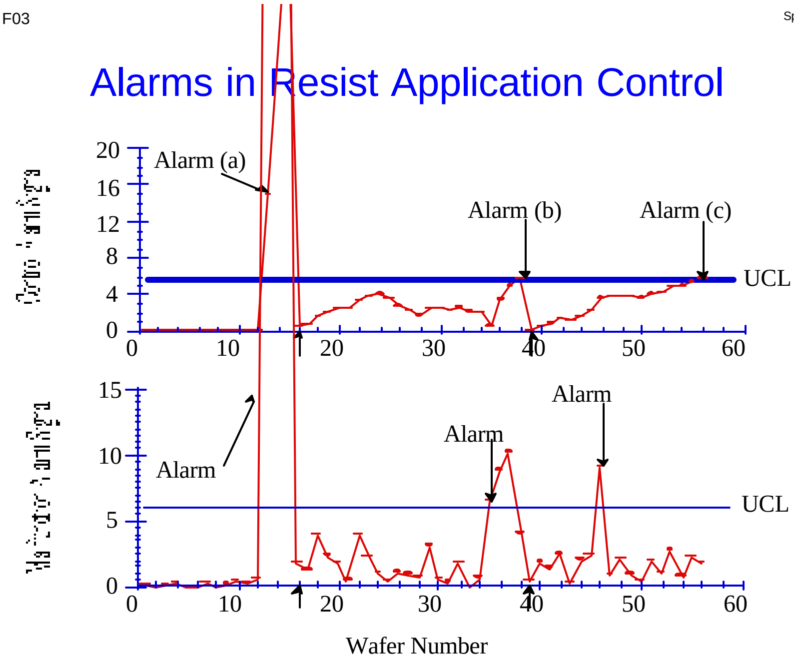
Feedback Control in Resist Application



Feedback Control in Resist Application (cont.)



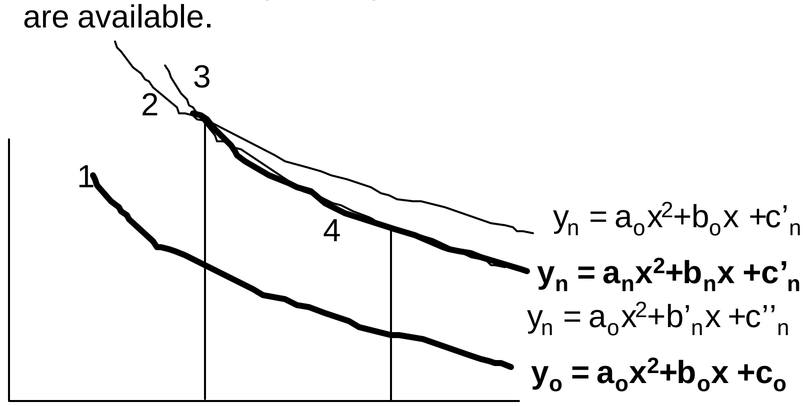
Alarms in Resist Application Control



Adapting the Regression Model

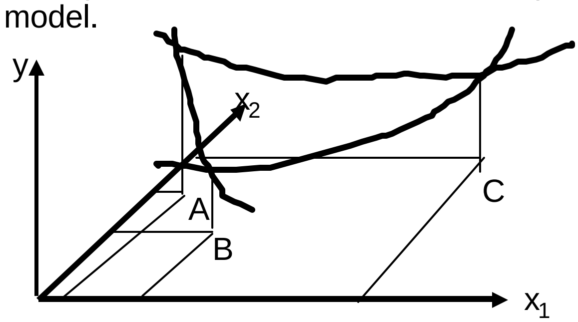
The regression model has many coefficients that may need adaptation.

What can be adapted depends on what measurements are available.



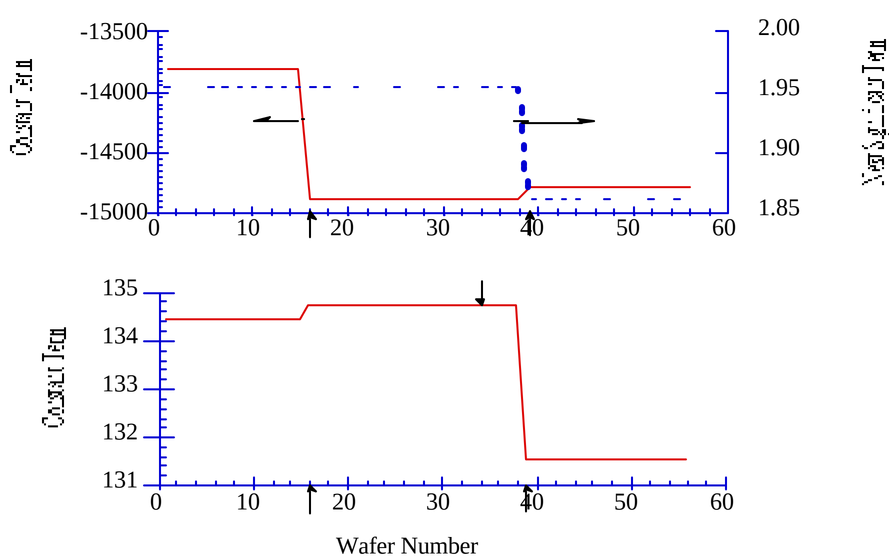
Adapting the Regression Model (cont)

In multivariate situations it is often not clear which of the gain or higher order variables can be adapted in the original model.



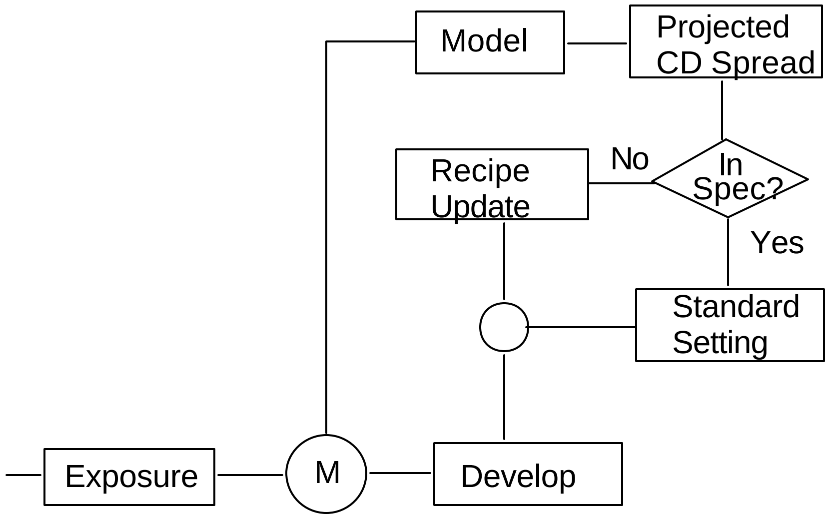
In these cases the model is “rotated” so that it has orthogonal coefficients, along the principal components of the available observations. These coefficients are updated one at a time.

Model Adaptation in Resist Application Control

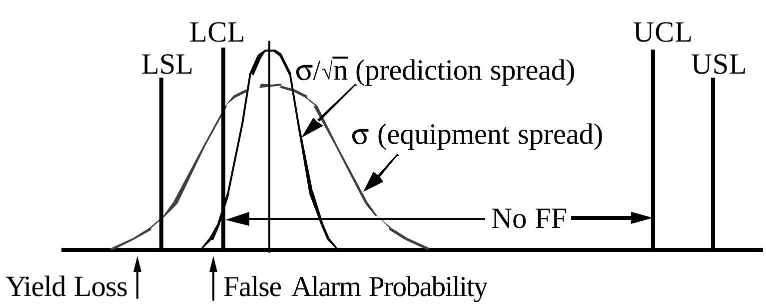


Feed-Forward Control

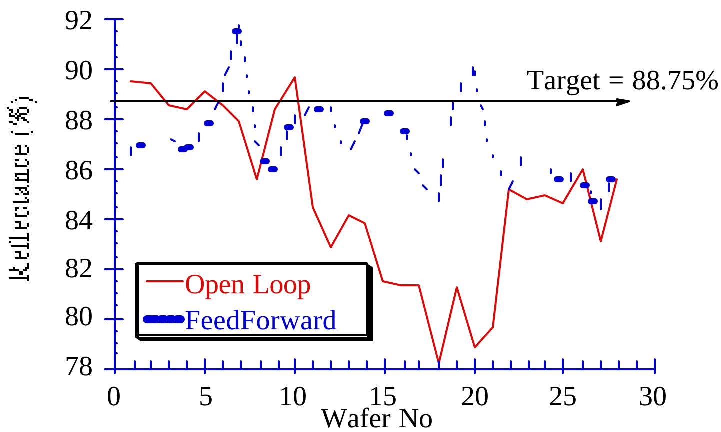
Models can also be used to predict the outcome and correct ahead of time if necessary.



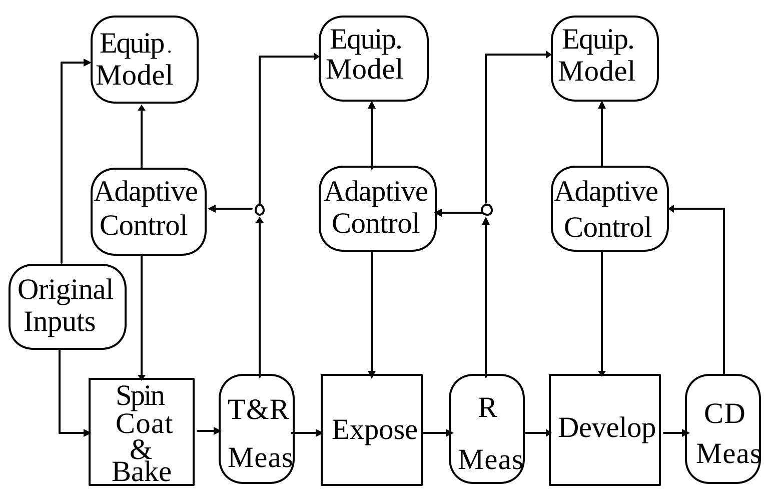
Modified Charts for Feed Forward Control



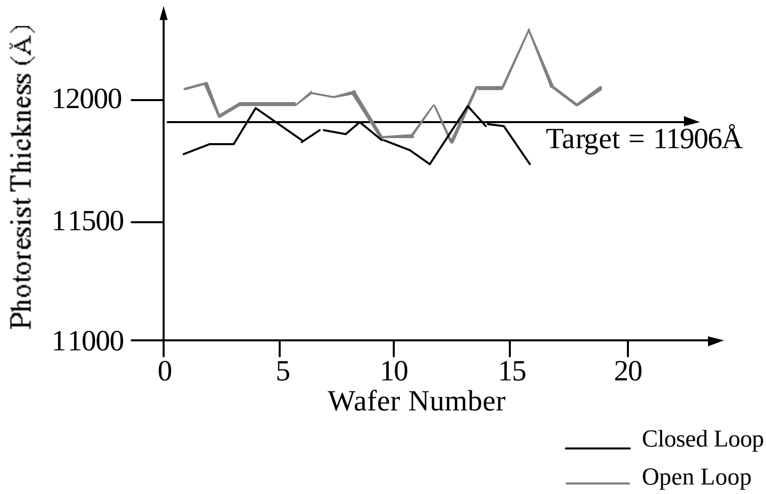
Feed Forward/Feedback Control Results (cont)



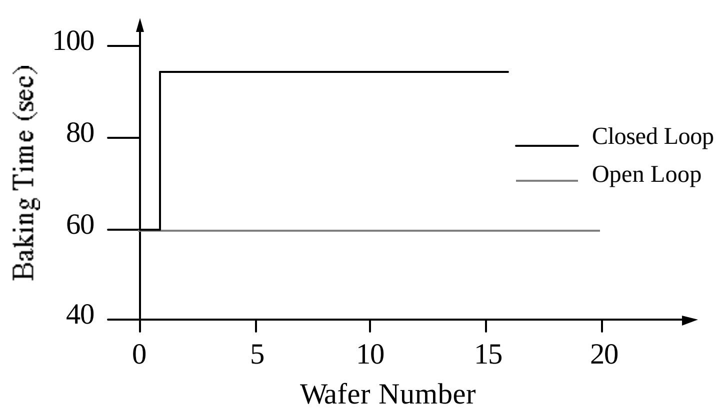
Concurrent Control of Multiple Steps



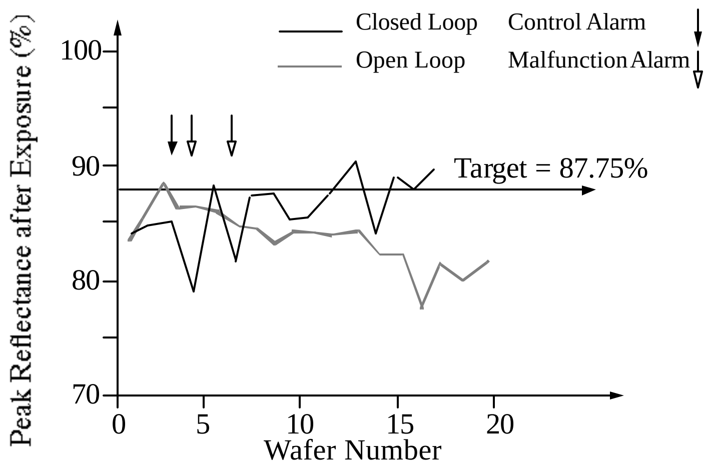
Resist Thickness Example



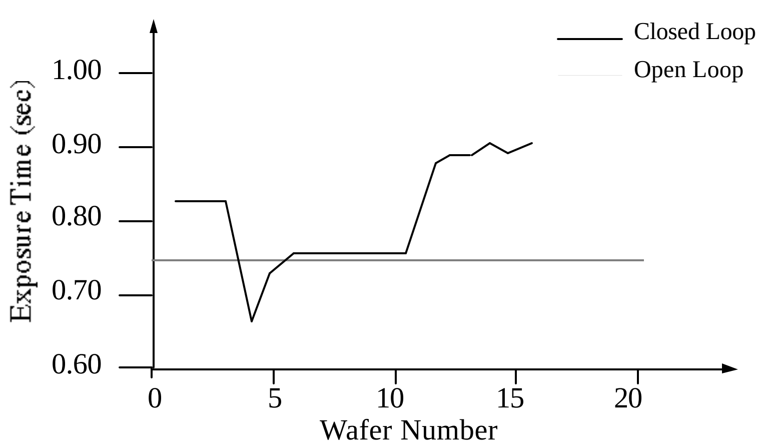
Resist Thickness Input



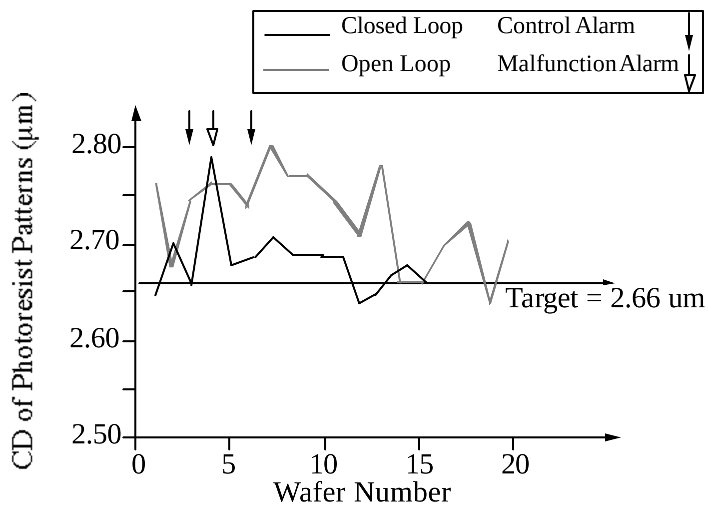
Latent Image output



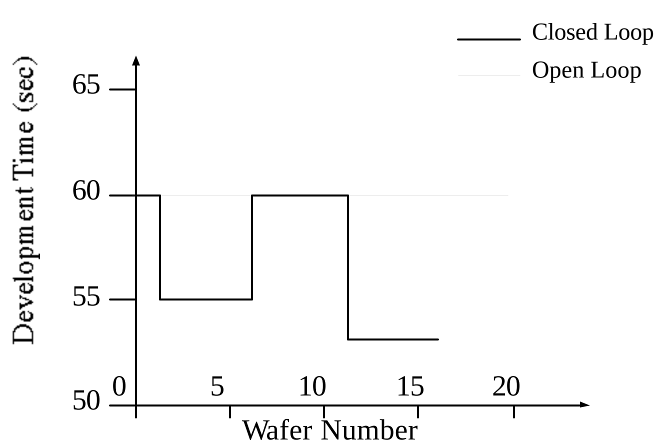
Latent Image Input



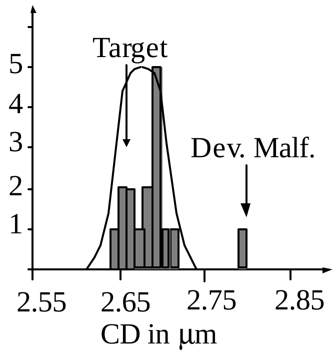
Developer Output



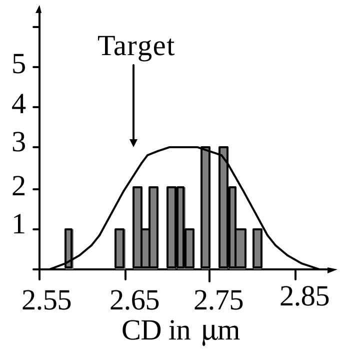
Developer Input



Process Improvement Due to Run to Run Control



Closed Loop Operation

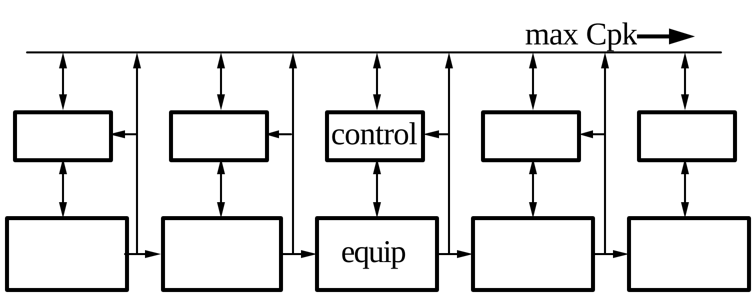


Open Loop Operation

Supervisory Control

The complete controller must be able to perform feedback and feed-forward control, along with automated diagnosis.

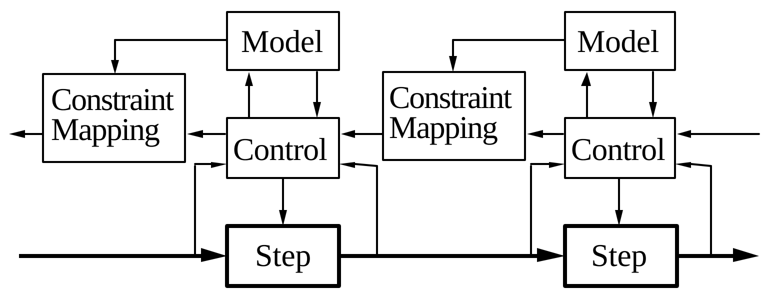
Feed-forward control must be performed in an optimum fashion over several pieces of the equipment that follow.



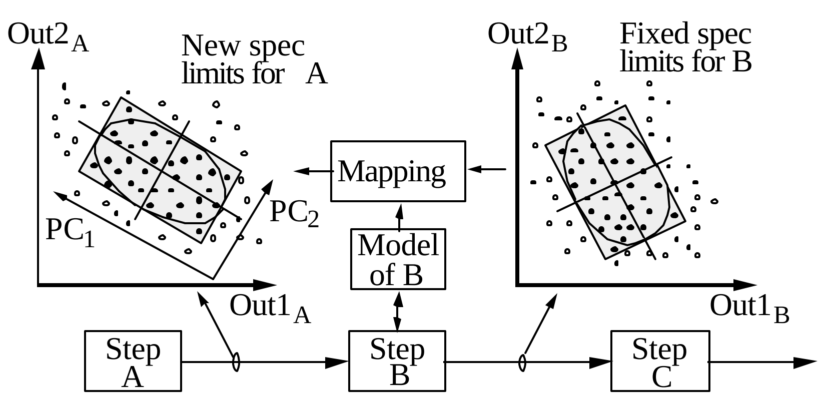
The Concept of Dynamic Specifications

Specs are enforced by a cost function which is defined in terms of the parameters passed between equipment.

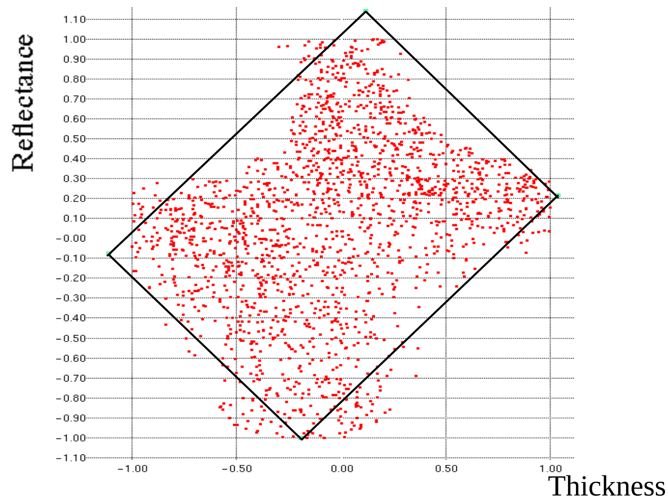
A change is propagated upstream through the system by redefining specifications for all steps preceding the change.



Specs to step A must change if step B "ages"

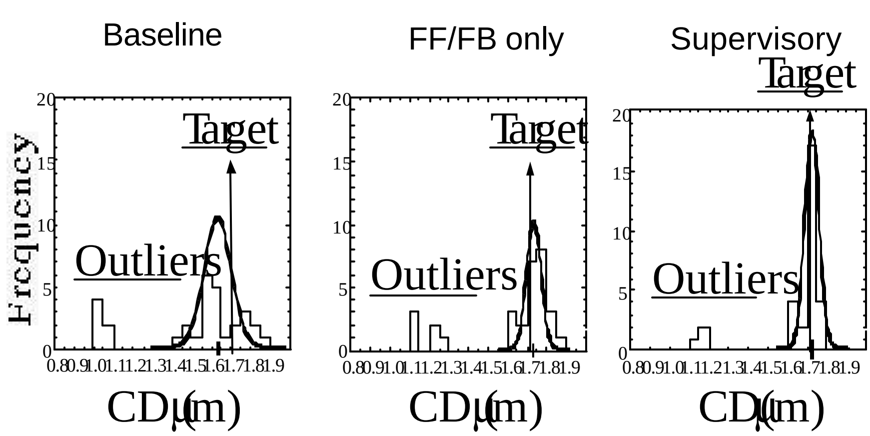


Specs are outlined automatically - Stepper example



(Develop time varies between 55 and 65 seconds)

An Example of Supervisory Control



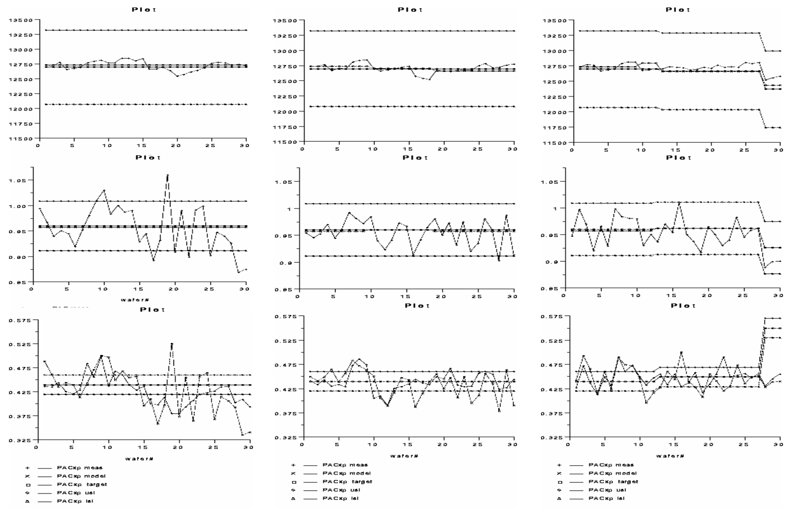
Results from Supervisory Control Application

Baseline FF/FB Only Supervisory

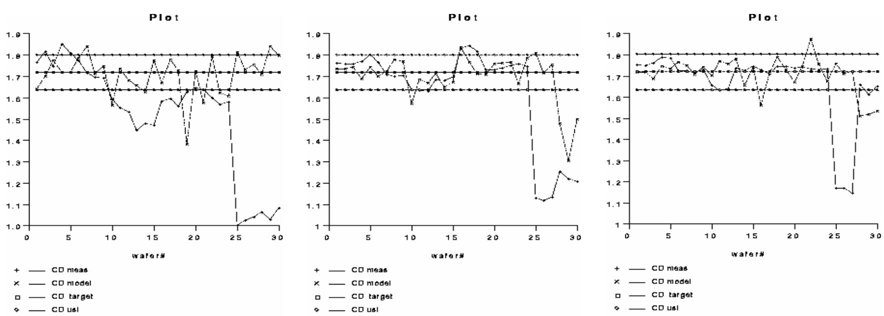
Th

PAC

LI



Control Results - CD



Baseline FF/FB Only Supervisory

Summary, so far

Response surface models can be built based on designed experiments and regression analysis.

Model-based Run-to-Run control is based on control alarms and on malfunction alarms.

RSM models are being updated automatically as equipment age.

Optimal, *dynamic* specifications can be used to guide a complex process sequence.

Next stop: Real-time Statistical Process Control!

Auto-correlated Data

One important and widespread assumption in SPC is that the samples take random values that are *independently* and *identically* distributed according to a *normal distribution*

$$y_t = \mu + e_t \quad t = 1,2,... \quad e_t \sim N(0, \sigma^2)$$

With automated readings and high sampling rates, each reading statistically depends on its previous values. This implies the presence of *autocorrelation* defined as:

$$\rho_k = \frac{\Sigma (y_i - \overline{y})(y_{i+k} - \overline{y})}{\Sigma (y_i - \overline{y})^2} = 0 \quad k = 1,2,...$$

The IIND property must be restored before we apply any traditional SPC procedures.

Time Series Modeling

Various models have been used to describe and eliminate the autocorrelation from continuous data.

A simple case exists when only one autocorrelation is present:

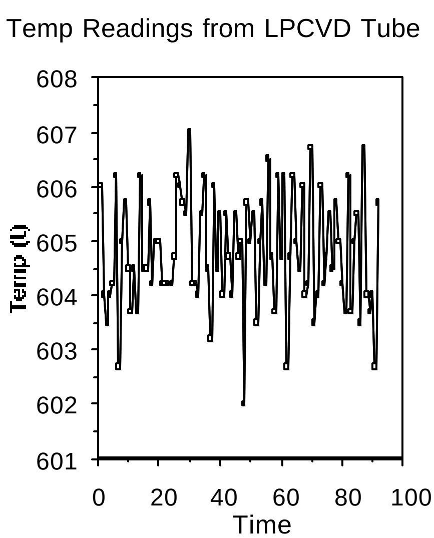
$$y_t = \mu + \varphi y_{t-1} + e_t \quad e_t \sim N(0, \sigma^2)$$

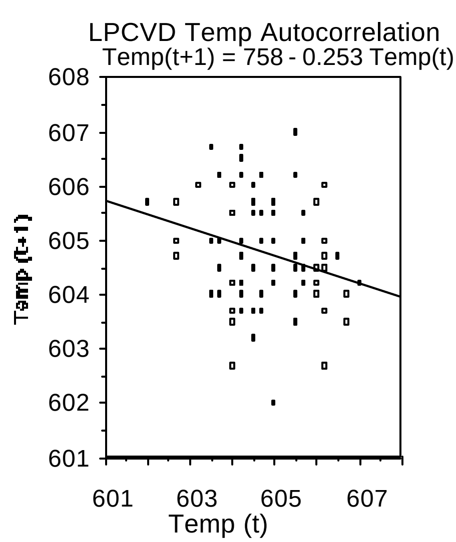
$$\mu' = \mu / (1 - \varphi), \quad \sigma' = \sigma / \sqrt{1-\varphi^2}$$

$$e_t = y_t - \hat{y}_t$$

The IIND property can be restored if we use this model to "forecast" each new value and then use the forecasting error (an IIND random number) in the SPC procedure.

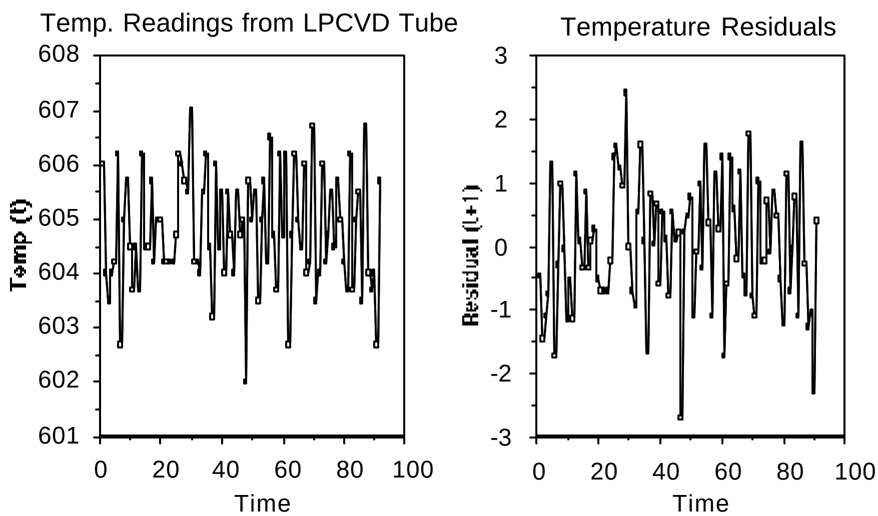
Example: LPCVD Temperature Readings





Temps are *not* IIND since future readings can be *predicted*!

The Residuals of the Prediction can be Used for SPC..



Estimated Time Series

A "Time Series" is a collection of observations generated sequentially through time.

Successive observations are (usually) dependent.

Our objectives are to:

Describe - features of a time series process

Explain - relate observations to rules of behavior

Forecast - see into the future

Control - alter parameters of the model

Two Basic Flavors of Time Series Models

Stationary data (i.e. time independent mean, variance and autocorrelation structure) can be modelled as:

Autoregressive $z_t = \varphi_1 z_{t-1} + e_t \quad e_t \sim N(0, \sigma^2)$

$$z_t = y_t - \mu$$

Moving Average $z_t = \theta_1 e_{t-1} + e_t \quad e_t \sim N(0, \sigma^2)$

$$z_t = y_t - \mu$$

Mixture (i.e. Autoregressive + Moving Average) models.

$$y_t = \mu + \varphi_1 z_{t-1} + \varphi_2 z_{t-2} + \ldots + \varphi_p z_{t-p}$$
$$+ e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} - \ldots - \theta_q e_{t-q}$$

φ: autoregressive

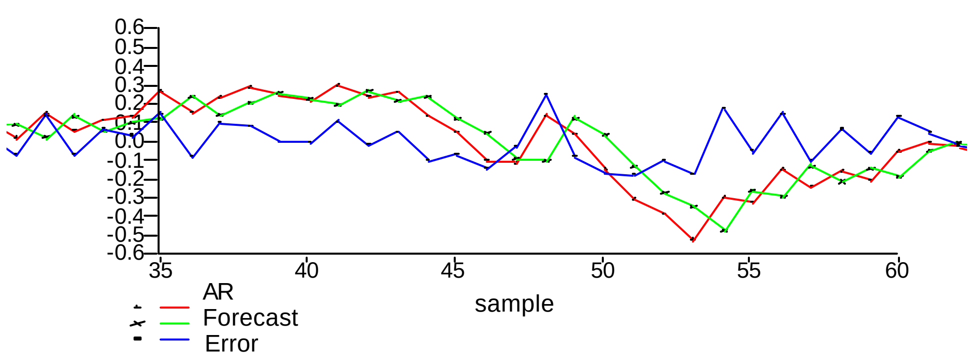
θ: moving average

First Order Autoregressive Model AR(1)

This model assumes that the next reading can be predicted from the last reading according to a simple regression equation.

$$z_t = \varphi_1 z_{t-1} + e_t \quad e_t \sim N(0, \sigma^2)$$

$$z_t = y_t - \mu$$

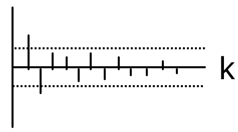


Higher order AR(p) and ACF, PACF representation

Higher order autoregressive models are common in engineering. Their structure can be inferred*acf* and *pacf* plots.

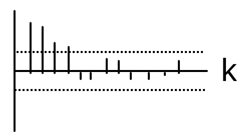
Autocorrelation Function (acf):

$$\rho_k = \frac{\Sigma\,(y_i - \overline{y})(y_{i+k} - \overline{y})}{\Sigma (y_i - \overline{y})^2} = 0 \quad k = 1,2,...$$



Partial Autocorrelation Function (pacf):

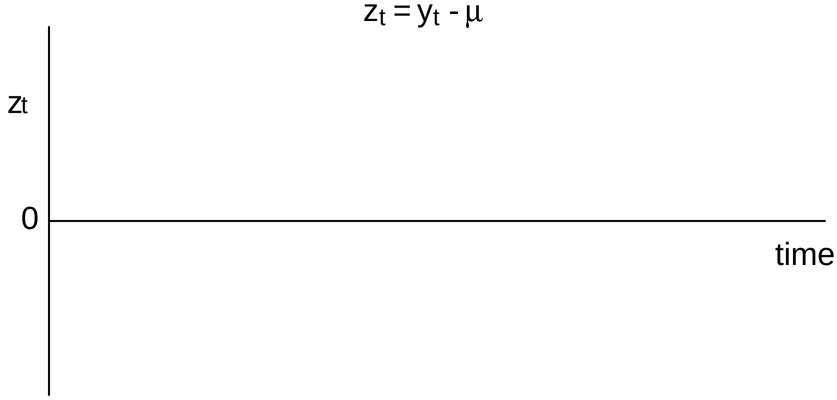
$$\hat{z}_t = \varphi_1 z_{t-1}$$
$$\hat{z}_t = \varphi_1 z_{t-1} + \varphi_2 z_{t-2}$$
$$\hat{z}_t = \varphi_1 z_{t-1} + \varphi_2 z_{t-2} + \varphi_3 z_{t-3}$$
$$\hat{z}_t = \varphi_1 z_{t-1} + \varphi_2 z_{t-2} + \varphi_3 z_{t-3} + \varphi_4 x_{t-4}$$
$$...$$



First Order Moving Average Model MA(1)

This model assumes that the next reading can be predicted from the last residual according to a simple regression equation.

$$z_t = \theta_1\, e_{t-1} + e_t \qquad e_t \sim N\,(0, \sigma^2)$$
$$z_t = y_t - \mu$$



Mixed AR & MA Models: ARMA(p,q)

In general, each new value depends not only on past readings but on past residuals as well. The general form is:

$$y_t = \mu + \varphi_1 z_{t-1} + \varphi_2 z_{t-2} + \ldots + \varphi_p z_{t-p}$$
$$+ e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} - \ldots - \theta_q e_{t-q}$$

φ: autoregressive

θ: moving average

This structure is called ARMA (autoregressive moving average). The particular model is an ARMA(p,q).

If the data is differentiated to become *stationary*, we get an ARIMA (Autoregressive, *Integrated* Moving Average) model.

Structures also exist that describe seasonal variations and multivariate processes.

Summary on Time Series Models

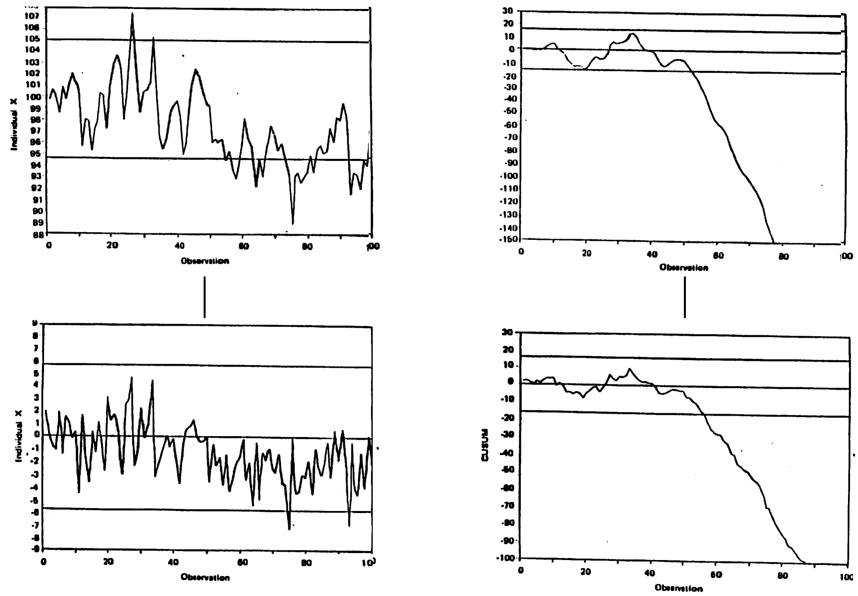
Time Series Models are used to describe the "autocorrelation structure" within each real-time signal.

After the autocorrelation structure has been described, it can be removed by means of time series filtering.

The models we use are known as Box-Jenkins linear models.

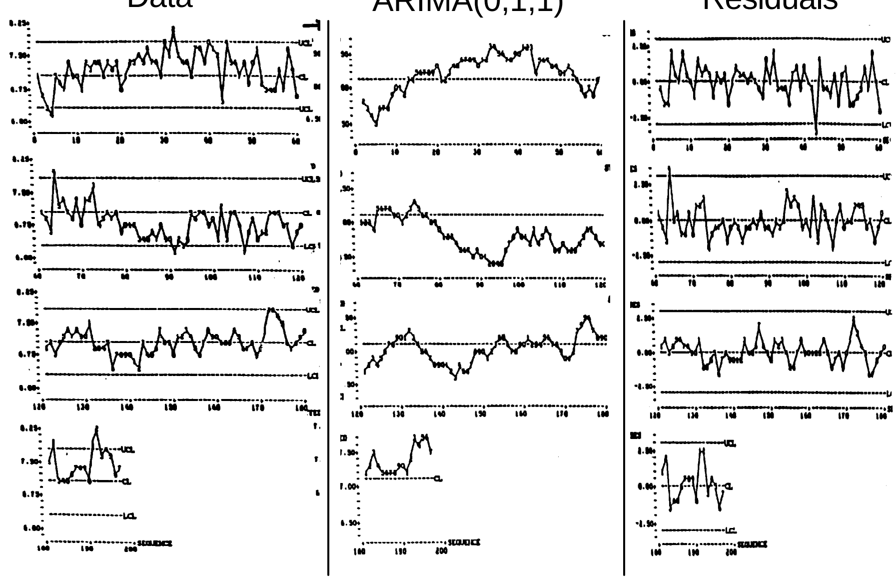
The generation of these models involves some statistical judgmenttically.

Shewhart and CUSUM time series residuals



Fitted ARIMA(0,1,1) Example

Data ——— ARIMA(0,1,1) ——— Residuals



So, what *is* RTSPC?

RTSPC reads real-time signals from processing tools.

It automatically does ACF and PACF analysis to build and save time series models.

During production, RTSPC "filters" the real-time signals.

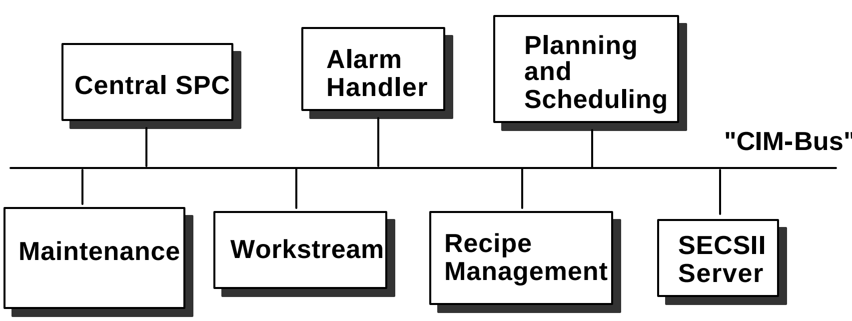
The filtered residuals are combined using T^2 statistics.

This analysis is done simultaneously in several levels:

- Real-Time Signals
- Wafer Averages
- Lot Averages

The multivariate T^2 chart provides a robust real-time summary of machine "goodness".

Emerging Factory Control Structure



The SPC Server

Accesses data base and draws simple X-R charts.

Disables machine upon alarm

Benefits from automated data collection

Performs arbitrary correlations across the process

Can to build causal models across the process

Monitors process capabilities of essential steps

Maintains 2000+ charts across a typical fab

Keeps track of alarm explanations given by operators and engineers.

Training for SPC

Operators: understand and "own" basic charts.

Process Engineers: be able to decide what to monitor and what chart to use (grouping, etc.)

Equipment Engineers: be able to collect tool data. Understand how to control real-time tool data.

Manufacturing Manager: understand process capabilities. Monitor several charts collectively.

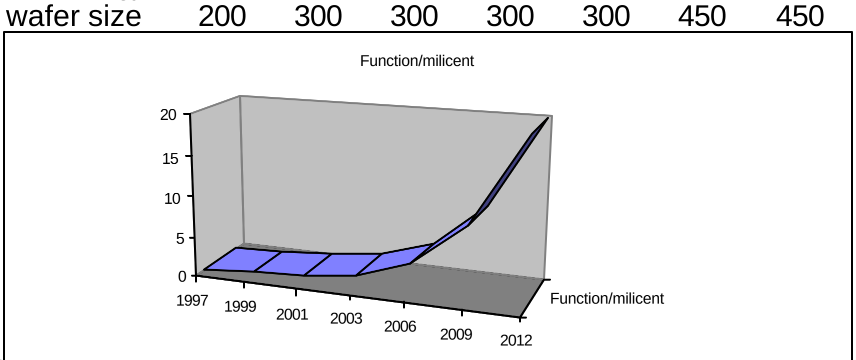
Fab Statistician: understand the technology and its limitations. Appreciate cost of measurements.

Summary of SPC topics

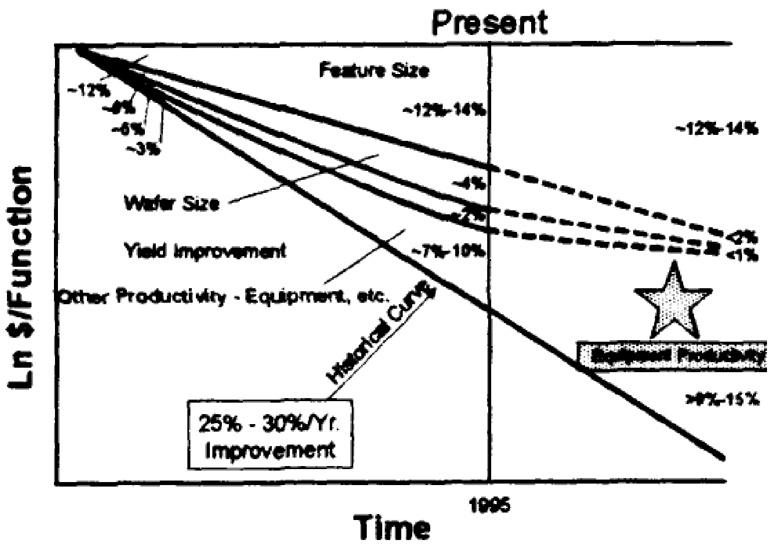
Random variables and distributions.
Sampling and hypothesis testing.
The assignable cause.
Control chart and operating characteristic.
p, c and u charts.
XR, XS charts and pattern analysis.
Process capability.
Acceptance charts.
Maximum likelihood estimation, CUSUM.
Multivariate control.
Evolutionary operation.
Regression chart.
Time series modeling.

The 1997 Roadmap

Year	1997	1999	2001	2003	2006	2009	2012
Feature nm	250	180	150	130	100	70	50
Area mm^2	300	340	385	430	520	620	750
Density cm^{-2}	3.7M	6.2M	10M	18M	39M	84M	180M
Cost $\mu c/tr$	3000	1735	1000	580	255	110	50
technology	248	248	193?	157?	14	14	14
wafer size	200	300	300	300	300	450	450



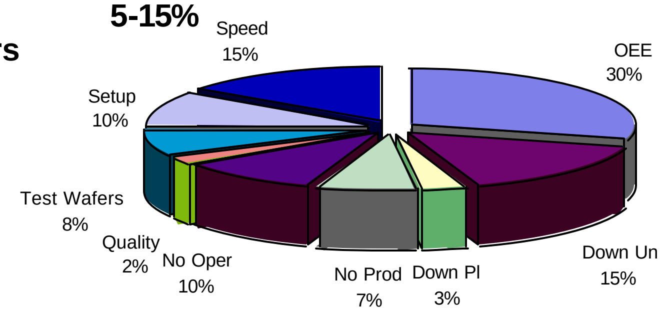
Where will the Extra Productivity Come from?



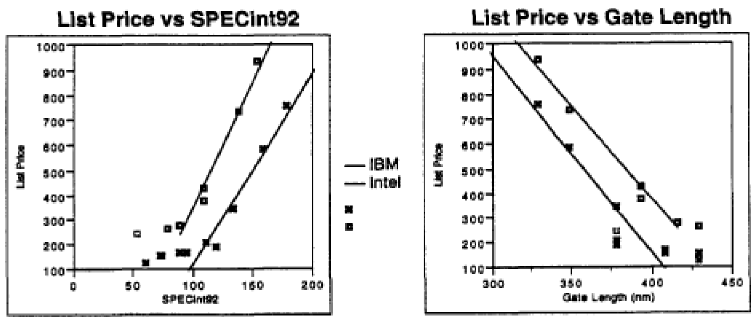
(Jim Owens, Sematech)

The Opportunities

Year	1997	1999	2001	2003	2006	2009	2012
Feature nm	250	180	150	130	100	70	50
Yield	85%	95%	100?	100?	100?	100?	
Equipment utilization	**35%**	**50%**					
Test wafers	**5-15%**						



Basic CD Economics



Source: MicroDesign Resources

Leading Edge CD Control Revenue Leverage:

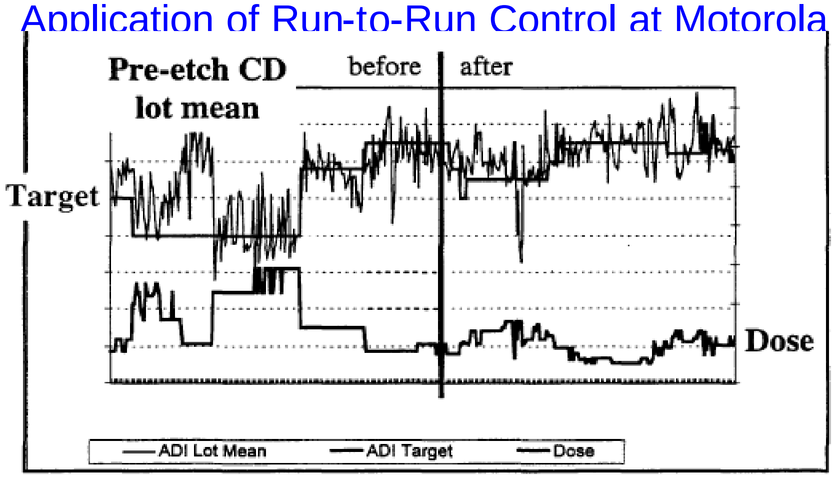
~ $7.5/nm

Semiconductor Technology

MOTOROLA

(D. Gerold et al, Sematech AEC/APC, Sept 97, Lake Tahoe, NV)

Application of Run-to-Run Control at Motorola



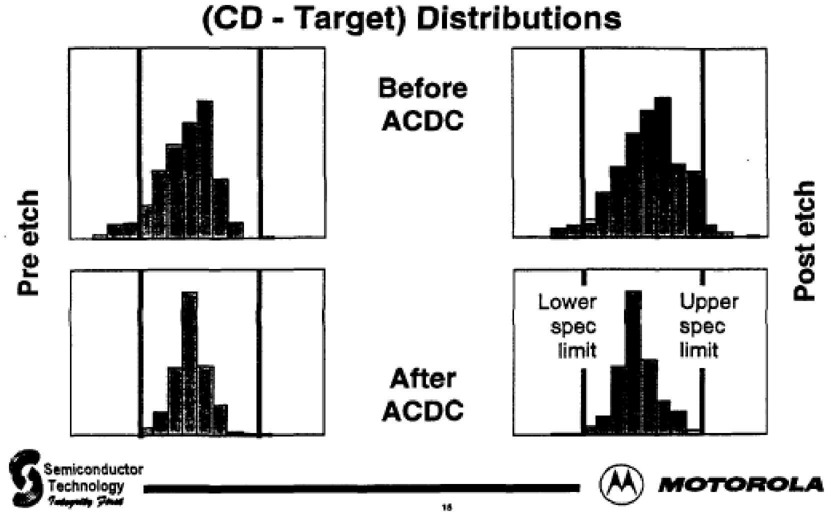
Semiconductor Technology

MOTOROLA

$$Dose_n = Dose_{n-1} - \beta \, (CD_{n-1} - CD_{target})$$

(D. Gerold et al, Sematech AEC/APC, Sept 97, Lake Tahoe, NV)

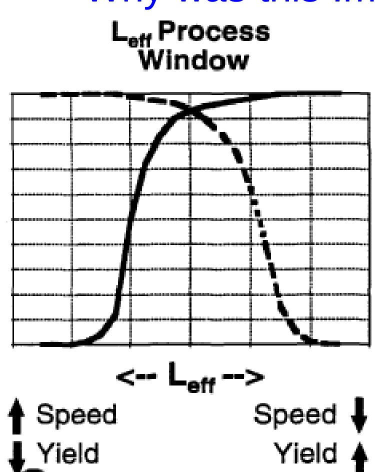
CD Improvement at Motorola



σ_{Leff} reduced by 60%

(D. Gerold et al, Sematech AEC/APC, Sept 97, Lake Tahoe, NV)

Why was this Improvement Important?



Tighter lot CD distribution allowed target shift to shorter L_{eff} without yield hit

Speed Bin	% Pre-ACDC	% Post-ACDC
1	1.6	0.0
2	8.8	0.0
3	39.6	3.1
4	44.2	91.1
5	5.8	5.8
Mean ASP:	$ $	$ $

$ 2M / wk / 1K starts

Semiconductor Technology MOTOROLA

600k APC investment, recovered in two days...

Less Tangible Opportunities

Reduce cost of second sourcing (facilitate technology transfer)

Dramatically increase flexibility (beat competition with more customized options)

Extend life span of older technologies

Cut time to market (by linking manufacturing to design)

What is the current extend of “control” in our industry?

Widespread inspection and SPC

Systematic setup and calibration (DOE)

Widespread use of RSM / Taguchi techniques

Factory statistics is an established discipline

Advances for the Semiconductor Industry

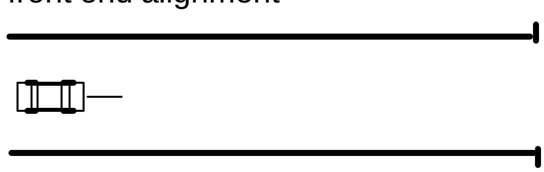
An old idea - ensure equipment integrity - automatically

A new idea - perform feedback control on the workpiece

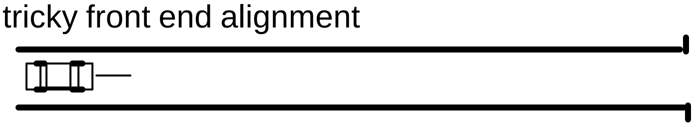
Isolate performance from technology
Isolate technology from equipment
Create a process with truly interchangeable parts

How do you steer your Process?

1980: short distance, wide road, but no steering wheel, bad front end alignment



1998: longer distance, narrow road, no steering wheel, tricky front end alignment



2005?

Changing the "do not touch my process" attitude

A stable process is one that is locally characterized and locked. SPC is used to make sure it stays there.

An "agile" process is one that is characterized over a region of operation. Process data and control algorithms are used to obtain goals.

Can we reach the 2010 process goals with a "stable" process?

In Conclusion

SPC provides "open loop" control.

In-situ data can be used for tighter run-to-run and supervisory control.

Several technical (and some cultural) problems must be addressed before that happens:

- Need sensors that are simple, non-intrusive and robust.
- User interfaces suitable for the production floor.

Next step in the evolution of manufacturing:
From hand crafted products, to hand crafted lines to lines with interchangeable parts.