2.830J / 6.780J / ESD.63J Control of Manufacturing Processes (SMA 6303)
Spring 2008

Massachusetts
Institute of
Technology

Control of Manufacturing Processes

Subject 2.830

Spring 2007

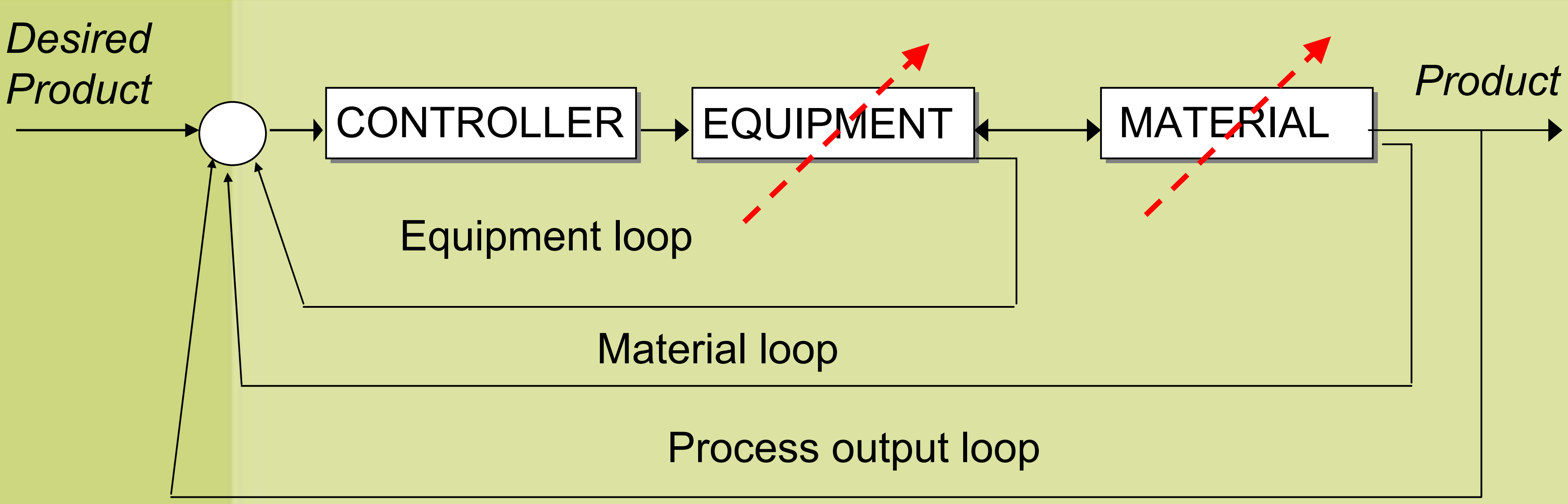
Lecture #20

“Cycle To Cycle Control:

The Case for using Feedback and SPC”

May 1, 2008

The General Process Control Problem



Control of **Equipment**:
- Forces,
- Velocities
- Temperatures,
- , ..

Control of **Material**
- Strains
- Stresses
- Temperatures,
- Pressures, ..

Control of **Product**:
- Geometry
- and
- Properties

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Output Feedback Control

$$\Delta Y = \frac{\partial Y}{\partial \alpha}\Delta\alpha + \frac{\partial Y}{\partial u}\Delta u$$

$$\frac{\partial Y}{\partial u}\Delta u = -\frac{\partial Y}{\partial \alpha}\Delta\alpha$$

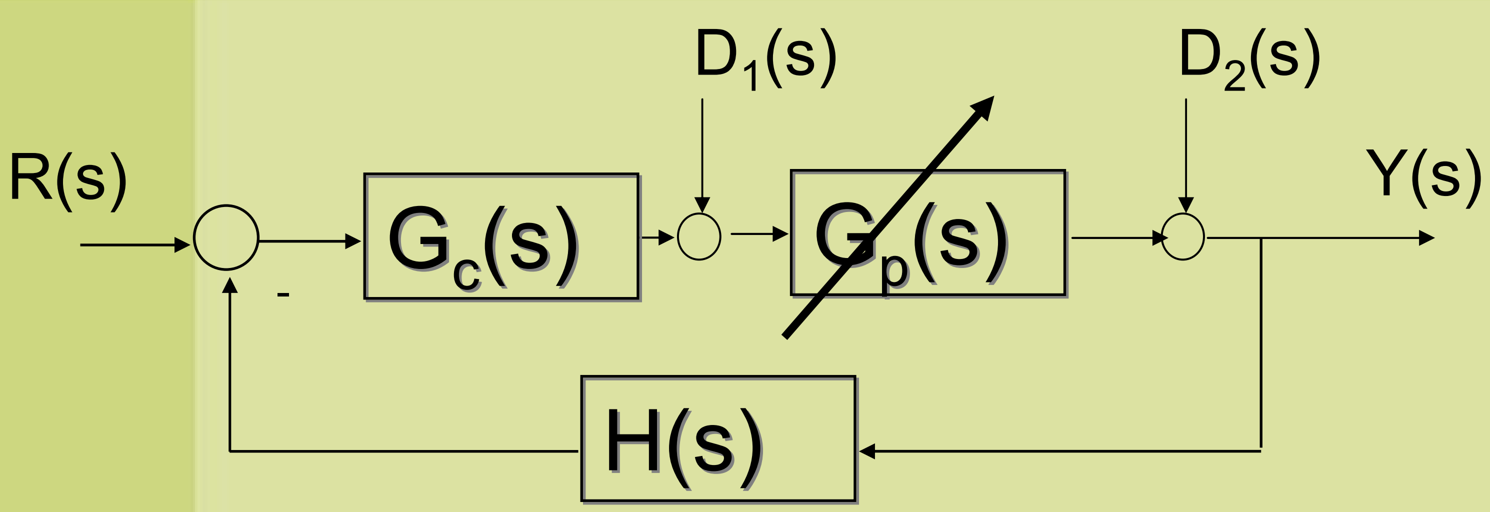
Manipulate Actively Such that

Compensate for Disturbances

Process Control Hierarchy

- Reduce Disturbances
  - Good Housekeeping
  - Standard Operations (SOP's)
  - **Statistical Analysis and Identification of Sources (SPC)**
  - **Feedback Control of Machines**
- Reduce Sensitivity (increase "Robustness")
  - **Measure Sensitivities via Designed Experiments**
  - Adjust "free" parameters to minimize
- Measure output and manipulate inputs
  - **Feedback control of Output(s)**

The Generic Feedback "Regulator" Problem



- Minimize the Effect of the "D's"
- Minimize Effect of Changes in G_p
- Follow R exactly

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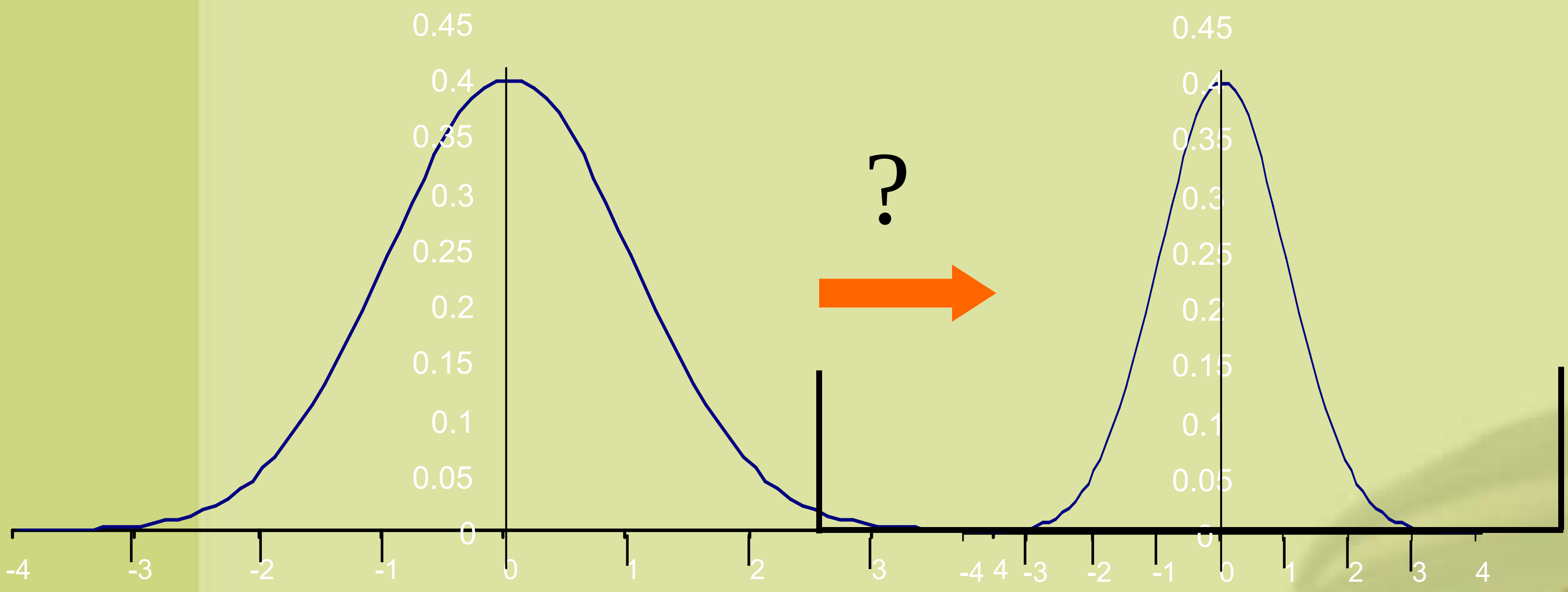
Effect of Feedback on Random Disturbances

- Feedback Minimizes Mean Shift (Steady-State Component)
- Feedback Can Reduce Dynamic Disturbances



Typical Disturbances

- Equipment Control
  - External Forces Resisting Motion
  - Environment Changes (e.g Temperature)
  - Power Supply Changes
- Material Control
  - Constitutive Property Changes
    - Hardness
    - Thickness
    - Composition
    - ...

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The Dynamics of Disturbances

- Slowly Varying Quantities
- Cyclic
- Infrequent Stepwise
- Random

Example: Material Property Changes

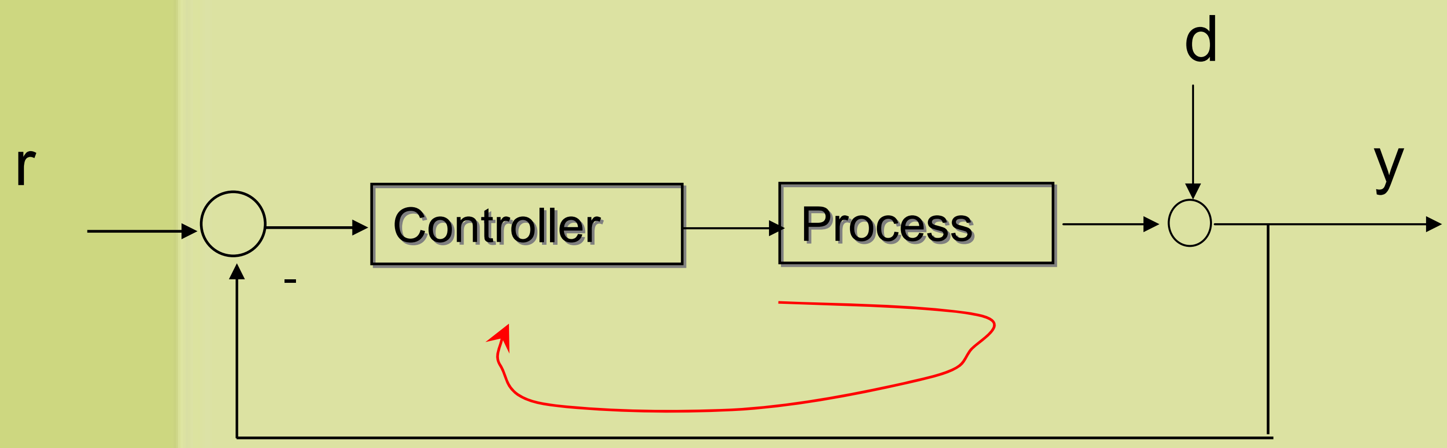
- A constitutive property change from workpiece to workpiece
  - In-Process Effect?
    - A new constant parameter
    - Different outcome each cycle
  - Cycle to Cycle Effect
    - Discrete random outputs over time

What is Cycle to Cycle?

- Ideal Feedback is the Actual Product Output
- This Measurement Can Always be made After the Cycle
- Equipment Inputs can Always be Adjusted Between Cycles
- Within the Cycle Inputs Are Fixed

What is Cycle to Cycle?

- Measure and Adjust Once per Cycle



Execute the Loop Once Per Cycle

Discrete Intervals rather then Continuous

Run by Run Control

- Developed from an SPC Perspective
- Primarily used in Semiconductor Processing
- Similar Results, Different Derivations
- More Limited in Analysis and Extension to Larger problems

Box, G., Luceno, A., “Discrete Proportional-Integral Adjustment and Statistical Process Control,” *Journal of Quality Technology*, vol. 29, no. 3, July 1997. pp. 248-260.
Sachs, E., Hu, A., Ingolfsson, A., “Run by Run Process Control: Combining SPC and Feedback Control.” *IEEE Transactions on Semiconductor Manufacturing*, 1995, vol. 8, no. 1, pp. 26-43.

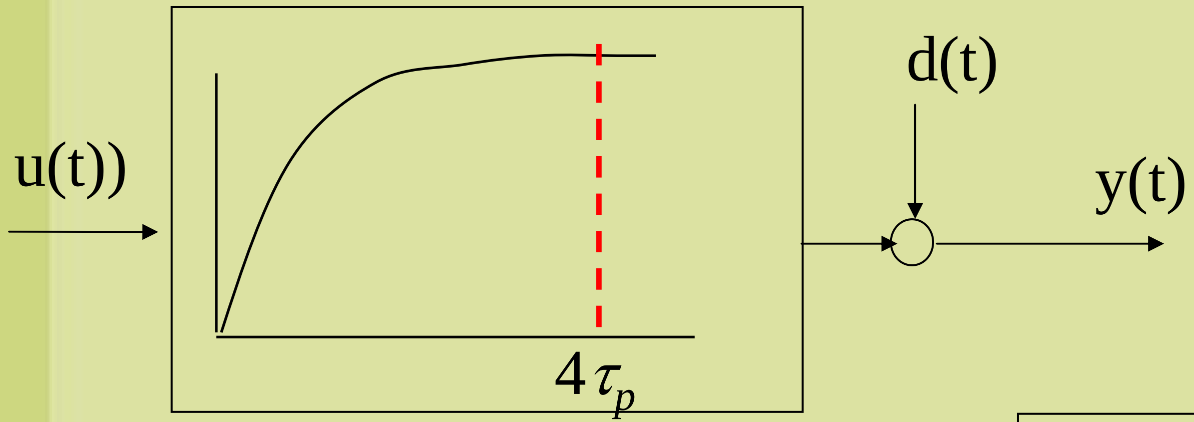
Cycle to Cycle Feedback Objectives

- How to Reduce E(L(x)) & Increase C_{pk} with Feedback?

- Bring Output Closer to Target
  – Minimize Mean or Steady - State Error
- Decrease Variance of Output
  – Reject Time Varying Disturbances

A Model for Cycle to Cycle Feedback Control

- *Simplest* In-Process Dynamics:



Cycle Time $T_c \geq 4\tau_p$

d(t) = disturbances seen at the output (e.g. a Gaussian noise)

τ_p = Equivalent Process Time Constant

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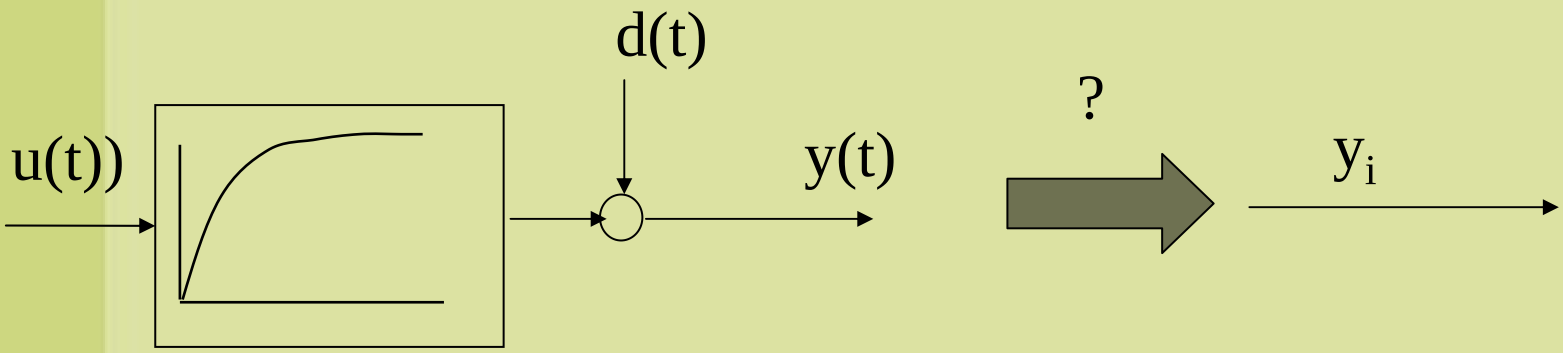
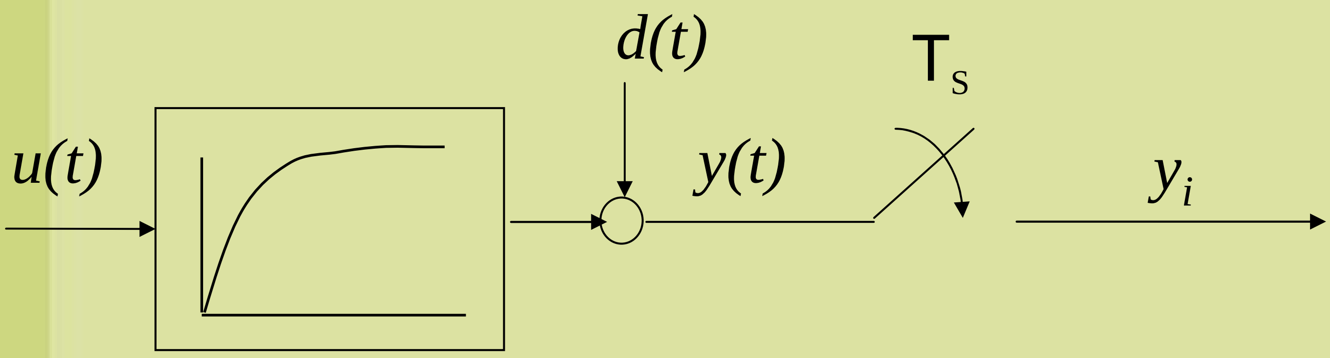
Discrete Product Output Measurement

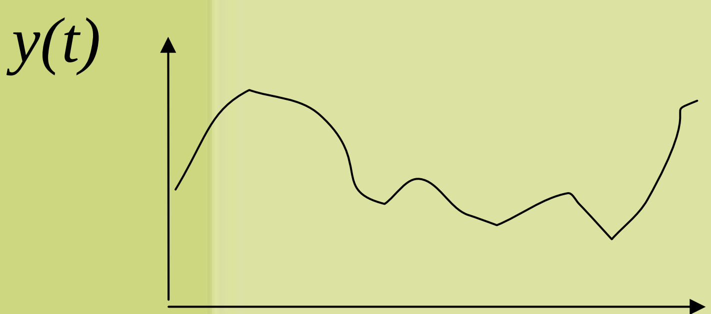


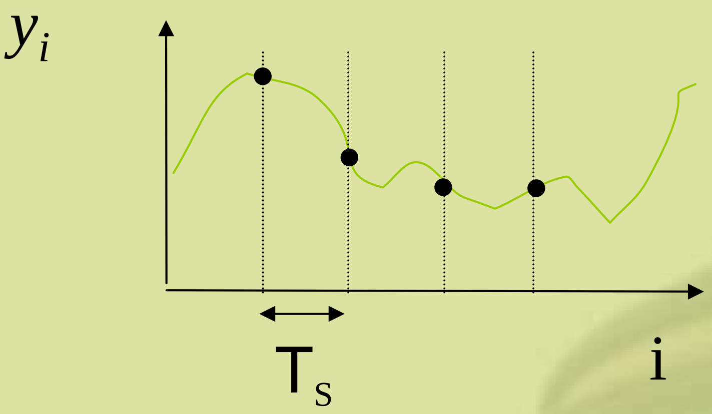
Continuous variable *y(t)* to sequential variable y_i

i = time interval or cycle number

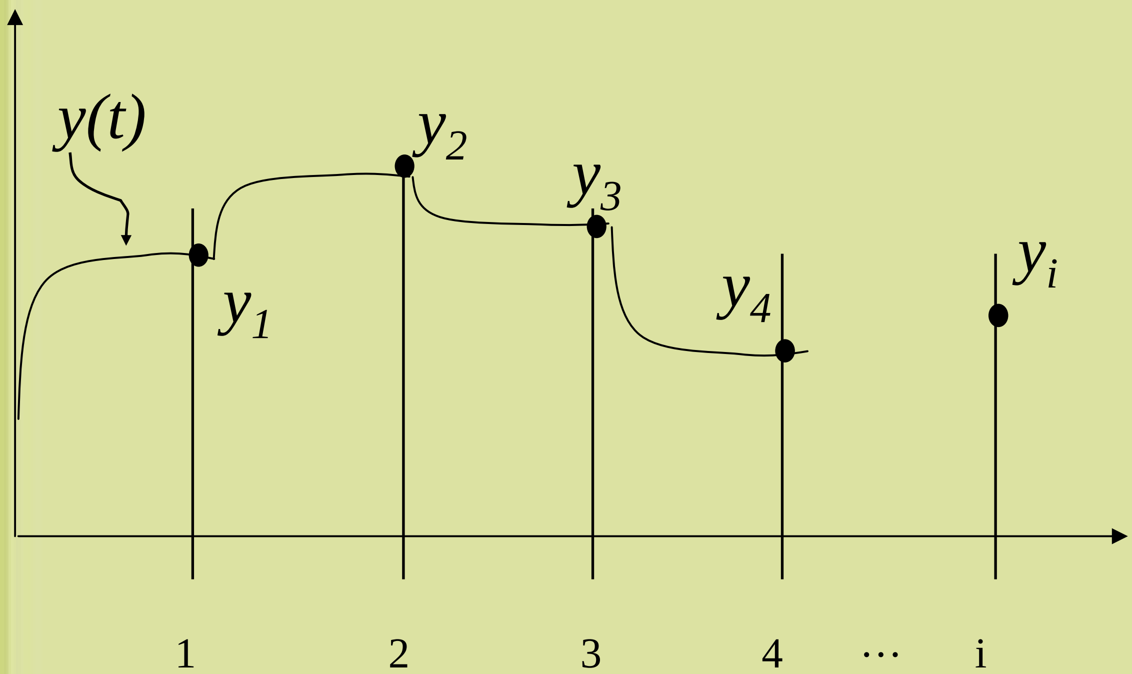
The Sampler







A Cycle to Cycle Process Model



With a Long Sample Time, The Process has no Apparent Dynamics, i.e. a Very Small Time Constant

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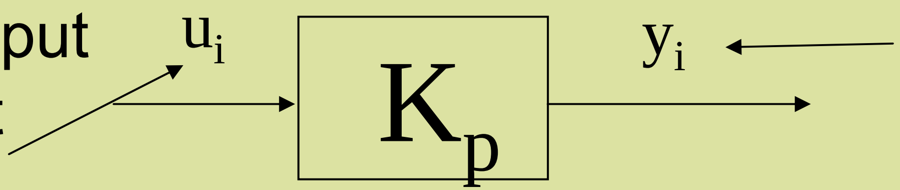
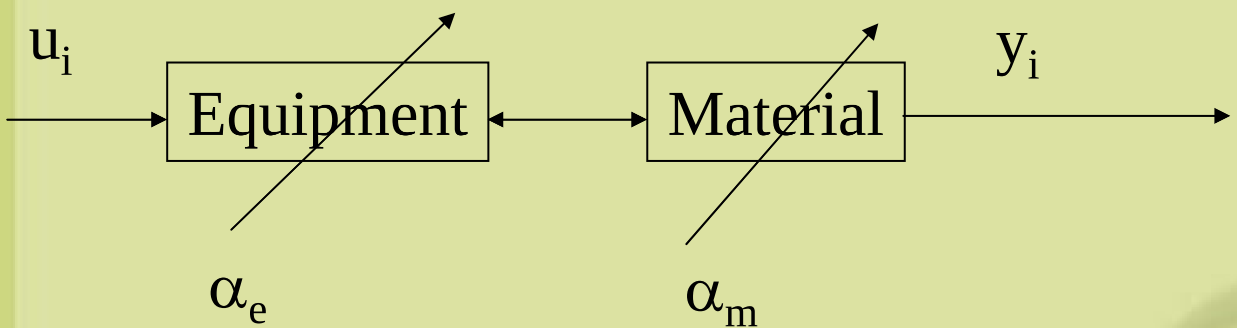
A Cycle to Cycle Process Model

a discrete input sequence at interval T_c



a discrete output sequence at time intervals T_c

- or -



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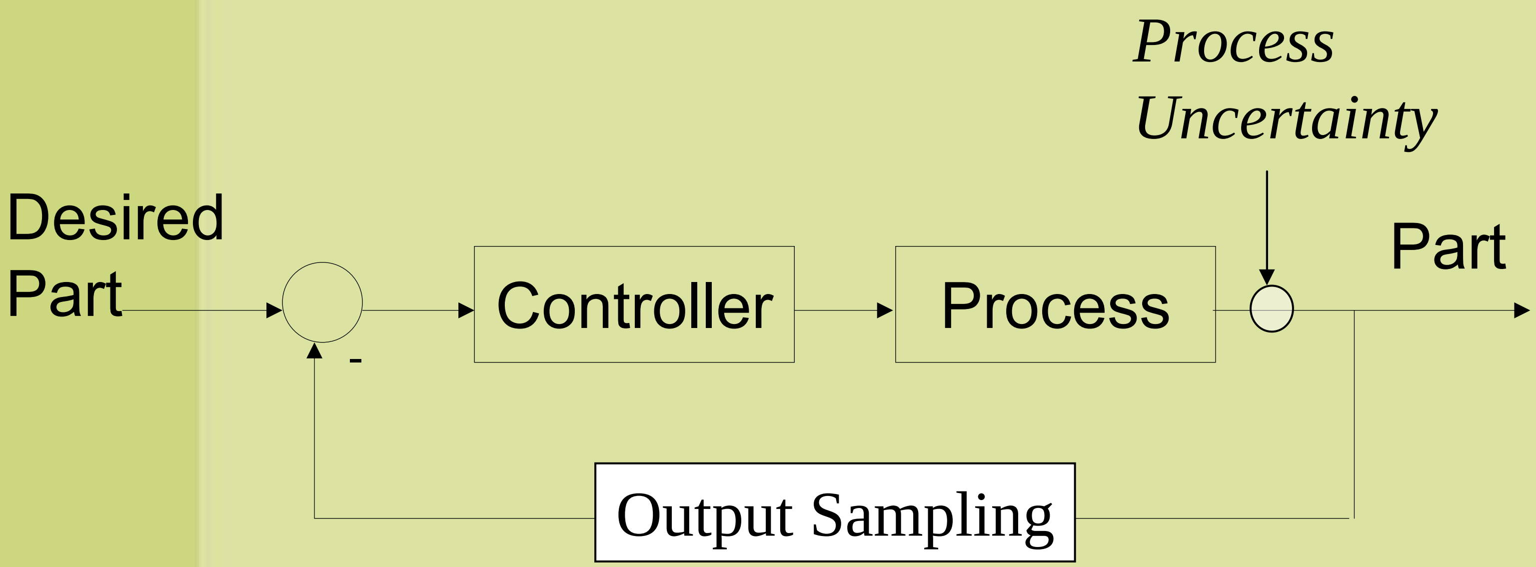
Cycle to Cycle Output Control



Delays

- Measurement Delays
  – Time to acquire and gage
  – Time to reach equilibrium
- Controller Delays
  – Time to “decide”
  – Time to compute
- **Process Delay**
  – Waiting for next available machine cycle

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Delays

$$z^n = \text{n - step time advance operator}$$

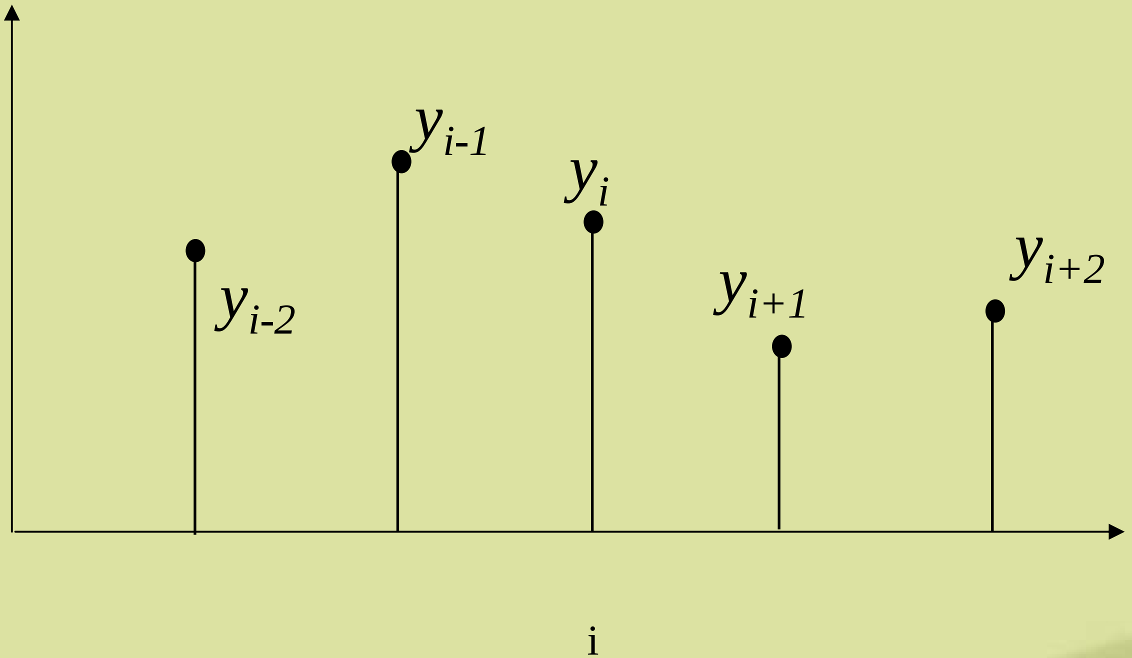
e.g.

$$z^1 * y_i = y_{i+1}$$

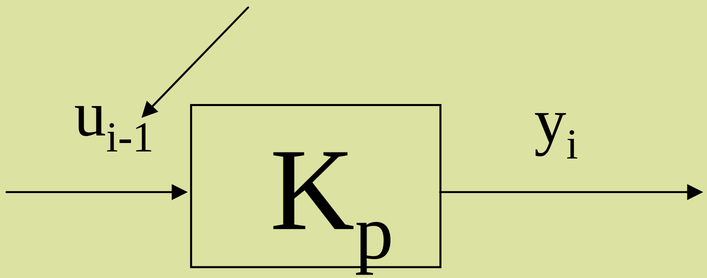
$$z^2 * y_i = y_{i+2}$$

and

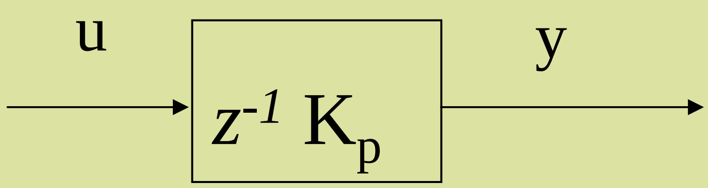
$$z^{-1} * y_i = y_{i-1}$$



A Pure Delay Process Model

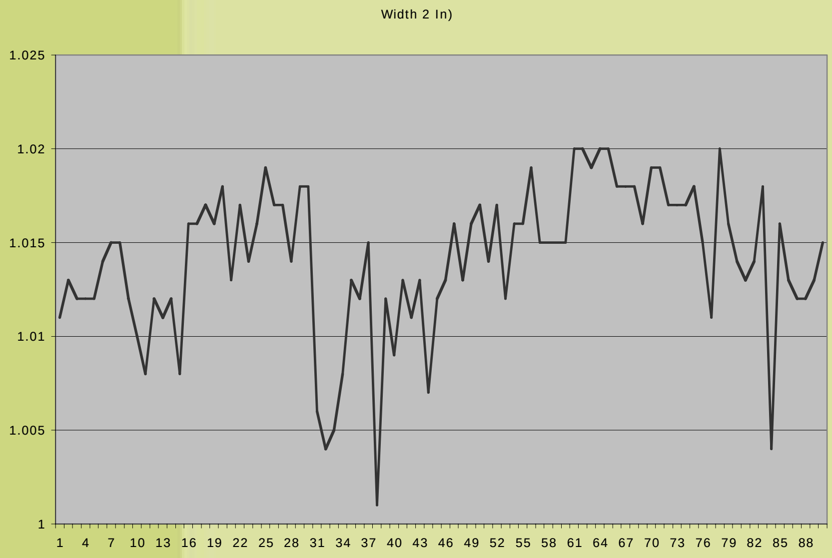


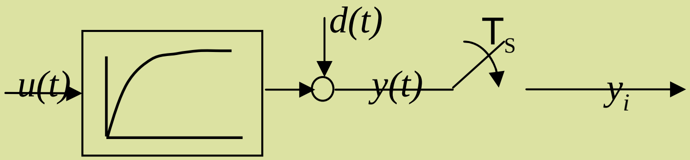
$$y_i = K_p u_{i-1}$$



Modeling Randomness

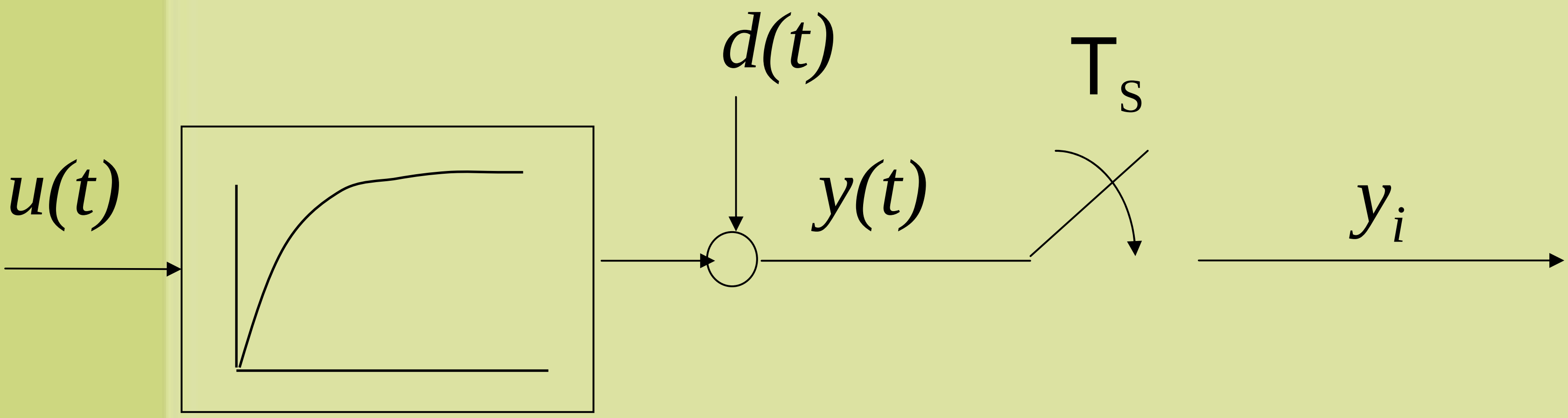
- Recall the Output of a "Real Process"





- Random even with inputs held constant

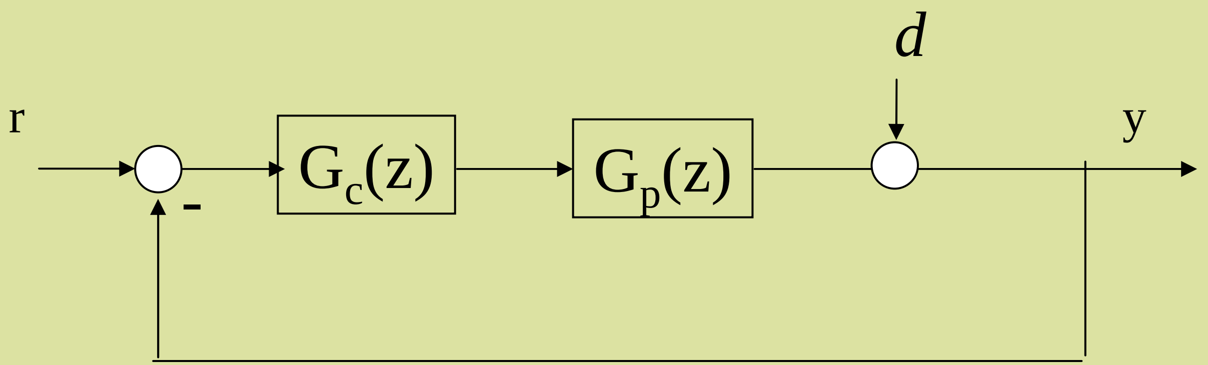
Output Disturbance Model



Model:

d(t) is a continuous random variable that we sample every cycle (T_c)

Or In Cycle to Cycle Control Terms



Where:

d(t) is a *sequence* of *random* numbers governed by a stationary normal distribution function

Gaussian White Noise

- A continuous random variable that at any instant is governed by a normal distribution
- From instant to instant there is no correlation
- Therefore if we sample this process we get:
- A NIDI random number

Normal — Identically Distributed — Independent

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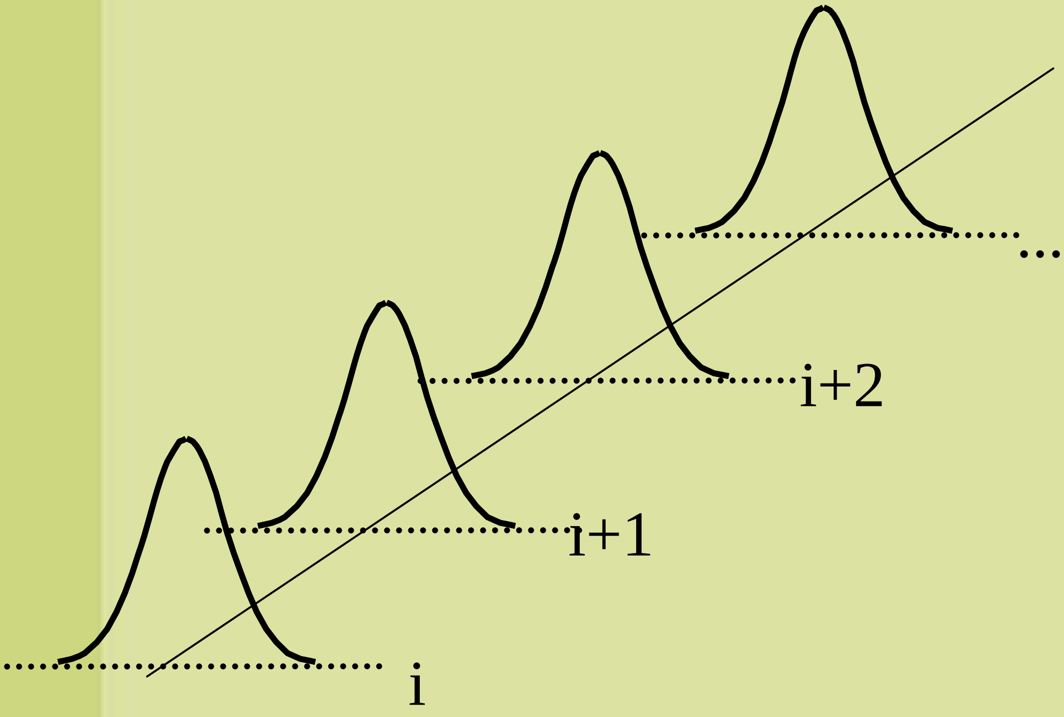
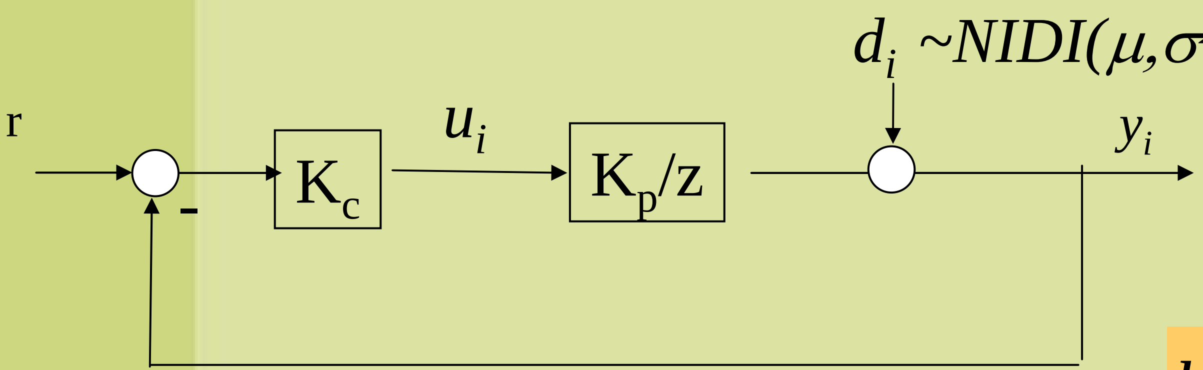
The Gaussian "Process"



Constant (Mean Value) Disturbance Rejection- P control



$$y_i = d_i + K_p u_{i-1}$$

$$u_{i-1} = K_c(r - y_{i-1})$$

$$y_i = d_i + K_p K_c (r - y_{i-1})$$

if $d_i = \mu$ *(a constant)*, we can look at steady - state behavior:

$$y_i \Rightarrow y_{i-1} \Rightarrow y_\infty = \frac{d_i}{1 + K_p K_c} + r\frac{K_p K_c}{1 + K_p K_c}$$

And For Example

Thus if we want to eliminate the constant (mean) component of the disturbance

$$\frac{y_\infty}{d_i} = \frac{1}{1 + K_p K_c} = \frac{1}{1 + K}$$

Higher loop gain K improves "rejection"

but only

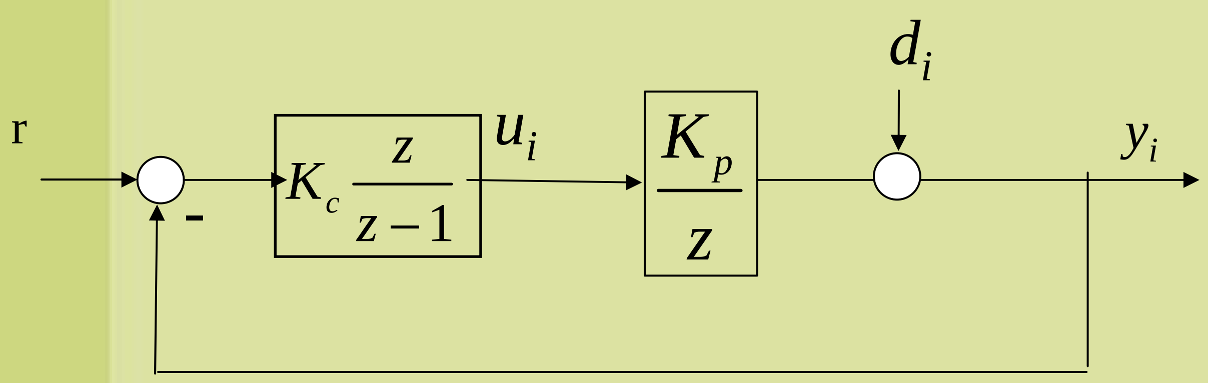
K = ∞ eliminates mean shifts

Error: Try an Integrator

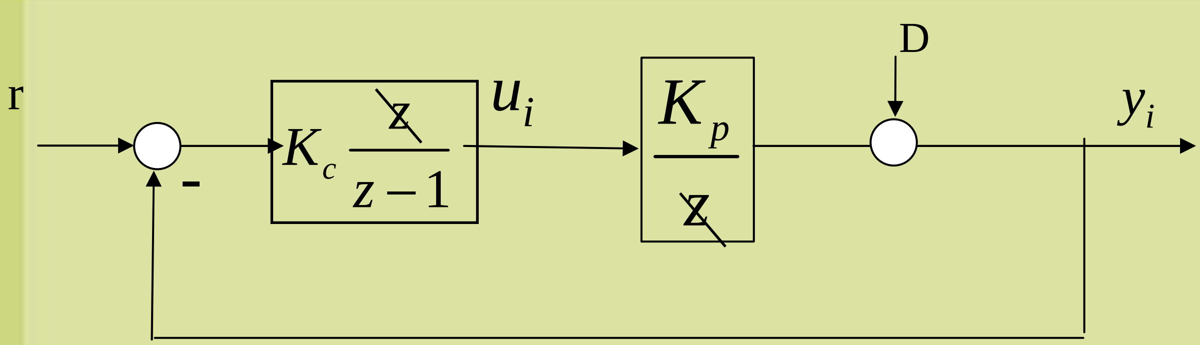
$$u_i = K_c \sum_{j=1}^{i} e_i$$ running sum of all errors

$$u_{i+1} = u_i + K_c e_{i+1}$$ recursive form $(e_i = r - y_i)$

$$zU = U + K_c zE \quad \Rightarrow \quad G_c(z) = K_c \frac{z}{z-1} = \frac{u}{e}$$



Constant Disturbance - Integral Control



$$Y(z) = \frac{z-1}{z-1+K_cK_p} D$$

(Assume r=0)

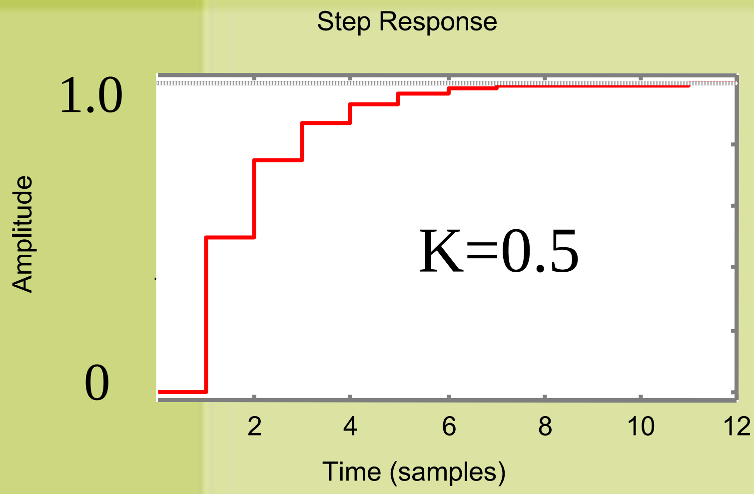
or $$y_{i+1} + (1 - K_cK_p)y_i = d_{i+1} - d_i$$

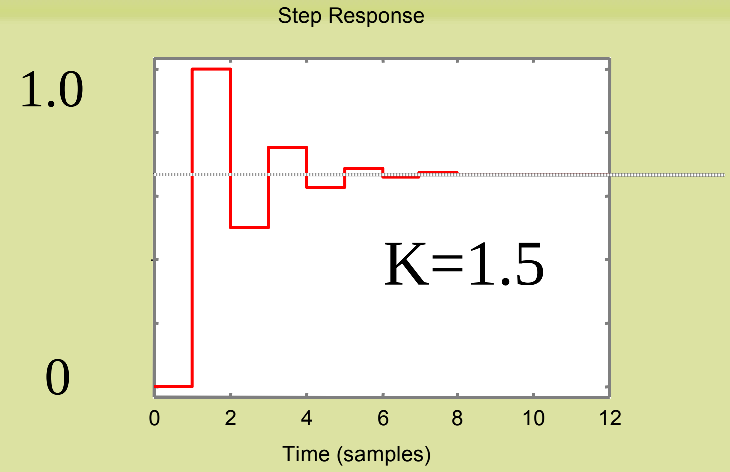
Again at steady state $y_{i+1} = y_i = y_\infty$

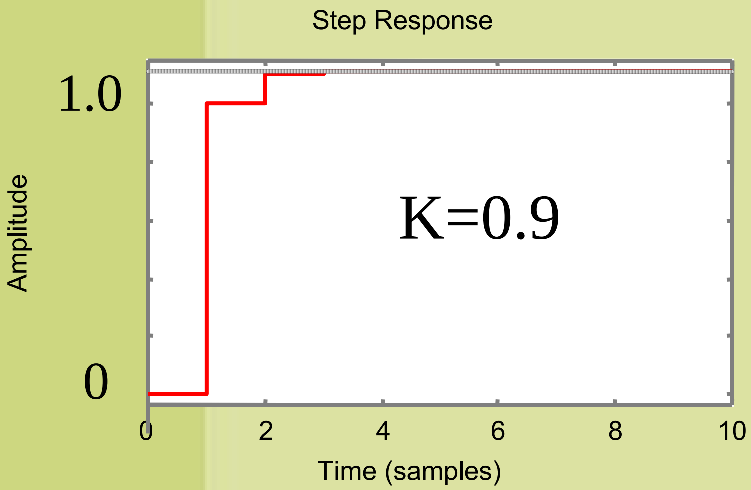
And since *D* is a constant $y_\infty(2 - K_cK_p) = 0$

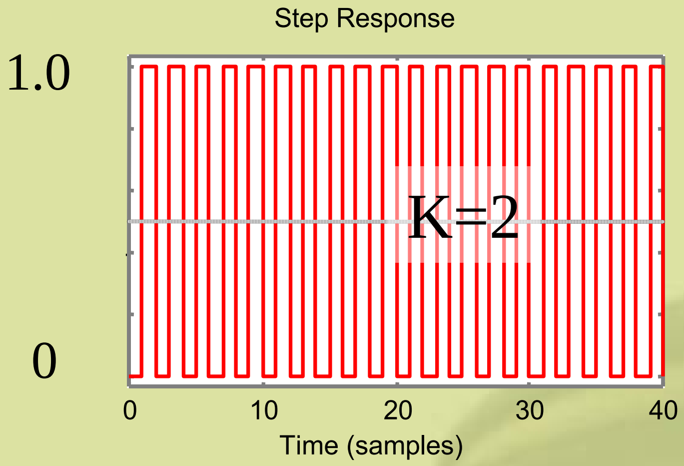
Zero error regardless of loop gain

Effect of Loop Gain K on Time Response: I-Control

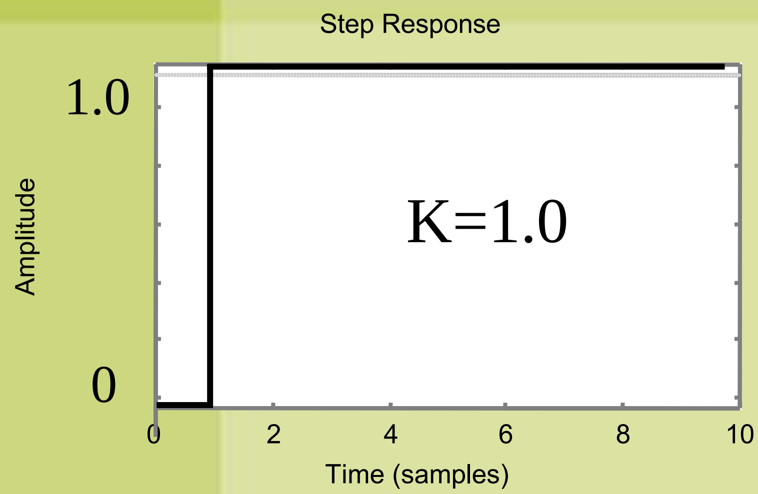








Effect of Loop Gain $K = K_c K_p$



Best performance at Loop Gain K= 1.0

Stability Limits on Loop Gain $0<K<2$

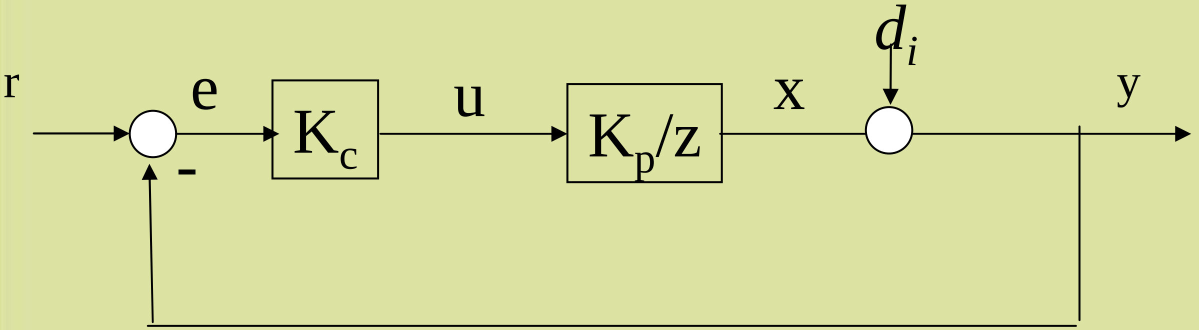
What about random component of *d*?

- d_i is defined as a NIDI sequence
- Therefore:
  - Each successive value of the sequence is probably different
  - Knowing the prior values: $d_{i-1}, d_{i-2}, d_{i-3}, \ldots$ will not help in predicting the next value

e.g. $d_i \neq a_1 d_{i-1} + a_2 d_{i-2} + a_3 d_{i-3} + \ldots$

Thus

This implies that with our cycle to cycle process model under *proportional* control:



The output of the plant x_i will *at best* represent the error from the previous value of d_{i-1}

$$x_i = -K_c K_p d_{i-1}$$

will not cancel d_i

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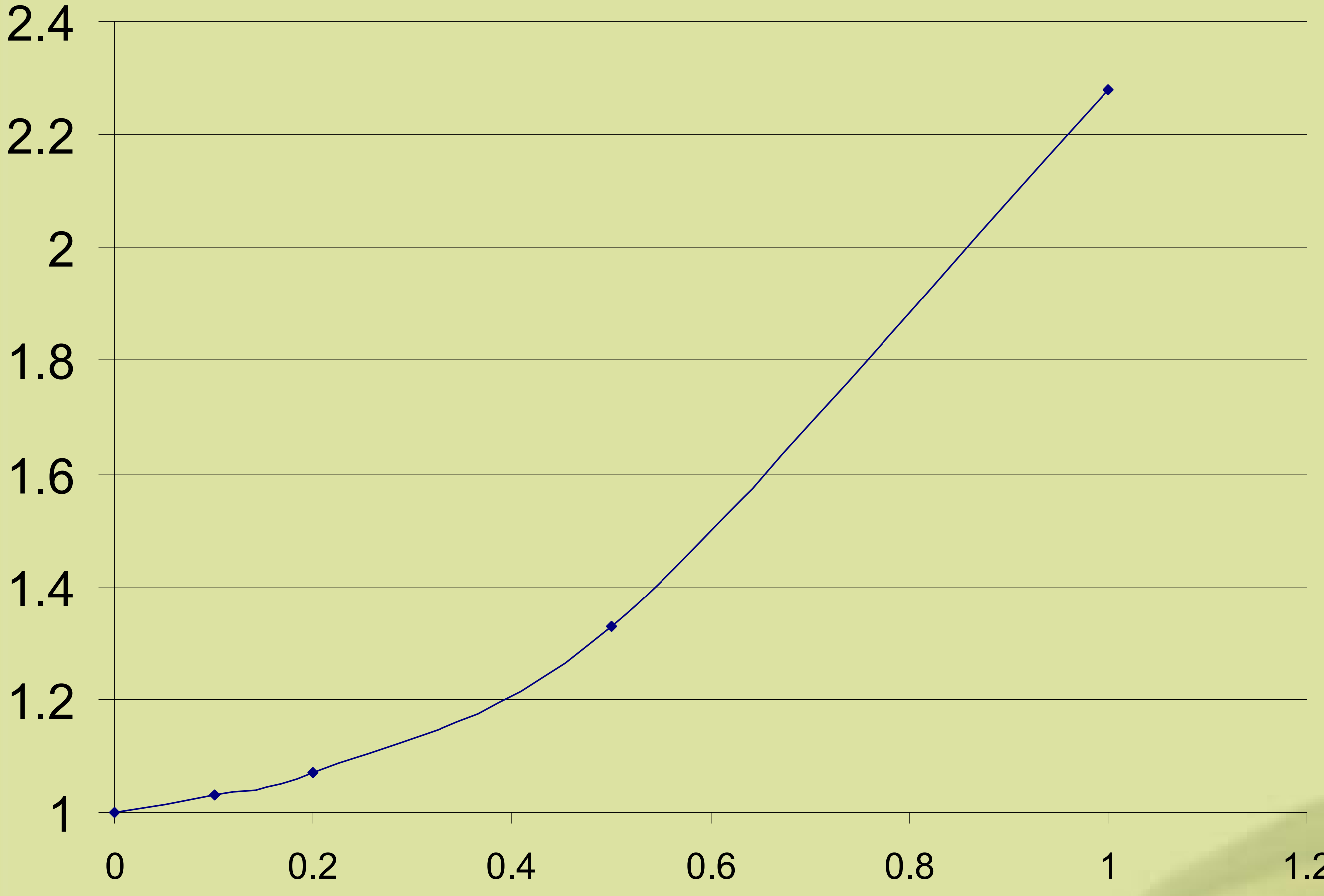
Variance Change with Loop Gain

$$\frac{\sigma_{CtC}^2}{\sigma^2}$$



Loop Gain

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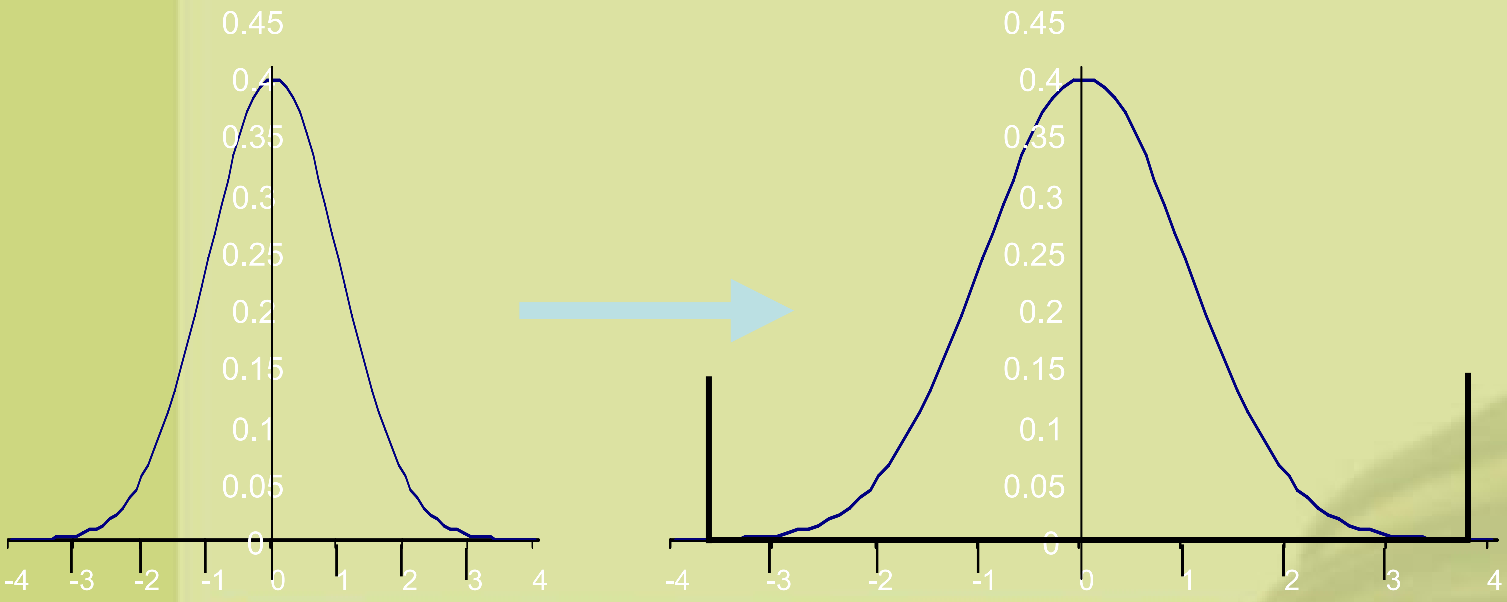
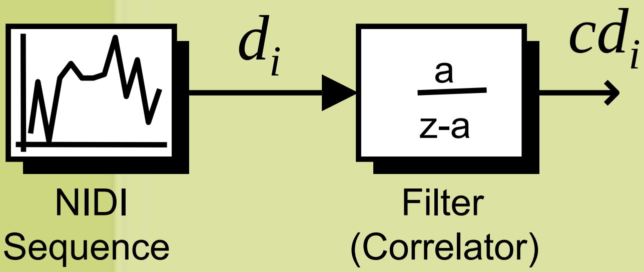
Conclusion - CtC with Un-Correlated (Independent) Random Disturbance

- Mean error will be zero using "I" control
- Variance will increase with loop gain
- Increase in σ at K=1 ~ 1.5 * $\sigma_{\text{open loop}}$



What if the Disturbance is not NIDI?



$$CD(Z)(z-a) = aD(z)$$

$$cd_{i+1} = a(d_i - cd_i)$$

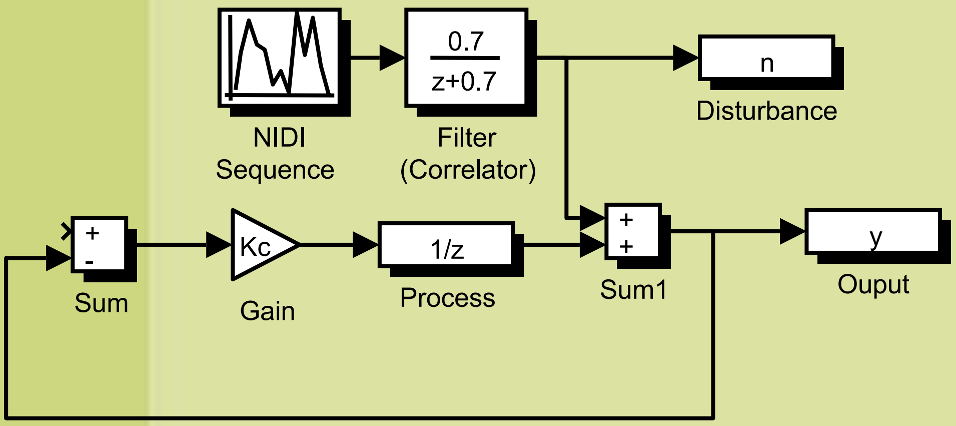
unknown (d_i) known (cd_i)

expect some correlation, therefore ability to counteract some of the disturbances

What if the Disturbance is not NIDI?

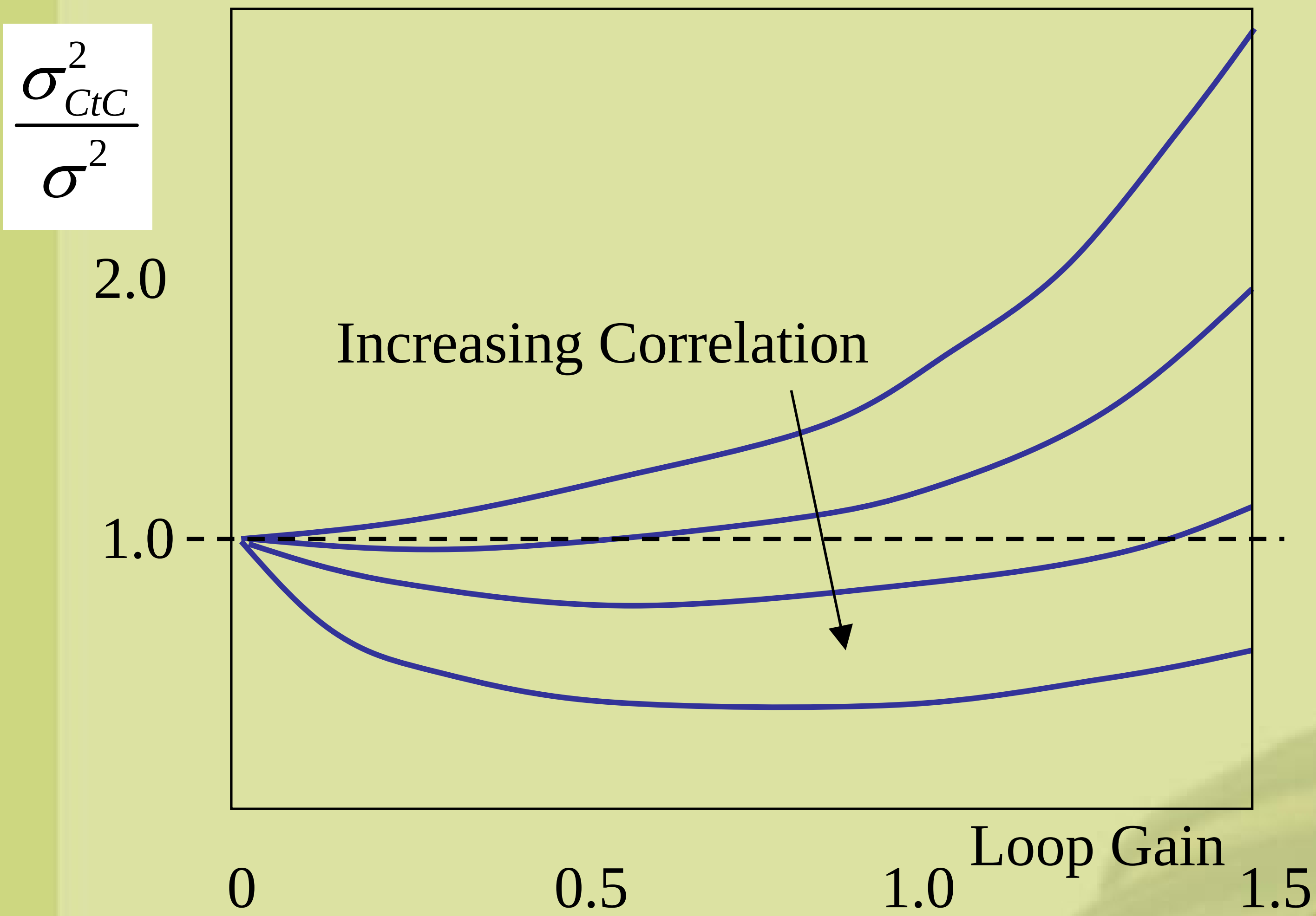
Proportional Control

Simulation



K_c	$\sigma^2_{Ctc} / \sigma^2_o$
0	1
0.1	0.89
0.25	0.77
0.5	0.69
0.9	1.39

Gain - Variance Reduction



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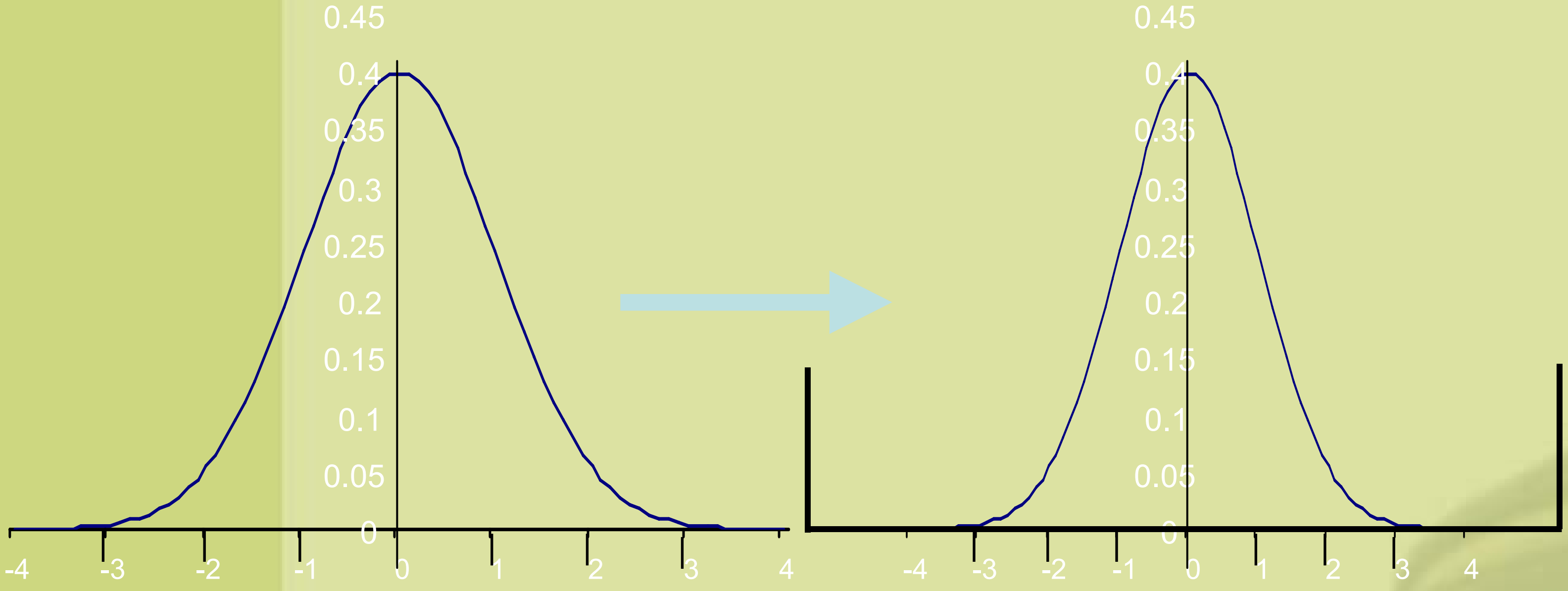
Conclusion - CtC with Correlated (Dependent) Random Disturbance

- Mean error will be zero using “I” control
- Variance will decrease with loop gain
- Best Loop Gain is still K_cK_p =1



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Conclusions from Cycle to Cycle Control Theory

- Feedback Control of NIDI Disturbance will Increase Variance
  - Variance Increases with Gain
- BUT: If Disturbance is *NID* but not *I*; We CAN Decrease Variance
  - Higher Gains -> Lower Variance
  - Design Problem: Low Error and Low Variance

How to Tell if Disturbance is Independent

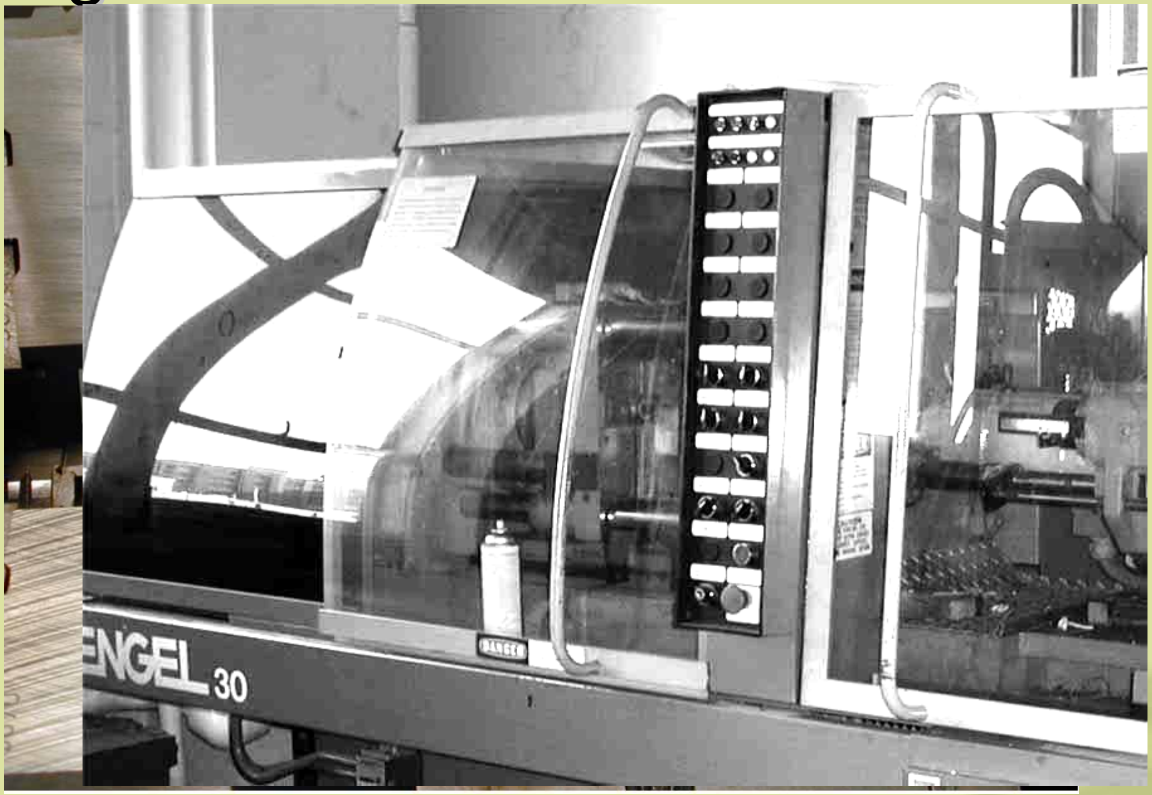
- Correlation of output data
  - Look at the Autocorrelation
  - Effect of Filter on Autocorrelation
- Reaction of Process to Feedback
  - If variance decreases data has dependence

Is Disturbance is Independent?

- Correlation of output data
  - Look at the Autocorrelation $\Phi_{xx}(\tau) = \int_{-\infty}^{\infty} x(t)x(t-\tau)dt$
  - Effect of Filter on Autocorrelation
- Reaction of Process to Feedback
  - If variance decreases then data must have some dependence

But Does It Really Work?

– Let's Look at Bending and Injection Molding



Experimental Data

Cycle to Cycle Feedback Control of Manufacturing Processes

by

George Tsz-Sin Siu

SM Thesis

Massachusetts Institute of Technology

February 2001

Experimental Results

- Bending
  - – Expect NIDI Noise
  - – Can Have Step Mean Changes
- Injection Molding
  - – Could be Correlated owing to Thermal Effects
  - – Step Mean Changes from Cycle Disruption

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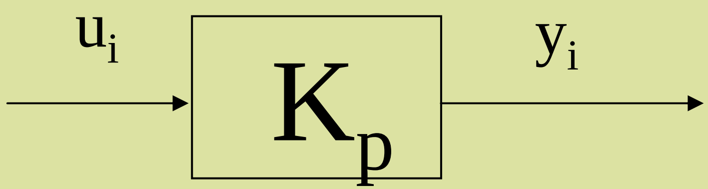
Process Model for Bending

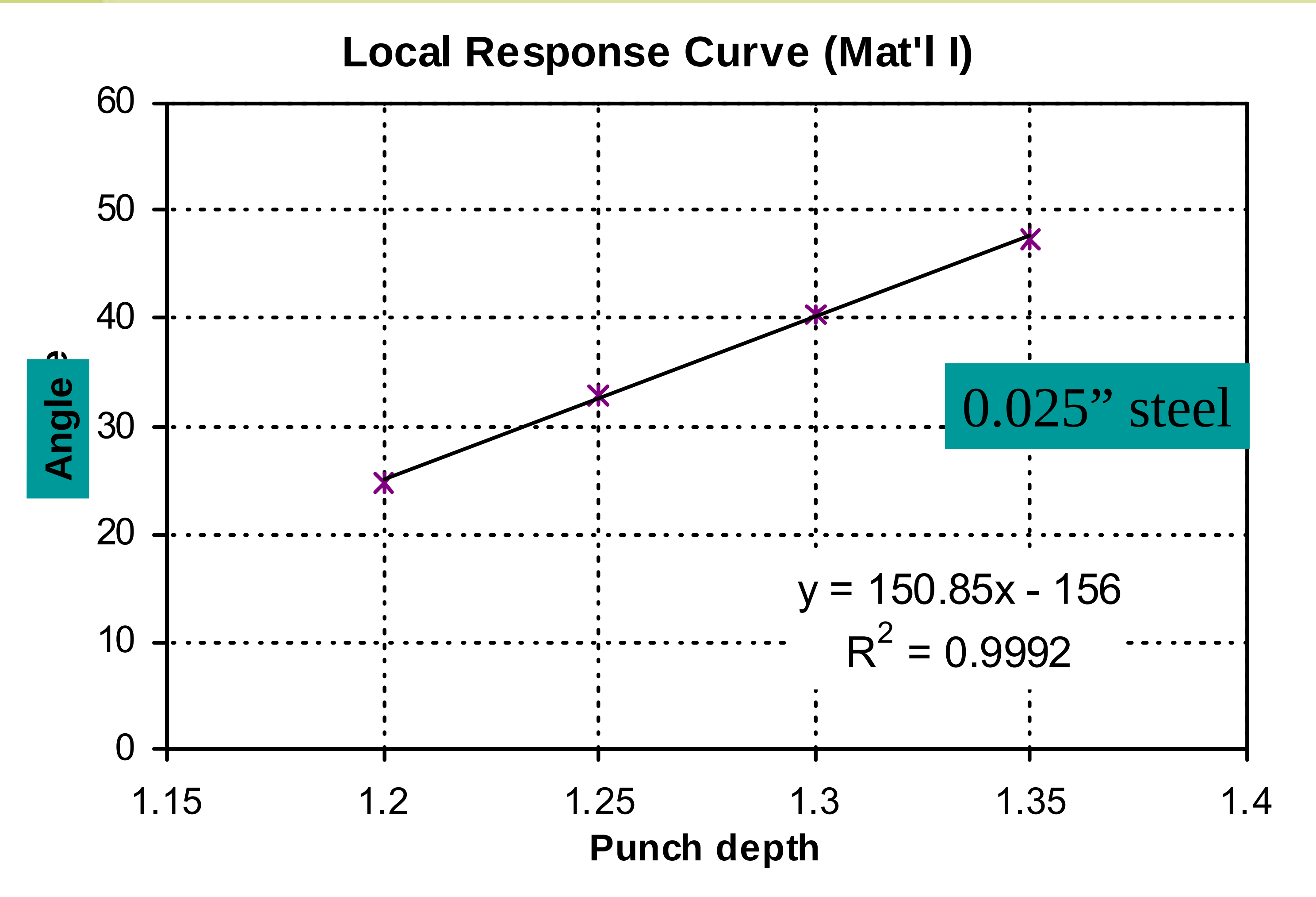


$$y_i = K_p u_{i-1}$$

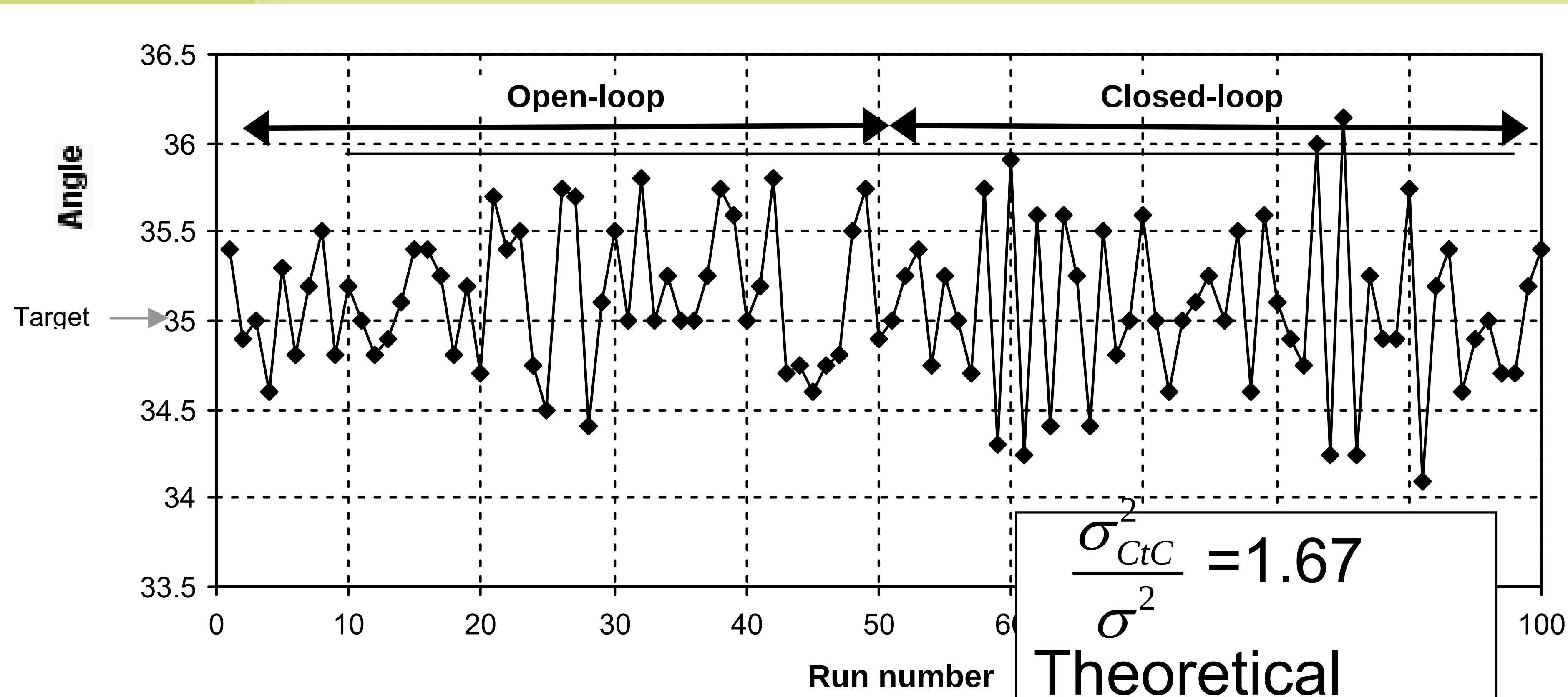
$$Y(z) = \frac{K_p}{z}$$

$$K_p = ?$$

Process Model for Bending



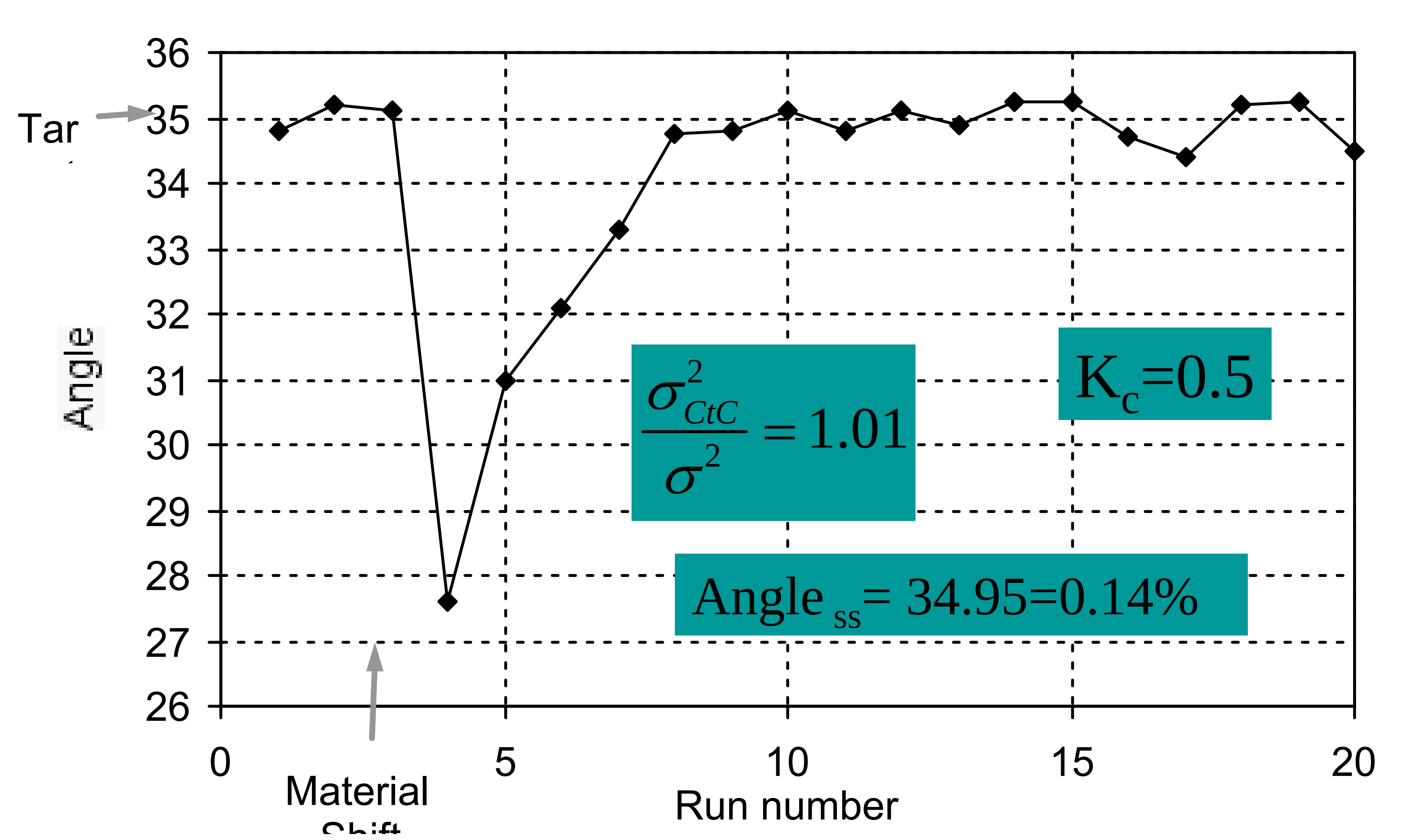
Results for K_c=0.7;$\Delta\mu$=0



$$\frac{\sigma^2_{CtC}}{\sigma^2} = 1.67$$

Theoretical =1.96

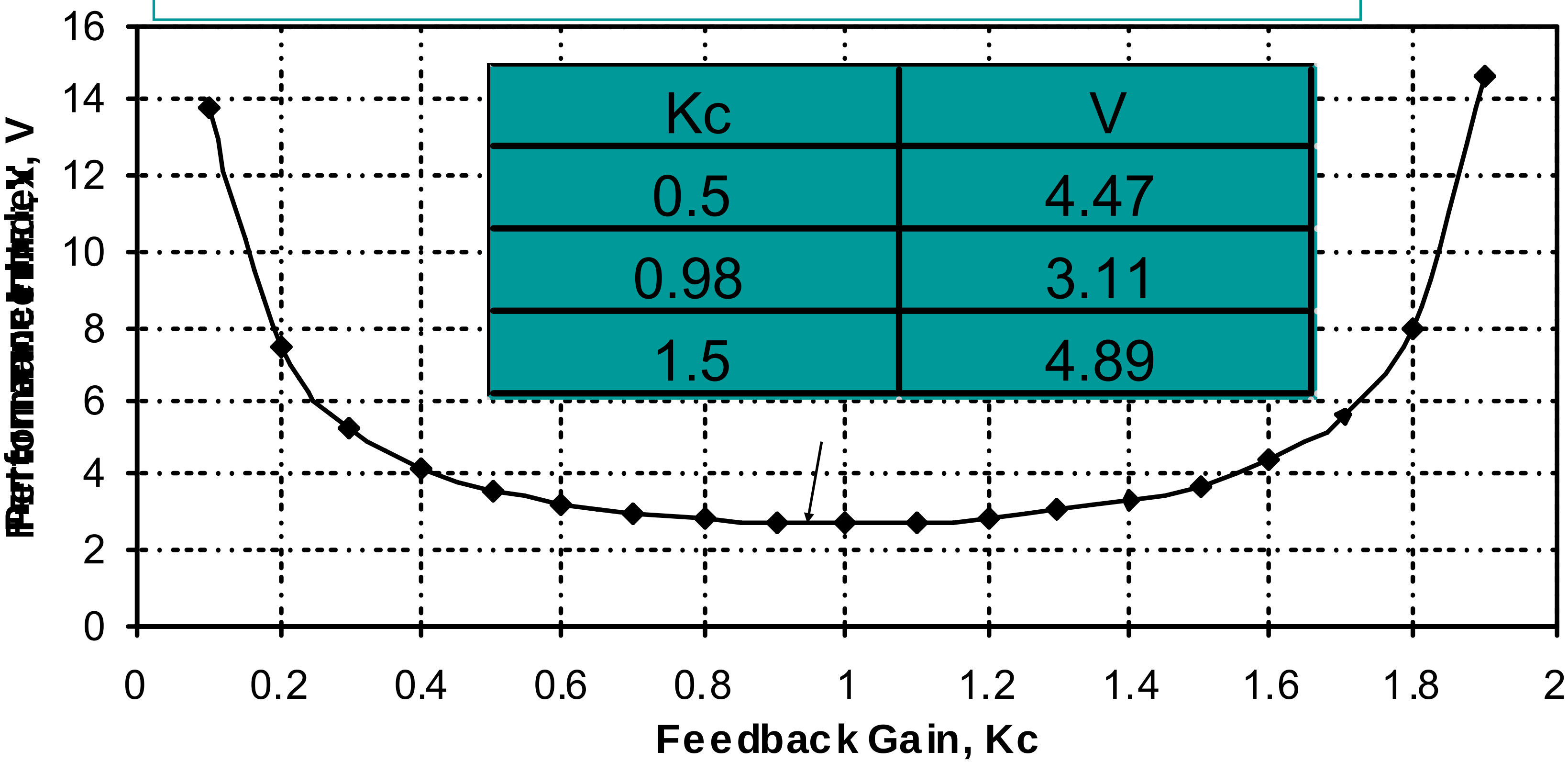
I-Control $\Delta\mu \neq 0$



Minimum Expected Loss Integral-Controller

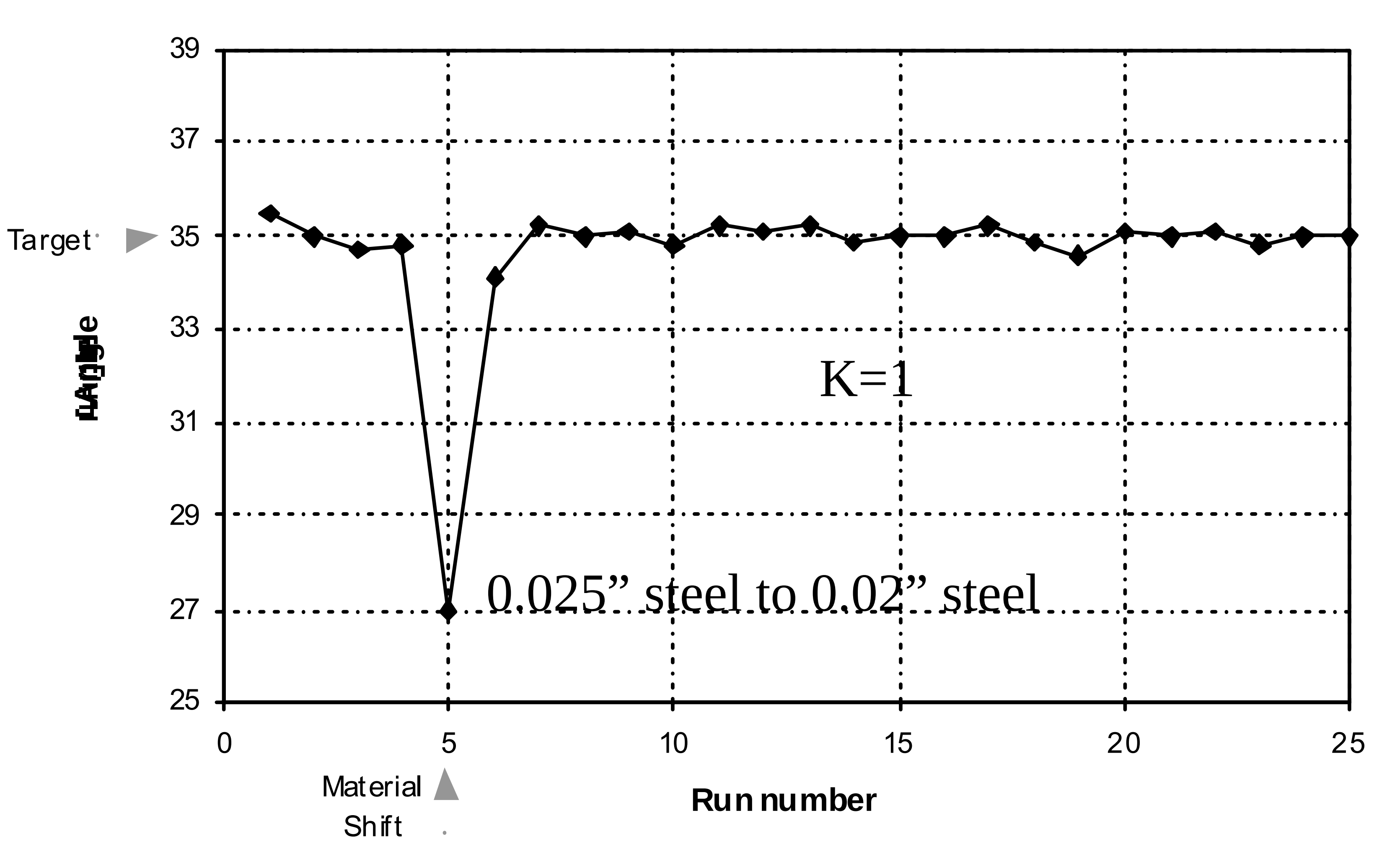
Calculated Expected Loss vs. Gain

Experimental Verification



Kc	V
0.5	4.47
0.98	3.11
1.5	4.89

Disturbance Response for "Optimal" Integral Control Gain



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Injection Molding: Process Model

$$\hat{Y} = \beta_0 + \beta_2 \cdot X_2 + \beta_3 \cdot X_3 + \beta_{23} \cdot X_2 \cdot X_3$$ Initial Model

Process inputs	Levels	
X2 = Hold time (seconds)	5 sec	20 sec
X3 = Injection speed (in/sec)	0.5 in/sec	6 in/sec

ANOVA on model terms

Effect	beta	SS	DOF	MS	F	Fcrit	p-value
1	1.437	49.6	1	49.568	2E+07	4.35	0
X2 (Hold time)	-1.04E-03	0	1	2.60E-05	10.593	4.35	0.004
X3 (Injection speed)	-3.75E-04	0	1	3.38E-06	1.373	4.35	0.255
X2X3							
(Hold time*Injection speed)	2.92E-04	0	1	2.04E-06	0.831	4.35	0.373
Error		0	20	2.46E-06			
Total		49.6	24				

$$\hat{Y} = \beta_0 + \beta_2 \cdot X_2$$ Final Model

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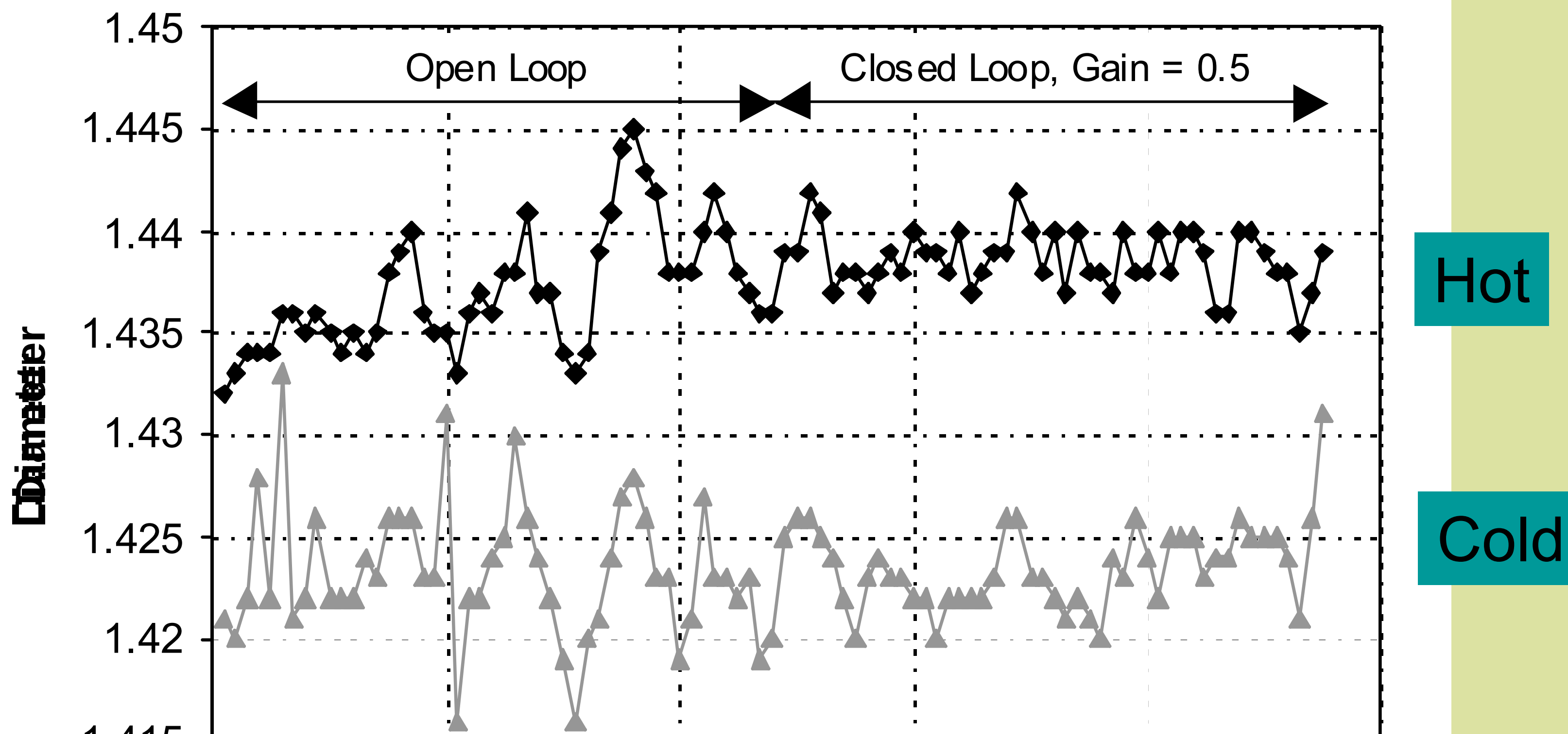
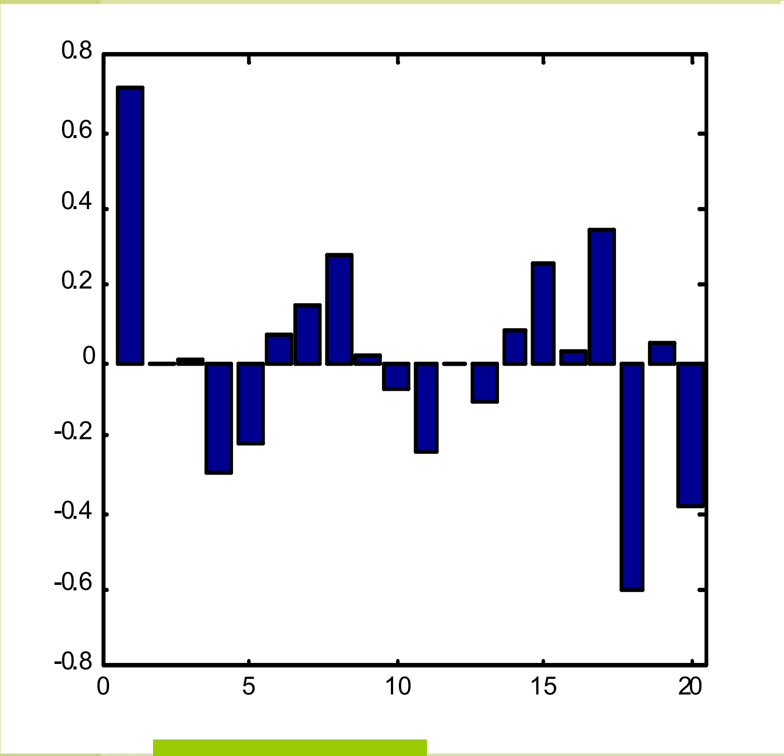
P-Control Injection Molding

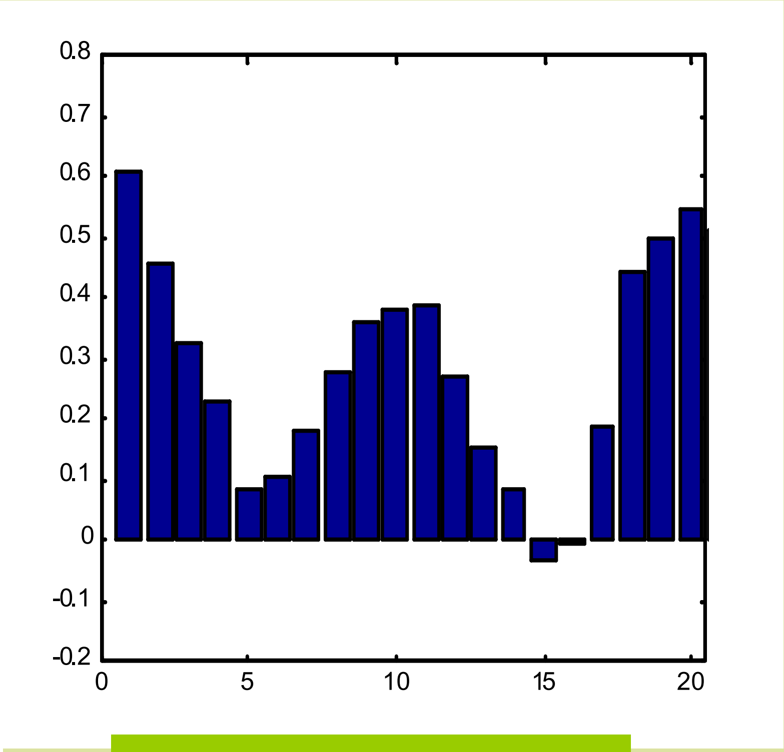


Experiment	Mean(Hot measurement)	Variance	Variance Ratio
Open-loop	1.437	9.97E-06	
Closed-loop	1.439	2.34E-06	0.234

Output Autocorrelation



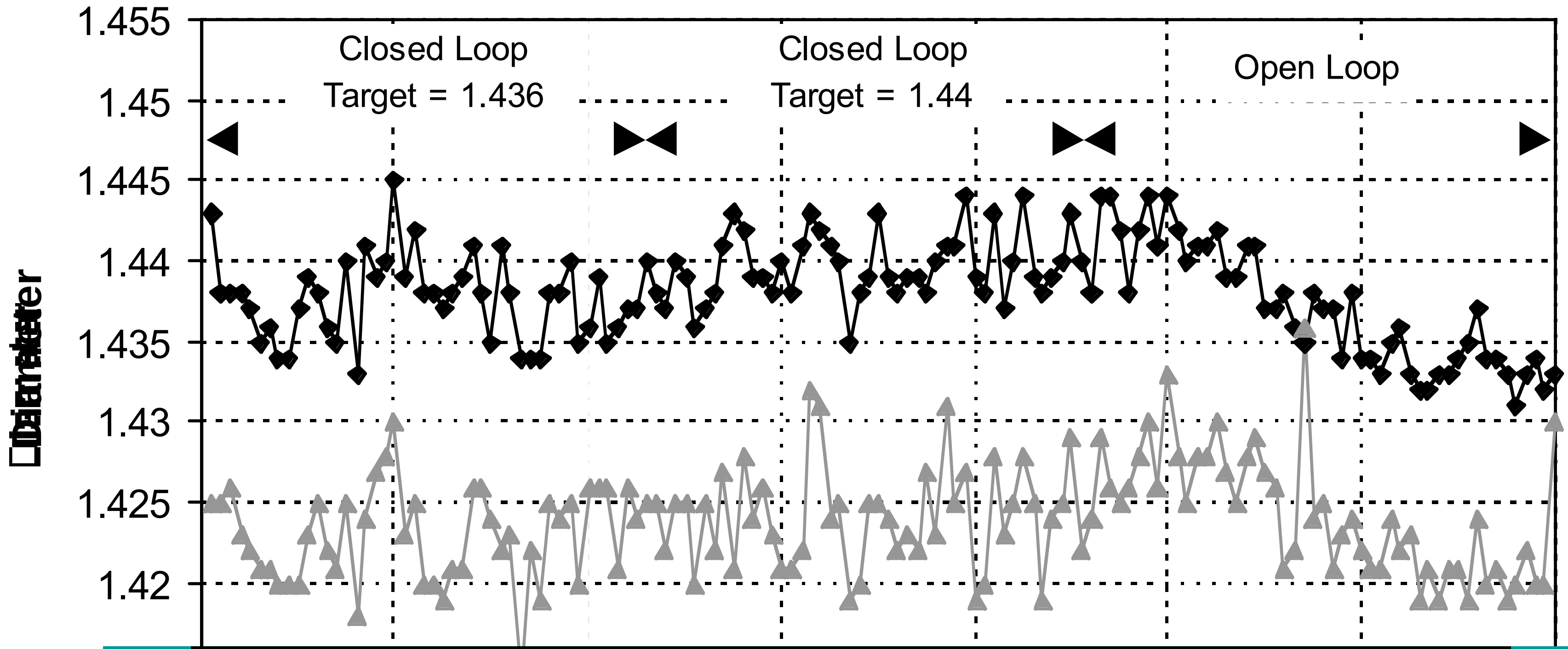
Bending



Injection Molding

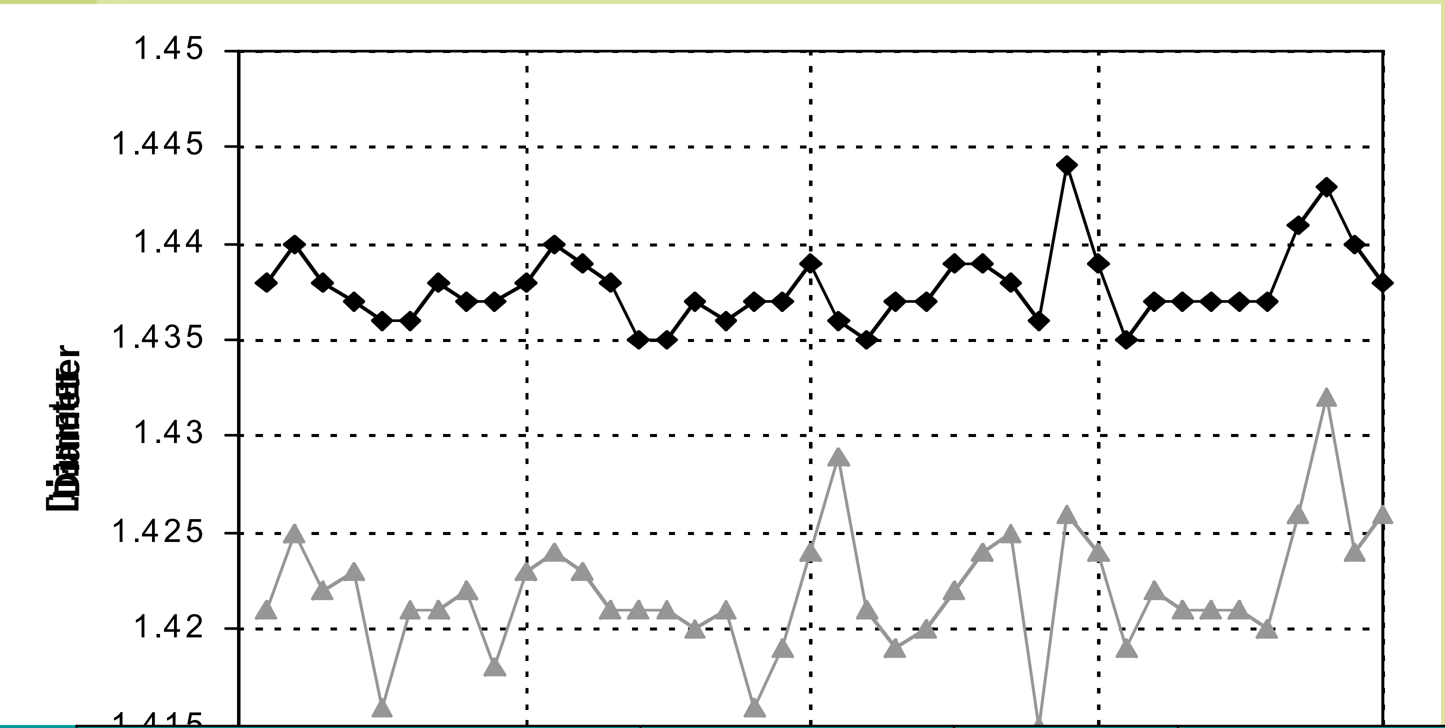
Matlab function XCORR

P-control: Moving Target



Experiment	Mean(Hot measurement)	Variance	Variance Ratio
Closed-loop, target = 1.436Ó	1.438	6.79E-06	0.471
Closed-loop, target = 1.440Ó	1.440	4.54E-06	0.315
Open-loop	1.437	1.44E-05	-

Injection Molding: Integral Control



Experiment	Mean (Hot measurement)	Variance	Variance Ratio
Closed-loop, target = 1.436	1.438	3.94E-06	0.395
Open-loop, from first experiment	1.437	9.97E-06	-

Conclusion

- Model Predictions and Experiment are in Good Agreement
  - Delay - Gain Process Model
  - Normal - Additive Disturbance
  - Effect of Correlated vs. Uncorrelated (NIDI) Disturbances

Manufacturing

Conclusion

- Cycle to Cycle Control
  - Obeys Root Locus Prediction wrt Dynamics
  - Amplifies NIDI Disturbance as Expected
  - Attenuate non-NIDI Disturbance
  - Can Reduce Mean Error (Zero if I-control)
  - Can Reduce "Open Loop" Expected Loss
  - Correlation Sure Helps!!!!
- Can be Extended to Multivariable Case
  - PhD by Adam Rzepniewski (5/5/05)
    - Developed Theory and demonstrated on 100X100 problem (discrete die sheet forming)